Artificial Intelligence based tool for decision-making in urban stormwater management

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Artificial Intelligence based tool for decision-making in urban stormwater management

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Abstract
Artificial Intelligence (AI) is rapidly evolving and demonstrating potential for climate change adaptation in urban planning, including urban stormwater management. Through the case study of InflowGo, an AI-based stormwater model, this research identifies and appraises potential opportunities and challenges that such a tool can provide for decision-making in urban stormwater management. By the means of semi-structured interviews with urban water professionals, it was revealed that conventional decision-making, i.e. without AI application, is complex due to technical and organisational challenges, as well as insufficient speed, flexibility, and collaboration. AI has the potential to address these challenges and fill these gaps as it can accelerate decision-making, both technically and by facilitating the selection of different alternatives earlier in the process. It can also foster interdisciplinary collaboration and participation of stakeholders in decision-making by running the models during meetings, helping to break silos, and supporting educational purposes. To do this, the user-friendliness and web-based nature of the tool were identified as two contributing success factors. Although appearing as potentially relevant, AI was found not capable of overcoming the complexity and uncertainty of the field, the world, and climate change. Moreover, it can bring new challenges and shortcomings related to the ethical responsibility of making decisions, resistance to change and fear of the unknown, as well as legal and cybersecurity aspects. Further research is encouraged to investigate the application of AI-based tools in different contexts and with fully developed products, and to explore the potential educational added value of AI in decision-making.

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Abbreviations

AI	Artificial Intelligence
DL	Deep Learning
DSS	Decision Support Systems
EU	European Union
GDPR	General Data Protection Regulation
GIS	Geographic Information Systems
ML	Machine Learning
NbS	Nature-based solutions
SWMM	Storm Water Management Model

Summary

Several trends are affecting urban water systems, both external, such as climate change and population growth, and internal, such as urbanisation and ageing infrastructure (Hering et al., 2013; Romano & Akhmouch, 2019; Wamsler, 2014), forcing their conversion towards greater sustainability (Daniell et al., 2015). To mitigate the risks associated with these pressures and adapt to a changing climate, municipalities are striving to make better decisions about their hydrological networks, despite the complexity of this process and the challenges pertaining to this dynamic reality (Alves et al., 2016; Larsen et al., 2016; Romano & Akhmouch, 2019). Simultaneously, Artificial Intelligence (AI) and Machine Learning (ML) are evolving quickly, allowing fast and efficient data processing and pattern identification to be applied to complex tasks in stormwater management (Eggimann et al., 2017; Makropoulos & Savić, 2019).

This changing technological context with promising opportunities has motivated this research to explore the potential of AI in urban stormwater management decision-making. In this regard, this thesis builds on an inductive strategy to *identify and appraise the potential opportunities and challenges that an AI-based tool can provide to decision-making in urban stormwater management*. The research is based on the case study of the InflowGo tool, an AI-based stormwater model, and 16 semi-structured interviews conducted with urban water management professionals.

The findings confirm the emerging nature of AI in the field and the growing interest around it. Moreover, they describe the conventional, i.e. without AI, decision-making process in urban stormwater management as broad, complex, and iterative. It was also identified as relying on knowledge and expertise all along its different phases, including goal setting, comparison of alternatives, and implementation of solutions (Gregory et al., 2012). Furthermore, this decision-making process is characterised by: its political aspect, as framed by laws, regulations, and recommendations of the authorities (Saraswat et al., 2016); its collaborative aspect, as interdisciplinary communication, deliberation, and participation are essential traits for sustainable outcomes (Hadjimichael et al., 2016; Kvamsås, 2021; Stern and Fineberg, 1996); and its technical aspect, as relying on expertise, data, parameters, tools, and models (Larsen et al., 2016; Leskens et al., 2014a; Lombardi & Ferretti, 2015).

Several challenges and shortcomings were identified in the conventional decision-making process. The first group of challenges is technical, including the complexity of the modelling tools and expertise needed that can make the process isolated and non-inclusive (Haris et al., 2016). Additionally, the large amount of data that needs to be processed further complicates the matter. In this regard, AI shows potential with its ability to analyse large amounts of data in a shorter time than conventional tools, and promises superior capabilities compared to those of humans (Habbal et al., 2024; Yigitcanlar et al., 2020). Moreover, the case study demonstrated the prospect of an educational added value, which is worth investigating more.

The second group of challenges identified was organisational, characterised by the high number of diverse stakeholders that needs to be involved (Bohman et al., 2020; Cettner et al., 2013; Skrydstrup et al., 2020), and contextual considerations linked with available resources. In this matter, AI appears as beneficial with accelerating hydraulic simulations which can in turn improve interdisciplinary collaboration and participation. This way, the number of necessary meetings to make a decision is reduced, which can result in reduced costs and resources spent.

Furthermore, miscellaneous shortcomings in conventional decision-making were identified, as the process was described as too slow as well as lacking flexibility, collaboration, communication, and ownership, which creates silos (Bohman et al., 2020; Grum et al., 2023; Leskens et al., 2014a; Palmitessa et al., 2022; Skrydstrup et al., 2020). As previously stated, these issues could be addressed thanks to AI's reduced computational time and its use for educational purposes, by involving stakeholders from different disciplines earlier and quicker in the process. AI can also improve the flexibility of the process by enabling real-time simulations and the comparison of alternatives in the first stages of decision-making during meetings, while being complementary with conventional tools.

Consequently, the utilisation of AI/ML shows potential for decision-making in the field of urban stormwater management, and thereby seems relevant for disaster risk management and climate change adaptation. The case study of InflowGo also revealed two contributing success factors for AI-tools. The first factor involves their user-friendliness for better accessibility (Hadjimichael et al., 2016) and potential learning outcomes. The second factor is their web-based nature, which can increase participation thanks to cross-platform use that does not require prior installation, thus reducing costs and computational power needed.

However, AI-based tools cannot address all challenges identified, such as the complexity and uncertainty inherent to the field, the world, and climate change, and bring new shortcomings with their application. These involve several different concerns about ethics and responsibility of decision-makers (Bianco, 2021; Booyse & Scheepers, 2024), reluctance to change and to use new tools (Daniel & Pettit, 2021; Oschinsky et al., 2021; Warrick, 2023), lack of transparency and understanding of AI (Arun et al., 2020, as cited in Bianco, 2021; Booyse & Scheepers, 2024; Wagner & De Vries, 2019), legal considerations (European Commission, 2020; Musch et al., 2023), and cybersecurity.

To conclude, further research is encouraged to investigate the replication of these findings in another case study, i.e. within a different context and with a fully developed AI tool. In addition, it is deemed worth exploring the added value of such AI-based tools in their use for educational purposes, delving deeper into their potential training and learning outcomes.

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1. Introduction

Cities are increasingly affected by climate change, population growth, and rapid urbanisation. This impact is not limited to low- and middle-income countries, but extends to most industrialised ones (Romano & Akhmouch, 2019; Wamsler, 2014). This increase in complexity as well as in frequency and intensity of unfavourable weather events negatively impacts the exposure and vulnerability of city residents to natural hazards. In this context, urban water systems face enormous pressure to perform multiple functions, such as protecting public health, reducing flood risk, supporting urban agriculture, and ensuring sufficient quantity and quality of water for domestic and recreational use (Larsen et al., 2016; Mittal et al., 2022). In addition, these pressures are further constrained by a decreasing permeability of cities, an ever-increasing demand for water in parallel with issues in quantity and quality of its supply, as well as by the limitation of investment and the ageing of infrastructures (Makropoulos et al., 2018; Skrydstrup et al., 2020).

