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RESEARCH ARTICLE

Modularity, learning, and the mitigation of power-law distribution of delay in large-scale technological infrastructure delivery

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Abstract
Megaprojects, despite their crucial role in infrastructure delivery, consistently underperform in terms of time, especially when integrating technological innovations. Their reliance on the quantum leap approach struggles because of the temporary nature of project organizations and their inability to transfer experience across endeavors, producing a power-law distribution of delivery delays in which extreme overruns become inevitable. Grounded in the perspectives of system interdependency and self-organized criticality, our results from computer simulation of 50,000 instances show that piecemeal-incremental approaches reduce both average delays and their variability, thereby defying the power-law behavior. The paper offers three propositions for mitigating delays in the delivery of large-scale technological infrastructure: phased delivery, continuous learning from successful practices and experiences, and enabling learning capabilities.

Keywords
megaprojects; project design; learning; modularity; self-organized criticality.

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1. Introduction

Megaprojects are large-scale undertakings characterized by scale, extended delivery horizons, substantial financial investments, and far-reaching societal impacts (Flyvbjerg, 2014). They are often deployed to deliver complex systems intended to address major infrastructure development challenges. In 2017, global infrastructure investment was estimated to reach about $4 trillion for the years from 2016 to 2040 (Global Infrastructure Hub & Oxford Economics, 2017). Likewise, global spending on megaprojects was estimated to exceed $2.2 trillion in 2024 (Statista, 2024). These investment patterns span sectors such as transportation, energy, and urban development, contributing to economic growth and improvements in societal welfare through underlying technologies.

Despite these anticipated benefits, megaprojects frequently underperform as an infrastructure delivery approach, a phenomenon encapsulated in what Flyvbjerg (2014) terms the "iron law of megaprojects." A well-documented illustration of this is the United Kingdom (UK) NHS National Programme for Information Technology (IT). The system was expected to deliver benefits valued at £10.7 billion; however, it incurred costs of £9.8 billion, resulting in a £3.8 billion cost overrun and a six-year delay. The program was ultimately dismantled in 2011 (National Audit Office, 2013).

The underlying logic of megaprojects is rooted in the concept of a quantum leap (Ansar & Flyvbjerg, 2022), whereby changes in the system's structure must be both concerted and dramatic to minimize the duration of a turbulent, unsettling, and costly transition process (Miller & Friesen, 1982). However, the delivery of megaprojects is often protracted, exposing projects to multiple forms of turbulence that frequently result in poor performance (Denicol et al., 2020).

The delivery of technology-enabled infrastructure follows a different logic, as its objective is not only to construct innovative physical technological assets but also to develop technological innovations as an integral component of the infrastructure, with the intention of transforming infrastructure and, more broadly, society (Kipp et al., 2008; Tshabalala & Marnewick, 2025). This interplay between technological innovation and infrastructure delivery aligns with Hirschman's notion of the trait-making project, in which project owners are engaged in discovering the capabilities required to address specific technological problems (Hirschman, 1967).

In this regard, most trait-making projects lack a clear recipe for success and offer benefits that are uncertain or ambiguous. Consequently, project owners explore both the recipe for success and the benefits that these technologies may deliver during the course of infrastructure delivery (Liu et al., 2022; Nyman & Öörni, 2023). Moreover, trait-making projects create tensions for formal cost-benefit analysis, as many of the benefits associated with technological innovation for both project owners and society are difficult to quantify (McLeod, 2023). In this paper, we refer to the combination of technological innovations and infrastructure delivery as *large-scale technological infrastructure*.

Given the definition of trait-making projects as involving experimentation within a temporary organizational form, both successes and mistakes identified or explored in previous deliveries cannot be directly applied to subsequent projects, due to the absence of structural and organizational linkages between the past and present project organization (Denicol et al., 2021; Duffield & Whitty, 2015). In this vein, traits or capabilities are created and extinguished within individual projects due to the temporariness of the project organization, as well as the uniqueness of those traits which limits their direct transferability to other contexts (Flyvbjerg et al., 2024). As a result, lessons learned from other projects, both internal and external, tend to have limited relevance to the current delivery attempt.

In computer science research, the term "divide-and-conquer" refers to an approach that decomposes a complex problem into multiple modular, simpler subproblems, solves them, and then aggregates the solutions to obtain a solution to the original problem (Chen & Saad, 2009). By breaking down problems into small, modular components, humans can solve them more efficiently and with higher quality (Jacobs et al., 2007). This approach can serve as a building block for capability creation (Liao et al., 2010).

To retain and apply the traits developed through project execution, experience from previous projects should be treated as a continuum rather than as isolated episodes (Chhetri & Du, 2021; Volden & Klakegg, 2025). Accordingly, a modular delivery approach is required to retain experience throughout the infrastructure delivery process. Against this background, the research question of this paper is: *Can modular delivery approaches, combined with a learning mechanism, improve the on-time performance of large-scale technological infrastructure deliveries?*

To explore this research question, we developed a simulation model that proposes a framework for delivering large-scale technological infrastructure. The model employs the concepts of modularity (Baldwin & Clark, 2000) and learning (Argote & Miron-Spektor, 2011) to mitigate schedule delays in the delivery of large-scale technological infrastructure. We model the delivery of large-scale technological infrastructure through the lens of system interdependencies (Rinaldi et al., 2001), where delivery delays are represented by self-organized criticality (Bak et al., 1987), a key mechanism underlying IT project cost overruns (Flyvbjerg et al., 2022).

To build the framework, we run the model on synthetic data. The structure of a large-scale technological infrastructure delivery system in our simulation is based on prior research by Santolini et al. (2021). Our findings reveal that, by relying on a piecemeal-incremental approach, both the average level and uncertainty of schedule delays decrease with the number of delivery iterations. The reduction in delivery uncertainty is driven by learning effects and the modular delivery process.

We further substantiate this claim by fitting the simulation results to a power-law distribution, which characterises the behavior of IT project overruns (Flyvbjerg et al., 2022). Based on our findings, we present three propositions that offer novel insights into how project owners can effectively deliver large-scale technological infrastructure. These three propositions aim to advance our conventional wisdom on the delivery of large-scale technological infrastructure and may also be extrapolated to discussions on trait-making and capability-building projects.

This paper is structured as follows. In the next section, we relate our work to previous research on megaprojects as an infrastructure delivery process, project misperformance from a systems perspective, and studies examining how learning and modularity can lead to improved delivery outcomes. We then describe our simulation framework and the method developed to align the simulation outcomes to a power-law distribution. Our results are presented in a set of displays and are subsequently discussed. We conclude the paper with three propositions derived from the model's sensitivity analysis and discuss the paper's limitations and possible implications for future research and practice.

2. Related works

Megaprojects have long been conceptualized in the project management literature (Flyvbjerg, 2014; Merrow, 2011). Early work by Miller and Friesen (1982) introduced the "quantum view", which posits that organizations undertake major structural changes in a single, dramatic manner rather than through small, incremental adjustments. While incremental approaches can sometimes foster continuous improvement, Miller and Friesen (1982) argued that small changes in large systems either generate chaos or fail to produce meaningful improvements. Thus, the quantum view posits that if change is to be delivered, it should occur rapidly and dramatically, thereby minimizing the time spent navigating turbulence, disputes, and costly, unnecessary transitions. From this perspective, a megaproject can be understood as a process for achieving significant societal change. In this section, we review prior project management literature on the causes and prevailing responses to misperformance associated with using megaprojects as the preferred approach to delivering infrastructure, from a systems perspective. Further, we review the concepts of modularity and learning, which we propose as potential remedies. Finally, we integrate these concepts, arguing that both are required to address this persistent issue.

2.1. Megaproject as delivery process

Megaprojects aim not only to deliver infrastructure but also to develop and enhance technological knowledge. Hirschman (1967) referred to this type of project as "trait-making" projects, which seek to foster new skills, competencies, and capabilities. These outcomes typically extend beyond the immediate economic benefits of the infrastructure itself and contribute to broader societal change. If a trait-making project is successful, it generates values for society not only through its physical output but also through the social and behavioral changes it enables (Hirschman, 1967).

