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Chapter 6

Data analytics, digitalization, and decision-support systems in wastewater management

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ABSTRACT

Recent advances in wastewater treatment systems have made data an integral part of planning, operation, and long-term management. The traditional methods based on periodic sampling and reactive decision-making are no longer able to cope with changing influent loads, energy constraints, and tightening regulations. This chapter reports on how data analytics and digitalization are changing wastewater management in ways that enable more informed, timely, and adaptive decisions. This chapter also examines how real-time data acquisition, advanced analytics, and decision-support systems can help improve process efficiency and operation reliability. The emphasis is on the application of predictive models, performance indicators and digital platforms to translate complex data into actionable insights for operators and planners. Instead of presenting digital tools as part of a solution, the chapter reflects how useful they are when incorporated into existing infrastructure and human expertise. In addition, concern is raised with data quality, system interoperability, and institution readiness, particularly with limited resources. This chapter draws out the potential for technology as well as the actuals of implementation by emphasizing how data-driven approaches can lead to sustainable, resilient, and transparent wastewater management systems.

Keywords: Data analytics, digitalization, decision-support systems, predictive modeling, smart wastewater management, system optimization

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6.1 INTRODUCTION

Wastewater management today is an increasingly uncertain and complex process. With rapid urbanization, industrial diversification, population growth, and changes in water-use patterns, treatment plants must deal with increasing amounts of wastewater that are highly variable in characteristics (Beni *et al.*, 2025). Climate change has created an additional layer of challenge, where intense rainfall events cause sudden hydraulic overloads and prolonged dry periods lead to the concentration of pollutant loads (Ma *et al.*, 2020). Along with these operational requirements, wastewater utilities must also comply with increasingly stringent discharge standards, manage odors and emissions, limit energy consumption, and demonstrate transparency and accountability to regulators and the public (Perfect Pollucon Services, 2025). Under such circumstances, traditional management strategies based primarily on periodic sampling, routine inspections, and standardized operating procedures are becoming insufficient (García *et al.*, 2024). These approaches often capture only a snapshot of system performance and fail to reflect long-term fluctuations that may significantly influence treatment efficiency (Li *et al.*, 2024). As a result, operational decisions tend to be reactive, with interventions occurring only after process disturbances, compliance failures, or equipment malfunctions have already taken place. This reactive approach increases operational costs and energy consumption and may compromise effluent quality and system reliability (Hussain *et al.*, 2024).

Information technology has also played a key role in addressing these limitations. Online sensors, computerized monitoring systems, and digital control platforms provide a continuous stream of data, enabling real-time observation of wastewater treatment processes (Forhad *et al.*, 2024). Parameters such as flow rate, dissolved oxygen concentration, nutrient levels, energy consumption, and equipment status can be continuously tracked, allowing operators to better understand system behavior and anticipate when minor deviations may escalate into major operational problems (Newhart *et al.*, 2019). This transition from retrospective assessment to real-time awareness represents a significant advancement in wastewater system management (Ntalaperas *et al.*, 2022). The value of such data extends beyond day-to-day operations. When systematically aggregated and maintained, operational datasets can reveal long-term performance trends, seasonal variations, and the overall impacts of operational strategies (Mohammadi *et al.*, 2024). These insights support more effective planning for maintenance scheduling, capacity expansion, and process optimization. Furthermore, they enable wastewater utilities to transition toward performance-based management, where operational decisions are guided by empirical evidence rather than assumptions or historical practices (Prabu *et al.*, 2025) (Table 6.1).

Importantly, the growing role of data does not diminish the importance of human expertise. Experienced operators and engineers remain essential for interpreting data, understanding local system behavior, and making context-sensitive decisions (Ntalaperas *et al.*, 2022). Data serves as a decision-support tool that complements professional judgment rather than replacing it (Newhart *et al.*, 2019). When operators are equipped with reliable and timely information, their ability to manage complex wastewater treatment systems

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Table 6.1 Types of operational data and their role in wastewater management.

