Technical Note

Adoption of Artificial Intelligence in Drinking Water Operations: A Survey of Progress in the United States

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Abstract: In recent years, a vision has been shared of how artificial intelligence (AI) can optimize the increasingly complex operations of drinking water utilities. However, it has been unclear if and how water utilities use the technology. Here, we surveyed a simple random sample of 49 large US water utilities to provide a snapshot of progress. We found that 12 of them (24%) have used some form of AI. Of those that have not, the majority plan to use or may plan to use AI in the next 5 years. The reported AI uses were experimental, manual, or partial models rather than fully integrated, ongoing applications. Respondents are motivated to use AI for improving water quality, detecting leaks, and automating complex systems, but they cited payback uncertainty and lack of AI expertise as the most common barriers to implementation. To better demonstrate how AI can join other tools available to assist human operators, researchers should focus on the top motivations and barriers identified here and partner with water utilities on convincing case studies of full-scale AI projects. These steps will support further responsible adoption of AI to optimize water utility operations as part of more sustainable communities. **DOI: 10.1061/JWRMD5.WRENG-5870.**

Author keywords: Artificial intelligence (AI); Machine learning; Drinking water; Optimization; Water utility.

Introduction

Drinking water systems are one of the most essential pieces of infrastructure in modern cities. By providing clean water year-round, they enable economic activity and support important functions in public health and safety. They are sociotechnical systems: many water users (social) drive what ends up being a variable water demand, whereas the infrastructure (technical) merely responds. As such, water utility operations are inherently dynamic, requiring many decisions. On a daily basis water operators decide, for example, which pumps to run, how much alum to dose at the head of a plant, or how high to fill a tank. At other time scales, decisions are made about responding to emergencies and planning for infrastructure improvements.

Growing Complexity

The complexity of operational decisions—and thus the need for technologies to assist with them—grows with both the size of the system and the number of variables being considered. Operations are often facilitated through a supervisory control and data acquisition (SCADA) system with programmable logic controllers (PLCs) offering some degree of automation; 93% of North American water utilities have a SCADA system (Wallis-Lage 2020). Simply as a result of population growth and urbanization, water systems will continue to grow, as will the scale of their operations.

The number of operational variables is also increasing. Because of the obvious public health implications, customers (and regulators) have long had high expectations of water quality and pressure, and water utilities are accustomed to framing their operational decisions around just a few variables measured at a few times and places. But recent trends in sensor technology, smart cities, cloud computing, the internet of things (IoT), and real-time control (RTC) are now pushing water utilities to monitor system performance indicators at more locations and with greater frequency than before (Saravanan et al. 2018; Ramos et al. 2019; Smith 2020; Wallis-Lage 2020). Further, the list of customers' expectations has now swelled to include accountability for water loss (AWWA WLCC 2019), affordability (Rubin 2018; Pierce et al. 2020), energy management (Patel et al. 2022; Sowby 2023), and continuity of service, even during extreme events (Sowby and Lunstad 2021). Some of these expectations are starting to be regulated in certain jurisdictions.

In short, water utilities are getting bigger and having to consider many more variables whose interdependent patterns may not be clear to humans. All these forces are making their operations more complex than ever before, suggesting that technologies beyond SCADA may be necessary to help manage them in the context of more sustainable infrastructure and communities.

AI as a Solution

Considerable research in recent years has explored the use of artificial intelligence (AI) in water utilities (Fu et al. 2022), including various machine learning (ML) techniques and other optimization heuristics that allow a program to develop itself over time from new data, beyond strict human programming. AI may run on top of SCADA—which is the most advanced computing center in most water systems—but the difference is that SCADA merely executes preprogrammed operations, whereas AI actively learns, predicts, optimizes, and recommends new operations as it encounters new conditions. Digital transformations are already occurring in the water sector (Sarni et al. 2019; Boyle et al. 2022), and AI is a key point of discussion. The general claim is that AI, because of

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Note. This manuscript was submitted on May 27, 2022; approved on February 12, 2023; published online on May 12, 2023. Discussion period open until October 12, 2023; separate discussions must be submitted for individual papers. This technical note is part of the ***Journal of Water Resources Planning and Management***, © ASCE, ISSN 0733-9496.

its ability to dynamically process large amounts of information and identify complex relationships, can assist human operators and lead to more optimized water systems (Lunani 2018; Doorn 2021; Garzón et al. 2022).