In high-income countries, infrastructures are indeed becoming increasingly vulnerable and obsolete, considering that the future challenges they face differ from the ones of the industrialisation era, when they were created (Hering et al., 2013). In that respect, Van Breugel (2017) noted that most infrastructures were built between the 1950s and 1980s, meaning that their lifetime of 50 to 80 years is coming to an end. Moreover, Romano and Akhmouch (2019, p. 2) stressed that: "For a total of 92% of surveyed cities [in the Organisation for Economic Co-operation and Development] obsolete or lacking infrastructure represents the most important challenge for the future of water management". Hence, the current situation of the water infrastructure of these cities does not allow them to sustainably supply and sanitise water as required by international frameworks and treaties.

Urban water management is an integral component of global sustainability challenges. Due to the above-mentioned global shifts and increasing vulnerabilities, there is an urgent need to convert existing urban water systems towards more sustainable ones (Daniell et al., 2015). This narrative is reflected in global agreements and frameworks, such as the Sendai Framework, the New Urban Agenda, and the Sustainable Development Goal 6 for clean water and sanitation. These initiatives not only draw attention to the issue, but also highlight the need for innovative approaches to create inclusive, safe, and sustainable cities (Romano & Akhmouch, 2019).

To cope with these pressures and prevent risks, city authorities make decisions to replace and adapt urban water supply systems (Larsen et al., 2016; Romano & Akhmouch, 2019). However, these decisions are very costly and can also reinforce socio-economic vulnerability and physical exposure to hazards. Thus, this increases adverse consequences, which highlights the importance of adequate decision-making (Wamsler, 2014). Moreover, the quality of decisions is limited by several factors, such as the use of poor information or poor rationale, lack of clarity about values and trade-offs, and difficulty in securing the commitment of key stakeholders (Spetzler et al., 2016, as cited in Mittal et al., 2022). In this regard, Alves et al. (2016) stated that the complex physical ramification of the urban water drainage also complicates the decision-making process, and in turn, technological innovation. Additionally, the latter is further hampered by the decision-makers' risk aversion in respect to the great amount of money invested in the expected performance of water infrastructure (Hering et al., 2013). Indeed, Romano and Akhmouch (2019, p. 4) argued that the "water sector is typically capital-intensive, requiring huge investment for infrastructure development and maintenance". On another note, decision-making in the urban water management field is further constrained by the timescale mismatch between the slow-onset pressures and the politics of policy-making.

Whereas current trends of climate change, population growth, and urbanisation affecting cities are creeping with a slow onset and long-lasting consequences, the politics of urban areas are short-sighted due to pressing short-term issues and quick turnover of elected politicians (Pot, 2020).

Current technological development is associated with large amounts of available data and more powerful computational capabilities (Eggimann et al., 2017; Pina et al., 2016), where modern cities are now “recognized as complex social-ecological-technological systems in which sustainability and climate resilience require environmental function to be paired with innovative technology” (Li & Nassauer, 2021, p. 1). In this context, Artificial Intelligence (AI) technology is rapidly developing and increasingly applied to disaster risk reduction (Kuglitsch et al., 2022; Linardos et al., 2022), for instance with the concept of “smart cities” (Yigitcanlar et al., 2020). This new technology can efficiently process large datasets, identify patterns, and provide optimal solutions through reinforcement learning, or Machine Learning (ML). It therefore appears as an opportunity to support decision-making in water management “in performing complex operational, tactical or strategic tasks” (Makropoulos & Savić, 2019, p. 3) and achieving greater reliability and precision (Eggimann et al., 2017). Indeed, according to Makropoulos and Savić (2019), utilising AI can help decision-makers visualise and assess different scenarios for long-term urban development and for existing and new infrastructure through realistic stress-testing simulations, while enhancing proactivity and appraising potential trade-offs. In that sense, Hering et al. (2013, p. 4) called for the development of next-generation technologies and tools for “bridging technologies that facilitate the integration of new approaches into existing systems”, for example, to “account for non-monetary benefits, manage trade-offs among alternatives and more effectively engage stakeholders”. In the context of rapid urbanisation and ageing water infrastructure, Larsen et al. (2016) recalled that this furthermore is a context of opportunities to develop such new technological (and managerial) innovations.

Existing models supporting flood management are limited for several reasons. They require special expertise to adequately use the model (input, data processing, output) and to translate this information to decision-makers (Leskens et al., 2014a). Moreover, they are seldom used due to the practitioners’ fear of complexifying the information in the decision-making process (Leskens et al. 2014b). Additionally, Grum et al. (2023, p. 1) emphasised that: “Tools that enable quick but physically accurate evaluations of flood risk and the environmental impact of urban plans and water management are not currently available”. According to these authors, this leads, firstly, to decisions being made intuitively in a paced manner, without acknowledging water considerations, and, secondly, in the use of accurate but slow water models only after important decisions have been made. More authors further criticised current conventional hydrological models due to their poor accessibility and user-friendliness (Haris et al., 2016). In this regard, Martel et al. (2017, p. 1307) explained how tools are generally complicated with steep learning curves and lacking open-source coding, “thus limiting the ability to tweak the model to local particularities”. Furthermore, Palmitessa et al. (2022) presented the hard compromise to find between low- and high-fidelity hydrological models, and thus the need to fill this current gap, potentially with ML. Indeed, on the one hand, simplified models are quick but display a reduced resolution only suitable for limited functions, which restrains holistic decision-making. On the other hand, realistic models are very accurate, but the significant computational power and simulation time they require make decision-making much more difficult, which hinders, if not prevents, stakeholder engagement, uncertainty analysis, and real-time use (Palmitessa et al., 2022).

In accordance with the above, this research is driven by the emerging nature of AI/ML, which are still in their infancy and not commonly applied neither to the domain of urban planning, nor to the field of urban stormwater management (Daniel & Pettit, 2021; Sanchez et al., 2023; Wagner & De Vries, 2019; Yigitcanlar et al., 2020). The research problem identified is that the pressing issues of climate change, population growth, and urbanisation, coupled by the challenges faced by the urban water system such as its ageing infrastructure, call for effective decision-making in the sector of urban stormwater management. At the same time, AI and ML are developing quickly and have immense potential in disaster risk reduction, urban planning, and urban stormwater management, including decision-making (Abid et al., 2021; Palmitessa et al., 2022). Consequently, the contributions AI/ML can make to knowledge and to current conventional decision-making processes, are yet to be seen.

The purpose of this research is to *identify and appraise the potential opportunities and challenges that an AI-based tool can provide to decision-making in urban stormwater management*. Therefore, this thesis is guided by the following questions:

1. *What decision-making tools and methods are currently used in urban stormwater management, and what are their challenges and shortcomings?*
2. *What gaps does an AI-based tool fill and what new shortcomings does it present?*

The study is based on semi-structured interviews with urban stormwater management professionals and a new AI-accelerated stormwater management model, InflowGo, as a case study. To answer the questions posed above, interviews were conducted with developers of the tool, urban stormwater management professionals who participated in the InflowGo development workshops, and practitioners who have no experience with AI. As the tool is still under development, this study explores its potential and possible applications in practice.

The structure of the thesis is as follows. The *Methodology* part introduces the research strategy and motivates the data collection and analysis methods utilised. The *Conceptual framework* is laid out to understand the keywords of this study, and how they relate to each other, forming the thesis' framework. The *Case study description* presents in detail the AI-based decision-making tool studied, InflowGo. The *Findings and discussion* are merged together in this chapter to present and discuss the results of the interviews undertaken, connecting them to each other and putting them in relation to the conceptual framework, the purpose of the thesis, and existing literature. Finally, the study is summarised and further research is encouraged in the *Conclusion*.