Data Type	Source/Sensor	Typical Measurement Frequency	Management Relevance
Flow rate	Flow meters in influent/effluent lines	Continuous/ 5–15 min intervals	Detect hydraulic overloads, optimize pump scheduling, and maintain compliance with discharge limits
pH	Inline pH sensors	Continuous	Ensure chemical dosing is correct, maintain biological treatment efficiency, and prevent corrosion
Dissolved oxygen (DO)	DO probes in aeration tanks	Continuous	Optimize aeration energy use, maintain biological treatment efficiency, prevent oxygen deficits
Turbidity/TSS	Turbidity sensors, total suspended solids (TSS) meters	Continuous/ hourly	Track solids removal efficiency, prevent clogging, monitor effluent quality
Nutrients (N, P)	Online nitrate, ammonium, and phosphate analyzers	15–60 min intervals	Support nutrient removal optimization, regulatory compliance, and predictive modeling
Temperature	Thermistors or digital temperature sensors	Continuous	Biological reaction rates depend on temperature; guides process control and energy optimization
Energy consumption	Smart meters on pumps, aerators, and blowers	Continuous/ 15 min intervals	Monitor operational costs, identify inefficiencies, support energy-saving strategies
Equipment status/Alarms	SCADA system sensors, vibration or current sensors on motors	Real-time	Early fault detection, preventive maintenance scheduling, reduce downtime
Chemical dosing	Flow-proportional dosing sensors	Real-time/batch	Optimize reagent use, control treatment costs, ensure compliance
Influent characteristics (BOD, COD, SS)	Online analyzers or lab sampling	2–4 h intervals (or daily)	Adjust treatment process, predict operational loads, support predictive models

improves significantly (Benettin *et al.*, 2023). In contemporary wastewater management, data has therefore shifted from being a secondary record-keeping function to a critical operational resource (Forhad *et al.*, 2024). Continuous data streams support more adaptive, efficient, and resilient systems by enabling

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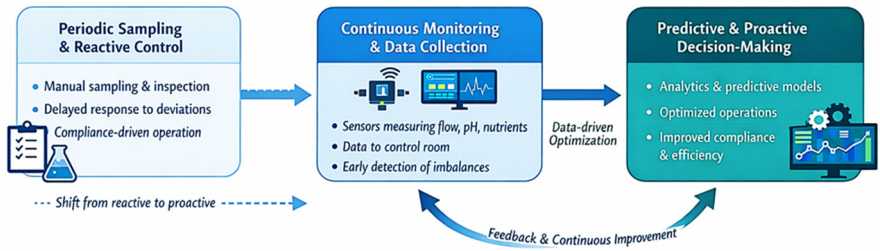


Figure 6.1 Transition from reactive to data-driven wastewater management.

informed decision-making at both operational and strategic levels (Prabu *et al.*, 2025). As wastewater systems continue to face increasing operational demands and environmental constraints, the effective use of data will be essential for ensuring environmental protection, regulatory compliance, and long-term sustainability (Newhart *et al.*, 2019) (Figure 6.1).

6.2 DIGITALIZATION OF WASTEWATER INFRASTRUCTURE

The digitalization of wastewater systems, which have traditionally been mechanical and manually operated, has become one of the primary drivers in the modernization of wastewater infrastructure. At the core of this transformation is the installation of sensors and monitoring devices that continuously measure critical parameters such as flow, pH, dissolved oxygen, turbidity, nutrient concentrations, energy consumption, and equipment performance. These sensors generate a continuous stream of information reflecting real-time operating conditions, allowing utilities to move beyond assumptions and respond to actual system behavior. Monitoring systems connect individual sensors across treatment plants, pumping stations, sewer networks, and receiving environments (Campisano *et al.*, 2002). Through wired or wireless communication systems, data from multiple assets can be transmitted to centralized control rooms or cloud-based platforms. This connectivity enables operators to manage large and complex wastewater systems through a unified interface, improving situational awareness and operational coordination. For utilities managing extensive sewer networks or multiple treatment facilities, such integrated monitoring systems are particularly valuable for identifying leaks, blockages, and abnormal flow patterns at an early stage before they result in service disruptions or environmental damage (Mohammadi *et al.*, 2024) (Figure 6.2).

