Leveraging Causal Models to Craft AI Strategy

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***Abstract* - In the dynamic field of Artificial Intelligence (AI), strategic integration is crucial to avoid the pitfall of optimizing peripheral processes at the expense of organizational goals. This paper presents a nuanced AI strategy framework that combines Causal Loop Diagrams (CLD) with Agent-Based Modeling (ABM) to address the intricacies of complex, growth-oriented organizations. By marrying empirical data with theoretical constructs and broad meta-knowledge, this approach enables the practical application of common sense to AI planning. The use of CLDs helps reveal and tackle ingrained patterns that could hinder organizational progress, while ABM facilitates the testing of AI strategies through extensive simulations within varied market and product scenarios. This study exemplifies the benefits of a causal-model-enabled AI strategy for strategic alignment and sustainable growth, suggesting a shift from mere efficiency-driven AI applications to those grounded in a thorough comprehension of complex system interdependencies. The proposed framework paves the way for organizations to develop a robust, anti-fragile AI ecosystem that is attuned to the nuances of their operational environment.**

Keywords - Systems Thinking, Causal Models, AI, Supply Chain Management, Agent-Based Models, Antifragility

I. INTRODUCTION

Given the rapidity with which AI is evolving, and the speed with which organizations are seeking to embed AI into their operations, it is critical to engage in a trajectory of development that will allow the organization and its AI initiatives to continue to be on the bleeding edge. An ad hoc approach of plugging existing processes with efficiency-enhancing applications may quickly show the power of AI in reducing costs, and even in enhancing revenue in the short-term, paradoxically reinforcing the utility of such an approach. However, that is a trap that will need to be carefully maneuvered through. This paper reinforces the point that the way to avoid falling into this alluring trap, is to employ a system thinking approach in which causal modeling and AI move hand-in-hand to continue to keep the organization on the bleeding edge.

While AI influenced by causal modeling has been projected by Gartner to be a few years away [1], we have already engaged in such an approach during consultations with various companies. In this paper we are going to share parts of the path we have tread, the capabilities this bestows upon the organization and on the development of AI, and on valuable lessons that other organizations may employ were they to engage in causal-based AI.

This paper is organized as follows: Section II focuses on the importance of systems thinking in contrast to the easier followed linear thinking by using an example of supply chain management. Section III focuses on moving from weak to strong AI. Strong AI involves the use of appropriate causal models. Section IV focuses on model validation. This becomes even more important given that causal models will underpin a strong AI effort. Section V focuses on valuable lessons in crafting AI strategy. Section VI suggests that a causal based approach to crafting AI strategy is also within the reach of small to medium-sized businesses. Section VII will offer a summary and conclusion.

II. THE IMPORTANCE OF SYSTEMS THINKING

The first step is to identify a foundational process instrumental to the success of the organization. The focus here is on one such process that proves critical regardless of industry: Supply chain management (SCM). This business process usually encompasses all activities from sourcing raw materials to delivering the finished product to the customer. It includes planning, procurement, manufacturing, logistics, and warehousing. When thinking about SCM it is easy to map it as a linear process organized by inputs, activities, and outputs. In reality though, every single activity itself interrelates with many different activities through a system of feedback loops. When employing systems thinking, it is this latter approach that becomes the foundation for understanding the de facto logic animating SCM. With a linear approach a lot is missed, and this is the reason why problems tend to reoccur. It is also the reason that patchwork fixes are put in place that may offer the semblance of a solution but prove to have a marginalizing effect on overall operations over time.

The following simplified example in Diagram 1, ‘Connecting Supply Chain Vulnerability With New Product Growth,’ highlights the kinds of interconnections that are easily missed with linear thinking.