2. Methodology

Due to the novelty of the field of integrating AI into urban stormwater management decision-making, no specific theoretical framework was identified before the beginning of data collection. Thus, the general logic of inquiry is based on an inductive research strategy where the framework emerges from the data, which suits the exploratory nature of the research detailed thereafter. The description and identification of the current state of decision-making in urban stormwater management and its gaps were made, by conducting a complementary literature review and drawing generalisations from the patterns discovered during this process (Blaikie, 2010). Moreover, potential changes that the use of an AI tool brings in the decision-making process were distinguished.

For the research methodology, the case study method was chosen, where the InflowGo tool is the subject of research. “A case study is both the process of learning about the case and the product of our learning” (Stake, 1995, as cited in Crowe et al., 2011, p. 4). Taking into account the uniqueness of the studied AI-based tool for the sector of urban stormwater management, it was deemed this approach to be the most relevant. It was assumed that through this method, it was possible to achieve the empirical exploration of the implementation of the AI-based tool InflowGo within its real-life context (Crowe et al., 2011). The case study has an exploratory nature as it investigates how the application of the AI-based tool alters the decision-making process and what the outcomes of its implementation are. Exploratory research is often used when there is a general lack of knowledge about a topic and when the issue being studied is new (Elman et al., 2020). This approach is appropriate when there is a specific issue that needs to be investigated but there is no pre-existing knowledge or paradigm to investigate it. Thus, taking into account the above-mentioned novelty of the topic under study, the exploratory approach seems to be the most suitable for this research.

2.1. Data collection

To answer the research questions, qualitative primary data was collected through direct contact with the source of evidence by means of semi-structured interviews (Blaikie, 2010). The semi-structured interview method was chosen as it is considered versatile and flexible (Kallio et al., 2016). This method allows for reciprocity between the interviewer and interviewee, provides the opportunity to ask clarifying questions, and gives participants the opportunity to express their opinions (Kallio et al., 2016).

In order to collect data, a connection was established with the CEO of WaterZerv, the company developing the tool InflowGo, who eventually became a ‘gatekeeper’ to reach the participants of the tool’s development workshops. This was very important for the process, as the ‘gatekeeper’ allowed to gain access to and establish trust with the participants (Cresswell, 2013). WaterZerv has been doing several workshops with participants from three Danish and three German municipalities and public utilities. In total, eight key informants were provided from the aforementioned public facilities, however, by using the snowball sampling technique, the list of interviewees was expanded.

In total, 16 online interviews were conducted, lasting an average of 35 minutes, which enabled a better understanding of the different perspectives of various stormwater stakeholders who have or have no experience with InflowGo. Interviewees who are professionally relevant to the topic of the study were purposefully selected, such as civil engineers, urban land-use planners, stormwater specialists, hydraulic modellers, and researchers. Eight interviewees were participants of InflowGo’s workshops, including six from Germany and two from Denmark.

Two were members of InflowGo's development team, both from Denmark. Finally, six interviewees were other urban water professionals, of which three from Germany and three from Sweden (*Appendix 3*). By approaching specialists with different backgrounds and expertise in the field, it was assumed that their experience and knowledge in urban stormwater planning and decision-making would provide a clear and comprehensive understanding of the subject. Moreover, it helped cover the nuances that highlight the practical significance and effectiveness of such AI-based tools in this particular field, and enriched the research with diverse perspectives and substantial empirical support. Nevertheless, it was given equal weight to each interview conducted, treating them as equally valuable sources of data.

An interview guide was elaborated to ensure flexibility while simultaneously attempting to anticipate important potential themes for the data collection. The questions were divided into seven sections identified as relevant for the research based on the literature review. Beginning with the general introductory questions, the participants were then asked about their understanding of the decision-making process, and of conventional methods and tools to support it. In the subsequent step, the interviewees were interrogated about their opinion of the application of AI-based tools in the decision-making process in stormwater management, and then in particular with the InflowGo tool (for interviewees having used it). Moreover, they were questioned about their perceptions and ethical considerations regarding the integration of AI in their professional field, as well as about its relevance for the future. Finally, the interviewees were left with the opportunity to finish the interview by expressing their own thoughts, or by adding any information to their liking. The interview guide was sent to the participants prior to the interviews to allow them to prepare and to mitigate any language limitations described thereafter, while giving them the opportunity to assess if their expertise match with the questions and if they are comfortable answering them. In that respect, few of the professionals declined the interview. The document shared with the interviewees was, however, a reduced version that did not include the interviewers' probing questions and the 'Further remarks' section (*Appendix 2*).

In addition to the primary data collection method, a complementary literature review was conducted in order to provide a more comprehensive and robust analysis of the subject, establish conceptual background, and support the findings. This method is considered appropriate for this exploratory study due to the novelty of the subject explored. Although there is enough scientific literature on conventional stormwater management decision-making methods, it is not sufficient to answer the research questions posed due to the limited number of sources on AI applications in this area. This process involved a review of existing decision-making research to gather additional information about the decision-making process in urban stormwater management with and without the application of AI-powered tools. For this purpose, "Elsevier", "Elicit", "ResearchGate", "Google Scholar", and "Web of Science" were used. Preference was given to scientific articles published within the last decade. As a starting point, the same key words mentioned at the beginning were used. Moreover, a snowball search was undertaken by reviewing the bibliographies and citations of previously identified articles, as well as where those papers were cited (Wohlin, 2014).

2.2. Data analysis

For better analysis of qualitative data of a case study, the data analysis spiral approach proposed by Cresswell (2013) was applied, as follows. In accordance with its steps, after collecting the data, the transcription of the interviews' recordings was made and organised into a coherent structure. As mentioned earlier, the case study explores an emerging aspect of the stormwater management field with a limited scope of knowledge, thus an inductive coding approach was applied to analyse the raw data. This approach refers to the extraction and creation of concepts, themes, and patterns from the raw data by comparing and identifying repetitions (Chandra & Shang, 2019). Thus, the next important step was to process and code the data.

According to Elliott (2018), coding is a universal practice in qualitative research and a fundamental element of the analytical path that allows researchers to deconstruct their qualitative data in order to create something new. All interviews' transcripts were processed to identify various patterns, themes, frequencies, similarities, and differences. Then, labels were assigned to words and phrases that reflected important aspects of the research. For the efficacy of the process, the data analysis software NVivo 14 was used.

Subsequently, the identified themes were organised by the codes developed into larger units of abstraction to make sense of the data, by comparing and contrasting the patterns, and highlighting the unexpected ones. This interpretation of the data is supported by additional research from the scientific literature and reports, i.e. triangulation, to support the validity of the findings (Wieringa, 2014). Additionally, it enabled the case study to be generalised in order to draw lessons from it (Cresswell, 2013). Even though the research is qualitative, and the sample could be deemed little and thus non-representative, it is important to emphasise that it is unique in terms of locations and time frame. Thus, its objective is not to produce standardised results applicable to any types of cities, but "a coherent and illuminating description of and perspective on a situation that is based on and consistent with detailed study of that situation" (Blaikie, 2010, p. 217), while acknowledging its limitations. Moreover, as the topic of this research is still in its infancy, further research could find value in this case study by establishing whether some of the findings are replicable or not, and why.

Finally, by extracting and analysing the data from interviews, it was possible to identify similarities and differences in the challenges and shortcomings between the current decision-making process and the AI-based approach. Moreover, gaps were found in the current decision-making process that may be covered by the AI tool, and, furthermore, what the new technology can learn from the conventional methods for a better decision-making process, feeding on both initial and future success factors.