Despite this big ambition, most trait-making projects often end up as trait-taking projects, in which key capabilities and expertise are imported from other countries (Hirschman, 1967; Ika & Donnelly, 2017). Although outsourcing to specialized global firms can improve the odds of project management success (Davies & Brady, 2000), it can also be a double-edged sword for client organizations' capabilities. A lack of owner-side competence, particularly in systems integration, can lead the owner to provide capital without control, thereby increasing the likelihood of project misperformance (Denicol et al., 2021; Winch & Leiringer, 2015). Thus, client organizations or project owners require foundational knowledge of both technology and project management, enabling them to function as system integrators who can orchestrate the interplay of multiple suppliers and align the project with their operational goals (Xia et al., 2024; Zani et al., 2024). However, the strong-owner model works well when the client organization seeks to expand its service portfolio, as it leverages system integration capabilities under the assumption that the project organization already possesses substantial technical and managerial knowledge—essentially implying that the means for achieving the desired outcomes have already been established (Denicol et al., 2021). Classic examples of strong project owners include the British Airport Authority (BAA) and UK Network Rail, which can be described as "megaproject-based firms" with existing service portfolios that benefit from the system or infrastructure being delivered (Denicol & Davies, 2022).

However, this approach may not be suitable when project owners lack the specialized knowledge required to govern complex projects due to the divergence from their core business (Winch & Leiringer, 2015). To compensate, public agencies often delegate system integration and management to external consultants or primary suppliers, prioritizing short-term delivery over the development of in-house capabilities and relying on the assumption of faithful delivery (Flyvbjerg & Sunstein, 2016). This reliance weakens oversight and diminishes the authority of project owners, creating a lock-in effect in which governments are forced to continue supporting delivery despite its challenges, as abandoning it could lead to political, financial, and social disputes (Altavilla et al., 2019; Hetemi et al., 2020).

2.2. Causes and cures of misperformance from a system perspective

Public infrastructures, particularly in sectors such as transportation, energy, and telecommunications, comprise extensive technological subsystems operating within a dynamic environment that encompasses a wide array of interconnected subsystems, activities, information flows, and resources (Abdoli & Kara, 2020; L. Chen & Whyte, 2022; Rinaldi et al., 2001; Vistnes et al., 2023).

The delivery of these systems involves reciprocal interdependencies, as subsystem adjustments create rework loops, thereby adding another layer of complexity to delivery (Bathallath et al., 2015; Söderlund, 2012). The existence of reciprocal interdependencies creates favorable conditions for self-organized criticality (SOC), in which a single disturbance can trigger a chain reaction that ultimately causes the entire system to transition into a critical state (Bak et al., 1987). For example, in IT projects, a failure in one activity can propagate structurally through reciprocal dependencies, driving cost and schedule overruns that follow power-law distributions (Flyvbjerg et al., 2022; Vazquez et al., 2023).

This critical state emerges from the system's inherent complexity and interdependence (Santolini et al., 2021). However, given the limited empirical data in their study, it is inconclusive whether large-scale technological infrastructure delivery schedules or cost overruns follow the power-law distributions. System integration, defined as a governance process for managing complexity and uncertainty (Davies & Mackenzie, 2014; Whyte & Davies, 2021), mitigates the SOC phenomenon in infrastructure delivery by coordinating interdependent subsystems and actors, designing interfaces, and ensuring interoperability, stability, and managed change in subsystems across all phases of the project lifecycle (Zani et al., 2024).

In practice, system integration activities rely on dynamic control processes because initial information is often incomplete and must be continuously updated throughout the project lifecycle (Sanderson, 2012). Decisions made early, such as the project baseline during the design phase, must be revised later in response to changing conditions and stakeholder feedback (Chhetri & Du, 2021). To integrate systems effectively, especially in the delivery of technological infrastructure, a project organization possesses system integration capabilities to mitigate SOC by coordinating across different integration levels (Hobday, 2005; Lane & Boehm, 2008; Zani et al., 2024).

Despite the existence of system integration processes, the megaproject approach remains complex and uncertain, and there are no one-size-fits-all solutions for governing the complexity of infrastructure delivery (Geraldi et al., 2011; Nyarirangwe & Babatunde, 2019). System integration as a governance mechanism requires a certain level of knowledge from the project owner. Without sufficient system integration capabilities, the project is likely to misperform due to the inability to address the requirements of different phases and transitions and to unite all stakeholders (Denicol et al., 2020). For instance, the London Crossrail project faced significant delays due to underestimated system integration challenges during the planning phase (Whyte & Davies, 2021).

Similar issues occurred with the Berlin Brandenburg Airport project, where poor integration of technological subsystems contributed to extended delays and cost overruns (Luke et al., 2017). Outsourcing system integration capabilities can put project delivery at risk, as owners lose the ability to manage or even influence system-wide decisions; thus, it is important for project owners to build system integration capabilities to effectively manage the delivery, especially in public infrastructures where accountability and long-term operational concerns are paramount (Winch & Leiringer, 2015).

2.3. Organizational learning

Organizational learning positions knowledge as a key resource for firms to sustain competitive advantage. The organizational learning concept evolved from an interest in how organizations create, capture, and apply knowledge from the past to enhance current business performance (Argote & Miron-Spektor, 2011). This knowledge can be encoded and stored in various forms, ranging from tacit to explicit.

The organizational learning concept suggests that firms striving for long-term success should engage in building competence by upgrading skills and knowledge to align with the requirements set by their vision or mission (Yeo, 2003). In acquiring skills and knowledge, the organization must either extensively and iteratively explore choices, consequences, and outcomes or bypass this process by importing external knowledge (Longauer et al., 2024; Ngereja & Hussian, 2021). The outcome of learning is often most tangible in iterative processes, where agents are exposed to repeated identical tasks, leading to efficiency gains or cost reductions. This is the so-called learning curve effect, in which performance growth follows an inverse exponential function (Leibowitz et al., 2010; Wright, 1936). This function can be observed at all levels, from individuals (Kim et al., 2012) and teams (Muthulingam & Rajaram, 2022) to firms (Ryu & McCann, 2023).

In project organizations, the lessons-learned process is the primary mechanism for transferring knowledge by either codifying tacit knowledge into explicit knowledge through post-project reviews, documenting successes and failures to inform future teams (Duffield & Whitty, 2015; Project Management Institute, 2021; Volden & Klakegg, 2025), or by directly applying past tacit knowledge to current projects (Chhetri & Du, 2020). However, applying these insights in new contexts is challenging, as each megaproject is perceived as a unique, technologically sophisticated, and socially complex endeavor (Flyvbjerg et al., 2024), and because of knowledge loss during transitions between temporary and permanent organizational layers, as well as during conversions between tacit and explicit knowledge and vice versa (Denicol et al., 2021; Reich et al., 2014). By contrast, sectors where safety is paramount, such as aviation, rail, and healthcare, exhibit more structured approaches to institutionalizing lessons learned via compliance standards and iterative safety reviews (Duffield & Whitty, 2015).

2.4. Modularity

Modularity reduces system complexity by decomposing large systems into smaller, loosely coupled subsystems with standardized interfaces, enabling parallel development, component reuse, and scalable and flexible architectures (Baldwin & Clark, 2000; Xue et al., 2013). This approach enables the early detection of potential failures or design flaws before they propagate across the entire system (Xue et al., 2013). This modular system architecture is commonly adopted in industries such as automotive, software, and aerospace to enhance product variety without incurring major cost growth, thereby supporting economies of scale.

From a project management perspective, the benefits of modularity extend beyond the technical system being delivered. At the project organization level, modularity is crucial for determining how project team members should work together while minimizing complexity (Whyte & Davies, 2021). Standardizing methods and interfaces across teams not only reduces ambiguity in task execution but also streamlines communication protocols, thereby promoting consistent solutions among multiple suppliers on the project (Lammers et al., 2022). These practices are particularly important in megaprojects, where prolonged, multi-actor collaboration can lead to misaligned objectives or duplicated efforts (Hellström & Wikström, 2005; Phillips et al., 1999).

