International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 2
***Article Received:** 25 May 2026 **Revised:** 12 June 2026 **Accepted:** 15 July 2026*

Leveraging Artificial Intelligence in Utility Finance and Accounting

Devyani Bajaj,

Power & Utilities Transformation Leader, EY Americas

devyani.bajaj93@gmail.com

Abstract

President Trump in his long-awaited AI Action Plan stated [7], "The United States is in a race to achieve global dominance in artificial intelligence (AI). Whoever has the largest AI ecosystem will set global AI standards and reap broad economic and military benefits… Just like we won the space race, it is imperative that the United States and its allies win this race."

Artificial Intelligence (AI) adoption across U.S. regulated utilities has accelerated in recent years [3][4], particularly in forecasting, asset planning, financial analytics, and self-service capabilities through agents and chatbots. Yet despite growing analytical and execution sophistication, many utilities have struggled to translate AI-driven insights into durable financial decisions, accounting outcomes, or favorable regulatory treatment.

This paper argues that the primary constraint on AI's impact is not data or model maturity, but the absence of process transformation prior to AI deployment. In regulated utility environments where prudence standards, accountability, and cost recovery mechanisms dominate AI must be embedded within redesigned finance and accounting processes to create measurable enterprise value. AI does not transform utility finance by being smarter; it transforms utility finance by being embedded into smarter processes.

To achieve President Trump's vision for AI, it is imperative that the Power & Utilities industry move beyond isolated AI use cases and instead adopt an integrated operating model that connects operational execution, financial outcomes, and regulatory recovery. This requires re-architecting the capital and operating lifecycle from planning and work execution to accounting treatment and rate recovery so that AI-enabled insights are systematically translated into defensible decisions, auditable outcomes, and regulator-aligned value realization.

Utilities that succeed will not be those that deploy the most AI models, but those that redesign their processes, governance, and data architectures to operationalize AI at scale elevating finance from a transactional function to a strategic partner in capital allocation, performance management, and regulatory strategy.

Executive Summary

Utilities are not struggling to adopt artificial intelligence (AI). Many have already invested heavily in forecasting models, capital planning tools, and advanced analytics. Insights are faster and models more sophisticated, yet outcomes remain largely unchanged; capital allocation decisions look familiar, accounting interpretations are consistent, and regulatory friction persists.

This raises a practical question: ***if analytics are better, why aren't decisions?*** The answer lies not in the technology, but in the underlying processes.

The root cause is not technological, it is structural [6]. Utilities are attempting to embed AI into legacy finance and accounting processes that were designed for stability, linearity, and hindsight review, not for probabilistic insight or dynamic tradeoffs.

In regulated environments, outcomes depend not only on analytical rigor, but on whether decisions are accountable, aligned with prudence and affordability principles, and documented in ways that withstand scrutiny. Without redesigning how decisions and processes are structured and governed, improved insight cannot translate into different outcomes.

AI simply optimizes within existing constraints rather than changing them i.e., AI cannot compensate for processes that separate insight from ownership, formalize decisions after they are effectively made and/or treat accounting and regulatory defensibility as downstream steps.

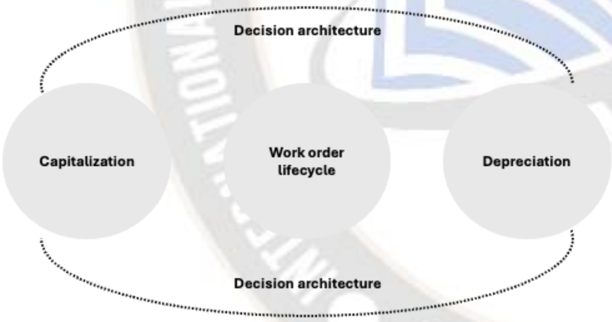
International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 2
***Article Received:** 25 May 2026 **Revised:** 12 June 2026 **Accepted:** 15 July 2026*

This limitation is most apparent in operational domains such as the work order lifecycle, where performance is shaped not just by decisions, but by process flows, systems, and data that define how work is executed and recorded. Fragmented workflows, inconsistent system usage, and poorly structured data limit both decision quality and AI effectiveness. Similarly, in this context, AI inherits weaknesses rather than overcoming them.