2.3. Ethical considerations

One of the main ethical considerations in the research was to obtain informed consent from interview participants. Every interviewee was informed about the nature of the research activities at the very beginning, during the establishment of contact via email, by providing them with an electronic consent form (*Appendix 1*). While ensuring full anonymity to the participants, their professions were asked to be indicated for a more holistic analysis, since cross-sector collaboration for decision-making is an essential aspect under study. Moreover, the country in which they work was displayed as considered relevant due to the geographically limited application of the tool and attempt to assess contextual differences. Furthermore, raw data is securely stored without displaying information that could precisely determine the identity of any participant.

The physical integrity of the participants was not violated, as interviews did not require any type of unsafe activities. Moreover, to ensure no psychological or emotional distress, and in line with the confidentiality and impartiality principles, it was made sure to maintain a strictly scientific-oriented approach aligned with the research objectives. No personal or sensitive questions were asked, and no funding or vested interests were involved in the study. The interview questions were designed with precautions to not influence participants into answering what the researchers want to hear. The transcriptions of the interviews did not contain misleading or deceiving information for answering the purpose of the study. Once the study is published, the findings will be shared with the interviewees.

2.4. Limitations

AI/ML technologies is an emerging field of research and practice in decision-making and urban stormwater management. Even though scientific literature was found on the current state of the decision-making process in urban stormwater management, literature regarding the application of AI/ML in this particular field is still limited at the time of the research. To address this limitation, practical real-life examples from the interviews were included as they can serve as illustrations of the application and impact of AI/ML technologies in the context of the study.

Another significant limitation worth mentioning is that the AI tool InflowGo is still under development and cannot be considered a finalised product. It is therefore only possible to assess its application during workshops as an early version accessible to few end-users where AI is emulated. Therefore, it is the potential of this tool and, by extension, of AI that are under research.

An additional limitation of the study relates to the scope of practitioners interviewed. Since the interview language was English, which is not the native language of the interviewees, interviews were conducted only with those comfortable to speak English. Consequently, the variety of specialists chosen for the purpose of the research may have been limited. To address the language limitation, as previously mentioned, the interview guide was sent to the interviewees before the interviews to enable them to prepare and anticipate potential difficulties in expressing themselves in a foreign language.

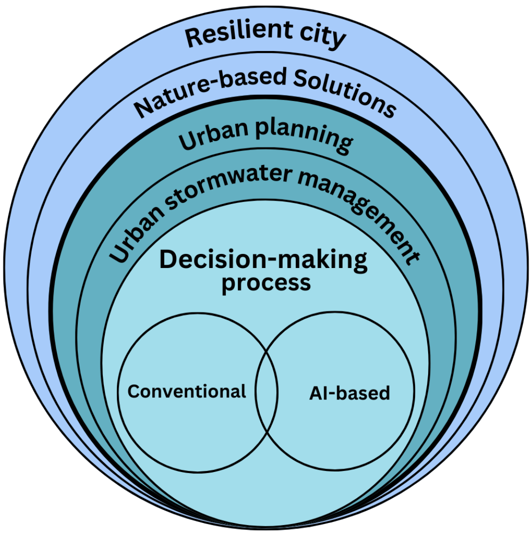
It should be noted that the majority of the interviewees related to InflowGo was initially interested in introducing new technologies into the urban stormwater management, and thus does not have an impartial attitude towards the development of AI in this field and the present conventional state. In this regard, the study’s findings about benefits, challenges, and shortcomings rely on the interviewees’ perspectives, and thus may not be perceived as benefits, challenges, and shortcomings by other stakeholders. Despite this, it is believed that this did not have a significant impact on the data obtained. Indeed, it was possible to interview other stakeholders without prior AI experience, and to document both the potential benefits and challenges of the implementation of an AI-based tool for the decision-making process by engaging with the literature, to counterbalance the interviewees’ perceptions.

3. Conceptual framework

Based on the purpose and research questions stated above, three main research domains were identified, from more central to overarching importance (*Figure 1*). The focus of the thesis is the *decision-making* process, separated between *conventional* and *AI-based* methods, that are overlapping due to the expected similarities they have. The concept of decision-making is included within the concept of *urban stormwater management*, itself within the broader concept of *urban planning*. Finally, *nature-based solutions* and *resilient city* are overarching concepts important for the context of the research, but not explored in detail due to the narrower focus of it. This is why they are separated from other concepts by a thicker line on the figure.

Figure 1

Conceptual framework



Note. Authors' contribution providing an overview of the conceptual framework.

3.1. Decision-making

3.1.1. Evolution of the concept

The concept of decision-making has been the subject of academic interest in a number of different disciplines for the last centuries (Oliveira, 2007). In the middle of the 1900s, a significant amount of groundbreaking work in the field of economics and management greatly influenced the conceptual development of the field. In this regard, in 1947, Simon's book *Administrative Behavior* associated decision-making with the field of management and conceptualised it into three phases: identification of alternatives, determination of their consequences, and evaluation of these consequences (Simon, 1947, as cited in Pomerol & Adam, 2004).

Thirty years later, after incorporating psychological aspects revolving around human cognitive processes, Simon defined four steps of decision-making: intelligence, design, choice, and review. According to Pomerol and Adam (2004), Simon emphasised the importance of access to information in restraining the decision. This introduced Simon's next work about the concept of bounded rationality. The latter defines that information and knowledge can never be complete because of the human cognitive limitations, the different values that various individuals have, and the world's complexity, which thus affects decision-making (Simon et al., 1987).

In their article, Simon et al. (1987, p. 30) also highlighted the growing importance of computer simulation in the decision-making process, "both for purposes of testing its empirical validity and for augmenting human problem-solving capacities by the construction of expert systems". The latter refer to AI and the modelling of environmental systems, demonstrating the precursor character and influence of this seminal work. Indeed, Simon et al. (1987) already described the potential quantitative capacity of computers to process information and recognise patterns that humans cannot match for problem-solving and decision-making.

In parallel, Kahneman and Tversky (1979) conceptualised the prospect theory, which diverged from the widespread model at that time describing the rationality of decision-makers under risk. They found effects influencing the choices and behaviour of people, emphasising the importance of uncertainty and framing. The perception of risk is subjective as people tend to overestimate low-probability high-consequence events, and underestimate high-probability low-consequence events. There is thus an asymmetry between gains and losses, implying that people are more sensitive to losses than to gains of the same magnitude, and therefore leading to risk-averse behaviour for sure gains and risk-seeking behaviour for avoiding losses. Moreover, these evaluations depend on the reference point of the decision-maker, i.e. how the choices are presented. Indeed, the isolation effect explains how people are more likely to focus on the differences rather than similarities between alternatives, and thus how choices framed in isolation are more valued. Another consequence is people's "inconsistent preferences when the same choice is presented in different forms" (Kahneman & Tversky, 1979, p. 263).

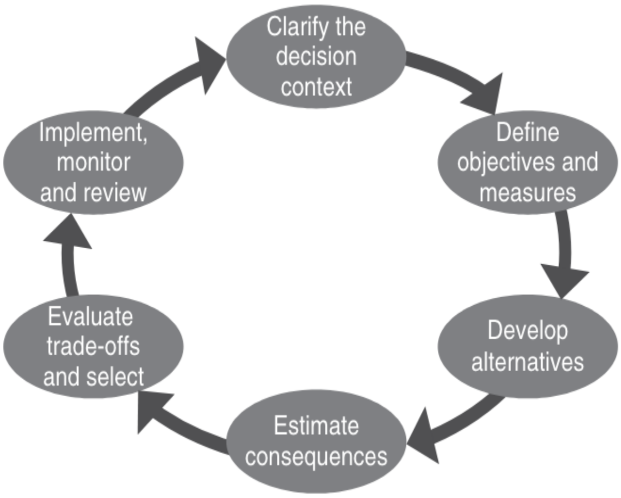
In the field of risk management, Stern and Fineberg (1996) described the decision-making process as an "analytic-deliberative process" (p. 3) for risk characterisation, the latter meaning the "translation of the results of technical analysis for the use of a decision maker" (p. 1). The decisions are thus informed, made, and accepted through the participation and collaboration of various affected stakeholders aiming for a consensus, and thanks to contextualised, accurate, understandable, and accessible information (e.g. description of risk factors, potential gains and losses, uncertainty, trade-offs). This process necessitates transparency, accountability, learning, feedback, organisational capability, and the consideration of societal values, ethical considerations, and stakeholder perspectives. It goes against the sole analysis of technical expertise and scientific evidence overlooking the complexity of decision-making (Stern & Fineberg, 1996).

