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Operationalizing AI at Scale: Repeatable frameworks for integration, adoption and performance measurement across enterprise and startup environments

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Abstract

Scaling to Artificial Intelligence (AI) is a major shift between experimental proof-of-concept to an industrial quality of integration into complex socio-technical systems. Although AI is often touted as a force of exponential efficiency, numerous organizations are facing a scaling crisis wherein projects are stalled because of a lack of alignment between technical possibility and administrative machinery. The study uses a systems-thinking framework to rebrand AI implementation not as a software implementation, but as a restructuring of the production role within the organization.

Studies show that the adoption of AI is a multidimensional change that depends on the internal preparedness of a firm, technological maturity, and external competitive forces (Gupa, 2024). This paper illustrates that structural antecedent to enhancement of effective system capacity is the reducing administrative intensity, time and resources redirected to compliance, documentation and redundant monitoring.

We suggest that the latent access tax created by administrative friction, close to the 266 billion of administrative waste in U.S. healthcare, needs to be counterbalanced by standardized orchestration and capacity building that are humanity-centered. Finally, this paper offers a replicable framework of closing the gap between nominal AI potential and successful operational output within both enterprise and startup contexts.

Keywords: Artificial Intelligence (AI) Scaling; Administrative Intensity; Capacity Wedge; Queueing Theory; Socio-Technical Systems and Organizational Transformation

1. Introduction

The current state of health care and finance presents a great paradox in which dramatic spending in technology fails to proportionately translate into better access or efficiency. In 2023, health care expenditures in the United States were estimated to amount to about 17.6 percent of gross domestic product, that is, about 4.87 trillion, yet waste is still truly mind-boggling as administrative complexity alone was estimated to cost about 266 billion. This systemic friction reflects the challenges faced by corporate environments in trying to operationalize Artificial Intelligence; the so-called scaling

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crisis is not necessarily a failure of the underlying algorithms, but is a failure of the organizational production function to align to new technical realities (Mecca, 2025).To go to scale with AI, a repeatable structure is necessary to meet the unique requirements of two organizational archetypes: big companies, which experience a high administrative intensity and historical fragmentation, and startups, which need to develop capacity at the base and face harsh liquidity and resource constraints (Gupa, 2024). In the same way that structural requirements in clinical settings such as the minimization of administrative friction are a pre-condition to enhance patient access, the integration pathways of AI are also to be simplified in order to achieve its potential. Administrative complexity is an implicit tax on the provision of care, and technical overhead is the same latent access tax on AI-driven innovation. When time, attention, and resources are redirected to compliance and documentation, they are subtracted out of the time to do core production or innovation (Akhiwu, 2025).To ensure that organizations go beyond the concept of complexity as a financial issue, this paper suggests a four-dimensional socio-technical model, which incorporates structural integration, behavioral adoption, queueing calibration, and institutional alignment.

2. Literature review

2.1. Multidisciplinary AI Adoption and Administrative Friction Foundations.

The theoretical premises underpinning AI adoption lie at the crossroads of technological preparedness, organizational behavior, and the economics theory of production functions. Studies indicate that the use of AI is a multidimensional change based on the internal preparedness of a firm and the external competitive landscape, and not a linear occurrence (Gupa, 2024). In the tradition of health economics, the administrative overheads are recorded as a latent tax on productivity that wastes labor time on secondary goals like compliance, documentation and billing. These expenses have been as high as $1,055 per capita in the United States, which is almost tenfold of the 97 per capita observed in the United Kingdom more integrated system.

This theoretical framing gives a way to understand the effects of AI; when the administrative cost of cleaning the data, monitoring the model and ensuring compliance with the regulations surpasses the marginal efficiency benefit, the technology will continue to be a net loss to the effective capacity (Xue et al., 2025). In addition, the human component of adoption is frequently described in terms of the Unified Theory of Acceptance and Use of Technology (UTAUT), with the belief in the enhancement of throughput due to the use of a tool being the main stimulus to use it, performance expectancy.

