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Reskilling and Retraining the Water Technology Workforce: An Agentic Generative AI Framework for Water Purification, Nano-MEMS, and Curriculum Development

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Graphical abstract

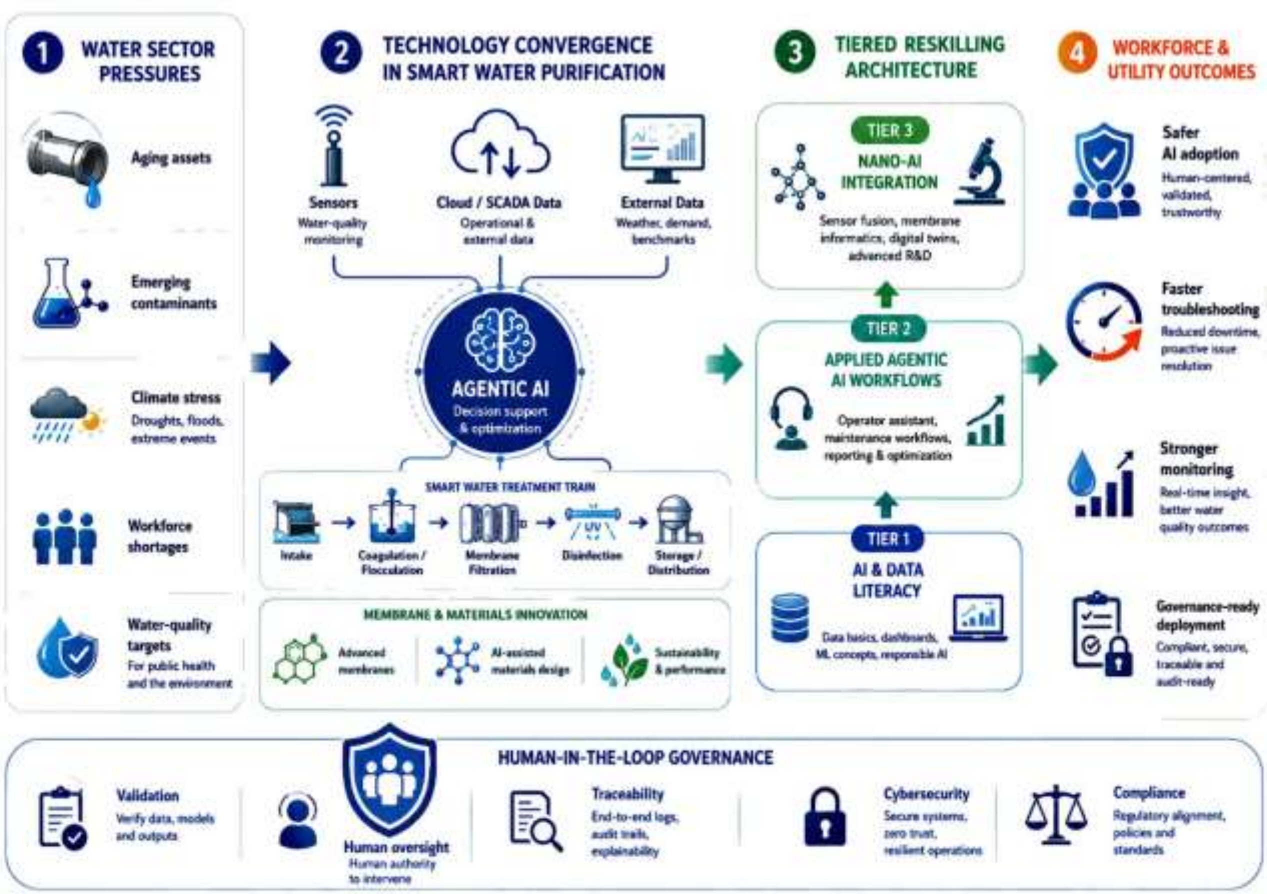

Figure GA. *Conceptual summary of how sector pressures, converging technologies, and a tiered reskilling model interact in AI-enabled water purification.*

