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Feature

The Fourth-Revolution in the Water Sector Encounters the Digital Revolution

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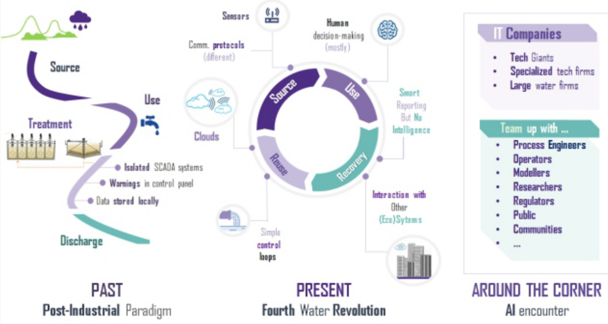
ABSTRACT: The so-called fourth revolution in the water sector will encounter the Big data and Artificial Intelligence (AI) revolution. The current data surplus stemming from all types of devices together with the relentless increase in computer capacity is revolutionizing almost all existing sectors, and the water sector will not be an exception. Combining the power of Big data analytics (including AI) with existing and future urban water infrastructure represents a significant untapped opportunity for the operation, maintenance, and rehabilitation of urban water infrastructure to achieve economic and environmental sustainability. However, such progress may catalyze socio-economic changes and cross sector boundaries (e.g., water service, health, business) as the appearance of new needs and business models will influence the job market. Such progress will impact the academic sector as new forms of research based on large amounts of data will be possible, and new research needs will be requested by the technology industrial sector. Research and development enabling new technological approaches and more effective management strategies are needed to ensure that the emerging framework for the water sector will meet future societal needs. The feature further elucidates the complexities and possibilities associated with such collaborations.



1. THE FOURTH-REVOLUTION IN THE WATER SECTOR ENCOUNTERING THE AI REVOLUTION

The water sector is undergoing the so-called fourth revolution,[1] which involves establishing water conservation strategies and transitioning toward closing water loops. Meeting our water requirements should not rely only on imported water, but on our ability to turn our urban wastewater, stormwater, and other potential hydric sources into a reliable and sustainable water supply. An example is the transition of conventional wastewater treatment toward the conception of water resource recovery facilities (WRRFs) where wastewater will not only be considered as a resource for water, energy, heat, and chemicals,[2,3] but also a source of data-rich information.

While the academic and industrial water sectors are pushing for the consolidation of the fourth revolution, another revolution concerning big data and artificial intelligence (AI) has recently emerged in all societal sectors. There are divergent views about the potential of big data analytics to disrupt the water sector, but there is little doubt it will change progressively, and inevitably, the way we think and provide infrastructure services. An estimate 80% and 50% of the utilities in developed and developing countries, respectively, are expected to undergo a digital transition, to some extent, by 2025.[4]

Fast advances in affordable sensors, high-resolution remote sensing, communication technologies, and social media are contributing to the proliferation of big data in the water sector and are likely transforming traditional decision-making strategies. Big data analytics together with AI (and its associated machine learning methodologies) are set to bring new opportunities and challenges into the water sector.[5] The intertwining of AI with big data science, with new ways to analyze, organize, and extract information from large volumes of varying types of information, is bringing new opportunities for data-driven discovery.[5,6] Decisions once based on experience and intuition could soon be guided by the analysis of massive amounts of data. How long this process will take is unclear, but critical changes in the water sector are looming.