2.2. Nonlinear Queuing Theory, Congestion, and Capacity Constrictions.

(Gupa, 2024) points out that in SMEs and startups where there is no strong administrative architecture, faster experimentation may be possible, but unless it is systematically built up, the gains in the beginning can be quickly exhausted as the system reaches its service frontier (Haefner et al., 2023). This is in line with the queueing and congestion literature that gives the nonlinear mechanism of how small services capacity cuts give large delay increases. The expected wait time in a standard M/M/1 queueing model increases indefinitely at the point of utilization saturation. Replacement of the administrative burden (a) into the service rate equation (a full form is: (1-a) μ0(1-a)) reveals the nonlinear amplification of access congestion by complexity. The use of institutional counterfactuals like the Core20PLUS5 framework in the UK demonstrates how efficiency targets can be obtained with much lower overhead than multi-payer systems with fragmented administrative requirements (Cornelsen, 2026). Using the concept of administrative intensity as a negative productivity shock, organizations can gain a better insight into the structural constraints that have to be eliminated in order to ensure sustainable AI performance.

2.3. Capacity Wedge, System Design and Orchestration Efficiency.

Elaborating on this, the capacity wedge indicates the gap between the potential of AI and the throughput in the delivery system. Even quite small administrative loads are capable of creating disproportionately high wait times and congestion already when the system is already pushing against its capacity frontier. Administrative complexity can be treated as an endogenous capacity constraint to enable organizations to maximize throughput so that AI integration acts as positive productivity shock instead of a generator of latent access taxes (Gurudaas, 2025; (Font-Cot et al. 2025). Similarly to how a single-payer system narrows the gap between administrative cost in the US and the UK, an integrated AI coordination layer also decreases the weighted-average administrative intensity that an employee will experience in working across several internal departments.

Finally, the transition to a coherent PoCs to continuity of production needs a consistent alignment of technical architecture to the overall population health or business goals of the company (Gurudaas, 2025; (Font-Cot et al. 2025).

This necessitates a shift toward front-end analytics as well as predictive risk scoring to focus compliance in areas of greatest risk, instead of a uniform administrative burden that is spread across the workforce.

3. Integration Frameworks: PoC to Production.

3.1. AI System Integration based on a layered architecture.

To transform Artificial Intelligence into something beyond a proof-of-concept (PoC) into a production-grade asset, organizations should abandon brittle, point-to-point connections in favor of a layered, socio-technical integration architecture.: High administrative intensity in systems such as health care and finance is often the result of fragmented standards and conflicting documentation requirements across various internal departments or external payers (Krishnasamy and Gopalakrishnan, 2023). Likewise, AI scaling cannot succeed in the situation when data is fragmented without a single orchestration layer to standardize inputs and redirect AI-powered insights straight into the core systems such as ERP or CRM platforms.

The suggested framework suggests using a three-level framework, including the Data Layer, the Model Layer, and the Orchestration Layer that is specifically tailored to eliminate the so-called friction of a billing-type characteristic of the legacy environment. With such layers standardized, organizations are able to essentially decrease the weighted average administrative intensity in which an employee is placed, which (Gupa, 2024) is a key barrier to digital transformation.

3.2. Divergent Integration Pathways: Enterprises vs. Startups

In the case of big businesses, the integration is a structural reform, eliminating the division that restricts the capacity of the workforce to push tasks with lower complexity into automated systems. This can be compared to the "Scope of Practice" changes in the clinical practice, which lowered the administrative load on the specific labor by enabling the delegation of routine tasks. In comparison, startups use AI as the driver of new ideas, enabling entrepreneurs to automatize business planning and initial stages of development to maintain essential liquid capital (Gupa, 2024). Startups are concerned with maximizing their raw technical supply at the very beginning whereas enterprises aim at minimizing the redundant overhead of the legacy systems. A single-payer system, as much as it narrows the administrative cost difference between the UK and the US, a single unified AI orchestration layer narrows the cognitive burden on the workforce, permitting an increased effective service rate across the board, denoted by the Greek letter, mu.