2.5. Summary of related works

The successful delivery of infrastructure through the megaproject approach relies on the project owner's ability to function as a competent system integrator. Project owner organizations that possess or actively build system integration capabilities can better orchestrate suppliers and align delivery results with their operational objectives. In contrast, those lacking knowledge of the technology and the delivery process often outsource system integration tasks to suppliers or consultants. In doing so, they transfer governance power to those firms. Such reliance can threaten project performance by weakening oversight and reducing the capacity to influence system-wide decisions, potentially leading to misalignment and underperformance in delivery. One way to mitigate these risks is to embed and maintain system integration capabilities within the project owner's organization. Organizational learning is crucial for developing and maintaining system integration capabilities in infrastructure delivery. However, this is often not the case when megaprojects are viewed as uniquely complex endeavors that restrain the application of lessons learned from within the organization or from others. The separation between temporary projects and permanent organizational layers further restricts the effectiveness of knowledge transfer. As a result, delays in megaprojects have become the norm, with on-time completion perceived as an outlier. This has led some recent project management scholars to call for alternative approaches to infrastructure delivery (Ansar & Flyvbjerg, 2022; Brunet, 2025; Thuesen et al., 2024). Figure 1 summarizes the flow of project owner system integration capabilities in delivering technological infrastructure under the megaproject approach.

In this regard, one promising approach to improving poor infrastructure delivery performance is to couple the modular delivery process with the learning mechanism. This allows project organizations to detect and resolve issues early, preventing them from cascading into system-wide crises by segmenting large-scale delivery into manageable, sequential modules. Each iteration becomes a live experiment, embedding technical and managerial insights directly into subsequent phases without relying on centralized knowledge storage in the permanent operational layer (i.e., infrastructure managers). This approach enables project owners to incrementally build system integration capabilities, mitigate SOC, and reduce the likelihood of project misperformance.

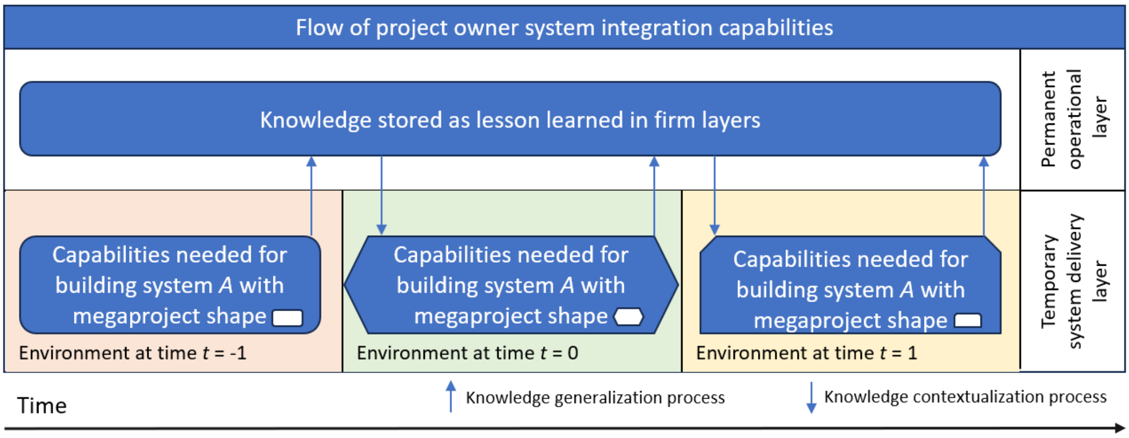

Fig. 1. Conceptual framework of project owner system integration capabilities flows under the megaproject approach.

3. Method

Theory building via computer simulation has a long tradition in management research. It offers a methodological sweet spot between theory creation and theory testing, leveraging the strengths of simulation methods, including high internal validity and the ability to handle longitudinal, nonlinear, and process-oriented phenomena that are difficult to reproduce experimentally or empirically in the real world (Davis et al., 2007). For modeling complex systems, stochastic simulation provides insight into how different sources of stochasticity influence system outcomes (Davis et al., 2007). To answer the research question, we developed a simulation model that draws upon project network structure, incorporating self-organized criticality as a source of project schedule overruns, as well as learning effects and modularity. We argue that these latter two constructs have the potential to reduce the magnitude of schedule overruns.

3.1. Simulation design

Based on the findings from Santolini et al. (2021), which reported a range of 282 to 50,101 activities in megaprojects, we specified 2,520 nodes to represent activities in a project activity network for delivering the entire infrastructure system. We chose that number based on our expertise in railway signalling projects, which typically involve 1500-3000 activities. To operationalize modularized infrastructure delivery, we divided the 2,520 nodes into delivery strategies, each comprising 1 to 10 module strategies. The number of activities assigned to each module in each strategy was determined by dividing 2,520 by the total number of modules.

The strategy comprising a single module is equivalent to the traditional megaproject approach, which involves 2,520 activities. For strategies containing two to ten modules, we assigned modules to be delivered sequentially, as this study aims to observe the effects of modularity and learning through self-experience (capability building) rather than knowledge transfer from parallel or past deliveries. Table 1 summarises the number of activities and modules associated with each delivery strategy.

Table 1. Number of activities (nodes) and modules of each delivery strategy.

Strategy	1 (megaproject)	2	3	4	5	6	7	8	9	10
Modules contained	1	2	3	4	5	6	7	8	9	10
Nodes contained	2,520	1,260	840	630	504	420	360	315	280	252

We then randomly generated a project activity network consisting of 2,520 nodes. The network's degree distribution follows a power-law distribution with a decay rate $\alpha = 2$ and a lower bound $x_{min} = 1$, based on prior research (Santolini et al., 2021). For each module, we assumed that completing each delivery task (node) takes one unit of time, and one node was randomly assigned to experience a delay.

For each module, we modeled the learning effect as the probability of successfully delivering a node using the standard exponential learning equation from Leibowitz et al. (2010), as shown in Equation (1), where n indicates the delivery iteration. P_n represents the probability that a randomly selected node will experience an overrun in delivery iteration n. E_{max} and E_0 represent the maximum and minimum task-delivery capabilities, with universal thresholds ranging from 1 to 0.01. a represents the project organization's learning capability coefficient, and A denotes the learning mode or strategy. A value of A of 0.5 implies that the organization learns equally from success and failure. A value of 0 means the organization learns exclusively from failures, whereas a value of 1 means it learns only from successes.

In our study, success is defined as on-time delivery, and failure as delayed delivery. If a previous attempt results in delay (failure) and $A = 0$, experience from that attempt increases the likelihood of success in subsequent attempts. Conversely, with $A = 1$, failed experience is not incorporated, and the probability of success remains unchanged. This logic also applies when the previous attempt is successful; under a failure-based learning strategy ($A = 0$), successful experience is discarded.

(1) $$P_n = E_{max} - (E_{max} + E_0) \cdot e^{-a \cdot A \cdot n}$$

Next, for each delivery module, if the effect of learning occurs, the selected node is not delayed, and its duration remains 1. This means that the duration of each delivery module will match the number of nodes contained in each strategy, and the total delivery time will be 2,520. When learning does not take effect, a delay phenomenon occurs, with the magnitude of delay ranging from 0.1 to 6, distributed uniformly. These magnitudes are based on our previous research on project schedule overruns for deliveries of European Railway Traffic Management Systems in the EU, where we treated these systems as large-scale technological infrastructure (Mahitthiburin et al., 2024).

The modeling of the delay phenomenon in this paper was conducted using self-organized criticality (SOC). We modeled this phenomenon in the same manner as Flyvbjerg et al. (2022) demonstrated for cost overruns. For updating module duration, we used the Breadth-First Search (BFS) algorithm to search all nodes connected to the randomly selected node within the project activity network, where all connected nodes would experience an identical magnitude of overrun as the source node as there is no guiding theory or empirical finding on the magnitude of the cascade effect, and based on optimism bias, the allocated buffer in each node is usually eliminated by top management; thus, we assigned no buffer to all nodes. To calculate the total duration of the entire infrastructure delivery, we aggregated the durations of all modules in each delivery strategy through summation. A summary of our simulation procedure is displayed in Table 2.

We ran the simulation 5,000 times for each delivery strategy, with the parameters in Equation (1) fixed at $a = 0.4$, $A = 0.5$, $E_{max} = 0.99$, and $E_0 = 0.01$. For each instance, both the module and total delivery times required to complete the project were computed, along with the magnitude and location of the delay at the source node under the scenario in which a delay occurs. Then, we computed the overrun ratio for all instances (module cost/node within the module), which were then used to fit the power-law and to perform descriptive statistics.