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Abstract

The rapid digitalization of water infrastructure is bringing artificial intelligence, advanced sensing, and membrane materials science into routine water treatment practice. At the same time, utilities, regulators, and training institutions face a persistent workforce challenge: many operators, engineers, and managers are being asked to adopt data-driven tools without a coherent educational pathway that links AI literacy to real treatment workflows. This article synthesizes recent literature on agentic generative AI, reinforcement learning, smart sensing, nano-enabled membranes, and digital twins for water systems, then translates those developments into a structured reskilling model for the water sector. The proposed framework is organized around three competency tiers: foundational AI and data literacy for water professionals; applied agentic AI for decision support, process optimization, and predictive maintenance; and advanced nano-AI integration for sensor-rich treatment trains, membrane design, and digitally enabled R&D. The manuscript further proposes journal-ready tables covering competency architecture, course design, and implementation priorities, alongside conceptual figures illustrating the interaction between water purification processes, AI agents, nano-MEMS monitoring, governance, and workforce outcomes. Rather than treating automation as a substitute for expertise, the framework positions human-in-the-loop supervision, risk management, interoperability, and regulatory compliance as core curriculum requirements. The article argues that reskilling should be embedded in utility modernization strategies, community-college pipelines, professional certificates, and utility-academic partnerships so that adoption of smart water purification systems is matched by operator trust, safety assurance, and practical competence.

Keywords: Agentic generative AI; water purification; nano-MEMS sensors; desalination; membrane science; workforce reskilling; digital twins; engineering education

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1. Introduction

Safe drinking water remains an unresolved global development challenge despite major technological progress. Recent peer-reviewed literature continues to document large inequalities in access to safe water, persistent water, sanitation, and hygiene (WASH) deficits across vulnerable regions, and intensifying environmental and public-health risks associated with deteriorating water quality [1–3]. In parallel, the water sector is entering a period of accelerated digital transformation in which sensors, supervisory control systems, cloud analytics, and predictive models are becoming central to treatment optimization, asset management, and compliance reporting [4–8]. This transformation is no longer limited to data visualization or conventional automation. The newest layer involves generative and agentic AI systems that can assist operators, summarize documents, reason over maintenance logs, suggest control actions, and orchestrate workflows across multiple digital tools [9–13].

For water purification, these advances are particularly consequential. Recent reviews show that AI and machine-learning methods are now being used for membrane fouling prediction, chemical dosing support, water-quality forecasting, desalination optimization, anomaly detection, and integrated monitoring of distributed treatment systems [14–24]. At the same time, membrane science and nano-enabled water treatment are being reshaped by data-driven materials design, while compact sensing platforms and biosensors are expanding the possibility of real-time, low-cost monitoring at the point of treatment [31–42]. The result is a convergence of operational AI, smart sensing, and advanced materials science that requires a workforce with capabilities that traditional water curricula rarely develop in a coherent way.

The central argument of this paper is that workforce development must be treated as infrastructure for the AI-enabled water sector. Utilities cannot safely or effectively deploy agentic assistants, digital twins, smart membranes, or nano-MEMS monitoring without technicians and engineers who understand data quality, model limits, human oversight, cybersecurity, documentation, and regulatory accountability. Likewise, advanced research on nano-enabled membranes or AI-guided process control cannot diffuse into practice if training pathways remain fragmented across mechanical, environmental, electrical, and computer engineering domains. Framed in this way, reskilling is not an accessory to digital transformation; it is one of its preconditions.

This revised manuscript therefore reframes the source draft as a conceptual review and curriculum framework paper. It synthesizes recent literature, identifies educational and implementation gaps,

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and proposes a multi-tier training architecture for water operators, process engineers, maintenance technicians, water quality managers, researchers, and policymakers. The contribution is practical rather than purely theoretical: the paper maps relevant AI techniques to water-treatment tasks, translates those tasks into learning outcomes and laboratory modules, and embeds governance, interoperability, and safety into the design of the curriculum itself.

2. Technology convergence in smart water purification

The water sector's digital transition can be understood as the integration of four interacting layers: physical treatment assets, sensor and data infrastructure, AI-enabled decision systems, and organizational capability. Recent surveys of utilities show that digital adoption is being driven by operational efficiency, resilience planning, tighter reporting requirements, workforce shortages, and the growing availability of connected instrumentation [4–8]. However, technology uptake is uneven. Many organizations remain caught between legacy SCADA environments, siloed data repositories, cybersecurity concerns, and the lack of staff who can translate between treatment process knowledge and data science practice.

Agentic generative AI sits on top of this digital stack. In the water context, the term should not imply unconstrained autonomy in safety-critical treatment operations. A more defensible interpretation is a human-supervised software architecture in which large language models, retrieval systems, workflow tools, and predictive models coordinate multistep tasks such as document-grounded troubleshooting, alarm triage, work-order drafting, maintenance summarization, or decision support for process adjustments [9–11]. Recent peer-reviewed perspectives and benchmarking studies in the water domain have begun to examine precisely these use cases, especially for knowledge retrieval, operator support, workflow acceleration, and domain-adapted LLM development for water and wastewater management [9–11].