3.3. Governance and system design to reduce Capacity Friction.

The effectiveness of this framework also depends on the reduction of the capacity wedge -the gap between the potential of AI and the actual throughput in the delivery system (Bai et al., 2022). With the system running close to its capacity frontier, even small administrative overheads, like manual data entry or unnecessary model validation, may cause disproportionately large increases in wait times and operational congestion. Organizations can optimize throughput instead of merely technical precision by assuming that administrative complexity is an endogenous constraint of capacity instead of a given externality. This includes the application of prospectively integrated governance in which compliance and audit trails are automatically created by the orchestration layer, not by providing manual documentation of the post-event.

Moreover, the integration should consider the heterogeneity of administrative intensity of various departments. According to (Gupa, 2024), this absence of rigid administrative structure in startups is a temporary benefit, though as these organizations grow, they tend to enter the same complexity trap as businesses unless an efficient system of integration is built at the outset. The system can shift to front-end analytics and predictive risk scoring to focus its monitoring resources where the risk of failure or non-compliance is greatest (Cole, 2023). Such a structural precondition is necessary to enhance system efficiency in the sense that it eliminates the tendency of the nominal supply of labor to be stifled by the technical friction of the technology itself. Finally, transitioning into a consolidated PoCs to a coherent production environment will necessitate integrating the technical architecture with the overall institutional objectives of the company, making AI a beneficial productivity shock, instead of a form of latent access tax.

4. Adoption Strategies: Organizational Change.

4.1. Building Workforce Capability and Resistance of Behaviors.

Adoption is the key to implementing an effective AI integration into an organization, and a fundamental change in workforce behavior and institutional culture is needed. Studies point to the fact that employee capacity building is a crucial intermediary between technology and performance; otherwise, AI will be a waste of time that consumes cognitive focus without improving systemic throughput (Gupa, 2024). In highly regulated industries, uptake is often prevented by defensive practice: a behavioral reaction in which staff members discourage the use of automated insights or outsourcing tasks to AI in order to reduce the perceived risk of being held liable or being audited (Treharne et al. 2023; Brennan, 2024). This is especially acute in places with high administrative intensity like in the U.S. health care system, which is already operating in a multi-payer, fragmented environment. In response, successful adoption should be positioned as an access policy, reclaiming time to do high-value work, and making AI not a perceived financial liability but a structural necessity of efficient system performance.

4.2. Equity-Aligned Governance and Contextual Adoption Model.

The strategies of effective adoption must reflect the UK Core20PLUS5 framework by integrating accountability and equity tracking within the prevailing governance frameworks instead of adding it as an additional compliance layer, which is extraneous. This potential integration will make sure that the workforce perceives AI as an instrument of clinical and operational quality and not a documentation obstacle. According to (Gupa, 2024), this anthropocentric model is especially critical in SMEs and startups, where a proper cultural fit between the leadership and the front line will be decisive when it comes to the effectiveness of AI-enabled tools.

These smaller organizations can have a bottom-up adoption process in which initial business planning and development success maintain liquid capital that is necessary to sustain the business (Treharne et al. 2023; Brennan, 2024). Nonetheless, these organizations will need to implement commonized accountability procedures as they grow to avoid the market-driven complexity that is ad hoc, and common in larger, fragmented entities.

4.3. Minimizing Friction of Latent Access by Culture and System Design.

The aim of an effective adoption plan is to offset the so-called latent access tax, the implicit decline in throughput caused by the administrative demands, in such a way that it does not cancel the productivity benefits of the AI system. This will mean going past a mere training and rollout mentality to a paradigm of Staff Training, Innovation Culture, and Ethics '(Gupa, 2024). Organizations can enhance 'Performance Expectancy, the fundamental force behind the Unified Theory of Acceptance and Use of Technology (UTAUT) by instituting Explainable AI (XAI) systems and lowering the intensity of the coding audit.

Moreover, the plan has to consider the ''Nonlinear Access Amplifier''. Even slightly behavioral resistance to AI during the time when a given system is functioning close to its capacity will create long queues. An example of this is where a provider wastes an extra 10 minutes checking an AI suggestion because of lack of trust, the subsequent capacity loss is a negative productivity shock that will cascade across the entire schedule (An et al., 2025). The reforms in adoption should thus be directed at alleviating the "supervision documentation requirements" which tend to slow down the middle level management.