Applying Big Data beyond Small Problems in the Water (Research) Sector. Recent literature shows examples of big data and AI for urban water infrastructure operation and asset management (see the following section). Such examples

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range from classical theory-based science approaches (e.g., using mechanistic models or empirical knowledge) to theory-free data-driven models (i.e., "pure" big data). Small problems (i.e., online recommendations) are well-structured cases characterized by repeated evaluation of predictions even if the statistical techniques may be complex and the computational and storage cost may be very large.[7] Such small problems can be tackled with "pure" big data. However, the water sector faces complex problems due to its multi-disciplinary nature and needs strategic solutions toward new sustainable water infrastructure.[8−10] Hence, water research is finding useful intermediate approaches between the two extreme cases of classical theory-based science and pure big data. The following examples are provided to illustrate the benefits and implications of big data and AI for (1) urban water asset management; (2) enhancing the operation of urban water infrastructure; and (3) recovering crucial information about the health and lifestyle habits of individual citizens and communities from data sources coming from the water sector. Afterward, a discussion is provided concerning the transition toward new workforce that enables the integration of big data and AI with the fourth revolution.

1.1. Benefits of Big Data and AI in Urban Water Infrastructure Asset Management. In most western countries, the water infrastructure is clearly aging, and (re)investment is not able to keep up with current needs which will likely worsen the existing stagnation of the sector.[10,11] Public utilities have often missed out on charging full-cost tariffs and engaged with highly discounted rates, leaving themselves confronted with a backlog of investments,[12] and compromising their current ability to embark on large-scale infrastructural projects or even to meet the required maintenance of the drinking water and wastewater infrastructure. As an example, EPA estimated the cost of the capital investment that is required to maintain and upgrade the water systems across the U.S. in 2010 at $91 billion.[11]

Collection systems have a lifespan of approximately 100 years or more, while WRRFs are expected to last at least 50 years.[11,13] AI-powered approaches may provide opportunities to alleviate the (re)investment needs of water utilities by extending the service life of existing long-term water infrastructure assets through a set of strategies to intensify, maintain, rehabilitate, and replace infrastructure. Numerous are the examples of advances on leakage detection which can improve the prediction capabilities in both collection networks and treatment facilities to reduce inefficiencies and breakdowns with their associated costly downtimes and repair.[14,15] The case of the White House Utility District that saved more than $20 million by identifying leaks in their infrastructure system with digital technologies illustrates the potential of these strategies.[16] In just a few years, unthinkable advances were made in infrastructural supervision with the support of AI capabilities, from cost-effective leak detection powered by satellite imaging[17,18] to the use of magnetic sensors to measure pipeline thickening to detect weak walls,[19] or even to pinpointing almost undetectable leaks through vibration-based signals.[20,21] Similarly, a data driven model developed by Cameron et al. (2017) enabled the prediction of the number, location, and type of chokes in collection system assets.[22] Further improvements extending asset life are being obtained from the integration of various types of data (i.e., structured and unstructured) from sources across utility departments such as the finance department, work order systems, GIS system, and supervisory control and data acquisition (SCADA) systems.[23−25] Available cloud services support such approaches, for they not only facilitate the integration of numerous signals but also incorporate data mining capabilities to unveil hidden pieces of information that can improve the anticipation of problems through pattern recognition.[26,27]

Furthermore, a wide array of applications combining AI methodologies with low-cost sensors and affordable communication networks will create dynamic, strategic, and financial operations for their utilities. Various examples and applications of AI-based strategies providing support on early detection and prediction are (1) proactive maintenance with real time monitoring and event detection;[28−30] (2) smart metering;[31−34] or (3) remote sensing products to provide early detection and prediction of wastewater conditions.[35−39]