Then, in the domain of environmental decision-making, Gregory et al. (2012) presented three typical approaches conventionally used but not suited for complexity, followed by their own framework of structured decision-making. The first conventional method is the science-based decision-making, which as criticised by Stern and Fineberg (1996), lacks subjectivity, values, dialogue, and social and ethical considerations. Secondly, the consensus-based decision-making is also criticised, this time differentiating with the previous authors. Gregory et al. (2012) found this approach to be too 'rushed' in its process. Indeed, because of the focus on finding an agreement early on, the authors argued that it relies too much on opinions rather than understanding, that it hinders creativity, innovation, and minority perspectives, and that it neglects the exploration of uncertainty and trade-offs. Finally, the last typical method they described and criticised is the economics and multi-criteria analysis. This one is deemed too technocratic, based mostly on expertise, formulas, scores, and cost-benefit evaluations, again to the detriment of creativity, understanding, and community support (Gregory et al., 2012).

The structured decision-making that Gregory et al. (2012) recommended is argued to be more adequate to deal with complexity, uncertainty, and the multiplicity of objectives and stakeholders' preferences. Instead of being 'normative', i.e. defining "how decisions should be made, based on the theory of rational choice", or 'descriptive', i.e. describing "how people actually make decisions", the authors presented their approach as 'prescriptive', i.e. to "suggest ways to help [...] to make better decisions" (Gregory et al., 2012, p. 6). In other words, it is a framework guiding decision-makers with a set of questions about the decision's context, objectives, alternatives, consequences, uncertainties, pros and cons, as well as follow-up lessons learnt for future applications.

Figure 2

Structured decision-making



Note. From Gregory, R., Failing, L., Harstone, M., Long, G., McDaniels, T., & Ohlson, D. (2012). Structured Decision Making: A Practical Guide to Environmental Management Choices (1st ed.). Wiley. https://doi.org/10.1002/9781444398557.

3.1.2. Decision support systems

Hydroinformatics is the field that allows the interaction of different stakeholders through the computational modelling of their environment and of water-related solutions. It is increasingly incorporating social considerations to support decision-making, for a more holistic planning (Vojinovic & Abbott, 2017). This field usually employs computer software to make decisions, named decision support systems (DSS). They aim to improve the quality of complex decisions by using data to design and evaluate different alternatives (McIntosh et al., 2011). According to Crossland (2008, p. 1095), DSS "are increasingly being combined with geographic information systems (GIS) to form a hybrid type of decision support tool known as a spatial decision support system". By integrating both the logic of DSS and the spatial components of GIS, they solve even more complex problems and become more efficient for urban planners (Lombardi & Ferretti, 2015). Nonetheless, as recalled by Pomerol and Adam (2004), DSS have a disadvantage since they heavily depend on the quality of the data fed into them, regardless of the quality of the model itself, even though the latter is given greater attention. This phenomenon is defined in computational sciences as 'garbage in – garbage out', where incoherent, sparse, or inaccurate data input eventually leads to unreliable, non-representative output (Kilkenny & Robinson, 2018).

3.1.3. Stormwater modelling

Among DSS in hydroinformatics are hydrological models, including urban stormwater models. They can be defined as "simulation tools that include algorithms and methods to describe the main physical processes related to the flow of stormwater across urban catchments" (Pina et al., 2016, p. 1). These computational tools are standardly utilised by decision-makers, from engineers to city planners, to understand and simulate hydrological processes, to then design, monitor, and control urban drainage systems (Haris et al., 2016; Palmitessa et al., 2022). For instance, such models can simulate the quality of urban water, helpful for pollution and water supply management, and its quantity through the "rainfall–runoff, overland flow and sewer flow" (Pina et al., 2016, p. 1), useful to manage the risk of both flooding and overflow. The use of hydrological models entails the provision of input data in the form of "spatial and temporal distribution of precipitation" (Zoppou, 2001, pp. 199-200). Moreover, a realistic, accurate, and reliable depiction of the hydraulic system is needed to make informed decisions. Therefore, a stormwater model needs to be calibrated so that its predictions closely match the actual water levels and flows. Calibration can be made thanks to measurements, and then by adjusting parameters such as the runoff coefficients or the pipes diameters (Gupta et al., 1998).

According to Zoppou (2001), hundreds of hydrological models exist to simulate the characteristics and physics of water, and they are developed by various types of stakeholders such as private engineering companies, governments, regulatory institutions, or scientific academies. These actors have different resources and objectives, which is reflected in the diversity of available models and of their applications, from risk assessment and flood forecasting to urban drainage and agriculture (Martel et al., 2017). For instance, different modelling approaches allow for more or less detailed simulations and fidelity of the reality, and can be applied to a various range of geographical scales, from reduced to vast watersheds (Haris et al., 2016; Palmitessa et al., 2022). Moreover, the accessibility to them varies greatly as public tools are generally open-source and free to download, allowing technological tweaking to tailor their utilisation to different applications and contexts. Conversely, private tools are designed for commercial purposes, thus available at an expensive price, but providing more support from their developers (Martel et al., 2017; Zoppou, 2001).

As explained by Zoppou (2001), models can be divided into different categories: to plan infrastructure configurations for asset management, by evaluating different alternatives in regard to criteria; to design the infrastructure itself by accurately modelling the water flow; to operate hydrological resources in real time, like flood forecasting models; and for hybrid purposes. These different types of models generally require different types and amounts of data as input and can produce different kinds of output after various scales of simulation time, according to the level of specification and to the number of features analysed. As a result, it is difficult to associate real-time data with complicated operational data (Zoppou, 2001). Moreover, Zoppou (2001) stressed the importance of uncertainty analysis when interpreting the results of a modelling for decision-making. It can be inherent uncertainty, pertaining to the natural physical processes involved with water; model uncertainty, related to the simplification of the reality being modelled; or parameter uncertainty, about characteristics of the model. However, the author also highlighted that, at the time of the article, none of the models allowed uncertainty analysis.

The management of urban water by computer models started in the beginning of the 1970s in the United States of America, to simulate both its quality and quantity. At this point, governmental agencies had already developed various types of modelling approaches, from "very simple conceptual models to complex hydraulic models" (Zoppou, 2001, p. 197). One example is the Storm Water Management Model (SWMM), launched in 1971 by the USA's Environmental Protection Agency, which is still being updated and used today to simulate events with detailed modelling of stormwater, urban drainage, and measurements of watersheds (Haris et al., 2016; Pina et al., 2016). From this tool, several other tools were developed with different graphical user interfaces, like XP-SWMM or MIKE-SWMM. The latter is a combined model with MIKE 11 which, according to Zoppou (2001), couples their advantages and improves the mathematical calculations with water flow simulation. Moreover, its interface is very versatile as it can be connected to other models, allowing its application for different purposes such as production of rainfall patterns, simulation of sediment transport, analysis of coastlines, or assessment of the performance of wastewater treatment plants (Zoppou, 2001).