Digital infrastructure generates large volumes of information, making data-acquisition systems essential for organizing and archiving this data effectively (Taleizadeh & Jalali Naini, 2018). Supervisory Control and Data Acquisition (SCADA) systems and related technologies collect raw sensor data, store it securely, and present it in formats that facilitate informed decision-making (Venkatasubramanian, 2019). These systems enable operators to visualize performance trends, compare the efficiency of different treatment

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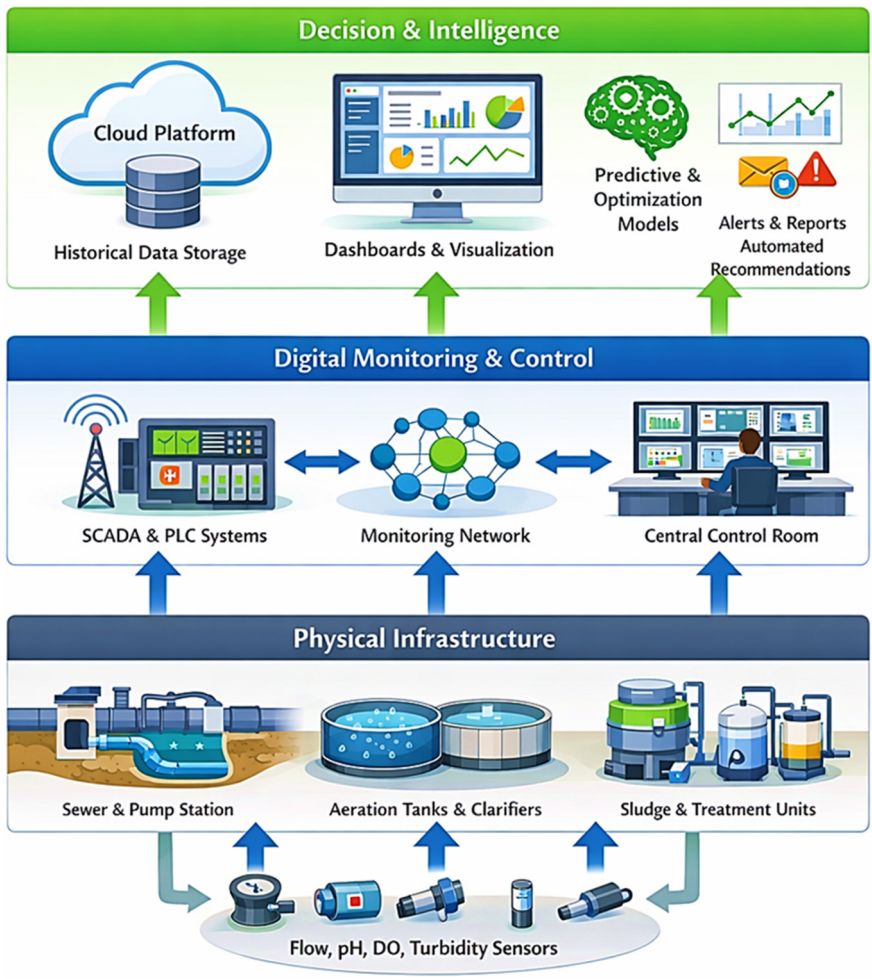


Figure 6.2 Integrated digital wastewater infrastructure.

units, and receive alerts when monitored parameters exceed predefined thresholds (Mohammadi *et al.*, 2024). Historical data retrieved from these platforms can further be used to evaluate operational performance, support regulatory reporting, and guide long-term process optimization (Stojanović & Milojković, 2016).

Digitalization is particularly transformative because it integrates physical infrastructure with intelligent digital tools. Advanced controllers embedded in pumps, valves, aerators, and other mechanical components increasingly adjust operational parameters based on real-time data. For instance, aeration rates can be dynamically optimized according to changing oxygen demand, thereby

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Table 6.2 Digital components used in wastewater infrastructure.