This paper makes a central claim: ***AI should be embedded only after the underlying finance and accounting processes are redesigned to function as intended and absorb uncertainty, judgment, and accountability.***

It reframes utility finance through a decision-centric lens, treating decision architecture as a core process and applying it across capitalization, depreciation governance, and the work order lifecycle; illustrating why each must be restructured not only in how decisions are made, but in how processes are executed, systems are configured, and data is structured to embed accountability and governance before AI can deliver meaningful impact.

Figure 1: A decision centric lens should be applied across all process areas



Redesigning Decision Architecture in Utility Finance: From Analytic AI to Decision-Centric AI

Most utilities deploy AI with the expectation that better analysis will naturally lead to better decisions [4]. In practice, this rarely happens. Forecasts improve, scenarios multiply, and models become more sophisticated [1]; yet financial decisions, capital outcomes, and regulatory treatment remain largely unchanged.

The primary limitation in current AI adoption is not tied to any single process, it is rooted in how decisions are made. AI generates dynamic insight; probabilities, ranges, and evolving signals. In contrast, legacy utility finance and accounting processes are linear, committee-driven, and anchored in fixed assumptions. Decisions are often shaped early, validated late, and documented after the fact, with accounting and regulatory considerations incorporated downstream.

Traditional utility finance processes share common characteristics:

- Decisions framed sequentially, not iteratively
- Capital approval divorced from capitalization and accounting treatment
- Regulatory defensibility assessed after decisions are locked in
- Accountability diffused across functions

Furthermore, utility financial outcomes are not determined by analytical superiority alone [6]. They are determined by whether decisions are:

- Made by clearly accountable owners
- Aligned with prudence and affordability constraints
- Documented in ways that withstand regulatory review
- Integrated with accounting and recovery considerations

These processes were optimized for deterministic planning and slow change, versus the probabilistic outputs, scenario ranges, and continuous updates AI introduces. ***This creates a structural mismatch: AI produces dynamic insight, but decisions remain static.***

AI that improves analysis but leaves decision processes unchanged often produces better insight with no practical implementation [6]. Addressing this gap requires redesigning decision architecture, not just enhancing analytics.

Without process redesign, AI highlights tension and exposes process weaknesses, but has nowhere to land and cannot deliver value. Redesigning finance processes does not mean adding more steps or bureaucracy. It means restructuring when and how decisions are made so AI insights become usable. At a minimum, process redesign requires:

- Defining explicit decision points where scenarios are evaluated
- Assigning clear ownership for accepting downside risk

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 2
***Article Received:** 25 May 2026 **Revised:** 12 June 2026 **Accepted:** 15 July 2026*

- Formalizing how tradeoffs (cost, risk, timing, recoverability) are resolved
- Integrating accounting and regulatory implications at decision time, not afterward
- Requiring documentation as part of the decision, not as a retrospective exercise

Figure 2: Decision making future state process

A decision-centric model shifts the unit of design from analysis to the decision itself. It defines where decisions occur, who owns them, and how trade-offs are evaluated. Constraints such as affordability, credit implications, prudence, and recoverability are incorporated directly into the decision rather than addressed after the fact. In this model, AI does not drive decisions. It raises the quality, consistency, and transparency of decisions already governed by clear processes.