Recent literature has described several applications of AI techniques to water utilities. The most common appears to be pipe condition assessment and leak detection (Baird et al. 2019; Zhou et al. 2019; Cantos et al. 2020; Fitchett et al. 2020; Snider and McBean 2020; Yazdekhasti et al. 2020; Dawood et al. 2020; Kahn 2021; Zhang et al. 2022; Fu et al. 2022). The consensus from these studies is that AI improves leak detection outcomes, recognizing patterns in the data that humans cannot see. In water treatment, AI techniques have helped in water quality diagnosis, process control, and pollutant modeling, as reviewed by Fan et al. (2018), Ismail et al. (2021), Li et al. (2021), and Alam et al. (2022). In water distribution, AI has helped detect contaminant intrusions and other water quality anomalies (Dogo et al. 2019; Grbčić et al. 2021; Mboweni et al. 2021).

Rahim et al. (2020) reviewed studies where AI has been used to analyze customer water use data from advanced metering infrastructure (AMI), as in water demand forecasts and water conservation programs. Similarly, Villarin and Rodriguez-Galiano (2019) developed water demand models leveraging AI, noting that the methods were more accurate than linear predictions. Lunani (2018) noted a few specific instances where AI has supported drinking water operations, such as capturing drift from optimal operating points, predicting bacterial hot spots in the distribution system, and identifying flaws in control strategies. Benefits such as energy savings in pump scheduling have also been observed with AI (Ostojin et al. 2011; Pasha and Lansey 2014; Helmbrecht et al. 2017; Bagolee et al. 2018).

Although water system planning and modeling are not the focus of our study, others have speculated that AI may facilitate automated hydraulic model calibration (AWWA EMAC 2020), optimized infrastructure planning (Beh et al. 2017), and preventive emergency repairs (Tripathi et al. 2021). Others have explored how AI can support digital twins in the water sector, which according to AWWA's recent consensus definition are "digital, dynamic system[s] of real-world entities and their behaviors using models with static and dynamic data that enable insights and interactions to drive actionable and optimized outcomes" (Karmous-Edwards et al. 2022). AI's capabilities in data processing, pattern recognition, and optimization make it a promising companion for digital twins.

The foregoing review illustrates the many possibilities AI can offer water utilities. Yet although similar industries like energy and transportation are readily adopting AI, its application to the water domain is relatively underdeveloped (Hadjimichael et al. 2016; Doorn 2021). Most of the reported results come from theoretical research or isolated experiments rather than full-scale implementations in real water utilities, and more development must occur if AI is to move from fundamental research into widespread practice (Sowby and Walski 2021). In particular, the literature is sparse in case studies describing actual AI implementations in water utilities. Further, most of the reported work has been produced by either researchers or AI vendors rather than drinking water practitioners, so one cannot easily gauge how water utilities perceive such developments.

We note that our study was completed before the release of ChatGPT and similar generative AI based on large language models (LLMs). All industries are exploring how to use such disruptive technology and the research literature is still emerging. For water utilities, we speculate that generative AI may find a place in customer service, staff training, and report creation, but not immediately in infrastructure operation which is the focus of our study. Obviously this is a quickly developing field and needs more attention.

Research Objectives

The research to date has provided a vision of what AI can do for the water industry, enumerating and testing several possibilities. AI is one of many tools a water utility may choose to use to assist human operators. But it is unclear how many water utilities actually use AI in their operations and if so, in what ways and to what effect. To find out, we surveyed a sample of large US water utilities on their use (or nonuse) of AI, seeking to learn something of their understanding, motivations, methods, and outcomes in doing so. From the survey results we develop a few insights about how the industry is approaching this technology and suggest actions to progress toward responsible AI adoption.

Methods

Survey Preparation

Our approach was an online survey directed to a simple random sample of large water utilities in the US. Based on the literature review, conversations with industry professionals, and the guidance of Robinson and Leonard (2019), we devised a survey of approximately 15 questions targeting the objectives just outlined. Due to question logic in the branching survey, the number of questions each respondent completed varied; some questions were skipped depending on certain responses. We deliberately kept the survey brief in order to facilitate responses from a wide cross section of respondents. The survey sought both quantitative and qualitative data.