Organizations can make sure that AI integration brings about a positive change in the production function by focusing compliance where the risk is most significant, instead of imposing an equal burden, through front-end analytics (An et al., 2025). Finally, restructuring the workforce and simplifying the administration are not merely parallel objectives, but structural complements to each other whose joint impact on system capacity is much greater than the effect of either of the reforms implemented separately.

5. Performance Measurement: Queueing-Based Framework.

5.1. Accuracy Metrics to System throughput Measurement.

Effective operationalization at scale demands a shift in the classical technical model accuracy to a repeatable metric framework, which quantifies system load, value realization and administrative friction (Treharne et al., 2023). The conventional approach to assessment of organizational performance tends to concentrate on direct financial expenditures without taking into account the so-called capacity loss created by the administrative machine around AI tools.

A queueing-based model will provide a better perspective on this, showing that the expected wait time (W_q) and operational lags increase nonlinearly with system utilization as it approaches the point of saturation (i.e. as). According to (Gupa, 2024), the core assumption of organizational performance is that employee productivity intermediates the performance of an organization, therefore, any AI-imposed administrative burden can be seen as a negative productivity shock, which lowers the effective service rate of the organization, as parameterized by the rate of service ($\mu $). When an AI tool needs manual validation all the time or complicated documentation, it brings in an administrative intensity that diverts queues, practically inhibiting the supply-side advantages of the technology.

5.2. Multi-Dimensional Performance measures and Capacity Wedge Analysis.

A sound measurement system should be able to monitor three dimensions: Utilization, Proficiency, and Value Realization. The firms can pinpoint the specific mechanisms by breaking down the administrative intensity index into its constituent parts, like claim denial rates in healthcare, prior authorization frequency, or manual audit intensity in finance (Veronesi et al., 2023). An example is that the results of calibration indicate that when a system is running at 75% capacity, adding a 20% administrative load can raise wait times 10 times (0.15 to 1.56 days). According to (Gupa, 2024), in the case of startups, these metrics need to also consider resource preservation, relating AI throughput to the duration of liquid capital (Sundaramurthy et al., 2022). When a latent access tax of a new ML structure is larger than the marginal benefits in efficiency, the company will incur a capacity wedge where the theoretical output of the AI will not be reflected on the balance sheet.

5.3. Throughput-Oriented Evaluation and Socio-Technical Feedback Effects.

The administrative simplification marginally increases the welfare is convex in the baseline congestion, i.e. the highest benefits of AI-based optimization is obtained in the most capacity-constrained environments (Paul et al., 2025). This involves calculation of effective capacity ($\mu0(1 - a) = (1 - a)0) = a) = fraction of time spent on administrative work. Front-end analytics and predictive risk scoring enable organizations to focus compliance efforts where risk of failure is most likely, instead of allocating a standard administrative load to all employees.

In addition, the Socio-Technical feedback loop has to be considered in performance measurement. The productivity of employees can be described as a partial mediator between AI implementation and organizational performance (Gupa, 2024). In case the performance measurements are based on the speed of the algorithm rather than the time-to-decision of the operator, the data will conceal the "bottlenecks of the human operator.

As an example, an AI that accelerates the process of data analysis, but doubles the time it takes to document the data, actually decreases the service frontier of the system (Sundaramurthy et al., 2022). Finally, a replicable framework needs to focus on Throughput more than Precision so that AI is a driver of system-wide digital transformation and not a cause of local technical debt.

6. Comparison Enterprise vs. Startup Implementation

6.1. Structural Fragmentation in Enterprises vs. integrated Startup Models

The implementation of AI scaling illustrates the vexed institutional dichotomy between the disjointed, multi-layered system of large enterprises and the agile, integrated system commonly used by startups, where each internal department, such as Legal, HR, IT, and Finance, has its own data standards, billing codes, and prior authorization to start a new project (Kabera et al., 2026). This disintegration creates an unnecessary administrative overhead which consequently leads to a much greater administrative cost per capita, which is a latent tax upon internal innovation. Startups, conversely, tend to follow a single-payer model of data and AI and, therefore, use cloud-native systems to reduce the administrative workload that every employee or process has to bear initially (Gupa, 2024).