Digital Component	Function	Example Application	Key Consideration
Flow meters	Measure wastewater flow rates	Monitoring influent/effluent flow to optimize pump schedules	Accurate calibration and maintenance in harsh wastewater conditions
pH sensors	Monitor acidity/alkalinity	Controlling chemical dosing and protecting treatment units	Sensor fouling and drift; regular calibration required
Dissolved oxygen (DO) probes	Measure oxygen levels in aeration tanks	Optimize aeration and energy consumption	Placement in tank critical for representative readings
Turbidity/TSS sensors	Measure suspended solids	Track sedimentation and clarifier efficiency	Sensor cleaning required to prevent fouling
Online nutrient analyzers (N, P)	Monitor ammonium, nitrate, phosphate	Support nutrient removal optimization and regulatory compliance	High maintenance; periodic verification with lab samples
SCADA/PLC Systems	Centralized data acquisition and process control	Real-time monitoring and automation of pumps, valves, aerators	Integration with legacy equipment can be challenging
Communication networks	Transmit sensor data to control systems	Wired (Ethernet, fiber) or wireless (LoRa, cellular, Wi-Fi) links	Network reliability, cybersecurity, and latency
Dashboards/visualization platforms	Display real-time and historical data for operators	Trend visualization, alarms, KPI monitoring	User-friendly interface and customization required
Predictive modeling platforms	Analyze historical data to forecast performance	Predict effluent quality, optimize energy use, detect anomalies	Accuracy depends on quality and completeness of data
Cloud storage/IoT platforms	Store and manage large datasets, enable remote access	Centralized data storage, remote monitoring, and analytics	Data security, privacy, and connectivity constraints

reducing energy consumption while maintaining treatment efficiency. This integration of physical and digital components enables more precise process control and minimizes the need for continuous manual intervention (Forhad *et al.*, 2024) (Table 6.2).

Despite its advantages, digitalization is not merely a matter of installing new technologies. Successful implementation requires careful consideration of

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system compatibility, maintenance requirements, and staff capacity (Ntalaperas *et al.*, 2022). Sensors must be reliable and robust enough to function effectively in harsh wastewater environments, data transmission systems must ensure security and integrity, and operators must be adequately trained to trust and utilize digital tools in their daily operations. When these elements are addressed in an integrated manner, digitalization strengthens the connection between physical infrastructure and information systems, enabling wastewater treatment facilities to operate more efficiently, transparently, and adaptively in response to future environmental and operational challenges (Forhad *et al.*, 2024).

6.3 ANALYTICAL TOOLS AND PREDICTIVE MODELING APPROACHES

Analytical tools play a critical role in transforming raw wastewater process data into meaningful knowledge. Data by itself has limited value unless it is thoroughly analyzed to uncover patterns, relationships, and system behavior (Singh & Sharma, 2023). A wide range of analytical approaches, from traditional statistical techniques to advanced machine learning models, are used to evaluate system performance, identify inefficiencies, and support informed operational decisions (Li *et al.*, 2025). Conventional statistical methods continue to be widely applied in wastewater treatment because they are relatively simple to implement and easy to interpret. Techniques such as trend analysis, correlation studies, regression modeling, and control charts help operators understand how key operational parameters respond to variations in influent characteristics or operational adjustments (Mohammadi *et al.*, 2024). For instance, statistical analyses can be used to estimate seasonal fluctuations in nutrient loads, assess regulatory compliance patterns, or evaluate the effects of process modifications on effluent quality. These approaches are particularly valuable for establishing baseline performance and supporting evidence-based decision-making in wastewater treatment operations (Rossi *et al.*, 2021) (Figure 6.3).

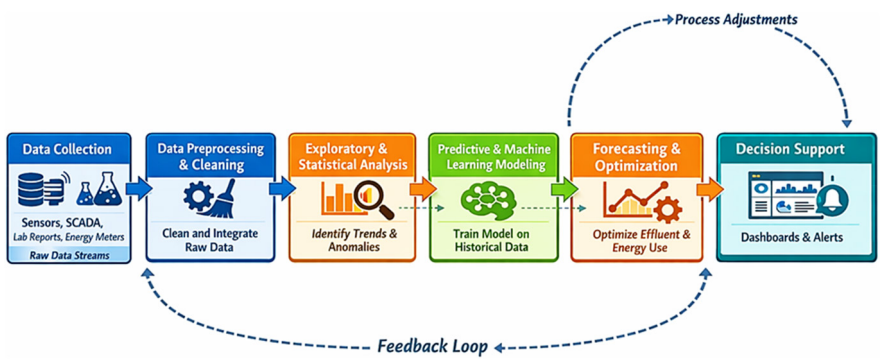


Figure 6.3 Workflow for data analytics and predictive modeling.