Where possible, rather than define particular AI uses, we deliberately kept the questions open-ended in order to gather as much information from the respondents as possible. We created the survey and collected responses through Qualtrics web-based software. Table S1 presents the questions and responses; the complete instrument is available as Protocol S1.

Sample Design

The sample was chosen from a database maintained by the USEPA in its Safe Drinking Water Information System (SDWIS) (EPA 2021). We downloaded the SDWIS Water System table and filtered it for "active" "community" water systems serving 100,000 people or more. Inactive water systems were not relevant to our study, nor were noncommunity water systems (e.g., self-supplied campgrounds, schools, or businesses). We restricted water utilities to the larger size because they would be the most likely to have implemented some form of AI for the reasons described previously and because we would be able to contact a greater percentage of them than the more numerous smaller water systems. After removing duplicates, we had a list of 493 water utilities and their basic information.

We then searched online for the email address of each one's operations director, manager, or supervisor (or equivalent employee who would be able to speak to the use of AI) and invited them to complete the survey or forward it to someone in their organization who could. Through this process, we ultimately invited 366 water systems to complete the survey. Other than providing the water utility's name for validation only within our team, the responses remained anonymous.

Results and Discussion

Survey Responses

From 366 contacted water utilities, we received 49 valid responses, making a response rate of 13%. Responses came from water

J. Water Resour. Plann. Manage., 2023, 149(7): 06023002

utilities in 21 states: Arizona, California, Colorado, Florida, Georgia, Idaho, Illinois, Iowa, Louisiana, Massachusetts, Michigan, Nevada, New Jersey, North Carolina, Ohio, Oregon, Pennsylvania, South Carolina, Texas, Utah, and Virginia (Fig. 1). A complete table of the survey results is provided as Table S1.

Use of AI

Fig. 2 shows an overview of the responses. About three-quarters of respondents [37 of 49 (76%)] have not used AI or were unsure if they have. About one-quarter [12 of 49 (24%)] have used AI in the past or currently use it. The finding confirms others' general observations that AI is not yet widely used among water utilities (Hadjimichael et al. 2016; Doorn 2021).

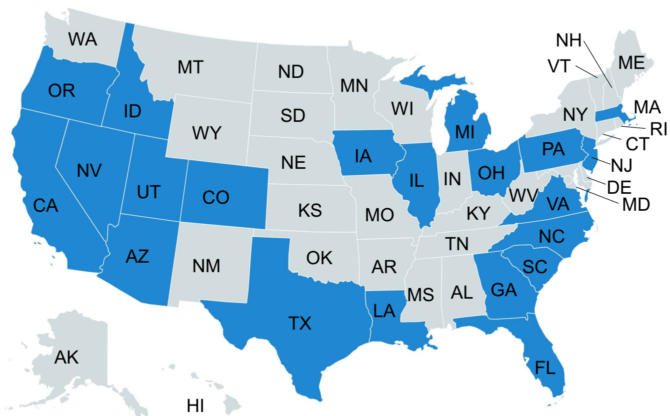

Fig. 1. States in which water utilities responded to the survey.

Among the 12 AI users, applications have been in early stages, including experimenting with predictions and training models, manually using AI models for analysis, and partially integrating AI into their water systems. No respondents reported any fully integrated AI applications (full-scale ongoing installations), or what Fu et al. (2022) call "industrial" applications. The results agree with the research reviewed previously that showed a lack of full-scale AI implementations in water utilities. Most have had fewer than 5 years' experience with the technology, although some apparent early adopters have had more. As for the area of the system where AI has been used, one respondent indicated raw water reservoirs, two indicated treatment, five indicated distribution, and two indicated both treatment and distribution.

Among the 37 who have not used AI, 68% (25 of 37) plan to use AI or may plan to use AI in the next 5 years. These respondents were generally open-minded about AI as suggested by their comments (e.g., "Having discussions about using AI," and "Technology is always advancing, we may look into AI in the future"). Many speculated that AI might be used to prioritize water main replacements, predict pipe breaks, forecast varying water demands, and optimize chemical doses, again agreeing with possibilities already explored in the literature. The comments also reflected a desire to explore AI in conjunction with upcoming projects rather than as a new stand-alone effort. A few, however, questioned the value of AI ("Not sure AI is useful or tells me something I don't already know," "Not sure how the AI will enhance our system," and "I'm not aware of what AI opportunities are available").