Decision-Centric AI reverses the sequence. It starts by redesigning how decisions are made, and only then embeds AI into that structure. Under this approach:

- AI is designed around decision points, not datasets, producing structured decision-relevant scenarios and tradeoffs rather than abstract predictions or single answers
- Constraints (affordability, credit, prudence, recoverability) are explicit inputs, discounting unfeasible paths and making uncertainty visible but manageable
- Decision ownership and judgment are defined in advance, allowing for action

In this model, the goal is not to optimize outcomes, but to improve the quality, transparency, and consistency of judgment within regulated constraints; ***shifting the paradigm from "better answers" to "better decisions."***

The value of a decision-centric architecture lies in its application; the section below demonstrates how it must be operationalized within core finance processes such as capitalization vs. expense determinations.

Capitalization — Shifting the Mindset from "Eligibility" to "Evaluation"

When finance and accounting teams talk about capitalization, they are usually referring to a very practical set of processes:

- How costs are tracked and coded
- How work orders and projects are structured
- How labor, materials, and overhead are captured
- How those costs are evaluated against capitalization policies
- If policies are consistently applied
- If cost treatment is auditable and defensible

These processes are foundational. They determine which expenditures are capitalized, which are expensed, and how consistently policies are applied across the organization. However, in a regulated utility environment, these operational processes do more than ensure accounting compliance. They quietly determine which costs become long-lived financial commitments; Capitalization is where permanence is created [5].

Once capitalized, costs enter the balance sheet, establish depreciation trajectories, become part of the rate base, and create expectations of recovery and sustained regulatory exposure [2]. In stable environments, this conversion has historically been low risk. In energy-transition environments, it is increasingly consequential. Current day Capitalization processes were not designed to consider:

- Transition or external policy risk associated with the asset
- The durability of recoverability over the asset's life
- The political or affordability constraints that may emerge
- Ownership of capitalization risk, not just policy compliance

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 2
Article Received: *25 May 2026* ***Revised:*** *12 June 2026* ***Accepted:*** *15 July 2026*

- Whether permanence itself creates asymmetrical downside risk

As a result, utilities may execute capitalization perfectly, while still embedding significant long-term risk. Yet traditional processes rarely evaluate whether these assumptions will hold. Considerations such as policy risk, durability of recovery, and affordability pressures are often implicit or absent, and ownership of resulting risk is unclear. Utilities are highly precise in executing capitalization, but not always in evaluating its long-term consequences [5]. Before AI can meaningfully support capitalization, the process itself must evolve beyond cost eligibility alone.

A decision-centric approach reframes capitalization as an evaluative decision point, introducing long-term financial and regulatory considerations when permanence is created. Once capitalization processes are redesigned to include these considerations, AI can add real value by:

- Identifying patterns in how costs are historically capitalized
- Flagging projects where capitalization assumptions differ from precedent
- Highlighting concentrations of capital investment exposed to transition or policy risk
- Surfacing mismatches between cost eligibility and recovery durability
- Comparing projected recovery timelines against historical outcomes and emerging signals
- Flagging scenarios where capitalization creates asymmetric downside risk

AI does not decide what gets capitalized. It supports earlier, more disciplined conversations about whether permanence is appropriate, while preserving accounting judgment and auditability. Rather than determining outcomes, it strengthens evaluation at the point where long-term exposure is created.

The same limitations that constrain decision-making at the point of capitalization persist in how utilities govern depreciation, where assumptions are set but rarely revisited. This makes depreciation governance a natural extension of the decision-centric redesign required in capitalization.

Depreciation — Shifting from "Static and Historical" to "Dynamic and Continuous"

In most utilities, useful lives and depreciation schedules are established at the time an asset is capitalized, based on historical experience, engineering estimates, and regulatory precedent [2][5]. Designed for stability and predictability, these assumptions are rarely revisited and typically persist unchanged for years unless external pressures force reassessment. Revisiting assumptions is common only when stress becomes unavoidable, such as:

- Accelerating asset retirement plans
- Major policy or regulatory shifts
- Utilization declining well below expectations
- Sudden impairment or securitization discussions

By the time useful-life assumptions are formally questioned, the financial consequences are often already material and contentious. This creates a familiar pattern: stable assumptions during calm periods, followed by abrupt and disruptive adjustments during stress.