All these enhancements in hydrological models were enabled throughout the years in parallel with technical and technological innovations as well as increasingly available data, as displayed by the addition of GIS between the 1990s and 2000s (Pina et al., 2016). Sahu et al. (2020) reviewed several studies applying another tool called HEC-HMS, developed by the USA's Army Corps of Engineers. The authors showed different examples of successful implementations of this hydrological model with GIS, for instance to prepare slope and soil maps by remote sensing, or to model a water basin through a digital elevation model for flood forecasting.

Nevertheless, according to Fu et al. (2022), hydrological modelling today faces a number of challenges which has led to stagnation in the development of new functionalities and improvements. Indeed, the authors noted five hurdles, as follows: the complexity of urban water systems and of their interplay with other climate, biodiversity, and human systems; the challenging urban water modelling combining various factors, assumptions, parameters, and processes; the lack of certainty and data; the high computational power required for detailed modelling; and the obligation to devote oneself to a single model and therefore difficulty to switch to another, due to the skills and resources required for "model development and maintenance" (Fu et al., 2022, p. 1). Contrarily, the authors then mentioned disruptive technologies and presented the recent advancements in AI/ML, thus appearing as potential solutions to address these obstacles.

3.2. Artificial Intelligence and Machine Learning

3.2.1. A disruptive technology

In this study, the above-mentioned methods and tools that are part of the current decision-making process are defined as conventional when not employing AI/ML. The latter constitute the prevalent example of current disruptive technologies, alongside for example the blockchain, internet of things, 3D printing, robotics, and drones (Munawar et al., 2022; Păvăloaia & Necula, 2023). Disruptive technologies are presented with different perspectives in the literature, making it difficult to find one universal definition (Nagy et al., 2016). However, they all encompass the notions of novelty, change, and improvement.

On the one hand, Millar et al. (2018, p. 254) explored the concept of disruption as "change that makes previous products, services and/or processes ineffective", indicating a notion of discontinuity and incompatibility with current conventional technologies. On the other hand, other authors described it as "new technologies [that] can create new markets or radically change, or disrupt, the status quo in existing markets" (Bower & Christensen, 1995, as cited in Nagy et al., 2016, p. 119), as well as in research, due to larger performance (Munawar et al., 2022). For this reason, disruptive technologies and in particular AI/ML show potential in the urban context for multiple applications such as planning, public safety, water management, governance, energy, mobility, and more generally for disaster risk management and climate change adaptation (American Planning Association, 2022; GFDRR, 2021; GSMA, 2020; Munawar et al., 2022; Păvăloaia & Necula, 2023; Spencer, 2021; UN-Habitat, 2022).

3.2.2. Theoretical and technical considerations

The definition of AI is constantly evolving along with the dynamic and fast nature of technological development in this area, resulting in a lack of a universally accepted definition (Duan et al., 2019; Huang & Peissl, 2023). A definition is suggested by the High-Level Expert Group on Artificial Intelligence, an independent body initiated via the European Commission, and restated by Huang and Peissl (2023):

> Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions. (p. 177)

Duan et al. (2019, p. 2) added that AI "is normally referred to as the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks". This ability is called ML, a subset of AI "that can make predictions [...] on new observations" (Zhou, 2021, p. 2). These predictions are made by identifying patterns in the input data, following mathematical models and statistical methods. In order to solve greater learning tasks and allow applications in complex contexts, a structure of numerous interconnected ML layers (called neural networks) was developed, forming Deep Learning (DL), a subtype of ML (GSMA, 2020; Zhou, 2021). This enables the parallelised processing of an enormous number of parameters in an accelerated manner (Grum et al., 2023), which suits urban stormwater management "where we often want to simulate water levels and flows in hundreds or thousands of links and nodes" (Palmitessa et al., 2022, p. 2). As a result, Fu et al. (2022, p. 1) emphasised that ML will "help tackle water challenges such as resource efficiency, water supply, water pollution, flooding and drought, contributing to achieving the water-related United Nations' sustainable development goals". However, they also noted that the application of such data-driven models is still in its early phases in the urban stormwater management field.

3.3. Urban stormwater management

3.3.1. Hydrological notions

In order to grasp the concept of urban stormwater management, it is important to first understand the origin of water and its different types to manage. One of the main components of the water cycle concerns the precipitation phenomenon, and is explained by Zoppou (2001) as follows. A portion of the water falling from the sky is lost due to evaporation and vegetation absorption. The surplus of water can then penetrate the soil and at some point re-emerge, accumulate in ground depressions, or flow on the surface. These different alternatives depend on the quantity of water and on the type of soil, as the latter can have varying levels of saturation and of permeability. Subsequently, the running water flows towards the various elements of the hydrographic network in the watershed. The latter can also be named catchment area or drainage basin, and the USA's National Oceanic and Atmospheric Administration (2023) defined it as "a land area that channels rainfall and snowmelt to creeks, streams, and rivers, and eventually to outflow points such as reservoirs, bays, and the ocean".

According to Jaber (2008, p. 3), the "precipitation that does not soak into the ground, but instead runs off its surface" is defined as stormwater. It is thus a natural process, whereas wastewater rather originates from human activities, either domestic, industrial, or commercial discharge of used water (Jaber, 2008). However, rainfall is mostly turned into runoff on impervious land, which is the case in urban areas (Zoppou, 2001) and alters the natural functioning of a drainage basin (Larsen et al., 2016). Indeed, a lesser extent of natural soil cover reduces the potential amount of water evapotranspiration made by the trees and of water infiltration in the ground, increasing the portion of rainwater to runoff from 10% to 45% (Jaber, 2008). Moreover, urban areas are characterised by numerous man-made built waterways (Zoppou, 2001) and more debris, chemicals, and pollutants that can get drained by storm- or wastewater, thus also increasing erosion and reducing biodiversity and the quality of supplied water (Jaber, 2008). All of this explains how in cities, the "increase in runoff volume and flow [...] can result in flooding, watercourse and habitat destruction" (Zoppou, 2001, p. 197), and highlights the need for urban stormwater management. Undoubtedly, stormwater management is also important to consider in rural areas, even if the increased permeability of the ground there slows down water runoff. However, the difference between both geographical areas is substantial as it implies a higher level of detail for urban models compared to rural models (Zoppou, 2001).

3.3.2. The concept of urban stormwater management

In their report, Jotte et al. (2017) stated that traditionally, stormwater management considered the diversion of excess water to nearby watercourses with a focus on minimising flood risks, and thus solely on water quantity. However, today the focus has expanded to also consider water quality and amenity, i.e. the contribution to the overall attractiveness, comfort, and well-being of urban residents (Jotte et al., 2017). This modernised approach seeks to achieve a variety of objectives, including reducing the water runoff, mitigating flood and erosion risks, facilitating natural groundwater recharge, lowering concentrations of stormwater pollutants, improving biodiversity, preserving water (and air) quality, minimising costs associated with stormwater treatment and pipe capacity, and enhancing the amenity and aesthetics of urban areas planned. According to Larsen et al. (2016), for these reasons, urban stormwater management has made a prevailing medical milestone and is of utmost importance for the hygiene and health of residents.