The digital water adoption curve proposed by Sarni et al. (2019) may be helpful for understanding progression toward AI and other digital technologies through basic, opportunistic, systematic, and transformational phases. Although our survey was not designed to evaluate the respondents' position on the curve, we suggest it as an exercise for water utilities to consider.

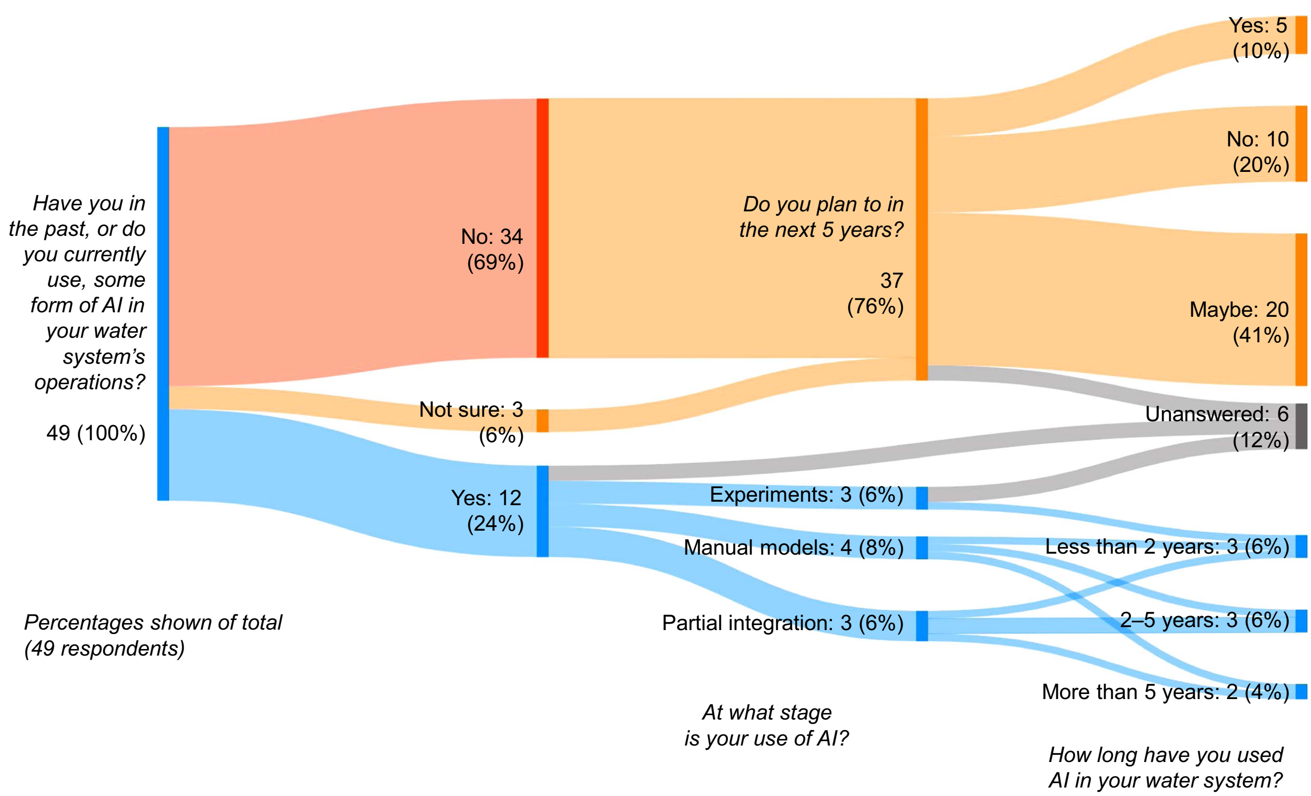

Fig. 2. Overview of water utilities' responses on the use of AI.