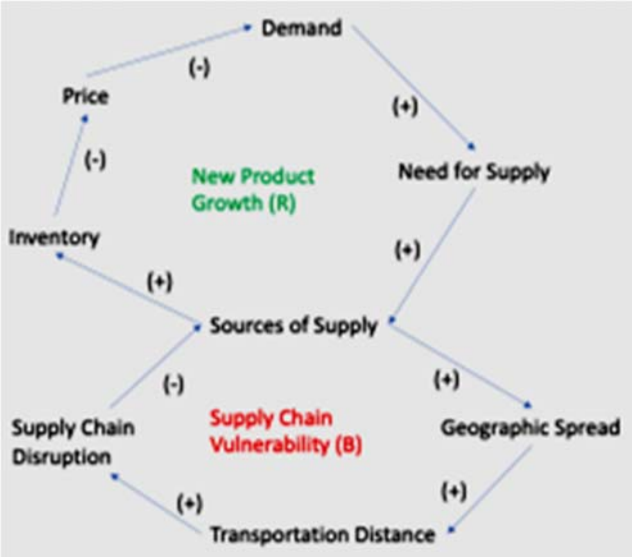

Diagram 1. Connecting supply chain vulnerability with new product growth

Starting with ‘sources of supply’ as the common node between the two loops, as sources increase, the ‘geographic spread’ also increases (depicted with ‘+’). This in turn increases (+) the ‘transportation distance’, which increases (+) the likelihood of ‘supply chain disruption’. As supply chain disruption increases then ‘sources of supply’ is inversely (-) affected. The net presence of an inverse correlation in the lower loop makes it a balancing loop, implying that it will have an effect on hampering growth of the upper loop. In examining the system of causality in the upper loop, if ‘sources of supply’ increase, then ‘inventory’ increases (+). As inventory increases there will be pressure to reduce (-) ‘price’. If price were to increase, then ‘demand’ will tend to go down (-). If demand were to increase, then the ‘need for supply’ would increase (+). If need for supply were to increase, then the sources of supply will also increase (+). The net presence of positive correlation in the upper loop makes it a reinforcing loop.

The combination of such a balancing and reinforcing loop points to a reality that will limit growth and refers to a pattern or ‘archetype’ called ‘limits to growth’ [2].

The implication of the ‘Limits to Growth’ archetype is that no matter what an organization tried, its growth would tend to be limited, unless it could change the de facto logic that animated this pattern. AI that just reinforces the current set of links through some local optimization, without seeing the larger causal patterns that animated the system would then become a constraining factor. It is critical to capture the true de facto logic running SCM operations, or for that matter all organizational operations, as this at the very least allows AI to truly make a more positive long-term impact.

Imagine if just a linear process is used, and an AI application seeks to address a problem symptom. It provides a short-term fix (Diagram 2: Fixes That Fail) but as a result there are unintended consequences because the deeper system of causality responsible for the problem was not being adequately addressed [5].

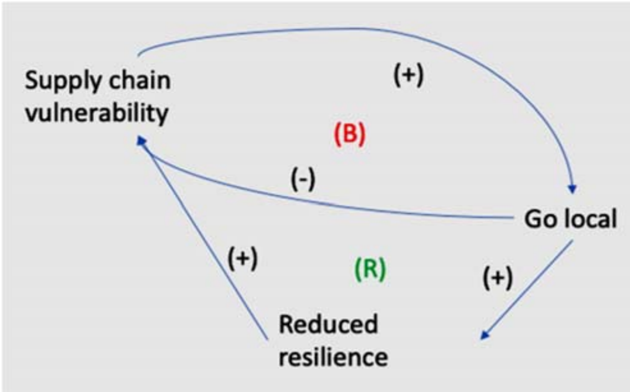

Diagram 2. Fixes That Fail

In Diagram 2, that tries to fix the ‘Supply Chain Vulnerability’ problem highlighted in Diagram 1, there are a few important things to pay attention to. First the presence of two loops will be notcied – a balancing loop specified by (B), and a reinforcing loop specified by (R). The way to follow the logic of these loops is as follows:

1. As the problem symptom - ‘supply chain vulnerability’ - increases, there is an increase in the desire to apply a short-term fix. Hence there is a direct correlation between ‘supply chain vulnerability’ and a short-term fix, to ‘go local’. As the former goes up the latter will also go up and is depicted by a ‘+’ on the connecter arrow.
2. As the ‘go local’ is put into place, the problem symptom decreases as is depicted by a ‘-‘ on the connector arrow. Hence, there is an inverse relationship between the two variables.
3. The causality between the two variables is summarized as a ‘balancing’ loop because the short-term fix will balance or keep the problem symptom in check.
4. At the same time, there is a larger ‘reinforcing’ loop in play. The ‘go local’ connects to another variable ‘reduced resilience’ that is an unintended consequence, so that as the former is put in place the latter will increase. There is a direct correlation between the two. Further, as the unintended consequence, ‘reduced resilience’ increases, the problem symptom, ‘supply chain vulnerability’ will also increase as depicted by the ‘+’ on the arrow. Hence the three variables in this loop reinforce one another and hence this loop is referred to as a reinforcing loop.
5. The net effect of the two loops is that while in the short-term the problem symptom will tend to decrease, in the long-term it will inevitably go up, because the true underlying cause has not been addressed.
6. This combination of loops describes a common archetype found in many organizations and is referred to as ‘Fixes that Fail’.

Any AI must in fact be able to recognize that the fix it is focused on will have marginalizing effects in the longer-term and that what it is doing is in fact contrary to what it should be doing. But for this to happen the AI will have to recognize that the area it is working on is part of a marginalizing archetype. There are in fact a larger set of such archetypes that will exist in the system of causality for any organization, and to become aware of these requires that the causal model of the organization first be mapped.

Causal loop diagrams (CLDs), developed at MIT by Jay W. Forrester [3], are visual tools used to represent the feedback loops within complex systems. These feedback loops can either reinforce (amplify) or balance (counteract) changes in the system. By identifying different archetypes of these feedback loops, the underlying dynamics and potential behaviors of a system can be better understood. Here are some other representative archetypes that are often found in CLDs:

- Balancing with Delay [4]: Similar to "Limits to Growth," but introduces a time delay between the initial action and the balancing feedback. This can lead to overshoot and oscillation before reaching equilibrium. For example, investing in new production capacity to meet rising demand, but the new capacity arrives after demand has already peaked.
- Escalation [6]: Two opposing forces reinforce each other, leading to a rapid escalation of both. For example, an arms race between two countries, where each nation's increased military spending prompts the other to do the same.
- Tragedy of the Commons [7]: Overexploitation of a shared resource by individuals acting in their own best interests, leading to its depletion and harm to everyone. For example, overuse of common grazing land by individual farmers leads to its degradation and decreased productivity for all.
- Shifting the Burden [4]: A temporary solution alleviates symptoms but doesn't address the root cause, leading to an even bigger problem later. For example, using painkillers to mask chronic pain without addressing the underlying injury can lead to dependence and worsening pain.

Creating a causal model becomes important so that awareness of the marginalizing patterns that have crept in over time, often unconsciously, becomes front and center so that AI can be used to change rather than reinforce archetypes.

III. Strong Vs Weak AI

The following diagram, Diagram 3: Weak & Strong AI, highlights an important trend [8] that is beginning to play out and will inevitably grow in importance with respect to AI. Basically, it has to do with keeping the potential power of AI relevant in the years to come:

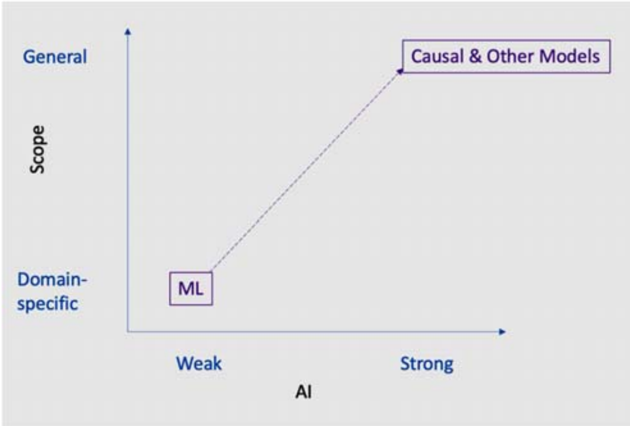

Diagram 3. Weak & Strong AI

The vertical axis highlights the scope of AI applications from ‘domain specific’ to ‘general’, and the horizontal axis highlights the effective power of AI ranging from ‘weak’ to ‘strong’. The trend today has to do with applying Machine Learning (ML) or off shoots of it in more and more specific domains. This is no doubt an important first step and allows organizations to quickly get their feet wet with AI. The results from it may also dazzle, and that is where the problem lies, because then we are allured into doing even more of the same. As the previous section suggests, continuing to invest in linear thinking and approaches to organization and enterprise problem solving will tend to cause a problem to increase and not decrease in frequency. Couple linear thinking with ML-based AI, and the trend is exacerbated so that the likelihood of problems reoccurring and needing even more ML-based AI will also only increase.

For AI to break out of being ‘weak’ and trending to becoming ‘stronger’ it has to be coupled with more sophisticated causal and other modeling [9]. An AI that can be founded on causal models, and other non-empirical bases that captures ‘common sense’, recognition and shifting of underlying archetypes, mathematical modeling, and other categories of non-empirical meta-knowledge will allow solutions and recommendations being recommended to become more sustainable and robust, because they are based on broader insight into how the organizational ‘system’ is operating. The following graphic (Diagram 4: Strong AI Data Layering) captures this idea of the appropriate AI systems “data” layering required to get to ‘Strong AI’:

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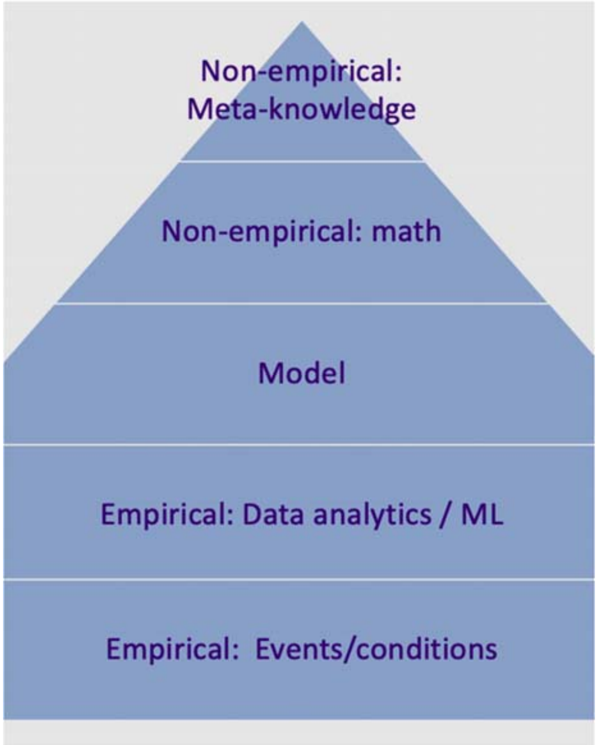

Diagram 4. Strong AI Data Layering

Our default approach is to use empirical data. Hence, we may map events and associated conditions, and mine how we have responded to these in the past. This leads us into the layer of data analytics and ML, which at its heart is also empirical. Empirical data can never anticipate edge cases or adequately prepare an organization to respond to changing markets. In best cases, we may then tend to build some kind of causal model that generalized situations and here the potential power of AI increases because we are embedding more of how a system truly operates. To get to 'common sense' and a more autonomous AI that can be categorized as strong, our models should also embed more non-empirical layers such as mathematical-based rules and insights, and also meta-knowledge, whether it tap into philosophical, or economic, or deeper scientific thinking.

IV. Model Validation

A causal model for AI serves two purposes. First, it leverages the benefits of systems thinking to get to more sustainable AI-based solutions to issues. Second, in mapping the organizational system causally, it contributes to a foundation necessary to create a meaningful 'Digital Twin'. In so doing, it allows for impact analyses of on-going and organic AI efforts relative to the whole organization. It does this by playing out how each AI effort will not only change the de facto system of causality, but also what incremental increases along economic, financial, and social dimensions will be. These analyses are based on feeding real project data back into the underlying causal model.