AI introduces the ability to continuously monitor asset performance, utilization, load patterns, maintenance data, and external signals. However, continuous insight by itself does not improve outcomes. Without process redesign, this results in awareness without action; signals accumulate, but ownership, thresholds for intervention, and pathways to decision remain unclear. In practice, utilities encounter recurring challenges:

- **Signal overload:** Continuous monitoring generates frequent alerts, trends, and deviations but no clear guidance on when action is required
- **Unclear authority:** Even when AI flags potential misalignment between assumed and actual performance, it is rarely clear who owns the decision to initiate an accounting review
- **Fear of unintended consequences:** Automatic adjustment of useful lives is neither appropriate nor acceptable in regulated environments, creating resistance to acting on early signals

As a result, AI insights are often acknowledged, discussed informally, and deferred until external pressure forces action. Continuous insight without a structured review mechanism creates awareness, not accountability.

The underlying issue is not the absence of data or predictive capability [6]. It is the absence of a defined process that connects insight to action. Traditional useful-life governance lacks formal review triggers, clear ownership, agreed-upon thresholds for reassessment, and separation between review and change. Without these, any AI-driven signal is perceived as either too weak to justify action or too strong to manage safely, both outcomes lead to inaction. Before AI can add value, utilities must redesign how useful-life assumptions are governed. At a minimum, this requires establishing:

- **Explicit review triggers:** Sustained deviations in utilization, long-term changes in load forecasts, or credible policy signals affecting asset relevance
- **Clear ownership:** Defined accountability for initiating a review, distinct from authority to approve changes
- **Structured review cadence:** Periodic assumption review windows that allow reconsideration without implying automatic revision
- **Separation of review and outcome:** Reviewing an assumption does not require changing it, only reaffirming or adjusting it with documented rationale

A decision-centric approach introduces structure around when and how action is taken by defining triggers, assigning accountability, and establishing formal review cycles. Within this redesigned process, AI can play a powerful and appropriate role:

- Detecting sustained deviations between expected and actual asset utilization
- Highlighting policy, regulatory, or load-related signals affecting asset relevance
- Prioritizing signals based on financial materiality and regulatory impact
- Triggering structured review workflows with defined documentation requirements
- Prompting structured reassessment rather than automatic change

In this role, AI does not set useful lives, adjust depreciation, or override accounting judgment. Instead, it functions as an early warning mechanism; reducing surprise and enabling gradual, managed adjustment rather than reactive correction under pressure. AI does not eliminate depreciation volatility; it enables earlier, more controlled decisions that help prevent it.

While depreciation governance focuses on how financial assumptions are monitored and adjusted over time, its effectiveness ultimately depends on the integrity of underlying operational and financial data. Without discipline in how work is planned, executed, and recorded, even well-structured decision frameworks cannot operate as intended. This shifts the focus to the work order lifecycle, where process, system, and data constraints are most deeply embedded.

The Work Order Lifecycle: Shifting from Reactive to Proactive

In regulated utilities, unitization accuracy is not a discrete accounting task, it is the outcome of an integrated work order lifecycle that connects planning, execution, and financial close-out to the physical asset record [5].