6.2. Dissatisfying AI Strategies and the threat of organizational debt.

Studies indicate that whereas startups apply AI as a disrupter to maintain liquid capital and speed up product-market fit, companies apply it as an administrative simplification tool to maximize the usage of the current labor. According to (Gupa, 2024), the absence of a strict, outdated administrative structure in startups enables one to experiment quickly and fail fast. The UK Core20PLUS5 counterfactual, however, demonstrates that it is not just the size of the gap in administrative efficiency but the very design of institutions. An example is that the U.S. healthcare system spends more than 1,055 per capita on administration versus the UK spending 97, which is reflected in the wedge of capacity between AI-integrated companies and AI-native startups (Mupa et al., 2025). The accumulation of organizational debt: as the startups grow larger, they tend to pile up the ad hoc collection of compliance layers, which likewise can at some point recreate the same inertia as a bigger company unless a repeatable framework is put in place.

6.3. Towards Convergence to Efficiency through Orchestration and Capacity Optimization.

With a smaller capacity wedge, the difference between nominal technical supply and effective operation throughput, both types of organizations can serve the service frontier better. Enterprises should aim to redesign structure, internal requirements that need to be standardized to minimize the weighted average administrative load (Hammad and Abu-Zaid,2024). To them, AI would help to recover the lost 30 percent of labor hours being wasted on the so-called billing-type friction. Startups, on the other hand, should be concerned with capacity building, whereby their initial agility does not transform into the market-based complexity that is fragmented and undermining of mature organizations. According to (Gupa, 2024), the success of AI in both settings is in how the organization is able to shift its focus to a coherent orchestration layer that focuses on Throughput instead of Documentation. In the end, it will be the one who considers administrative simplification as a condition of scale, and not an addition, the comparative advantage in the AI age.

7. Conclusion and Future Directions

Scaling AI is essentially a structural problem of overcoming capacity issues and not a technical or financial issue (Sundaramurthy et al., 2022). This study has shown that administrative complexity is a sort of tax on access latent that inhibits proper supply and causes system-wide congestion. As has been determined in the scope of this analysis, to succeed in the digital shift, AI must be reconsidered not as an external element, that is, an addition to the current processes, but as an organizational element of the production process. Studies by (Gupa, 2024) support the idea that employee productivity and capacity building mediates organizational performance in the AI era; therefore, any framework that does not take into consideration the human-administrative interface is bound to fail on the scaling frontier. Proper reform should combine technical orchestration, human-oriented adoption, and stringent performance measurement by queueing to recover the lost productivity to the so-called capacity wedge.

Moving forward, the operationalization of AI will probably take a different turn to "agentic workflows" which are autonomous systems that can navigate administrative redesign in real-time (Meinow et al., 2022). This is a reflection of the integrated health system trend, as seen in the UK 10-year health plan, which aims to shift towards prospectively integrated governance as opposed to the reactive post-payment audits. According to (Gupa, 2024), the future generation of AI structures is expected to emphasize more on the ethical and innovation cultures rather than on the accuracy of algorithms (Sundaramurthy et al., 2022). To businesses, it would represent a last step away from multi-payer-like internal architectures to a single data orchestration. In the case of startups, it entails establishing a scaled administrative base that does not allow an organization to accumulate organizational debt as it develops into a pilot and a market leader.

The results of this paper imply that the marginal welfare benefit of administrative simplification is convex; the larger the systems are the larger the marginal value of eliminating even minimal friction. Therefore, AI ought to be used as an access policy tool, to reclaim time to higher-value tasks and minimize the so-called nonlinear access amplifier that afflicts capacity-constrained environments. Further research efforts to be done in the future in the area of empirical validation of the Administrative Intensity Index in various sectors should help to narrow down the relationship between compliance burden and operational throughput. Finally, with the administrative simplification as a structural requirement to access and equity, organizations can eventually bridge the gap between the potential of AI in principle and its real result in economic output. The organizations that are successful in the competitive environment of the 2020s will be the ones that see AI integration as the way to free the human labor force of the latent tax of complexity, to transform the sustainable ecosystem of innovation and development.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Akhiwu, B. (2025). Operationalizing Innovation at Scale: Embedding Agile and Lean Principles into Enterprise Technology Workflows. https://www.researchgate.net/profile/Bryan-Akhiwu/publication/396694057_Operationalizing_Innovation_at_Scale_Embedding_Agile_and_Lean_Principles_into_Enterprise_Technology_Workflows/links/68f5c68b02d6215259bd4be8/Operationalizing-Innovation-at-Scale-Embedding-Agile-and-Lean-Principles-into-Enterprise-Technology-Workflows.pdf