1.2. The Role of Big Data and AI Enhancing the Operation of Urban Water Infrastructure. Classical theory-based science approaches (e.g., mechanistic or empirical models) have been extensively (and successfully) applied in the water field. The water treatment field has benefited from model developers and process engineers who have helped produce mechanistic models encapsulating knowledge to describe water fluxes and pollutants transformations occurring in drinking water plants, water distribution networks, collection systems, WRRFs, and rivers. These mechanistic models can now fall within the definition of digital twins; the term refers to virtual replicas of the infrastructure assets allowing the analysis of data and monitoring of systems to avoid problems before they even occur, prevent downtime, or plan for the future.[40−42] Examples of these digital twins are the well-known simulation platforms for drinking water distribution networks (e.g., EPANET), for collection systems (e.g., SWMM, infoworks), for WRRFs (e.g., Aquasim, Biowin, GPS-X, Simba#, Sumo, WEST), and, even for groundwater or other water-related domains (e.g., DHI, 2019). Such digital twins have been extensively used for process design/upgrade and optimization. However, the use of these mechanistic models in day-to-day operations is rather limited, especially for the infrastructure that relies on biological processes. Furthermore, to the best of our knowledge, there are not yet applications of mechanistic models operating in automated manner urban water infrastructure. The limiting prediction capabilities of existing mechanistic models under anomalous conditions is probably the limiting factor. An additional evident limiting factor is the inability of such digital twin to address processes yet to be completely modeled (e.g., greenhouse gas emissions from WRRFs).

Theory-free data-driven models have been applied to the enhancement of the operation of WRRFs,[14,44−48] and of drinking water treatment plants and distribution networks.[49,50] However, the scientific community is reluctant to accept black-box models (because they lack mechanistic explanation of the underlying processes), even though these models have the potential of achieving more accurate performance within a broader domain.

The hybridization of mechanistic and pure big data models has the potential to transform how the day-to-day operation of urban water infrastructure is traditionally done.[6] Whereas AI applications to the water sector focus on modeling, optimization, or data mining for knowledge generation, their encapsulation into functional decision support systems (DSS) is not fully explored. Few academic applications have made it

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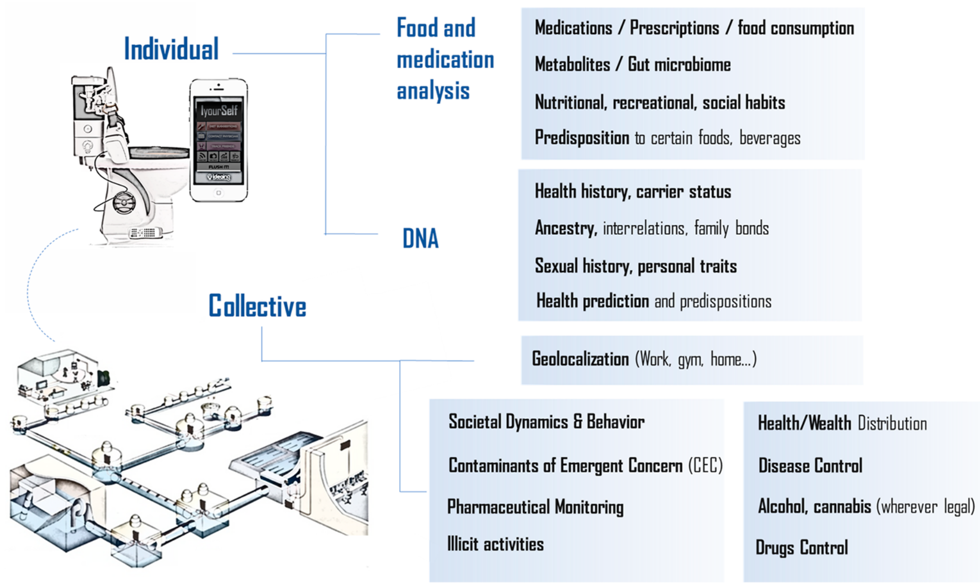

Figure 1. Technological advances in sewer mining and data analytics have the potential to open a new source of data-rich information, both at individual and collective level.

into decision making practice (e.g., Corominas et al., 2018). We believe that the reason behind this missed opportunity is not related to the methods themselves but rather to the historical disconnect between the fields of water and computer engineering, the limited practical experience of academics, and the great complexity inherently associated with these problems. Although pure big data models could enhance traditional control practice in the water infrastructure, a layer of intelligence should be added on top of the traditional control algorithms. Such layer can be based on AI self-learning capabilities using concepts such as supervised or reinforcement learning.[51−55] Such an intelligence layer would be able to detect the abnormal behavior of the process or of sensors and trigger fallback strategies that deliver maximum acceptable performance under certain equipment/process constraints (e.g., Schraa et al., 2018).[56]