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Recently, machine learning and data-driven modeling approaches have gained considerable attention for their ability to capture the complex and non-linear relationships inherent in biological and physicochemical wastewater treatment processes. Historical operational datasets can be used to develop predictive models such as artificial neural networks, decision trees, support vector machines, and ensemble learning methods, which are capable of forecasting system behavior under varying operational conditions. In practical applications, these models are increasingly used to predict effluent quality, anticipate equipment failures, and optimize energy-intensive operations such as aeration and pumping (Prabu *et al.*, 2025). One of the major advantages of these approaches is their scalability, as model performance and predictive accuracy tend to improve as larger datasets become available.

Table 6.3 Analytical and predictive methods applied in wastewater systems.

Method Category	Example Techniques	Application Area	Practical Limitation
Statistical analysis	Regression analysis, correlation studies, control charts, ANOVA	Trend detection, process performance evaluation, baseline assessment	Limited ability to capture non-linear or complex system behavior
Time-series forecasting	ARIMA, exponential smoothing	Predict influent flow/quality, effluent characteristics	Assumes stationary data; sensitive to missing values
Artificial neural networks (ANNs)	Feedforward ANN, LSTM	Predict effluent quality, process efficiency, energy demand	Requires large datasets; less interpretable; may overfit
Decision Trees & Random Forests	CART, random Forest, Gradient Boosted Trees	Predict system behavior, detect anomalies, optimize process settings	Can be computationally intensive; sensitive to noisy data
Support vector machines (SVM)	Regression SVM, Classification SVM	Fault detection, effluent quality classification	Requires careful parameter tuning; less intuitive for operators
Clustering & pattern recognition	K-Means, DBSCAN, PCA	Identify influent patterns, group similar process conditions	Does not provide direct prediction; results depend on selected features
Optimization models	Linear programming, multi-objective optimization	Optimize aeration, chemical dosing, pump scheduling	Requires accurate process models; may not capture real-time variability
Hybrid/ ensemble models	ANN + ARIMA, Random Forest + optimization	Improve prediction accuracy and robustness	Increased complexity; harder to implement in real-time operations

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In addition to predictive modeling, forecasting tools further enhance analytical capabilities by enabling forward-looking operational planning. Short-term forecasts can support daily operational decisions, such as adjusting process controls in anticipation of peak influent loads or wet-weather flow events. Long-term forecasting, on the other hand, assists in strategic planning related to capacity expansion, infrastructure upgrades, and resource allocation (Newhart *et al.*, 2019). When combined with scenario analysis, these analytical frameworks also allow utilities to evaluate the potential impacts of alternative operational strategies or external pressures such as population growth and climate variability (Singh & Sharma, 2023) (Table 6.3).

Despite their potential, analytical and predictive tools must be applied carefully in wastewater management systems. The reliability of these models largely depends on the quality and completeness of the data used for their development, and overly complex analytical tools may become difficult to interpret, implement, or maintain in practical operational settings (Newhart *et al.*, 2019). Therefore, the successful application of data analytics requires a balance between analytical sophistication and practical usability (Rossi *et al.*, 2021). When these tools are integrated with the experience of system operators and a strong understanding of local treatment dynamics, analytical models can serve as powerful instruments for improving process efficiency, reducing operational risks, and enhancing the overall performance of wastewater treatment and management systems (Newhart *et al.*, 2019).

6.4 DECISION-SUPPORT SYSTEMS FOR PLANNING AND OPERATIONS

The decision-support systems (DSS) act as the point of contact between the gathering, analysis, and actions of wastewater treatment. Sensors and analytical equipment produce huge amounts of data, but decision-support platforms must show this information in terms of operators, engineers, and managers can understand and apply easily. Their primary value is bringing the large volumes of data into tangible and actionable information that can be used to make informed decisions and improve decision-making. Dashboards are one of the most widely used components of DSS. They provide a graphic representation of performance measures such as flow rates, treatment efficiency, energy consumption, and compliance status. Dashboards provide users with easy access to trends, alerts, and comparisons that give them an opportunity to quickly check system performance and avoid anomalies. Users can search by data source instead of going through multiple sources, focusing on critical variables that need to be looked at: that is, increased response time and operational confidence (Figure 6.4).

Control platforms extend the functionality of data analytics by linking data insights directly to operational actions. When integrated with SCADA and other automation systems, these platforms enable operators to modify process settings, schedule equipment operations, or trigger alarms based on predefined rules or real-time system conditions (Venkatasubramanian, 2019).