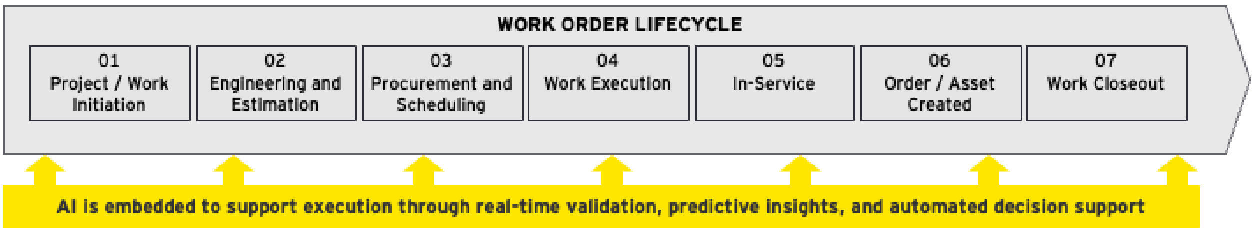
When this lifecycle is fragmented, breakdowns early in the process compound downstream. Incomplete or inaccurate planning, weak field documentation, inconsistent system usage, or delayed close-out create misalignment between operational activity and financial outcomes. These issues exaggerate delays in recognizing installed or retired assets and associating them with the correct costs, resulting in prolonged CWIP balances, delayed depreciation, increased property tax exposure, regulatory risk, and elevated audit complexity.

It is critical to standardize and redesign the lifecycle end to end [6]; eliminating process inefficiencies, strengthening system integration, improving data structures, and embedding structured decision points, continuous monitoring, and clear accountability across each stage. Without this foundation, AI cannot deliver sustained value. Instead, it amplifies existing weaknesses, reinforcing inconsistent processes, propagating poor data quality, and scaling flawed assumptions into more confident but unreliable outputs.

Once the lifecycle is transformed, AI can be embedded to support execution through real-time validation, predictive insights, and automated decision support [1][4].

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 2
***Article Received:** 25 May 2026 **Revised:** 12 June 2026 **Accepted:** 15 July 2026*

Figure 3: Agentic work order lifecycle



Planning and Estimation: From Static Inputs to Data-Backed Signals

Estimation is one of the first integration points between operations and finance in the work order lifecycle and is often riddled with challenges, including but not limited to:

- Manually assembled estimates using outdated templates or compatible units
- Over or under scoping due to inconsistent historical references
- Estimates built without systematic feedback from actual performance data
- Estimates created inaccurately during work order setup and never corrected

These weaknesses result in poor forecast quality, weak capital planning, and downstream rework when actual costs diverge materially from the estimate. Once estimation processes are standardized and data lineage is established, AI can fundamentally improve planning quality. At work order creation, AI can:

- Auto-generate draft estimates using historical actuals across similar asset classes, geographies, work types, and regulatory treatments
- Incorporate final actual costs and drivers of estimate-to-actual variance
- Recommend expected cost ranges with confidence intervals
- Suggest compatible units, bills of material, and labor hours aligned to scope
- Identify outlier risk and surface assumptions associated with regulatory or audit findings

The outcome is more reliable planning, reduced estimate-to-actual variance, stronger capital forecasts, and improved rate-case defensibility.

Execution and As-Builts: From After-the-Fact to Continuous Record

As-built records are frequently incomplete, retroactively created, or misaligned with financial postings. Field documentation may arrive late or not at all, and asset attributes captured in engineering systems often fail to reconcile with costs capitalized in financial systems. These gaps distort unitization and weaken the audit trail linking physical assets to booked balances.

With standardized execution and documentation processes in place, AI can convert as-builts from a static after-the-fact activity into a continuously updated asset record. By observing transactions across work management, asset, and financial systems, AI can identify signals that indicate asset installation, modification, or retirement as work occurs. In practice, this includes:

- **Invoice and receipt extraction:** Identifying asset-relevant details such as materials, quantities, serial numbers, and labor costs
- **Asset detection:** Flagging transactions that imply installations or retirements not yet reflected in asset systems
- **Financial to operational reconciliation:** Detecting misalignment between work performed, costs posted, and assets recorded

During execution and in-service, AI can also:

- Identify anomalies in material issuance or labor charging
- Detect misclassification between capital and O&M
- Identify missing in-service dates or incomplete asset attributes
- Highlight unreversed accruals and aged CWIP balances

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 2
***Article Received:** 25 May 2026 **Revised:** 12 June 2026 **Accepted:** 15 July 2026*

At close-out, delays and misalignment increase adjustment risk. AI can:

- Generate as-builts using unit estimates and recorded actuals
- Detect late or missing contractor invoices and highlight accrual gaps
- Flag work orders open after physical completion
- Trigger close-out workflows when prerequisite conditions are met

Timely and accurate as-builts enable faster unitization, earlier depreciation, reduced reconciliation between CWIP and fixed assets, and a defensible audit trail tying costs to physical reality [5].