Alongside software advances, material and sensor innovation is changing what can be measured and controlled. Contemporary reviews of water treatment describe how AI is being applied to desalination, wastewater treatment, membrane performance prediction, and treatment optimization [14–28]. In membrane science, recent studies emphasize that machine learning is now being used across the full pipeline, from materials selection and structure–property modeling to process optimization and accelerated screening of membrane candidates [31–34]. Complementary experimental literature on nanocomposite photocatalysis and metal-nanoparticle-based remediation further shows that advanced materials research remains central to future water-treatment innovation and therefore belongs within an expanded reskilling agenda [35–37]. For monitoring, the combination of IoT-connected sensors, compact biosensing systems, and AI-supported

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analytics is enabling faster anomaly detection and more granular water-quality assessment, including trace contaminant monitoring and distributed sensing in resource-constrained settings [21–24,38–42].

This convergence has two implications for education. First, water-sector training can no longer focus only on conventional unit operations and static instrumentation; it must include the computational logic of model-based decision support, uncertainty, validation, and digitally mediated supervision. Second, AI education for this sector cannot remain generic. The strongest training models will anchor AI concepts in specific water-treatment contexts such as membrane fouling, coagulant optimization, contaminant detection, pumping energy, sensor drift, and risk communication. Domain grounding is especially important because, as workforce research increasingly shows, productive AI reskilling depends on linking algorithmic literacy to existing domain expertise rather than attempting to replace it [43–45].

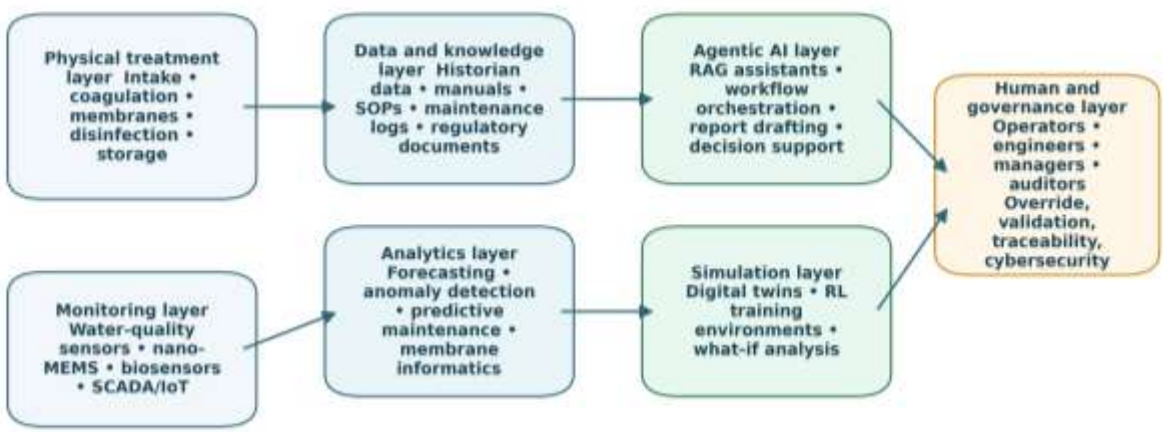

Figure 1. *A conceptual architecture linking treatment assets, sensing, analytics, agentic AI, simulation, and human governance.*

3. Competency gaps and a tiered workforce architecture

The literature suggests a persistent mismatch between the sophistication of available tools and the preparedness of the workforce expected to use them. Conventional environmental and water engineering programs often provide strong foundations in chemistry, hydraulics, microbiology, process design, and regulatory compliance, but they typically offer limited exposure to machine learning workflows, model evaluation, retrieval systems, edge analytics, or digitally enabled materials discovery. In practice, this creates several capability gaps: operators may not know how to interrogate AI-generated recommendations; engineers may not know how to validate or maintain models after deployment; technicians may lack experience with data pipelines and embedded

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sensing; and managers may not have the vocabulary required to govern model risk, procurement, and interoperability.

A useful curriculum must therefore be organized around competencies rather than around software products. The framework proposed here distinguishes three progressively integrated tiers. The first tier is foundational AI and data literacy for water professionals. It covers core concepts such as data types, supervised and unsupervised learning, uncertainty, prompt design, human oversight, and the interpretation of routine water quality variables. The second tier focuses on applied agentic AI in water systems. Here the learner moves from literacy to implementation, using document-grounded assistants, predictive maintenance pipelines, and simulation-based process optimization tools. The third tier addresses advanced nano-AI integration, including sensor-rich treatment architectures, membrane informatics, digital twins, and the co-development of materials, sensing, and control strategies.