Motivations, Benefits, and Barriers

When asked about their motivations for using or planning to use AI (Fig. 3), respondents most frequently cited saving money, detecting leaks, and improving water quality. These motivations, particularly leak detection, are well supported by the literature cited previously. Automating complex systems and saving energy ranked in the middle. The remaining motivations were enhancing water conservation, improving hydraulics (e.g., pressure management), integrating with other technologies (e.g., AMI and SCADA), saving time/labor, and improving public perception. Certainly some of the motivations overlap—saving energy will save money, and fixing leaks will conserve water—but the list is nonetheless a helpful categorization. Although AI has the potential to improve everything on the list, the responses show where water utilities' priorities lie and where future AI research should be directed.

Among the 12 AI users, three reported seeing benefits in automating a complex system, three in integrating with other technologies, two in saving money, and one each in improving hydraulics, improving water quality, enhancing water conservation, and saving time/labor. However, the benefits did not always match the motivations they gave. One water utility tried AI to save money, time, and labor but realized other benefits instead. Another saved time and labor as expected but did not realize its goals of automation or leak detection.

When asked about barriers preventing them from using AI (Fig. 4), general respondents most frequently cited personnel and finance issues. Both suggest reservations about the long-term risks of AI investments. They similarly appear in Sarni et al.'s (2019) barriers to water sector digitalization as "human resources impact" and "financing solutions without a clear value proposition."

Given the advanced nature of the technology, a water utility may worry about finding expertise to manage AI in an ongoing way, either in-house or with consultants and vendors. Brief comments like "Hard to find qualified staff," "Buy-in from key stakeholders," "Staff not skilled," and "Staff are too busy" typify respondents' concerns about supporting AI with the proper personnel. Shortages of AI skills have been noted in certain markets (Wolff et al. 2020), but such concerns are not well-addressed in the research literature or in professional associations specific to the water industry.

Naturally, financial barriers were near the top of the list. Because so few AI implementations exist in drinking water systems, and because such projects are new, private, and scarcely documented, the costs are not well understood. Each one is custom to the system's needs and it is infeasible to provide costs for a general case; further, the benefits can vary considerably. Without definitive case studies and with only vague descriptions of benefits, a water utility may not prioritize an AI investment over competing demands for money. Ultimately, customers pay the bill, and water utilities want to be sure their investment is worthwhile. One respondent said, "[AI] is expensive and hard to do consistently," and another said, "the expense of software and programmers is more than the expense of trained water professionals," underscoring the convincing financial and staffing case that AI must make.

The next level of barriers involved data, in both quantity and quality. To train useful AI, one needs a mountain of data. In the study by Sarni et al. (2019), these fell under "systems integration and interoperability." Accurate, ongoing field measurements are particularly important, one water utility in our survey said, and getting them can be a major task for a medium or large system.

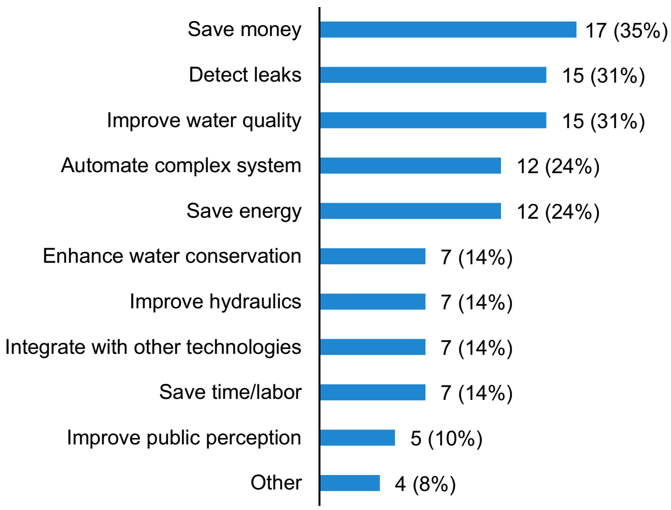

Fig. 3. Water utilities' responses on motivations for using or planning to use AI.