Table 2. Simulation step.

Procedure for the simulation
1. Create 2,520 nodes and randomly connect them, with the structure based on the results from Santolini et al. (2021).
2. For each module, assign a time to complete for all nodes in the network equal to 1
3. For each module, randomly select a node to experience
4. For each module, compute the probability of the selected node experiencing delay based on Equation (1)
4.1. Calculate the module duration if the selected node is not delayed.
4.2. Otherwise, the SOC phenomenon is simulated.
4.2.1. Randomly assign the overrun magnitude within a given range, as per Mathitthiburin et al. (2024), to the randomly selected node.
4.2.2. Search all nodes directly and indirectly connected to the overrun node using the Breadth-First Search (BFS) algorithm.
4.2.3. Update all nodes found in step 4.2.2. with the magnitude from step 4.2.1.
4.2.4. Calculate the duration of each module.
5. Calculate the total delivery duration by summing up the durations of all project modules.
6. Repeat steps 1-6, 5,000 times for each strategy

3.2. Fitting the delay phenomenon to power-law

This subsection describes how learning and modularity nullify the power-law nature of project schedule overrun. A power-law distribution is characterized as a statistical distribution in which the frequency of an event decreases rapidly as the magnitude of the event increases. In other words, it describes a phenomenon in which small or less impactful events are frequent, while significant events are rare but highly impactful. The key property of power-law distribution is that it has infinite variance. Earthquake size, for example, follows a power-law pattern, in which many earthquakes have small or unnoticeable impacts, while few have significantly large impacts (Clauset et al., 2009).

We used the synthetic data generated by our simulation in the previous section as input to determine whether it follows a power-law distribution, as described by the probability function in Equation 2. We repeated the power-law fitting method on the synthetic data under three strategies, 1, 2, and 5, to justify that learning and modularity can rule out the power-law behavior of schedule overrun. We employed the fitting procedure proposed by Clauset et al. (2009) to obtain the power-law fit of the schedule delay.

(2) $$f(x, x_{min}, \alpha) = \frac{\alpha-1}{x_{min}}\left(\frac{x}{x_{min}}\right)^{-\alpha}, x > x_{min}, \alpha > 1$$

4. Results

We presented our simulation results in two sections, in accordance with the method section: descriptive statistics and the power-law test. For each delivery strategy, 5,000 project activity networks were randomly generated in step 1, as illustrated in Figure 2. Our sensitivity analysis is presented and discussed along with the propositions in the discussion section.

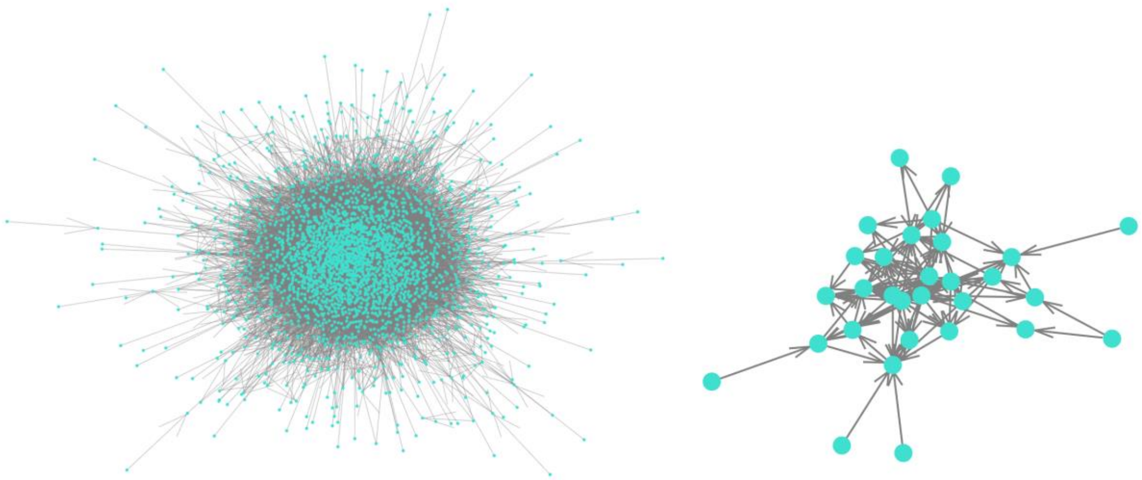

Fig. 2. Example illustrations of an activity network with 2,520 nodes (left) and 30 nodes (right), where the number of linkages follows a power-law distribution with decay rate α= 2 and x_{min} = 1.

4.1. Descriptive statistics

Table 3 presents descriptive statistics for the simulation results across 10 strategies, ranging from the traditional megaproject approach (strategy 1) to the iterative-modular approach (strategy 10). Each column captures the temporal dimension of infrastructure delivery performance. The average total delivery duration represents the mean time required to complete the whole infrastructure system across 5,000 simulation runs.

Although modularization does not dramatically reduce the mean delivery time, a clear downward trend is observable. The average duration decreases from 3,011.92 time units in strategy 1 to 2,893.35 time units in strategy 10, corresponding to an approximate 4.5% reduction. The average overrun ratio (defined as total delivery duration divided by the baseline duration of 2,520) follows a similar pattern.

The megaproject strategy gives an average overrun ratio of 1.1952, implying an average schedule overrun of nearly 20%. As modularity increases, the ratio steadily declines, reaching 1.1482 in strategy 10, equivalent to an average overrun of approximately 15%. Variance, however, benefits more. Strategy 1 gives a very high standard deviation of 855.69, indicating extreme variability and a high likelihood of unpredictable outcomes. In contrast, strategy 10 reduces this value to 283.89, representing a 67% reduction in variability relative to the megaproject approach. A similar pattern is observed in the standard deviation of the overrun ratio, which declines from 0.3396 in strategy 1 to 0.1127 in strategy 10. The maximum total duration column highlights each strategy's exposure to extreme delay events. The megaproject approach gives a maximum simulated duration of 11,637.66. As modularity increases, the upper bound of extreme outcomes decreases. For example, strategy 2 limits the maximum duration to 8331.06, while strategies 9 and 10 further constrain it to below 5,000 time units.

This reduction in worst-case outcomes underscores the resilience benefits of modular delivery, as cascading delays are increasingly contained within smaller subsystems rather than propagating across the entire project network. Macroscopically, both the average and the variance decrease in proportion to the number of modules. There is no significant reduction in the total average duration, which accounts for approximately 4.5% (comparing strategies 1 and 10); however, variance benefits more from our proposal, representing a 67% reduction (comparing strategies 1 and 10). This confirms that the iterative-modular approach provides a far narrower distribution of possible outcomes, making delivery performance more predictable.

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Figure 3 complements these findings by visualizing the effects of the iterative-modular strategy. The boxplots of total delivery duration (Figure 3, right) show that while the medians and interquartile ranges remain relatively stable across all 10 strategies, the upper tails shrink substantially as the number of modules increases. Strategy 1 gives numerous extreme outliers, reflecting rare but catastrophic delays characteristic of power-law behavior. In contrast, higher-modularity strategies exhibit fewer and less severe outliers, indicating that extreme overruns become increasingly unlikely.

Figure 3 (left) illustrates the progression of the overrun ratio across delivery iterations. In the first iteration, when learning has not yet accumulated, more modular strategies experience higher overrun ratios because each module is delivered without prior experience. In contrast, megaprojects yield the lowest schedule overrun ratio. However, a clear tipping point occurs around iterations 3–4, after which modular strategies outperform the megaproject approach. Beyond this point, accumulated learning has a significant effect. This dynamic explains why modularity may appear disadvantageous in early phases but becomes superior as experience grows. Note that these results are valid when the parameters in the learning equation are set to $a = 0.4$, $E_0 = 0.01$, $E_{max} = 0.99$, and $A = 0.5$.

Table 3. Result of simulation with fixed parameters in learning equation: $a = 0.4$, $E_0 = 0.01$, $E_{max} = 0.99$, $A = 0.5$.