In order to transform data into actionable insights, or knowledge, for enhancing the operation of urban water infrastructure, it is essential to ensure and verify the quality of signals coming from online sensors, as they can produce signals of questionable quality due to exposure to harsh environments, or due to inadequate or overzealous maintenance (e.g., Cecconi et al., 2019).[57] One essential research task is the development of algorithms for automatic data quality verification (e.g., from sensors used in control loops). In this sense, a plethora of methods have been applied such as artificial neural networks, principal component analysis, fuzzy logic, clustering, independent component analysis, partial least-squares, self-organizing aps, regression, support vector machines, and qualitative features detection (*inter alia*, Mosetlhe et al., 2018; Corominas et al., 2018).[58] However, limited guidance and no standard exist for the selection of methods to tackle a specific sensor failure detection, diagnosis, and isolation.

Nowadays, the implementation of AI approaches is hindered by challenges in data processing (turning data into information and into actionable knowledge), data availability (making useful information available to stakeholders), data quality, data costs (achieving low operation and maintenance costs for sensors and measurements), and the lack of general standards and protocols for data management (Eggimann et al., 2017). Therefore, the associated needs for skilled workforce appear evident, as discussed in Section 1.4.

1.3. The Role of Big Data and AI to Recover Information about the Lifestyle Habits of Citizens from Data Sources Coming from the Water Sector. Will Big Data Make Privacy Obsolete? Or it May Transform It into a Business? Innovation is quickly and inevitably changing the way we think and provide water services. Processes are being transformed and boundaries across sectors are shifting.[59] In many sectors, technology is disrupting processes and market structures. Solar-powered self-driving vehicles are blurring the boundaries between energy and transport sectors. In the water sector, however, there are unavoidable differences, as water has the potential to become one of society's most important sources of information. Technology will soon have the capacity to extract from water and wastewater-related services (e.g., through smart metering, sewer mining, etc.) the most intimate information from both individuals and communities about their state of health, genetics, nutrition habits, substance abuse, etc., blurring boundaries between water service, health, nutrition, and business as never before (Figure 1).

The information available through smart water metering is relevant for industries and complements the valuable information about citizens that is already available to information technology (IT) companies;[60−62] however, wastewater presents an untapped source of data-rich content about the citizenry. Cities and their communities/neighborhoods can make use of their collection system to understand lifestyle habits and overall health status through measuring human biomarkers, through information mining.[63] Human biomarkers can be either metabolites of exogenous substances (produced through metabolic processes after consumption) or endogenous compounds (produced naturally in the body), and they are continuously flowing through our collection system waiting to be harvested and measured. After toilet flushing, biomarkers end up in the collection system and, together with many other compounds, are diluted with water and transported to WRRFs

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where they are totally or partially removed before being discharged to receiving water bodies. The potential knowledge that could be distilled from analyzing our urban effluents offers a limitless array of possibilities ranging from monitoring population dynamics (i.e., medication usage, disease control, public health issues), elucidating dietary habits of entire societies (e.g., consumption of brand-specific food, drugs and alcohol use, prescription medication, etc.) and even providing advice on individual needs (detection of health risk factors, customized dietary advice, aging prevention counseling). The technology exists, and it is only a question of time before economy of scales and market forces will make reasonably feasible screening and processing data from individuals and communities connected to the collection system, unveiling our predisposition from developing cancer to which sport we should play.