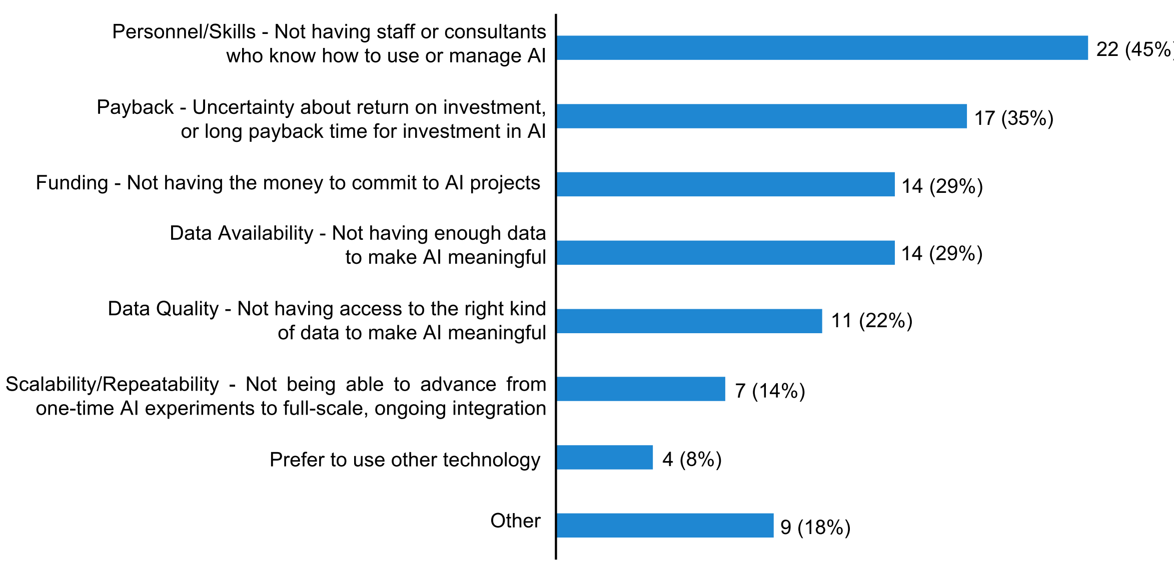

Fig. 4. Water utilities' responses on barriers to using AI.

Scalability and repeatability were noted barriers as well, which are to be expected when the reported AI applications, in both the literature and in this survey, are still preliminary.

Some respondents simply prefer to use other technology. One water utility said, "We are not aware of any process that isn't already automated in our SCADA system that could help us." Another respondent put simply, "AI is a popular topic, but I haven't seen many practical benefits compared to our current methods." Others were more skeptical: "So far, all the AI claimed [for the water industry] is questionable." Because AI has, by definition, so many possibilities, potential users apparently struggle to grasp specific applications and instead see only vague technology. Concerns about cybersecurity, safety, and reliability were expressed in the comments, but less so than other barriers at this stage, perhaps because of the low adoption rate of AI in the first place.

Continued Need for Human Operators

Respondents' comments throughout the survey emphasized a continued need for well-trained human operators in drinking water systems, whether AI is part of the picture or not. Water operators "have a conservative mindset when adopting new technology," one comment read. Because their duties are a matter of public health and safety, operators naturally hesitate to cede too much control to a technology they do not understand and that may put the system at risk. Several respondents acknowledged the value of AI in providing access to "previous experience" but said that "critical decisions" would be best left to humans. Another worried that "AI may keep people from learning and being able to perform their jobs in an emergency if the AI system went down." Finally, one respondent said, "A water system should never be 'set on automatic' and should always be monitored and operated by experienced staff."

Walski (2023) commented that, in contrast to physics-based models, AI models assume that the past is a good predictor of the future; however, many situations that arise in a water system will not have appeared in the training data. Harmful unintended consequences (Sowby and Hotchkiss 2022) may result from extrapolating beyond an AI model's training without oversight from human professionals. Indeed, the human element is still present. AI researchers and vendors would do well to better define the scope of useful AI assistance for this community and to assure water operators of their ongoing essential role.

We found that water utilities expressed concern on one hand about involving AI in tasks that are too risky and on the other hand about having human operators who are too busy. We suggest there is a middle ground where AI can work best. The potential for AI to handle certain low-risk tasks is an ideal benefit that may be considered. From the perspective of one water utility, "We are short on employees [and] may use AI to determine condition of pipe." Used in such a way, AI can be trained to handle mundane but data-intensive tasks and allow human operators to allocate their labor to tasks that better serve ratepayers. Sarni et al. (2019) concurred, noting that "intelligent automation solutions may be able to augment human performance ... thus freeing individuals to focus on more human-necessary aspects, ones that require empathic problem-solving abilities, social skills and emotional intelligence." In time, water utilities may develop enough confidence in AI to feel comfortable extending its use into other aspects of their operations. This is yet another argument for AI case studies involving water utility partners.