[2] Bai, T., Balagopal, A., Dohopolski, M., Morgan, H. E., McBeth, R., Tan, J., ... and Jiang, S. (2022). A proof-of-concept study of artificial intelligence–assisted contour editing. Radiology: Artificial Intelligence, 4(5), e210214. https://pubs.rsna.org/doi/pdf/10.1148/ryai.210214

[3] Brennan, A. (2024). Applying the CORE20PLUS5 to Address Health Inequalities for Patients Under the Rehabilitation and Recovery Service in the London Borough of Hackney. BJPsych Open, 10(S1), S223-S223. https://www.cambridge.org/core/services/aop-cambridge-core/content/view/06A38B23F0ED34ADD142497EB935D108/S2056472424005489a.pdf/div-class-title-applying-the-core20plus5-to-address-health-inequalities-for-patients-under-the-rehabilitation-and-recovery-service-in-the-london-borough-of-hackney-div.pdf

[4] Cole, M. (2023). (Infra) structural discontinuity: Capital, labour, and technological change. Antipode, 55(2), 348-372. https://onlinelibrary.wiley.com/doi/pdf/10.1111/anti.12887

[5] Cornelsen, S. (2026). Integration of artificial intelligence for enhanced organizational performance: developing a data-driven process measurement system (Doctoral dissertation, Vilniaus universitetas.). file:///C:/Users/User/Downloads/277679218.pdf

[6] Font-Cot, F., Lara-Navarra, P., Arnau, C. S., and Serradell-López, E. (2025). Scaling wheel framework: A holistic approach to startup scalability, governance models, and AI-driven innovation ecosystem competitiveness. Journal of open innovation: Technology, market, and complexity, 11(3), 100619. https://www.sciencedirect.com/science/article/pii/S2199853125001544

[7] Gupa, M. (2024). Operationalizing AI: Frameworks for Integration, Adoption, and Performance Measurement in Modern Organizations. Journal of Socio-Technical Systems and Digital Transformation, 12(3), 145-168.

[8] Gurudaas, R. K. (2025). Sustainable Ways for Early-Stage Startups to Build Scalable Business Models Leveraging AI in the Post-Pandemic Era. Digital Repository of Theses. file:///C:/Users/User/Downloads/853.pdf

[9] Haefner, N., Parida, V., Gassmann, O., and Wincent, J. (2023). Implementing and scaling artificial intelligence: A review, framework, and research agenda. Technological Forecasting and Social Change, 197, 122878. https://www.sciencedirect.com/science/article/pii/S0040162523005632

[10] Hammad, A., and Abu-Zaid, R. (2024). Applications of AI in decentralized computing systems: harnessing artificial intelligence for enhanced scalability, efficiency, and autonomous decision-making in distributed architectures. Applied Research in Artificial Intelligence and Cloud Computing, 7(6), 161-187. https://www.researchgate.net/profile/Ali-Hammad-25/publication/386219179_Applications_of_AI_in_Decentralized_Computing_Systems_Harnessing_Artificial_Intelligence_for_Enhanced_Scalability_Efficiency_and_Autonomous_Decision-Making_in_Distributed_Architectures/links/674934fe790d154bf9b3788f/Applications-of-AI-in-Decentralized-Computing-Systems-Harnessing-Artificial-Intelligence-for-Enhanced-Scalability-Efficiency-and-Autonomous-Decision-Making-in-Distributed-Architectures.pdf