The infrastructure for urban stormwater management is multiple. In industrialised countries, it is based on a network of pipes, most of the time buried underground, and reservoirs, for transporting and draining of stormwater and wastewater to protect lives and settlements, as well as for supplying water for domestic, industrial, or agricultural use (Larsen et al., 2016; Zoppou, 2001). Moreover, this equipment is "only designed for a particular storm event, usually the 1 in 2 year or 1 in 5 year event or the 1 in 10 year storm event for commercial and industrial areas" (Zoppou, 2001, p. 200). This represents a great limitation with the growing intensity and frequency of rainfall events in the current context of climate change (Arya & Kumar, 2023). Additionally, certain infrastructures are reserved for the treatment of water, for its drinkability but also to limit pollution before its release in the natural environment. This large diversity of essential functions makes the water infrastructure very complicated, demanding a high level of technical skills, and also costly in financial, social, and environmental matters (Larsen et al., 2016; Zoppou, 2001). According to Larsen et al. (2016, p. 929), this is the “consequence of ageing built infrastructures, increasing urbanisation, emerging contaminants, competitive water uses, and measures to mitigate the effects of climate change (e.g. water-saving measures)”. On a less technical and more institutional level, urban stormwater management is characterised by the intervention of public stakeholders for planning and governance considerations, usually municipal authorities in the case of industrialised countries. They generally follow various strict regulations and codes elaborated on higher administrative scales (Larsen et al., 2016).

3.4. Urban planning

The above-mentioned makes urban stormwater management fall under the concept and domain of urban planning. Bibri and Krogstie (2017, p. 190) identified urban planning as a systematic approach to strategic guiding and shaping of “the use and development of land, urban environment, urban infrastructure, and related ecosystem and human services” with the aim to “ensure the maximum level of economic development, high quality of life, wise management of natural resources, and efficient operation of infrastructures”. Moreover, urban planning is the purposeful intervention in the built environment through the development of programs and plans with the overarching goal of achieving a more sustainable, resilient, integrated, equitable, and just future for the city (Bush & Doyon, 2019).

Rapid urbanisation, development challenges, and growing pressure of climate change make urban planning inherently complex and adds pressure on urban systems, thereby placing stress in city life in terms of core operational and organisational processes, functions, and services (Bibri & Krogstie, 2017; Bush & Doyon, 2019; Frantzeskaki et al., 2022). To address these challenges, cities need to improve their resilience and capacity by developing, applying, and implementing innovative solutions and sophisticated methods in urban planning (Bibri & Krogstie, 2017). The urgency and importance of building and developing sustainable cities are also reflected in the goals of the global initiative, such as the Sustainable Development Goal 11 (sustainable cities and communities) and the New Urban Agenda (UN-Habitat, 2022).

Adaptation of new technologies such as AI in various aspects of urban planning has enormous potential and can offer new opportunities to address the above-mentioned challenges (He & Chen, 2024). Features such as analysing large and complex data sets, optimising the planning process, and providing more accurate forecasts and insights can greatly facilitate urban planning and ultimately lead to more sustainable urban environments (He & Chen, 2024).

3.5. The overarching concepts of nature-based solutions and resilient city

There is a wide range of definitions and interpretations of nature-based solutions (NbS) in the literature (Dorst et al., 2019; Sowińska-Świerkosz & García, 2022). The most commonly used was provided by the European Commission (2015, p. 5), where NbS are considered as “actions which are inspired by, supported by or copied from nature” with “the aim to help societies address a variety of environmental, social and economic challenges in sustainable ways”. In their work, Balian et al. (2014, as cited in Kabisch et al., 2016, p. 2) defined NbS with a clear depiction of those challenges “such as climate change, food security, water resources, or disaster risk management”. Specifically for the urban planning context, Albert et al. (2019, p. 14) characterised NbS as “actions that (i) alleviate a well-defined societal challenge, (ii) utilise ecosystem processes of spatial, blue and green infrastructure networks, and (iii) are embedded within viable governance or business models for implementation”. The concept arose from the need to develop new innovative solutions to achieve sustainable urban planning and to address climate change and disaster risk reduction through the integration of ecosystem services (Faivre et al., 2018; Sowińska-Świerkosz & García, 2022).

NbS is considered an umbrella concept that incorporates all other nature-based approaches for sustainable development, such as ecosystem-based adaptation and management, green infrastructure, ecosystem-based disaster risk reduction, and eco-engineering (Dorst et al., 2019; Johnson et al., 2022). Given the multifunctional and solution-oriented nature of the concept, it can help improve collaboration between actors from different disciplines and sectors, by providing a common language and pooling knowledge and experience that can contribute to achieving sustainable urban development for resilient cities (Dorst et al., 2019; Su et al., 2023).

A resilient city is one that is able to adjust and adapt in the face of change while moving along the desired development path (Bush & Doyon, 2019). Urban resilience depends on long-term, integrated approaches to urban planning and development. To identify viable development strategies, it is important to combine different disciplines, perspectives, mechanisms, as well as new technologies (Bush & Doyon, 2019). Moreover, solutions related to ecosystem services play an important role in increasing the resilience of cities, especially in regard to sudden changes, destruction, natural hazards, and the effects of climate change.

4. Case study description – InflowGo

This chapter provides a contextual background of the InflowGo tool to better understand the purpose, working mechanism, and development of an AI-based tool in the field of stormwater management. The information presented is based on open data extracted from the website of the tool's developer company WaterZerv, its LinkedIn page, and interviews with developers.

InflowGo is an AI-powered sustainable stormwater management model launched in 2023. According to the developers, the development of this tool combines years of experience in stormwater management, hydrology, hydraulics, ML, and software development with the initial goal of addressing current challenges and creating a new model for sustainable stormwater management. The main shortcomings of the current state of stormwater management identified by the WaterZerv company are outdated tools and software, and lack of collaboration among vital stakeholders, which in the end is deemed to hinder the urban planning process. By developing the tool, the company claims to facilitate the creation of sustainable and blue-green cities and to contribute to the Sustainable Development Goals, namely: Goal 6 – clean water and sanitation; Goal 11 – sustainable cities and communities; Goal 13 – climate action; and Goal 14 – life below water. The tool is positioned as a research and innovation project that aims to address the above-mentioned challenges through workshops and consultations with practitioners.

The company has determined that their product provides value to a wide range of professionals, including civil engineers, water utilities, traffic authorities, municipalities, environmental authorities, hydraulic engineers, urban planners, and policymakers among others. InflowGo intends to offer stakeholders a platform to improve collaboration, ensure participation from the beginning of the project's planning process, and explore different scenarios in real time. The tool is positioned as an advanced AI model, which, however, is still under development and improvement. At this moment, InflowGo is available in English, German, and Danish. The company plans to expand its language coverage further.

InflowGo uses advanced ML techniques to produce results very similar to traditional hydrologic models, which the company claims to achieve 100 to 10,000 times faster. This, by training a custom neural network to model the flows, levels, overflows, and carbon footprint of both stormwater and combined networks. Moreover, the use of a neural network makes it possible to simultaneously perform multiple calculations, for example, changing inflows from several areas at once.

The tool works on DL, i.e. neural networks that need to be fed and trained based on the data provided. With this AI implementation, it is claimed possible to predict and test the impact of construction projects, climate change, overloading of drainage systems, and other changes on the sewer systems. Moreover, it is expected that it will also be possible to obtain estimates of carbon dioxide emissions.

The development of the project is supported by the Innovation Fund Denmark as well as six utilities and municipalities in Germany and Denmark. This collaboration is reflected in joint cross-disciplinary workshops with land-use and landscape planners, storm- and wastewater planners, spatial data experts, hydraulic modellers, and sustainable urban drainage specialists from the aforementioned municipalities and utilities. At the workshops, invited experts and developers analyse modern planning processes and identify their strengths and weaknesses, jointly test the latest version of the tool through real development scenarios, and look for solutions to complex problems, considering the opinion of each specialist. The company has planned a total of 18 workshops with end-user experts with the main goal to receive feedback for further improvements and of their expectations from the InflowGo tool. By the time of the data collection, half of the workshops had been completed.