Limitations and Further Work

We recognize that our survey has a moderately high margin of error in its quantitative results (at most $\pm 14\%$ for a sample of 49 in a population of 493 at the 95% confidence level, according to the usual margin of error calculation). This is due to the small sample size and the low response rate, which are to be expected in the tedious and time-consuming activity of directly contacting large numbers of water utilities, as Chini and Stillwell (2017) and Sowby et al. (2019) described.

In conducting our survey, it was apparent that several respondents and would-be respondents did not have even a basic awareness of AI or why it would be relevant to their water systems. Although one of our objectives was to gauge their understanding of AI in the first place, the lack of understanding may have discouraged survey participation in some cases. Some contacts responded to our emails with statements like, "I don't know how to answer this survey." Similarly, given the variety of technologies that one may consider as AI or which may already be embedded in certain processes, some respondents may have answered that their water utility does not use AI when in fact it does.

A related limitation was contacting the right person to actually complete the survey. This had to be someone who knew whether the water utility uses AI in its operations or could at least find someone in the organization who did. Our impression from the written comments is that those who ultimately completed the survey were reasonably informed about AI; however, such respondents may not represent the water industry at large. As AI developments continue, educating water utility personnel about the technology should not be overlooked.

Where this study captured responses only from large US drinking water utilities, the results may not represent AI adoption and attitudes among smaller water utilities (where we speculate that AI uptake will be much lower because of less system complexity) or water utilities in other countries under significantly different regulatory environments, which future work may address.

Conclusions

Our study provides several key messages for both drinking water practitioners and researchers. Water utility operations are becoming more complex as water systems grow and address more operating variables. Artificial intelligence has been suggested as a technology to help water operators meet this challenge. Although AI impacts many industries and its potential applications to drinking water services are well researched, actual uptake among water utilities is limited. Our survey of 49 large US water utilities showed that 12 of them (24%) have used AI and that those uses have been experimental or manual analyses rather than full-scale, ongoing applications. General respondents were largely motivated by the leak detection and water quality potential of AI, and concerns about finding AI expertise and return on the investment were the most frequently mentioned barriers. AI clearly has the potential to help water operators manage increasingly complex systems, but the technology is not yet mainstream in the industry. In the opinion of some water utilities, AI is a vague technology whose benefits are not obvious and whose costs are high. AI is just one of many tools a water utility may choose to use, and although many currently choose not to, they are open to the idea.

Researchers can help overcome some of these barriers. To grant water utilities more confidence in fully integrating AI into their water systems, researchers should better connect their work to the daily practice of water utility operations and communicate the benefits to water operators (Sowby and Walski 2021). Leak detection in particular seems to be an appealing area. Where much of the literature has reported isolated experiments by researchers or AI vendors, we suggest that full case studies featuring water utility partners will be the most convincing. Researchers should work to address the main barriers to AI adoption as determined by this survey, namely staff expertise and payback. Finding low-risk entry points for AI and assuring water operators of their ongoing role alongside AI are essential.

These steps will support further responsible adoption of AI to optimize water utility operations as part of more sustainable communities.

Data Availability Statement

All data, models, and code generated or used during the study appear in the published article.

Acknowledgments

Sanjay Patel, chief technology officer and co-founder of Confluency, helped develop the survey questions. Emily Dicataldo, a BYU research assistant at the time, helped collect survey responses. The research was completed at BYU's Civil and Construction Engineering Sustainability Lab.

Author contributions: Alyson H. Rapp contributed to the conceptualization, methodology, investigation, writing the original draft, and writing—reviewing and editing. Annelise M. Capener contributed to the investigation and writing—reviewing and editing. Robert B. Sowby contributed to the conceptualization, methodology, resources, writing—reviewing and editing, supervision, and project administration.

Supplemental Materials

Protocol S1 and Table S1 are available online in the ASCE Library (www.ascelibrary.org).

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