Until now, the largest progress on wastewater information mining has been made on the estimation of illicit drug consumption.[64−67] Yet, the full potential has not been explored as there are still limitations in the analytical procedures in terms of accuracy and precision related to the development of capabilities to measure the concentration of these biomarkers in real-time.[68] The research in this field requires big data analytics, as the processing of information from one sample may need to be analyzed in tandem with other information such as gut microbiome diversity, sales in pharmacies, supermarkets, wastewater characteristics, etc. for reliable outputs. The penetration of the privately owned technology and service companies in the resource recovery sector would give them potential access to our genetic predispositions, diet, daily dynamics, ancestry, metabolism, health monitoring, alcohol, medications, illicit drug use, etc. The knowledge that can be potentially extracted either directly or indirectly (by applying correlations between other easily measured parameters) appears limitless and may unlock unforeseen scenarios.

Beside the technological potential of maximizing resource recovery, data mining and processing from the water sector has the potential of improving living conditions. Not only could our lives change due to the prospect of having the option to be continuously informed and guided about health (e.g., disease predisposition, recovering follow-ups, tailored health programs, etc.) and lifestyle (e.g., dietary recommendations, personal-suggested activities, sport-recommendation with its corresponding associated products, etc.), but also the job market will likely experience further deep transformations.[69] However, we should not overlook potential concerns with respect to privacy and ethics, which arise from the continuous extraction of sensitive (and valuable) data flowing from the water system.

1.4. The Role of Big Data and AI on Resource Recovery and Source-Separation. Although the prospect of retrieving information from urban wastewater streams is currently attracting the most attention, resource recovery from the water and wastewater cycle should not be overlooked. Developments in AI and new digital platforms could collate not only distributed data on resources (e.g., household-level water and energy data from smart sensors), but also data on produced resources at WRRFs (e.g., phosphate, cellulose fibers, biogas, recycled water, bioplastics, biopolymers, etc.). In a time when the production of these valuable resources is matching current market demand and prices,[2] AI-powered strategies could facilitate the market penetration of such products with precise monitoring of the product quality (e.g., image processing), optimal demand-supply balancing (e.g., dynamic pricing), and likely providing new proxy approaches to reduce current technical limitations as real-time analysis.

Similarly, the consolidation of concepts until now scarcely implemented but deemed as potential solutions to some of the most pressing challenges in the nearer future, as decentralization and source separation,[2,70,71] could also benefit from developments in digitalization and AI. Both the construction of smaller and simpler decentralized systems (enabling the minimization of costs and fewer imports), or source-separation approaches (avoiding energy-demanding, increased recovery rates, and reduced transport), should benefit from new digital strategies. Extracting increased value from the different streams also means increasingly complicated processing. Facilitating the interconnectivity and data sharing between different processes, technologies and decentralized sites would require higher intelligence, monitoring, and autonomous supervision. Powerful platforms together with secure data transferring (i.e., blockchain) could further value and improve trading of recovered resources, incentivizing individuals, companies and governments to unlock the financial value from materials traditionally regarded as economically invaluable.[72] It must be noted that information extraction when using source separation schemes would imply differentiated sampling and data-retrieving approaches than sewer mining. The different variants that may result from a successful source separation approach (i.e., urine separation, gray water, black water, etc.) will necessarily need tailored solutions to obtain the same data or information resolution."

1.5. The New Workforce and Water Research. 1.5.1. The Automation Paradox. The integration of AI within the fourth water revolution also has its counterpart. Consulting companies Price Waterhouse Coopers and Deloitte together with Oxford University projected that the water and waste management sector would suffer the most changes among a list of 50 sectors due to automation and AI irruption, predicting that close to 60% of the current related jobs are under threat within the next 15 years.[73,74] The most vulnerable jobs due to progressive digitalization are those related to the automation of low-level tasks, according to current forecasts. Many simple-repetitive tasks needed in the management of the urban water cycle elements could be potentially automated at relatively low-cost. For example, the implementation of a level meter in chemical storage tanks that could automatically trigger the purchasing procedure. However, some authors reject similar gloomy predictions suggesting that AI will likely not displace many of the workers, as automating certain tasks can free workers from repetitive tasks enabling them to focus on more highly skilled aspects (Abbatiello et al. 2017). Additionally, the requirement of licensed operators to take actions in treatment facilities will and should not be forfeited for efficiency, due to their associated authority and supervisory responsibility.