Given this, it becomes important to be able to validate the model. There are three steps required in accomplishing this [10]. First, there needs to be validation that a model of the right epistemic complexity – the cognitive challenge in a task and may involve multiple perspectives, interconnectedness, and dynamism - was used in modeling organizational reality. Second, there needs to be validation that the right resolution complexity given the epistemic complexity is put in place. Third, and this is where the rubber hits the road because the model has to be practically validated, the controllability of the process and modeled outcomes needs to be validated.

If an organization were to exist in an unchanging, completely predictable world, and further, if its value proposition also remained unchanged and predictable, then an appropriate set of mathematical equations could likely be used to model that situation. Correspondingly, the epistemic complexity may border on being complicated, but still would be able to be captured by a complicated static model. If, however, the organization is itself always changing, and exists in a market that is always changing, then the epistemic complexity will be higher and will require a model that correspondingly also was able to change in real-time.

Taleb's fragility-antifragility continuum [11] can be used to help frame epistemic complexity. If we consider just the area of SCM and the implicit challenges that surface ranging from material shortages, demand forecast complexity, congestion along parts of it and general lack of supply chain visibility, amongst others, we can already see that the number of players, the interconnections, and the unknowns are high, which translates into high epistemic complexity. Further, the real issue is reducing cycle time, while increasing profitability, revenues, and employee engagement. This requires that a state of antifragility be reached, such that the organization increases its capability to thrive as a result of stressors, shocks, volatility, noise, faults, attacks, or failures.

Building up to antifragility an organization may begin with fragility and pass through resilience and robustness to get there. Fragility can be thought of as a state of systems by which they are damaged by disorder and stress. In other words, if a goal is to reduce cycle time, how also do we ensure that the organization is not damaged as a result by losing inherent capacity and capability? A next stage of development in the continuum is that of resilience. Resilience can be thought of as the ability to recover from failure. This is already an important step forward and if the organization is agile enough may succeed with more sophisticated linear thinking in which all data and parts of processes are completely transparent. The next state in the continuum is robustness, which can be thought of as the ability to resist failure. This stage requires a change to systems thinking. Resisting failure after all, means that an organization is inherently adaptable and that requires that the organization function as a complex adaptive system. But the

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degree of success in functioning as a complex adaptive system will not be clear unless the lens of systems-viewing is itself used. It is impossible to see the process of an organization in terms of its maturity in acting as a complex adaptive system, with the lens of linear thinking. This is doubly true in the most mature stage in the continuum - that of antifragility. In other words, an antifragile organization operates as a full-fledged complex adaptive system.

Second, a key part of validation requires that the right level of resolution complexity is used. If epistemic complexity is low, then a simple linear-type mapping of the expected process would perhaps be sufficient. But if epistemic complexity is high, then some more sophisticated software-based approach involving simulating all combinations of normal and boundary conditions, would be required. If this could be done, and reasonable results continued to be generated that generally reflected reality, then confidence in resolution complexity would be high.

Third, the model would need to be practically validated in its actual real-time effects. This would require that model recommended changes that may have been implemented, would need to be controlled, with inputs, conditions, and outputs monitored to ensure that model predictions are actually what is reflected by reality. The higher the epistemic complexity the higher will be the level of validation complexity.

V. Lessons In Crafting AI Strategy

Given the high level of epistemic complexity encountered during consultations with various companies, Causal Loop Diagrams (CLD) and Agent-Based Modeling (ABM) have been utilized to model aspects of reality in service of an AI strategy.

A linear mapping of a process, say SCM, is used as a starting point. This gives insight into how, in an ideal world, activities that take place in an SCM are connected. In reality each activity is going to interrelate with many other activities in unique, non-linear ways, that may be the result of requirements and patches that were implemented at some point to keep short-term efficiencies and effectiveness going.

Hence, in creating a CLD many actors across the SCM would need to be interviewed to get insight into the world as each sees it. Interconnections would then need to be modeled at the right level of detail so as to not overwhelm, but still provide sufficient insight. Focusing on measurable variables as the nodes in the CLD is useful. This allows more concrete predictions to be made.