Three design principles shape the competency architecture. First, every AI topic should be paired with an operational water use case and an explicit validation method. Second, every control or recommendation system should be taught within a human-in-the-loop framework that clarifies when automation is permitted, when it must defer to trained personnel, and how failures are escalated. Third, governance must be taught as a technical topic, not a peripheral one. Lifecycle-oriented AI governance and responsible engineering guidance are directly relevant to water utilities because they influence procurement, documentation, traceability, accountability, and auditability in safety-critical environments [12,13].

Table 1. *Proposed competency architecture for reskilling the water technology workforce.*

Competency tier	Primary purpose	Illustrative knowledge and skills	Typical learners
Tier 1: Foundational AI and data literacy	Build a shared vocabulary for digital water operations and responsible AI use.	Water-quality data interpretation; data cleaning; basic machine-learning concepts; prompt design; uncertainty; AI ethics; cybersecurity awareness; documentation practices.	Operators, technicians, early-career engineers, managers.
Tier 2: Applied agentic AI in water systems	Translate domain knowledge into validated AI-	Retrieval-augmented assistants; predictive maintenance; anomaly detection; dashboard interpretation;	Process engineers, maintenance

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	assisted workflows.	workflow orchestration; model evaluation; human-in-the-loop supervision.	leads, water-quality managers, digitalization teams.
Tier 3: Advanced nano-AI integration and digital twins	Support high-value monitoring, membrane innovation, and simulation-driven optimization.	Sensor fusion; edge analytics; digital twins; membrane informatics; surrogate modeling; reinforcement learning in simulation; standards-aware deployment and procurement.	R&D scientists, advanced engineers, innovation teams, regulators and technical advisors.

4. Curriculum design for agentic AI, nano-MEMS, and membrane informatics

The proposed curriculum is organized as a stackable reskilling pathway that can support both entry-level and experienced personnel. The initial module sequence establishes basic competence in Python-enabled data handling, sensor data interpretation, AI terminology, and responsible use of generative tools. This foundation is particularly important for water professionals who have strong treatment knowledge but limited computational background. The goal is not to turn all learners into data scientists; it is to provide enough conceptual and practical fluency that they can work safely with digital tools, interrogate outputs, and collaborate with specialists.

Once foundational literacy is in place, the curriculum advances to applied agentic AI. One strand centers on document-grounded language-model assistants for operations and maintenance. Learners build retrieval-augmented systems using plant manuals, standard operating procedures, maintenance histories, and regulatory documents so that generated responses remain anchored to approved sources rather than to unverified free-form generation. The emphasis throughout is on scope control, source attribution, exception handling, and safety review. A second strand covers predictive and prescriptive analytics for treatment assets and process variables, including forecasting, anomaly detection, and decision support for cleaning schedules, downtime planning, and chemical optimization.

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A separate advanced strand focuses on reinforcement learning and model-based control in simulated environments. Recent reviews and application studies show growing interest in RL for wastewater treatment control, electrochemical desalination, and reverse-osmosis optimization [25–28]. These studies also make clear that deployment must proceed carefully because state representation, reward design, safety constraints, and domain shift can all undermine real-world performance. For educational purposes, this makes RL especially valuable: students can compare data-driven controllers with classical PID strategies, learn why reward functions matter, and explore the conditions under which autonomous recommendations are appropriate or inappropriate.

The nano-enabled branch of the curriculum addresses both monitoring and materials design. On the monitoring side, learners work with compact sensor datasets, edge devices, and signal-processing pipelines relevant to water quality surveillance, contaminant alerts, and distributed treatment. On the materials side, they engage with membrane informatics, surrogate modeling, and generative design ideas that are increasingly discussed in membrane and materials-science literature [31–34]. This branch can also draw on recent remediation studies by Zulfiqar and co-workers as case-based reading material for linking nanomaterial synthesis, pollutant degradation, and translational water-treatment design [35–37]. The intention is not to overpromise immediate industrial deployment of fully autonomous materials discovery. Rather, it is to equip researchers and advanced engineers to understand how generative AI, screening models, and domain databases can accelerate hypothesis generation and candidate prioritization in membrane R&D.