1.5.2. Water Workforce. Earlier sections discussed how AI has become a dynamic topic with many innovative applications promising to disrupt the field; however the full range of its impact on the water workforce and researchers remains nebulous. A few factors ranging from lack of incentives, risk of adoption, and preference for proven technologies could contribute to slowing the adoption of AI and big data analytics.[59] Nonetheless, few strategies could be crucial to scaling the adoption of digital technologies. While the creation of hubs working closely with utilities have already shown promising cases,[75−78] perhaps the most important approach to a successful digital implementation will require a new water

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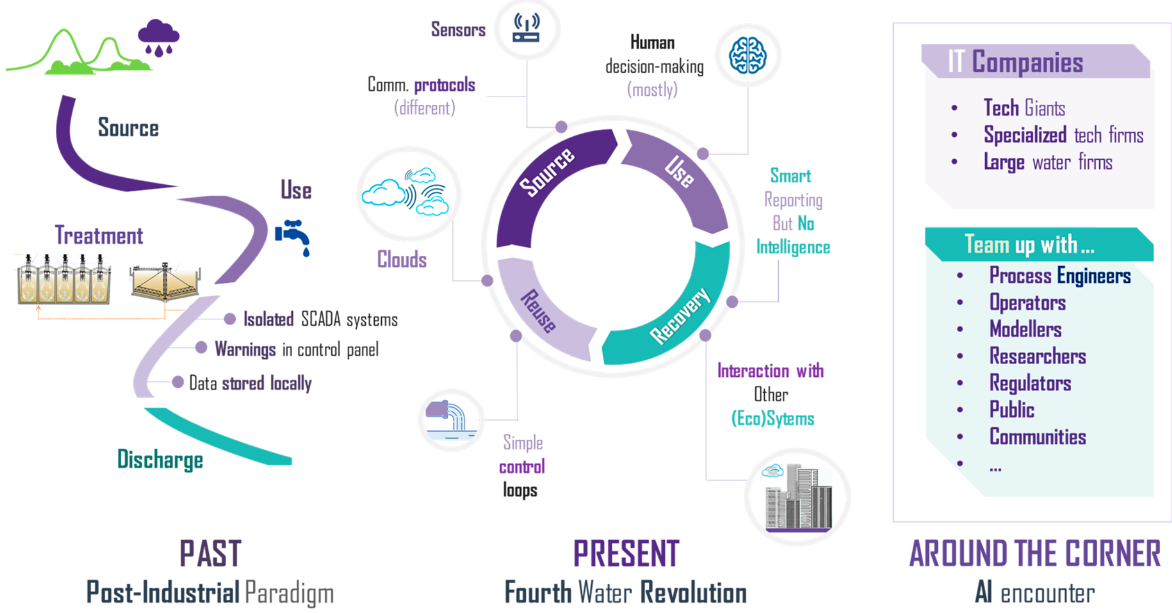

Figure 2. Conceptual evolution of the water management paradigm over the last decades: from the postindustrial third water revolution to the still settling fourth revolution, and to the upcoming AI encounter.

sector workforce adopting the required skills to keep up with the pace of digital evolution.[79] A few reviews offer further insights into the workplace challenges of adopting water data technologies (e.g., Cespedes and Peleg, 2017; Daigger et al., 2019)

1.5.3. Role of IT Companies. AI has the potential to create trillions of dollars of value across the economy.[81] It is estimated that the potential value unlocked by AI in the water resource recovery sector is up to \$22.8B in 2017 and is projected to grow by 7.2% annually from 2017 to 2021.[82,83] The water sector is slowly becoming attractive for technology giants who are unhurriedly testing the waters of a revenue-promising field by overlaying data management and AI capabilities on existing water and wastewater treatment businesses (e.g., IBM Bluemix, GE Predix, etc.; Krause et al., 2018). These platforms provide capabilities in remote asset monitoring, energy analytics, and water security. The integration of all types of data it is supposed to facilitate critical decision-making relative to assets and optimize security and reliability.