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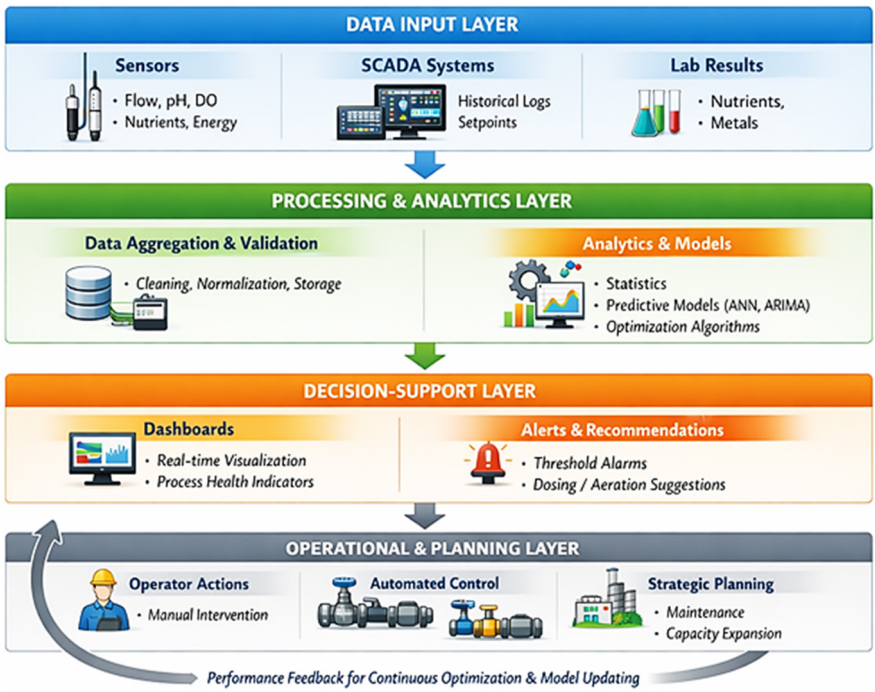


Figure 6.4 Decision-support system structure for wastewater management.

For instance, aeration intensity can be adjusted in response to fluctuations in oxygen demand, while pumping schedules can be optimized to reduce energy consumption during peak tariff periods. Such data-driven control strategies enhance process stability, reduce operational variability, and minimize the need for constant manual intervention.

Managerial decision-support tools also play an important role in assisting planners and decision-makers in evaluating long-term operational and investment strategies. These tools integrate historical datasets, predictive models, and scenario analysis to assess system performance under multiple operational or investment scenarios (World Bank, n.d.). They are particularly useful in areas such as capacity planning, asset management, and regulatory compliance, as utilities can justify their decisions through transparent and evidence-based assessments (World Bank, n.d.).

Importantly, DSS are not intended to replace human judgment but rather to enhance it. Their effectiveness depends on clear system design, reliable data inputs, and user-friendly interfaces that align with existing operational workflows (Kahneman & Klein, 2009). When implemented effectively, DSS enable wastewater professionals to make more informed, consistent, and proactive decisions, ultimately improving the efficiency, resilience, and sustainability of wastewater management systems (Table 6.4).

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Table 6.4 Decision-support tools and their users.

Tool Type	Primary User	Decision Level	Key Output
Real-time dashboards	Operators, shift supervisors	Operational/ Tactical	Current process status, alerts for abnormal conditions, KPI visualization
SCADA/control platforms	Operators, process engineers	Operational	Automated control of pumps, valves, aeration, chemical dosing; real-time process adjustments
Predictive modeling platforms	Process engineers, planners	Tactical/ Strategic	Forecast influent flows, effluent quality, energy use; support proactive interventions
Maintenance management tools (CMMS)	Maintenance teams, managers	Operational/ Tactical	Equipment status, preventive maintenance schedules, fault detection reports
Performance analytics/KPI tools	Managers, planners	Tactical/ Strategic	Evaluate plant efficiency, regulatory compliance, energy performance, trend reports
Scenario analysis/ optimization tools	Planners, decision makers	Strategic	Simulate operational or investment scenarios, optimize resource allocation, plan expansions
Alerts/notification systems	Operators, supervisors	Operational	Early warning of critical deviations, alarms for process or equipment failures
Mobile monitoring apps/ remote access	Field staff, managers	Operational/ Tactical	Remote monitoring, instant notifications, data access on the go
Cloud-based integration platforms	IT teams, managers	Strategic	Centralized data management, integration of multiple plants, support for analytics and reporting