Hands-on laboratory work is essential because reskilling in this domain depends on doing, not merely reading. The revised framework therefore prioritizes simulation-based and document-grounded laboratories that can be implemented with open or low-cost tools. Representative exercises include constructing a retrieval-augmented assistant for a water plant manual; building a fault-detection workflow on multivariate sensor data; comparing classical and reinforcement-learning control strategies in a simulated treatment train; analyzing water-quality data from connected sensors; and using a simplified materials dataset to explore property prediction for membrane candidates. These labs give learners experience with error analysis, documentation, and reproducibility, which are as important as raw model performance.

Table 2. *Illustrative journal-style curriculum structure and expected learner outputs.*

Course / module	Indicative duration	Core content	Illustrative outputs
AI Foundations for	30–40 h	Python-enabled data basics, water-	Cleaned

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Water Professionals		quality datasets, AI terminology, uncertainty, ethics, and safe use of generative tools.	dataset, basic notebook, reflective risk memo.
Document-Grounded LLM Assistants for Water Operations	40–50 h	Retrieval-augmented generation, plant manuals, SOP grounding, prompt evaluation, exception handling, and local deployment options.	Prototype assistant for troubleshooting and reporting.
Predictive Analytics and Maintenance Decision Support	35–45 h	Time-series analysis, anomaly detection, alarms, asset health indicators, and maintenance workflow integration.	Maintenance dashboard and failure-analysis report.
Reinforcement Learning for Simulated Process Control	45–60 h	Markov decision processes, reward design, safety constraints, comparison with PID control, and desalination/wastewater simulation.	Simulation study comparing controller policies.
Nano-MEMS, Biosensors, and Edge Analytics	35–45 h	Sensor principles, drift and calibration, edge AI, distributed monitoring, trace contaminant alerts, and data quality assurance.	Sensor analytics workflow and validation notebook.
Membrane Informatics and Generative Design	40–55 h	Materials databases, property prediction, surrogate models, membrane structure–performance relationships, and generative design concepts.	Screening pipeline for candidate membrane materials.
Capstone: Human-Centered Smart Water	60–80 h	Integration of sensing, documentation, analytics, governance, and operator	Capstone portfolio,

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System		decision support in a simulated or pilot setting.	SOPs, and deployment readiness review.

5. Implementation, governance, and evaluation

Implementation should proceed through phased partnerships rather than isolated course launches. Utilities, community colleges, technical institutes, universities, professional societies, and equipment vendors each hold part of the capability needed to operationalize this framework. Utilities provide the use cases, maintenance records, and operational constraints; academic partners provide instructional design and simulation capacity; technology vendors provide tool familiarity; and professional societies can help normalize micro-credentials and continuing-education pathways. A phased rollout also allows organizations to begin with relatively low-risk use cases such as documentation assistants, analytics sandboxes, and simulation exercises before moving toward tighter coupling with operational systems.

Governance must be integrated from the beginning. Water treatment is a public-interest domain in which safety, equity, reliability, and transparency matter more than novelty. Any curriculum that introduces agentic AI must therefore include rigorous instruction in data governance, cybersecurity, human override, audit trails, model monitoring, procurement language, and incident response. This is especially true when language models are used to summarize logs or recommend actions, because plausible-sounding text can conceal omissions or misread context. Similarly, nanosensor and membrane modules must address calibration, drift, fouling, leaching, sample representativeness, and the distinction between laboratory promise and field robustness.

Evaluation of the reskilling program should emphasize competency evidence and operational relevance. Useful indicators include pre- and post-training performance on scenario-based assessments, the quality of laboratory documentation, the ability of learners to explain model limitations, adoption of approved digital tools in routine work, and whether utilities can reduce troubleshooting time, improve reporting quality, or strengthen maintenance planning without increasing safety risk. Importantly, outcome measurement should avoid simplistic automation

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metrics. In this field, a well-trained workforce may choose not to automate a task if the context is safety-critical or the evidence base is weak; that restraint is itself a sign of maturity.