Strategy	Average total delivery duration	Average overrun ratio	S.D. of total duration	S.D. of ratio	Maximum total duration
1	3011.92	1.1952	855.69	0.3396	11637.66
2	3012.24	1.1953	637.41	0.2529	8331.06
3	3025.63	1.2007	545.68	0.2165	7335.99
4	3005.64	1.1927	462.68	0.1836	6441.74
5	2988.97	1.1861	420.86	0.1670	5645.09
6	2968.20	1.1779	387.05	0.1536	5524.88
7	2947.68	1.1697	346.08	0.1373	6025.54
8	2925.31	1.1608	321.20	0.1275	5313.16
9	2913.37	1.1561	297.24	0.1180	4830.58
10	2893.35	1.1482	283.89	0.1127	4861.60

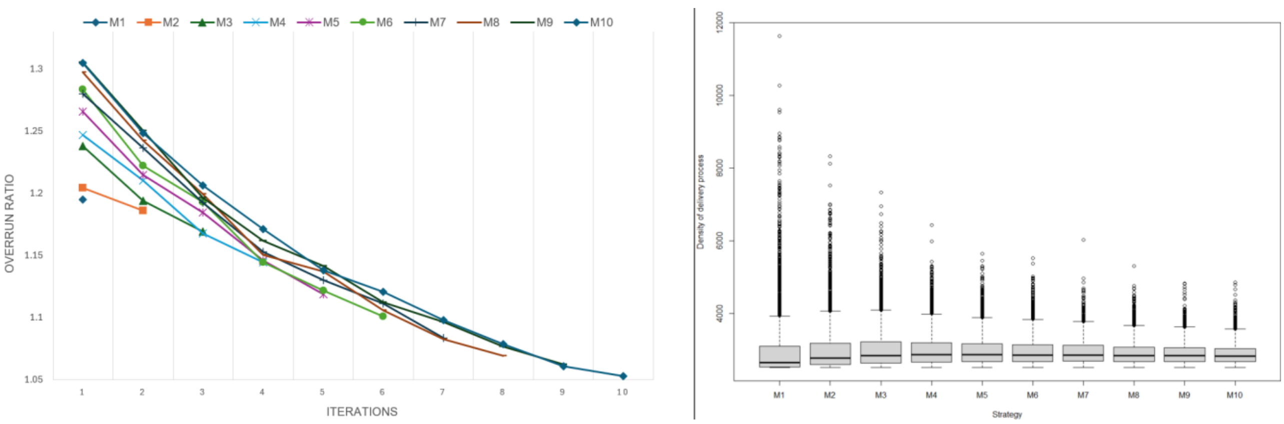

Fig. 3. (Left) Overrun ratio per iteration among 10 strategies. (Right) Boxplot of each strategy.

4.2. Ruling out power-law behavior

The analysis investigates the statistical behavior of schedule delay through power-law fit across three delivery strategies (1, 2, and 5) to understand how the increase in module and accumulated knowledge nullifies the fat-tail behavior of total project overrun. Table 4 summarizes the results of fitting our simulation results from the three selected strategies to power-law, based on the procedure outlined by Clauset et al. (2009).

The table shows that the megaproject approach (strategy 1) can be explained by a power-law distribution with a decay rate (α) of 5.01 (p-value = 0.1). This fat-tail behavior of the megaproject approach highlights its susceptibility to rare, large delays. However, the other two strategies do not fit the power-law pattern (p-values ≤ 0.01 for strategies 2 and 5), meaning that the likelihood of extreme overrun is lower than in the megaproject approach.

Figure 4 shows visual evidence of the power-law fits for three strategies: the left panel shows strategy 1 (megaproject), the middle panel shows strategy 2, and the right panel shows strategy 5. The figure illustrates the cumulative density functions (CDFs) on a logarithmic scale (y-axis). The red lines represent the maximum-likelihood power-law fit. The CDF of strategy 1 closely aligns with its red power-law fit (α = 5.01, p-value = 0.1), confirming power-law behavior.

However, the CDFs of strategies 2 and 5 deviate significantly from the power-law fit (p-values ≤0.01) due to the early drop in their high regions (overrun ratios of approximately 2 and 1.6 for strategies 2 and 5, respectively), leading to a divergence between the theoretical power-law fits and the empirical CDFs. The implication is that strategy one can be explained by a power-law distribution, which highlights its vulnerability to severe delays, while strategies 2 and 5 demonstrate how modularity and learning nullify the fat-tail behavior.

Table 4. Basic parameters of each strategy, along with their power-law fits and the corresponding p-value.

Strategy	Mean	S.D.	x_{max}	Power-law x_{min}	α	n_{tail}	p-value
1	1.20	0.34	4.62	1.11	5.01	1902	**0.10**
2	1.20	0.25	3.31	1.04	6.40	3450	0.01
5	1.18	0.17	2.24	1.17	9.13	2077	0.00

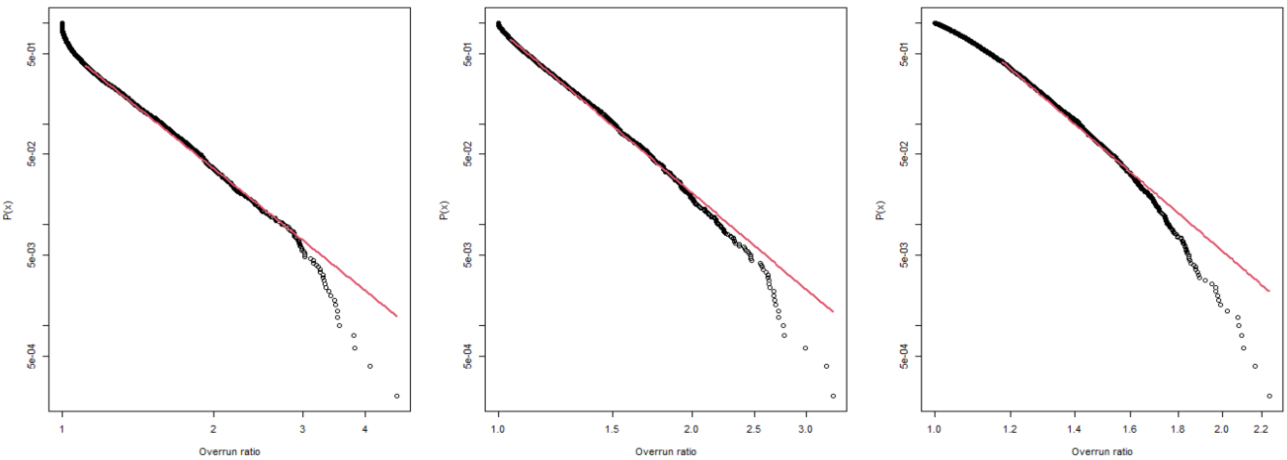

Fig. 4. Cumulative density functions (CDFs) on a log scale of the project schedule for the three strategies.

We also used Vuong's test to determine the best-fit distribution for each strategy. The contested distributions are log-normal, exponential, pure power-law, and power-law with exponential cut-off. We used a pure power-law distribution as the baseline for comparison. Table 5 reports the *p*-value for each strategy's fit to the power-law model, with statistically significant values highlighted in bold. Additionally, the table includes likelihood ratios (LR) and *p*-values from Vuong's test. Negative log-likelihood ratios indicate that the alternative model offers a better fit than the pure power-law model. The corresponding Vuong's test values are shown to the right of the LR column, with significant values in bold. The rightmost column indicates our verdict.

For strategy 1, the power-law with an exponential cut-off distribution provides a better fit to our phenomenon than the pure power-law (LR = -2.54, *p*-value = 0.02). In comparison, the other two distributions offer a non-significantly better fit compared to the power-law. Vuong's test of strategy 2 favors alternative models over pure power-law: power-law with cut-off (LR = -7.2, *p*-value = 0.00) and log-normal (LR = -6.20, *p*-value = 0.03. Strategy 5 rejects the pure power-law distribution, as Vuong's test favors all alternative distributions over it, as explained by the LR values (log-normal = -38.85, exponential = -36.14, power-law with cut-off = -37.6). Overall, modularity and learning nullify power-law behavior, as strategies 2 and 5 do not fit with pure power-law and can be explained by simpler distributions with finite variance, implying that the likelihood of being highly delayed is truncated.

Table 5. Test of best-fitted distribution.