[11] Kabera, S. T., Mupa, M. N., Siphatisiwe, P., Mtemeli, P., and Chihota, T. A. (2026). Machine-Learning-Augmented Sizing And Dispatch Of Pv-Grid-Bess Hybrid Microgrids To Achieve 100% Reliability At Lower Lcoe: A Replicable Framework For Critical Facilities. https://www.researchgate.net/profile/Munashe-Naphtali-Mupa/publication/400969283_Machine-Learning-Augmented_Sizing_and_Dispatch_of_PV-Grid-BESS_Hybrid_Microgrids_to_Achieve_100_Reliability_at_Lower_LCOE_A_Replicable_Framework_for_Critical_Facilities/links/6997ae7664ca8a38208efff0/Machine-Learning-Augmented-Sizing-and-Dispatch-of-PV-Grid-BESS-Hybrid-Microgrids-to-Achieve-100-Reliability-at-Lower-LCOE-A-Replicable-Framework-for-Critical-Facilities.pdf

[12] Krishnasamy, S., and Gopalakrishnan, B. N. (2023). Moving beyond proof of concept and pilots to mainstream: discovery and lessons from a reference framework and implementation. Blockchain in Healthcare Today, 6, 10-30953. https://pmc.ncbi.nlm.nih.gov/articles/PMC10770802/pdf/BHTY-6-280.pdf

[13] Mecca, A. (2025). The influence of artificial intelligence implementation on firm scaling: An exploratory approach. https://lutpub.lut.fi/bitstream/handle/10024/170162/Mastersthesis_Mecca_Annadina.pdf?sequence=1

[14] Meinow, B., Li, P., Jasilionis, D., Oksuzyan, A., Sundberg, L., Kelfve, S., and Wastesson, J. W. (2022). Trends over two decades in life expectancy with complex health problems among older Swedes: implications for the provision of integrated health care and social care. BMC public health, 22(1), 759. https://link.springer.com/content/pdf/10.1186/s12889-022-13099-8.pdf

[15] Mupa, M. N., Tafirenyika, S., Rudaviro, M., Nyajeka, T., Moyo, M., and Zhuwankinyu, E. K. (2025). Machine learning in actuarial science: Enhancing predictive models for insurance risk management. Iconic Research and Engineering Journals, 8, 493-504. https://www.researchgate.net/profile/Munashe-Naphtali-Mupa/publication/389132064_Machine_Learning_in_Actuarial_Science_Enhancing_Predictive_Models_for_Insurance_Risk_Management/links/67b60a83645ef274a4897f9a/Machine-Learning-in-Actuarial-Science-Enhancing-Predictive-Models-for-Insurance-Risk-Management.pdf

[16] Paul, K., Jyothi, B., Kumar, R. S., Singh, A. R., Bajaj, M., Hemanth Kumar, B., and Zaitsev, I. (2025). Optimizing sustainable energy management in grid connected microgrids using quantum particle swarm optimization for cost and emission reduction. Scientific Reports, 15(1), 5843. https://www.nature.com/articles/s41598-025-90040-0.pdf

[17] Sundaramurthy, S. K., Ravichandran, N., Inaganti, A. C., and Muppalaneni, R. (2022). AI-powered operational resilience: Building secure, scalable, and intelligent enterprises. Artificial Intelligence and Machine Learning Review, 3(1), 1-10. file:///C:/Users/User/Downloads/AI+Powered+Operational+Resilience+Building+Secure,+Scalable,+and+Intelligent+Enterprises%20(1).pdf

[18] Treharne, C., Beattie, A., Mitchell, G., and Chan, M. (2023). HTA191 discussion of health inequalities in the NICE single technology appraisal process: a review of recent submissions in NHS England Core20PLUS5 focus clinical areas. Value in Health, 26(12), S356. https://www.valueinhealthjournal.com/article/S1098-3015(23)05004-0/pdf

[19] Veronesi, G., Kirkpatrick, I., Altanlar, A., and Sarto, F. (2023). Corporatization, administrative intensity, and the performance of public sector organizations. Journal of Public Administration Research and Theory, 33(4), 701-715. https://eprints.whiterose.ac.uk/id/eprint/193425/3/JPART%20Final%20Manuscript%20November%202022.pdf

[20] Xue, L., Rashid, A. M., and Ouyang, S. (2024). The unified theory of acceptance and use of technology (UTAUT) in higher education: A systematic review. Sage Open, 14(1), 21582440241229570. https://journals.sagepub.com/doi/pdf/10.1177/21582440241229570