6.5 IMPLEMENTATION CHALLENGES AND INSTITUTIONAL CONSIDERATIONS

Data analytics and digital tools offer significant potential benefits, yet their effectiveness in wastewater treatment is often constrained by practical and institutional challenges (Ntalaperas *et al.*, 2022). One of the most fundamental issues is data quality. Sensors operating in harsh wastewater environments are prone to fouling, drift, and failure, which can lead to incomplete or unreliable datasets (Ntalaperas *et al.*, 2022). Confidence in digital outputs is further weakened by inconsistent calibration practices, data collection errors, and the absence of systematic validation procedures. Without reliable and high-quality data, even the most advanced analytical tools and DSS may produce misleading results.

Interoperability represents another significant concern, particularly in long-established wastewater systems. Many utilities operate a combination

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of legacy infrastructure and modern digital technologies that were not originally designed to communicate with one another (Singh & Sharma, 2023). Differences in data formats, software platforms, and communication protocols can make system integration costly and technically complex. As a result, data sharing across departments or facilities may be limited, restricting the potential for comprehensive system-wide analysis and coordinated decision-making (Kahneman & Klein, 2009; Singh & Sharma, 2023).

Digital adoption also depends strongly on human and institutional capacity (World Bank, 2016). The effective use of digital platforms requires personnel who possess the skills to operate, interpret, and maintain these technologies (Davis, 1989). However, many utilities—particularly in low- and middle-income regions—face constraints in training, technical expertise, and capacity-building programs (World Bank, 2020). Resistance to technological change may also arise due to concerns about system complexity, cybersecurity risks, or perceived threats to established roles and operational practices (OECD, n.d.). Addressing these challenges requires continuous training programs, clear communication strategies, and a gradual integration of digital tools into existing workflows (Kotter, 2007).

Socio-economic context also plays a critical role in shaping the adoption of digitalization strategies (Heeks, 2002). Utilities with limited financial and technical resources may struggle with the high upfront costs of digital infrastructure, limited technical support, and competing priorities such as expanding basic wastewater services (World Bank, n.d.). Conversely, well-resourced utilities may face challenges related to data governance, cybersecurity risks, and institutional coordination (European Union Agency for Cybersecurity (ENISA), n.d.). These variations highlight the need for context-specific implementation strategies rather than universal or one-size-fits-all solutions (Li *et al.*, 2023). Ultimately, the success of digital wastewater management depends as much on institutional readiness as on technological capability (Li *et al.*, 2023). Aligning digital initiatives with organizational objectives, regulatory frameworks, and local operational capacities is essential for effective implementation (OECD, n.d.). When these challenges are proactively addressed, digital tools can be integrated more successfully, supporting equitable, resilient, and sustainable wastewater management across diverse environmental and institutional contexts (International Water Association, n.d.).

6.6 CONCLUSION

The planning, operation, and management of wastewater systems is being reshaped through data analytics, digitalization, and decision support systems. As wastewater infrastructure is becoming more complex and work requirements continue to grow, reactive and experience-based approaches are no longer sufficient. Utilization of continuous data streams, analytical tools, and digital platforms provides utilities with a vantage point for understanding system behavior, to respond more adaptively to changing circumstances, and to develop longer-term sustainability plans. But it is not an automatic adoption of new technologies that unlocks the benefits of digital wastewater

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management. They have to be data-rich, dependable, and most importantly, useful to institutions and staff. Digital solutions are most useful when they complement the infrastructure and operational knowledge, rather than trying to replace them. The hybridity of technology and human experience allows the informational insights to be translated into practical and context-sensitive decisions. Looking ahead, the role of digitalization in wastewater management is likely to expand further, supporting greater transparency, resilience, and resource efficiency. By addressing implementation challenges and aligning digital strategies with local socio-economic realities, wastewater utilities can harness data not just as an operational asset, but as a foundation for sustainable and adaptive water management systems.

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