Strategy	Log-normal		Exponential		PL + cut-off		Supporting distribution
	LR	p	LR	p	LR	p	
1	-1.43	0.28	34.66	0.00	**-2.54**	**0.02**	power-law, power-law with cut-off
2	**-6.20**	**0.03**	5.73	0.46	**-7.2**	**0.00**	power-law with cut-off, log-normal
5	**-38.85**	**0.00**	**-36.14**	**0.00**	**-37.6**	**0.00**	power-law with cut-off, log-normal, and exponential

5. Discussion

Delivering large-scale technological infrastructure through the megaproject approach presents significant challenges due to the inherent complexity and uncertainty. Prior research suggests that the magnitude of overruns follows a power-law distribution due to the growth of project activity networks and their increasing interdependency (Santolini et al., 2021; Vazquez et al., 2023).

While traditional megaprojects (strategy 1 in the simulation) exhibit the lowest average schedule overrun ratios in the initial iterations (Figure 3), their rigidity makes them more vulnerable to uncertainty than the iterative-modular delivery approach. Moreover, our findings reveal that the delay of the megaprojects approach follows a power-law distribution with a decay rate $\alpha = 5.01$ (Table 4), indicating that the schedule ratio has a finite mean and variance but retains a heavy tail of extreme delays ($x_{max} = 4.62$, Table 4). This fits well with the power-law with exponential cut-off distribution (Table 5), in which catastrophic delays are still possible but rare.

In contrast, iterative-modular delivery strategies (e.g., strategies 2 and 5) nullify the power-law behavior of delivery delay as these two strategies yield significantly higher power-law decay rates ($\alpha = 6.40$ and $\alpha = 9.13$, respectively, Table 4), ruling out power-law behavior (Figure 4), and shifting the delay pattern to distributions with finite variance (e.g., log-normal, Table 5), minimizing the likelihood and magnitude of extreme delays.

The megaproject approach may appear advantageous initially (Figure 3). However, the likelihood of achieving such a performance is relatively low due to the high variability of the outcome. Macroscopically, modularity and learning slightly lower the average delays but drastically reduce the variability (Table 3). For instance, strategy 10 achieves a 4.5% reduction in total duration and a 67% decrease in variance compared to the megaproject approach. However, our results provide a lower bound on the overruns of all strategies due to model simplification, which assumes a single unit-time cost for all activities and a single SOC's source-node assignment per iteration.

Based on our analysis, we will, in the following paragraphs, propose three propositions to enhance the efficacy of delivery through modular iteration, which are:

- *Proposition A: Design a delivery approach that includes phased implementation.*
- *Proposition B: Continuously learn from previous successful practices and experiences.*
- *Proposition C: Design the delivery process to enable the effect of learning capability.*

5.1. Proposition A: Design a delivery approach that includes phased implementation.

Our results suggest that the project owner's initial capability matters for delivery performance. Its effect on the average duration over iteration is somewhat linear. However, it results in an exponential decrease in variability (Figure 5). With initial capability at its maximum ($E_0 = 1$), both the average and standard deviation of the total project duration are minimal, and all strategies experience approximately a 1% overrun (Figures 5 and 6). This means that trait-taking projects, where experts have a clear understanding of what to do, are less likely to be delayed.

For the trait-making projects, the average results would yield similar outcomes once the system was built in the 10th iteration, assuming a constant learning capability; however, variability is slightly higher (Figure 6). When a project owner delivers large-scale technological infrastructure with a low initial capability ($E_0 \approx 0$), the megaproject approach results in the highest average delay and variability, as indicated in the lower-left cell of Figure 5. In contrast, the iterative-modular approach yields lower average delay and standard deviation for the entire endeavor.

In situations where there are no initial capabilities for governing and executing the endeavor, the delivery process becomes as critical as the system itself (Ika & Donnelly, 2017); therefore, project owners delivering large-scale technological infrastructure without prior experience in governance and execution should adopt an iterative, modular delivery approach. Unlike the megaproject approach, which relies on exhaustive upfront planning, iterative-modular approaches allow incremental adjustments based on real-world feedback, which aligns with the nature of system integration in practice (Sanderson, 2012).

In an iterative-modular approach, the first iteration serves as both a prototype of the system's infrastructure and a testbench for improving the delivery process. The first iteration helps mitigate uncertainty by translating it into risks, enabling the identification and resolution of errors before full-scale deployment. This first iteration allows stakeholders to learn about the technological infrastructure itself and the delivery process in a real-world environment on a smaller scale, building the capabilities for delivering the technology, the essence of trait-making projects from Hirschman, which he defined the definition of success of trait-making projects as "for the project if it is successful, will be valuable not only because of its physical output but even more because of the social and human changes it will have wrought" (Hirschman, 1967, p.119).

The first iteration establishes credibility and public trust in both the delivery process and the system being delivered (if it is successful), as infrastructure delivery often faces systemic inefficiencies and governance failures, leading to delays and unmet expectations that provoke stakeholder skepticism (Altavilla et al., 2019; Hetemi et al., 2020). A successful first iteration provides empirical evidence of feasibility, effectiveness, and societal impact within its context, creating buy-in for the broader implementation. If it fails, the endeavor can be discontinued with minimal investment loss in the first phase.

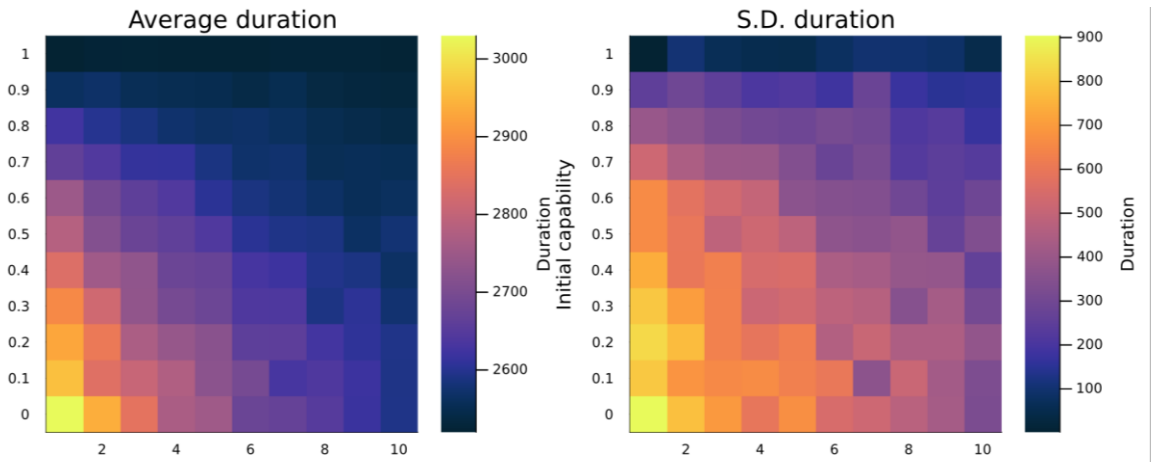

Fig. 5. Initial capability (E_0) (Y-axis) with delivery iterations (X-axis) on average and standard deviation of total overrun with fixed parameters, A = 0.5, Number of activities and baseline duration = 2,520, a = 0.4, E_{max} = 0.99.

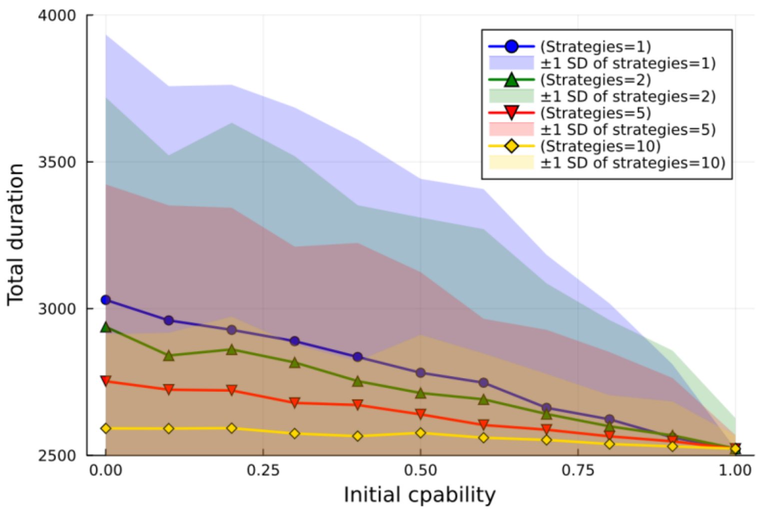

Fig. 6. Initial capability (E_0) under four strategies (1, 2, 5, and 10) in terms of the average and standard deviation (S.D.) of total duration, with fixed parameters: A = 0.5, number of activities and baseline duration = 2,520, and a = 0.4.