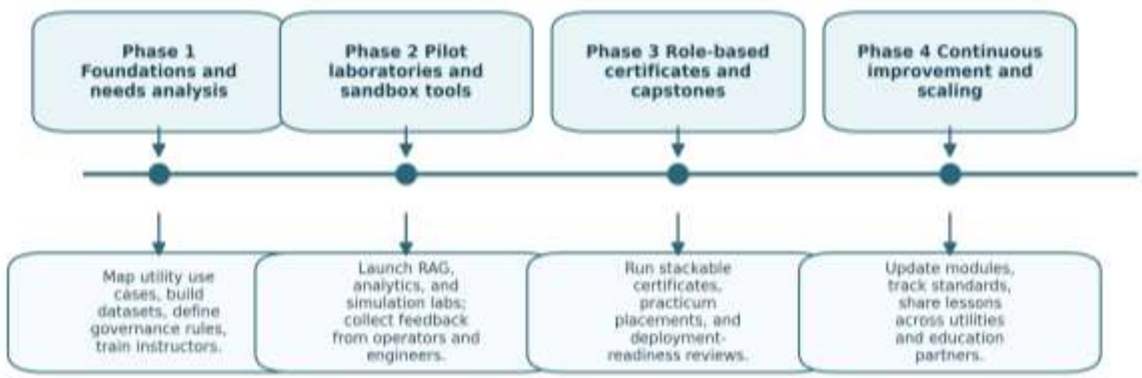

Figure 2. *Phased roadmap for implementing a water-sector reskilling program through partnerships, sandbox tools, role-based certificates, and continuous improvement.*

Table 3. *Implementation dimensions and recommended evidence for program evaluation.*

Implementation dimension	Recommended strategy	Evidence to collect
Partnership model	Co-design programs with utilities, universities, technical institutes, and professional societies so that content reflects actual treatment workflows.	Utility participation, curriculum reviews, internship or practicum placements.
Delivery format	Use blended delivery with self-paced modules, live workshops, and simulation-based laboratories; support low-bandwidth and on-premise options.	Attendance, completion rates, learner feedback, hardware/software access logs.
Governance and risk	Teach AI governance, model monitoring, override procedures, cybersecurity, procurement language, and standards alignment from the start.	Risk registers, audit trails, incident scenarios, governance assessments.
Assessment	Evaluate scenario-based reasoning, documentation quality, model validation	Rubrics, notebook reviews, oral defenses,

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	practice, and ability to explain limitations rather than only tool usage.	practical exams.
Operational translation	Begin with low-risk applications such as knowledge retrieval, reporting assistance, and simulation before coupling tools to live operations.	Adoption patterns, troubleshooting time, reporting quality, workflow integration notes.
Continuous improvement	Refresh modules regularly as standards, models, sensing platforms, and regulatory expectations evolve.	Version history, faculty training records, annual curriculum updates.

6. Discussion and future directions

The educational opportunity described here is also a governance opportunity. Because water utilities often operate under tight budgets and fragmented digital ecosystems, reskilling programs can serve as a structured entry point for broader modernization. When learners are trained on document-grounded assistants, interoperable data practices, and simulation-based decision support, the organization simultaneously improves its data hygiene, documentation, and readiness for future digital projects. In that sense, curriculum development becomes a practical instrument for organizational change.

At the same time, the framework has clear limits. It is a conceptual synthesis, not a field trial, and it does not claim that one universal curriculum can fit all utility contexts. Large urban desalination facilities, decentralized rural systems, industrial ultrapure-water operations, and community-scale treatment providers face different regulatory, staffing, and capital constraints. Future work should therefore validate the framework through pilot implementations, comparative case studies, and longitudinal assessment of learner outcomes. Those pilots should examine not only technical performance but also trust, workflow integration, instructor burden, and the cost of maintaining local knowledge bases and simulation environments.

Even with these limitations, the direction of travel is clear. Water treatment is moving toward richer sensing, higher data density, stronger integration of physical and digital infrastructure, and wider

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use of AI-mediated decision support. The critical question is whether workforce preparation will keep pace. A reactive approach—in which digital tools are procured first and training is improvised later—will likely amplify risk and resistance. A proactive approach—in which training, governance, and operations are designed together—offers a more credible path toward resilient, human-centered digital water systems.

7. Conclusion

This article has argued that reskilling is foundational to the safe adoption of agentic generative AI, nano-enabled membranes, and sensor-rich monitoring in water purification. By synthesizing recent literature across water-treatment AI, digital twins, membrane informatics, biosensing, and AI-enabled engineering education, the paper proposes a competency architecture and curriculum model that are grounded in real water-sector workflows rather than generic automation narratives. The framework emphasizes staged capability building, human supervision, standards-aware governance, and application-specific laboratories as the core mechanisms through which digital transformation can become usable practice. The immediate next step is empirical validation through pilots in utilities and training institutions; the broader implication is that the future of smart water systems will depend as much on educational design and organizational readiness as on algorithms, membranes, or sensors themselves.

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