Critically, AI can only augment as-built creation when foundational execution disciplines are in place. Invoices must be submitted timely, materials must be consistently issued to the correct work orders, and required attributes must be maintained with integrity. Absent these conditions, AI amplifies upstream data deficiencies rather than correcting them.

Lifecycle Governance: Reactive Correction to Proactive Control

Across the lifecycle, AI is uniquely positioned to operate as a cross-functional observer, monitoring alignment between physical completion, financial postings, and asset records. It can identify missing steps or incomplete documentation, detect discrepancies across systems, and trigger corrective actions before issues compound.

Over time, the system learns where breakdowns most frequently occur and proactively recommends corrective actions; enabling shorter close cycles, faster CWIP clearance, fewer post-close adjustments, improved regulatory compliance, and increased confidence in asset and financial reporting.

AI does not fix broken processes; it reveals, accelerates, and enforces them. In the work order lifecycle, utilities that first standardize estimation, execution, close-out processes, and end-to-end governance create the conditions under which AI can shift the organization from reactive correction to proactive control. Only then can AI deliver sustained improvements in speed, accuracy, and regulatory confidence.

Conclusion

Utilities often treat AI as an analytical challenge, but the real question is whether underlying processes are designed to use it. The constraint is not a lack of insight, it is how decisions are defined, governed, and executed. AI has improved visibility, but without process redesign, that visibility does not change outcomes.

This requires a shift from an analytical model to a decision-centric one, where decision-making itself is treated as a core process with clear ownership, accountability, and trade-off evaluation. This principle extends across the financial lifecycle: capitalization, where decisions create long-term exposure; depreciation governance, where those decisions require reassessment over time; and the work order lifecycle, where financial outcomes are impacted by upstream operational processes.

AI does not create value by generating better answers; it does so when embedded in processes that define how decisions are made and sustained. The path forward is sequential: define decision processes, redesign core financial processes, and then apply AI within that structure [7].

References

1. Electric Power Research Institute. (2024). *Generative AI in transmission and distribution asset management: Use cases, challenges, and the role of EPRI R&D*. Electric Power Research Institute. https://transmission.epri.com/resources/documents/AI_Whitepaper_240317_db.pdf
2. Financial Accounting Standards Board. (n.d.). *Accounting Standards Codification Topic 360: Property, plant, and equipment*. https://asc.fasb.org/asc-content/asc-360-property-plant-and-equipment
3. National Association of Regulatory Utility Commissioners. (2020). *Artificial intelligence for natural gas utilities: A primer*. NARUC. https://pubs.naruc.org/pub/F74D4EC2-155D-0A36-310F-F5B22DC3E286
4. Open Power AI Consortium. (2026). *Uniting the electric sector with advanced AI solutions*. Electric Power Research Institute. https://openpowerai.org/

5. PwC. (2026). *Property, plant, equipment and other assets guide*. https://viewpoint.pwc.com/dt/us/en/pwc/accounting_guides/property_plant_equip/property_plant_equip_US/About-this-guide.html
6. U.S. Government Accountability Office. (2021). *Artificial intelligence: An accountability framework for federal agencies and other entities* (GAO-21-519SP). https://www.gao.gov/products/gao-21-519sp
7. The White House. (2025, July). *America's AI Action Plan: Winning the race*. https://www.whitehouse.gov/wp-content/uploads/2025/07/Americas-AI-Action-Plan.pdf