5.2. Proposition B: Continuously learn from previous successful practices and experiences.

Overall, our findings support the notion that learning by doing reduces production costs and uncertainty (Ryu & McCann, 2023); however, there are two ends in the learning mode spectrum: success and failure. From our simulation, we observe that the success-based learning mode has a more substantial effect on both average duration and variability than the failure-based learning mode (Figure 7), supporting the findings of Baum and Dahlin (2007) and Muthulingam and Rajaram (2022) in other contexts.

We notice that the delivery of technological infrastructure and movie production operations shares similarities. In both contexts, each team member performs distinct tasks in coordination with others. When teams are composed of members with a history of success, each member will perform their task using the experience that led to past success, which can mitigate the impact of time pressure and contribute to the success of the current production (Muthulingam & Rajaram, 2022). In this vein, relying on histories of small successes with the iterative-modular approach rather than placing a big bet on the megaproject approach yields better overall performance on the delivery schedule (Figure 7).

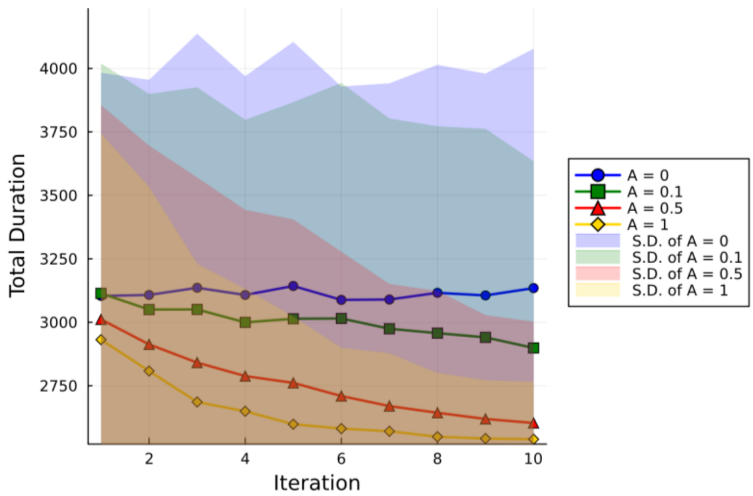

Fig. 7. The effect of learning mode on the reduction over iterations. $A = 0$ (failure-based learning), $A = 0.5$ (learning equally from success and failure), $A = 1$ (success-based learning). Number of activities = 2,520, $a = 0.4$.

Technological infrastructure prospers when it is institutionalized in society. The imported delivery process, although proven effective in its original contexts, may not be directly applicable to the country's unique conditions. Trait-making projects are not only about delivery infrastructure but also about building knowledge regarding their delivery. Knowledge of how to make (deliver) things is considered art, not science (Aristotle, 350 BCE/2009); thus, to excel in art, one must go through iterations of practice. Once these practices prove successful, they become embedded within routine as tacit knowledge, which can enhance the likelihood of successful innovation and decision-making (Longauer et al., 2024; Ngereja & Hussian, 2021).

Technologies are often developed through trial and error due to the inherent complexity and uncertainty of the process (Sommer & Loch, 2004). From the outset, knowledge about delivering large-scale technological infrastructure cannot be science but art, according to Aristotle's definition of knowledge, which requires understanding logic and experience for the development of knowledge (Aristotle, 350 BCE/2009).

In our context, scaling and sustaining technological infrastructure requires a project owner to continuously learn from past successful practices and experiences, generating experiential knowledge. By embedding identical experiences from the previous infrastructure delivery directly, the project owner can benefit from the continuous harvesting process of knowledge that can be directly exploited without generalization and contextualization processes, as displayed in Figure 1, to develop best practices tailored to specific conditions through adaptation and alignment processes, the two of the essences of trait-making projects (Ika & Donnelly, 2017).

5.3. Proposition C: Design the delivery process to enable the effect of learning capability.

Infrastructure delivery is time-consuming and highly vulnerable to volatility in the project environment, making adaptability and flexibility essential (Davies & Brady, 2000; Denicol & Davies, 2022). This adaptability is particularly crucial in large-scale infrastructure delivery, where project environments continually evolve (Geraldi et al., 2011; Nyarirangwe & Babatunde, 2019). Based on a sensitivity analysis of learning capability, we found that both the mean and the variability of delivery duration decrease exponentially as learning capability increased across iterations (Figure 8). This sensitivity analysis indicates that institutionalizing iterative learning in the delivery process can improve efficiency in large-scale technological infrastructure projects.

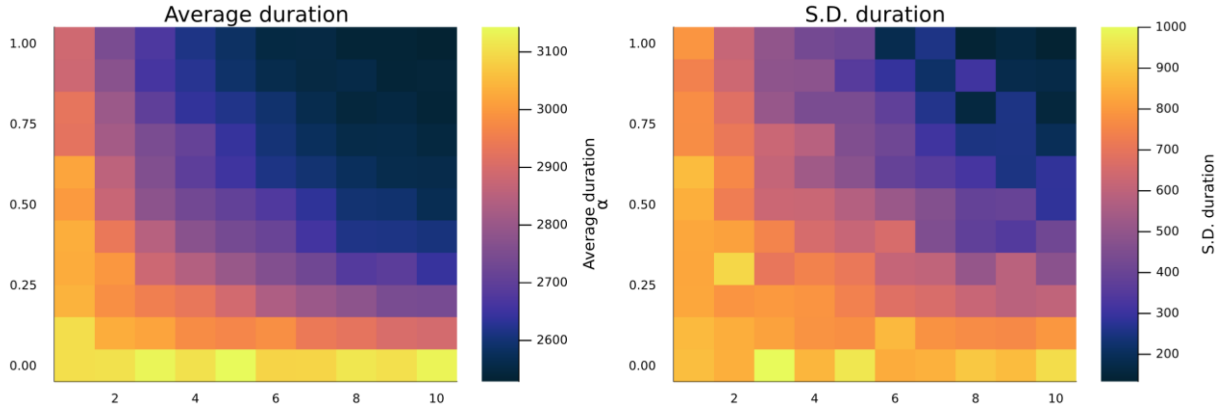

Fig. 8. The effect of learning capability (a) (Y-axis) with delivery iterations (X-axis) on average and standard deviation of total overrun in absolute value with fixed parameters, A = 0.5, number of activities, and baseline duration = 2,520, E_0= 0.01, and E_{max} = 0.99.

Our study demonstrates that modular delivery process design enables the realization of learning effects, as humans improve performance through repeated execution of identical tasks; by designing an identical system and sequentially delivering it, total production costs are reduced (Wright, 1936), while project estimation accuracy increases (Chhetri & Du, 2020). In the modular product system, components can be developed, tested, upgraded, and integrated separately and incrementally, enabling the resilience of infrastructure delivery by allowing for on-the-fly corrections (Baldwin & Clark, 2000; Lammers et al., 2022), and the ability to make such an action is dependent on the harvested capability, which also depends on learning capability. This is a key advantage of modular design, as it enables continuous improvement and adaptation, ensuring that the delivery remains aligned with evolving environmental conditions and technological advancements.

Big and complex deliveries are fragile to SOC (Vazquez et al., 2023). Another key benefit of modular process design is its ability to minimize uncertainty across iterations by breaking large, complex deliveries into smaller, independently manageable deliveries. Each module functions as a self-contained unit that can be developed and refined separately without threatening the entire delivery of technological infrastructure. Since the system to be delivered is smaller, the magnitude of the SOC effect is also small due to the reduced number of connections between activities, which allows for greater delivery resilience. This means that the overrun in one part of the system is less likely to propagate and cause widespread disruptions, thereby reducing the likelihood of extreme overruns, as confirmed by the increase in the decay rate (α) of the power-law distribution, as shown in Table 4.