A well-made CLD should also provide immediate insights into the problem trying to be addressed. This is provided by the number and kinds of archetypes that exist in the CLD. Each archetype as already discussed surfaces some deep-rooted way of doing things that in fact reinforces the problem being experienced. Unless these are changed, the problem will continue to exist. Further, the balance of feedback and reinforcing loops needs also to be considered. This will provide a quick sense, even without collecting any data, as to the type of behavior that problems being focused on may display. For example, will the problem tend to grow, tend to recur, or tend to diminish.

In situations where the epistemic complexity is high, resolution would require a sophisticated simulation approach. Agent-Based Modeling (ABM) [12] is then used in favor of Systems Dynamics Modeling (SDM) [13] since it is bottom-up as opposed to top-down and tends to capture the reality of largely independently run divisions better. An agent-based model (ABM) is a type of computational model that uses autonomous agents (individuals or collective entities such as organizations or groups) to simulate the behavior and interactions of a system in order to understand what governs its outcomes. It integrates elements of game theory, complex systems, emergence, computational sociology, multi-agent systems, and evolutionary programming. An ABM provides insight into the collective behavior of agents, such as company divisions, individual roles involved in SCM activities, or SCM process steps, with each type of agent following a prescribed set of unique rules.

The CLD surfaces opportunities for overall improvement because it provides insight into existing archetypes and the balance between reinforcing and balancing loops. In the ABM, corresponding strategies/levers are created that simulate the effects of the improvements.

The process of creating the CLD and ABM tends to span several months. Integral to this process is a series of well-planned interviews covering all divisions and all roles that interact with the process. The interviews need to not only give insight into potential bubbles – outdated and habituated ways of being that are thought to be correct - that the organization currently exists in, but also possible ideas for improving SCM. A broad span of interviews is essential to see the problem to be solved from different perspectives. The essential issue with increasing SCM efficiency tends to be related to cutting cycle time in such a way that the antifragility of the organization is in no way compromised.

Once the ABM had been created it becomes possible to run thousands of simulations to understand the kinds of AI strategies and changes that would reduce cycle time while keeping the organization anti-fragile. Tools such as insightmaker.com prove useful in creating such complex simulations [14]. A customized success metric combining antifragility and reduction in cycle-time can be created to assess the range of AI approaches imagined. Each AI strategy can be assessed in terms of its ability to increase the value of the combined metric. The best AI strategies are then identified based on that, and value-effort analyses performed to isolate the quick wins (low-effort & hi-value). This yields a number of strategies that will have to be executed in the short-term. A second tranche of strategies deemed to be imperative (highest value & medium-to-high effort) are then identified. These contribute to mid-to-long term efforts.

These results are then slotted into phases based on amount of effort required, with the first phase comprising easier effort

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projects, and latter phase projects progressively becoming more difficult. This phased approach results in the generation of an optimized 5-year AI Roadmap.

Several Phase 1 projects can then be executed through the use of middle-ware AI platforms such as Stack-AI.com [15] that allow no-code generative solutions leveraging a range of LLMS and other productivity tools, to quickly deploy AI assistance, chatbots, and workflow automations. These deployments become part of a progressively developing AI-ecosystem in line with the comprehensive logic possible through a causal-model enabled AI roadmap.

VI. Applicability Of A Causal Model Approach To Small And Medium Sized Business

A question often brought up has to do with the applicability of leveraging causal based models - such as the CLD and ABM - for small to medium sized businesses (SMBs). The following points reinforce or suggest how such applicability can be enhanced:

1. Under the slew of financial pressures often faced by SMBs it is easy to resort to getting things done as quickly and easily as possible using common linear thinking approaches. While this is important SMBs also need to proactively design for the future by leveraging systems thinking to the extent possible. This is particularly important because it will increase the likelihood that signals on the margin, that often are doorways into the future will be recognized and embraced.
2. The practice of getting attuned to archetypes, ranging from 'Fixes that Fail' to 'Escalation' amongst the others, that inevitably marginalize a system's operational, cultural, and strategic possibilities can prove to be invaluable.
3. Considering 'Escalation' for example, in a fledgling market if two competitors react to price drops begun by one or the other, this can escalate in such a way so as to drastically reduce profitability and even the likelihood of operational viability for both players over time. Instead, a preemptive CLD can be modeled that allows a player to engage with the market with more insight to thereby begin to compete on levers beyond just price. This would obviate the need to reduce price every time a competitor may do so.
4. Off-the-shelf type emotional intelligence (EQ) type software [16] can often help small teams become increasingly sensitive to mental models [17] that drive perceptions and assumptions. This can in turn attune a team to embedded archetype-type mental models that easily escape detection.
5. The CLD can be created to include key customers. In this way potential marginalizing dynamics at such interfaces can be better managed. This will serve to strengthen key relationships over time.
6. Rather than focus on 5-year roadmaps SMBs can focus on 1-2 year roadmaps to maximize short-term investments.
7. The onslaught of AI Tools can be overwhelming. In spite of this it is important that SMBs get their feet wet with AI in whatever way, to demystify, understand limits, and within the context of a CLD decide which marginalizing patterns may be best matched with the tools and approaches they are already aware of.
8. Similarly, there needs to be an incremental approach to the use of ABM, so that even though it may reflect only some aspects of the environment to begin with, width and depth are gradually added to continue to gain insight into market possibilities.
9. The ABM metric of success can also gradually change, based on where an SMB is at. Rather than reflect the complexity of antifragility at the get-go, the metric can first reflect resilience, then robustness, and finally antifragility.
10. The technology outlined in this paper is inexpensive. This is true of use of online platforms such as insightmaker.com that allows the build-up of expertise in the use of CLDs and ABMs, EQ-type software, and stack-AI.com that then allows existing AI tools such as LLMs and others on the market to be leveraged in accordance with a foundational causal based AI approach.

VII. Summary & Conclusion

This paper critically examines the imperative for organizations to adopt a strategic, systems-thinking approach to the implementation of Artificial Intelligence (AI) in their operations. As AI technology evolves at a breakneck pace, the temptation to hastily incorporate AI tools for immediate efficiency gains presents a perilous trap that can inadvertently steer organizations away from their strategic objectives. The allure of quick fixes, while showcasing the short-term prowess of AI in cost reduction and revenue enhancement, obscures the deeper systemic issues that, if unaddressed, may lead to long-term strategic misalignments.

Through a comprehensive review of systems thinking, particularly in supply chain management, this study illustrates the pitfalls of linear thinking and the benefits of embracing a causal modeling framework. The fact that causal loop diagrams (CLDs) and agent-based modeling (ABM) can unearth entrenched operational, cultural, and strategic patterns is demonstrated—thereby enabling AI to contribute meaningfully to an organization's resilience and growth.

Further, analyses underscore that transitioning from weak to strong AI necessitates the integration of empirical data with sophisticated causal models, including non-empirical meta-knowledge. This shift is essential for AI to move beyond mere short-term fixes and towards sustainable strategies that are robust against a backdrop of complex, dynamic market conditions.

In terms of model validation, a three-step process crucial for ensuring the practical applicability of AI strategies: validating the model's epistemic complexity, resolution complexity, and the controllability of outcomes, was delineated. Such validation enables organizations to not only weather volatility and disruptions but to thrive amidst them, epitomizing the essence of antifragility.

Drawing from the pioneering lessons encountered during consultations with various companies, the paper shares key lessons in crafting a causality-informed AI strategy. The integration of CLDs and ABM provided a rich, detailed understanding of the organization's dynamics, facilitating the design of AI strategies that advance operational efficiency without compromising the system's integrity.

The culmination of these efforts is a five-year AI Roadmap, informed by a phased approach that prioritizes initiatives based on the balance of effort and value. This roadmap is an actionable blueprint for organizations to embark on a journey towards a robust and antifragile AI ecosystem, underpinned by a causal-model framework.

In conclusion, this paper presents a compelling case for a paradigm shift in AI strategy—from a myopic focus on efficiency to a holistic view that recognizes and harnesses the complex interdependencies within both large and small-to-medium sized organizational systems. The strategic integration of systems thinking and causal modeling in AI initiatives emerges as a fundamental driver for sustainable growth and a competitive edge in the rapidly evolving digital landscape.

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