Digitalization is sought by multiple segments: from technology giants with rather limited process knowledge to specialized smaller water technology companies with the know-how but rather limited analytical platforms or infrastructure. Large water technology companies (technology developers and technology/service providers) are also investing in digitalization and are generating the demand for it. In either case, big or small technology companies will have to include water processes knowledge or water academics will have to adapt to this reality by embracing the new tools of big data analytics. The differing interests from the water research community and the technology giants might be a limitation to pursue the effective integration of AI tools in the sector. However, a clear opportunity arises for those utilities, clean-technology companies, academic institutions, or partnerships of them already operating in the water and resource recovery industry. Independent actors or partnership can enter this still untapped market and fill an important role in a meaningful way to the water industry. Figure 2.

1.5.4. Water Research Workforce. New skills will not only be required in water infrastructure but will also be fundamental to prepare the next generation of water researchers to be more proficient in data science and to design semantically rich and reproducible data products.[6] Nevertheless, reality is showing that researchers are not fully prepared to make use of the technological developments brought by digitalization to the fullest extent.[84] Debate exists on whether researcher skills for using fully the digital potential will be different from the long-recognized skills relevant in academia. Big data has the potential to change fundamentally the way that water researchers are conceiving, conducting, and analyzing experiments. Already the established rules in the scientific community supporting the indexing system, which prioritizes results and not data, are being called into question. As data continues its trajectory to become the new "currency" of research outputs for researchers,[84] data sharing in full transparency and repeatability become a new norm and current attitudes and behavior in the scientific community will need to adapt. While critical concerns from the implications of real open access, privacy, and legal aspects are arising from this trend of data sharing, the current trend is that communication through data is already being valued more than actual engineering or research skills.[85] Consequently, the researchers' skillsets will have to adapt toward not only strong data analysis, but also in the understanding of a new environmental and legal framework enabling the next level data communication.

To the greatest extent, water researchers today are not trained on digital technologies or implementing hybrid solutions between old theory-based modeling and the new array of emerging big-data elements. A new set of needs are necessary to scale the adoption of digital technologies for effective big data exploitation: (1) integration of knowledge from different types of sources; (2) successful hybridization between big data management platforms to address bottlenecks on using either pure big data-elements or solely theory-

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based modeling; and (3) ensuring data quality from sensors. A sound transition toward AI-driven urban water systems will indeed require that new generation of researchers/practitioners be trained in engineering, statistics, and computer science through the creation of multidisciplinary training programs.

Such integration of knowledge within the water sector is now being promoted by the International Water Association through its Digital Water Programme[86] and Water Environment Federation through intelligent water systems,[87] by including forums for discussions (e.g., Knowledge Development Forum, International Society of Automation's) collecting and exchanging of methodologies, and practical experiences. Specialist groups (e.g., Instrumentation, control and automation -ICA- and Digital Water Programme from IWA) have embraced significant progress in developing low-cost water-related sensors, models, and control algorithms with a very effective combination of process knowledge and ICA tools. Other groups (e.g., the WEFTEC Research and Utility Management Symposia) have focused dedicated tracks to data analysis/management and workforce training.

As computer capacity continues escalating and data management techniques (data curation, data mining, etc.) are improving, which in turn enhances knowledge extraction,[14,47,88] collaborations between teams of engineers, data and computer scientists, and researchers will be imperative to create the conditions to successfully embrace the digitalization of the water sector and leverage process knowledge, data analytics, and technology to bring out the full potential of data. Refs 43 and 80.

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Notes

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