6. Conclusion

The extent to which a project is completed within the initial time estimation is one of the key elements in project management success. This study advances the discourse on infrastructure delivery by challenging the traditional "quantum leap" approach, characterized by megaprojects, and advocating for a piecemeal, incremental approach known as the iterative-modular approach. From the perspective of system interdependencies, we demonstrate through computer simulation that the SOC phenomenon significantly contributes to the unpredictability of megaproject schedule overruns. The power-law distribution of schedule overruns stems from the fragility of the project activity network in the megaproject delivery model, where a small delay in an activity can cause a big magnitude of overrun (x_{max} = 4.62) across the entire delivery.

In contrast to megaprojects, the classical approach of infrastructure delivery, we show that by breaking down the delivery process into small modules, then delivering them in series and consider the learning mechanism of the delivery organization, the magnitude of overruns is reduced, as well as uncertainty, as explained by a higher decay rate and smaller upper bound in power-law parameters, ruling out the power-law behavior of overrun in infrastructure delivery. By embracing the dynamic nature of the project's environment, our study underscores the importance of adaptability in delivering large-scale technological infrastructure. The iterative-modular approach ensures delivery performance and allows incremental learning to build the project owner's capability, particularly in system integration and in dealing with technological novelty, which is central to trait-making projects.

Our key propositions argue for prioritizing learning from prior experiences, particularly successful experiences, rather than relying on imported expert solutions to cultivate localized expertise to scale up the initial technological infrastructure, and design both the delivery process and infrastructure system architecture in a modular manner to enhance resilience against schedule overrun, as modularity enables learning for growing large. By shifting towards an iterative-modular approach, the outcomes of large-scale technological infrastructure delivery could be more predictable in terms of scheduling, while fostering long-term sustainability in technological advancements.

6.1. Implications for research

Our research paper contributes to the literature on infrastructure delivery by highlighting the roles of a modular delivery process and practice-based learning in minimizing schedule delays, a key part of project management success. This research introduces a linkage between self-organized criticality (SOC) and schedule delays, extending Flyvbjerg et al. (2022)'s work on IT project cost overruns to infrastructure delivery. By demonstrating that modularity and learning can mitigate the power-law behaviors of delays in large-scale technological infrastructure delivery resulting from the megaproject approach, the study provides a framework for modeling project delays through the concept of SOC, which can also be extended to examine and address failures or misperformances in other complex systems deliveries.

Second, our research contributes to the organizational learning in temporary organizations by claiming that large-scale technological infrastructure delivery, a type of trait-making project, should prioritize local capability building over importing expert solutions, as the megaproject approach often overlooks the context of the country where technological infrastructure will be placed, leading to overall inefficiencies in delivery and project failure as the delivered technology and the delivery process fails to adapt to its context. By embedding continuous learning from their previous practices, such as trial-and-error, learning-by-doing, and improvisational learning, countries can build their expertise in developing their own delivery solutions to tackle their specific local contexts (Ika & Donelly, 2017), lowering the degree of exploration of the endeavor (Nyman & Öörni, 2023) and strengthens the argument that knowledge of how to make things is an art, not science (Aristotle, 350 BCE/2009).

Third, we advance the discussion on modular systems in infrastructure delivery by demonstrating how modular process design can overcome the effects of SOC. Unlike the traditional modular approaches, which reduce interdependencies between system components and deliver them in parallel (Baldwin & Clark, 2000; Lammers et al., 2022), we argue that the series modular delivery approach provides identical benefits as the parallel approach in comparison to big one-off delivery, which does not take into account the concept of modularity. We found that series modular delivery can potentially reduce delivery time in the context of trait-making projects where initial knowledge is limited. This discussion of modular systems in infrastructure delivery challenges the economies-of-scale paradigm that underpins the megaproject delivery approach, demonstrating that bigger is not necessarily better because of its fragility to extreme overruns. Our findings support a paradigm shift in infrastructure delivery (Ansar & Flyvbjerg, 2022; Brunet, 2025; Thuesen et al., 2024), advocating for approaches that incorporate the repeatability, adaptability, and learnability of infrastructure delivery processes.

6.2. Implications for practice

This study offers several implications for governments and organizations responsible for delivering large-scale technological infrastructure. By demonstrating the limitations of the traditional megaproject approach and highlighting the roles of modularity and learning in delivering large-scale technological infrastructure, this research provides the following practical insights for initiating such projects.

First, countries should break down infrastructure projects into smaller, sequential modules for deployment, minimizing the cascading effect of delays and isolating errors within individual modules. For example, a smart grid initiative could be rolled out incrementally, district by district, ensuring that failures in delivery in one module do not influence the entire system (Baldwin & Clark, 2000). Moreover, the first iteration enables stakeholders to early identify potential challenges in the delivery process and the impacts of the technological infrastructure in the open environment, which can be further refined in successive rounds of delivery.

Second, when building large-scale technological infrastructure without prior knowledge of such technology, the project owner should institutionalize the knowledge of creating things, which can be achieved through learning-by-doing, trial-and-error, and improvisational learning (Argote & Miron-Spektor, 2011). This can accelerate overall infrastructure delivery and reduce the likelihood of overrun, enabling effective utilization of a strong owner-project governance model. By doing so, the project owner organizations can develop localized system integration capabilities to handle such technology within the country’s context without relying on external expertise, thereby promoting the country’s long-term sustainability. The path to becoming a strong project owner is not about importing knowledge but about building capabilities throughout the history of the infrastructure manager. This requires deliberate, iterative efforts to harness in-house expertise through hands-on experience with the technology and the delivery process. For instance, UK Network Rail has refined its system integration skills and stakeholder coordination practices over decades, evolving into a megaproject-based firm (Denicol & Davies, 2022). This evolution, in which all parameters in the learning equation are high, enables them to deliver infrastructure effectively through the megaproject approach.

Third, the shift from a static, big-bet megaproject to a modular, learning-driven approach is necessary for the project owner’s sustainability. This approach not only mitigates delays and other project management performance measures but also transforms infrastructure projects into vehicles for innovation, trust, and sustainable growth. “The true success of trait-making projects lies not in their physical outputs alone but in their capacity to reshape human capabilities and institutional wisdom” (Hirschman, 1967). However, to achieve this, a new policy or framework for project evaluation is needed that aligns with the nature of phase-based deployment. The traditional framework often favors prestige benefits from megaprojects. We argue that the promised benefits of the megaproject approach are often deceptive, as they are frequently unrealized and frequently calculated by external experts without considering the dynamic nature of the local context. Thus, governments should explore flexible financing and project evaluation structures informed by the outcomes of earlier delivery iterations. This ensures that funds are allocated based on real, perceived benefits rather than long-term projections, which are highly uncertain.

6.3. Limitations and further research

All research is subject to limitations, including ours. First, our analysis relies on theoretical models and prior empirical findings on IT project and megaproject management literature. Future research should explore our propositions through empirical case studies of large-scale technological infrastructure projects that have adopted an iterative-modular approach, such as wind farms or small modular reactors (SMRs). In particular, quantitative data collection on cost and schedule overruns, as well as learning outcomes, could help substantiate our propositions.

Second, the generalizability of the iterative-modular approach may be constrained by industry-specific factors. While our study focuses on large-scale technological infrastructure projects, different sectors may exhibit distinct characteristics that influence the applicability of the iterative-modular approach. Accordingly, exploratory research across multiple industries to examine the boundary conditions of the iterative-modular approach is necessary.

Third, our study does not explore the governance mechanism of the iterative-modular delivery approach. As it is opposite to the traditional megaproject approach, we foresee that the governance mechanism, particularly the role of system integration, needs to be more comprehensive than it currently is. Also, organizational and institutional barriers might hinder the full adoption of our propositions. Future studies should investigate the role of stakeholders in governing our delivery approach.

Fourth, while our findings highlight the benefits of modular design in mitigating the self-organised critical (SOC) phenomenon, further research is needed to determine the optimal degree of modularity for large-scale delivery of technological infrastructure. Excessive fragmentation of the delivery process may introduce inefficiencies, whereas insufficient modularity may leave projects vulnerable to cascading failures. Exploring this tipping point through empirical testing would help to further our understanding of the design and implementation of an iterative-modular approach.

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