5. Findings and discussion

This chapter provides answers to the research questions through a critical analysis of the findings complemented by scientific literature. More precisely, 5.1. is focused on the first part of research question 1 – "*what decision-making tools and methods are currently used in urban stormwater management*"; 5.2. on the second half of research question 1 and the first part of the research question 2 – "*what are their challenges and shortcomings*" and "*what gaps does an AI-based tool fill*"; and 5.3. on the second half of research question 2 – "*what new shortcomings does it present*". Interviewees are anonymously cited by their number (*Appendix 3*). Firstly, the interviewees' perceptions of the definition of stormwater management decision-making, its practices, and the dynamics of its stages are discussed in relation to what was established in the *Conceptual framework* chapter. Secondly, the conventional decision-making's challenges and shortcomings identified by all practitioners are discussed in relation to the findings made about potential benefits of AI. This was achieved by analysis of the interviewees' overall experience with InflowGo and synthesis of the views of those who have not interacted with any AI-based tool. Thirdly, based on the interviewees' common concerns, new shortcomings and obstacles that may arise in practice when using an AI-based tool are summarised, as well as the shortcomings of the conventional decision-making process that cannot currently be solved with AI.

For transparency, the findings discussed present limitations that are essential to explicitly clarify the scope of the study. Besides the methodological constraints previously considered, it is important to note that the discussion is limited because it concerns a version of the InflowGo tool without AI/ML being implemented. As explained by the development team, AI/ML is currently emulated by a numerical model by doing the calculations on a small catchment, and by feeding the software with a small dataset of one 10-year rain event as input, instead of larger historical rainfall series. With AI/ML, the tool is expected to perform with more pace and stability, on larger areas, while displaying statistically more detailed results (quantity but also frequency of overflows at desired locations). However, as the aim of the research is to investigate an AI-based tool through its potential, the results are presented as only being feasibly obtainable. Furthermore, the following challenges, shortcomings, and potentials of AI were raised by multiple interviewees during the research and were thus deemed relevant for the purpose of the study. This list, however, should by no means be considered exhaustive.

First of all, the interviewees' experience with AI is presented. When asked about previous experience with it, out of 16 answers, seven of them had no background with AI tools. Out of the 10 interviewees related to InflowGo, either as workshop participants or developers, six referenced this tool as their first AI experience. These findings are consistent with the literature depicting the application of AI/ML to urban stormwater management and planning as a field in its infancy (Sanchez et al., 2023; Wagner & De Vries, 2019; Yigitcanlar et al., 2020). According to Fu et al. (2022, p. 2), "there are few well-tested deep learning algorithms or products readily available for solving UWS [(urban water systems)] problems", which was also highlighted by the interviewees:

> "*many of the current AI tools that I use are not really made for decision-making.*" (5)
>
> "*Actually, at the moment, I do not know any AI solution that is good enough for this diverse field of planning.*" (12)

To illustrate this further, the interviews showed that AI for professional use in the field is for the moment reduced to paperwork tasks, e.g. writing and translation purposes, where generative AI and ChatGPT were cited seven times.

However, five interviewees have heard about AI applications in stormwater during conferences or have participated in an AI project or research program within their organisation. One mentioned that their project did not work and was terminated, and another is considering starting a project for utilising the considerable amount of rain data available. Ongoing projects cited were both from Germany: KIWaSuS, an AI-based warning system for heavy rain and urban flash floods, and Ziggurat, an automated sewer system planner. Moreover, two interviewees had already utilised AI for decision-making purposes in stormwater management. One mentioned the German tool FloodWaive, for flood forecasting, early warning, and risk analysis. Another one mentioned the Danish tool Rehab-IT, developed for asset management in the renewal of water networks.

Thus, while AI in stormwater is only emerging, it seems to be at the centre of a growing attention thanks to its rapid development, and is experimented in few projects for its promising features for the field (Eggimann et al., 2017; Makropoulos & Savić, 2019). Likewise, Yigitcanlar et al. (2020, p. 2) described AI as "the most disruptive technology" in urban contexts. In this regard, twelve interviewees clearly stated that they are open and curious about the application of AI in their work, and overall in the field of stormwater management. Moreover, they shared that some of their colleagues "*are very eager to explore the opportunities and options [of AI], and to have it as an additional information source*" (14).

5.1. Characteristics of the conventional decision-making process

This section connects findings from academic literature to the responses of interviewees when asked about their definition of the decision-making process, and about the current conventional methods and tools used in stormwater management. All of them had a personal definition, or at least some views about what this concept entails, except one interviewee who instead focused their answer on risk assessment, particularly on the relation between flood management and critical infrastructure.

5.1.1. Definition

Two interviewees noted that 'decision-making' is a broad concept used in multiple fields of profession, and thus encompassing different definitions depending on who employs it. In the field of stormwater management, the interviewees defined it as a process relying on knowledge and experience, characterised by certain steps following a repetitive order. This is in line with the conceptual framework of the thesis, stressing that access to information constrains decision-making (Simon, 1947, as cited in Pomerol & Adam, 2004), and with Gregory et al.'s (2012) structured decision-making (*Figure 2*). This framework encompasses phases that were mentioned by seven interviews: definition of objectives, e.g. "*climate resilience*" (12); development and evaluation of alternatives; and implementation of solutions.

However, compared to the interviewees' point of view, Gregory et al.'s (2012) framework lacks the initial step of identifying requirements and needs to reach the objectives, and the feedback loops between each step. In this regard, interviewees described decision-making as "*iterative*" (11, 12, 14), with a lot of "*back and forth*" (14), and continuous repetitions of "*analogue*" phases (9). Moreover, after comparing scenarios, those selected are examined deeper before being assessed and compared again. Finally, finding solutions can be seen as the final aim, as illustrated:

> "*To me, decision-making is to decide what solution we need to use with regards to stormwater.*" (7)

5.1.2. Political aspect

The previous steps are furthermore influenced by the political sphere, as illustrated by an interviewee's definition of decision-making as "*organisational politics*" (11). This theme is recurrent for 11 interviewees, no matter their geographical context, highlighting the important role of legislation and authority. The latter is either within the city or municipality itself, or within the planning administration above the city in the chain of command. Early in the process, the authority confers "*recommendations*" (1) to follow to the stormwater professionals, dictating their range of action in addition to existing "*laws*" (1).

This point is found in the literature as well, with Saraswat et al. (2016) explaining how stormwater management depends on regulatory and institutional frameworks, especially for water quality and quantity. In addition, Larsen et al. (2016, p. 928) supported the idea that urban stormwater decisions are "delegated to municipal water authorities [that] follow well-formulated regulatory codes in their operations". The interviewees added that this legislative context also requires them to check their results with the authority after each step of alternative generation, comparison, and evaluation. Indeed, feedback can be useful, and an authorisation is needed to step onto the next phase, until the decision is implemented.

5.1.3. Collaborative aspect

The previous aspect of communication with authorities reflects another significant point of the process of decision-making that was highlighted by 13 interviewees: the collaboration aspect. Five interviewees described their teams, with only one appearing to be big, as part of a large city with many employees. The other four were on the contrary portrayed as small, due to the scale of the municipality or utility, with even one case where the interviewee was the only person involved in planning. It is however worth noting that one interviewee from a small team pointed out that they have to collaborate on a regular basis with neighbouring cities, as located in a very dense area, which considerably increases the number of stakeholders. Regardless of this context, according to them, it is essential for different planning stakeholders to communicate in order to find solutions all along the different phases.

> "*it also needs constant communication and feedback with and from various stakeholders.*" (4)

Similarly, decision-making was defined as a "*deliberative*" (2, 15) process "*with a lot of dialogue and talk*" (9) as well as with "*hearing and listening*" (15). This is coherent with Stern and Fineberg (1996) who likewise stress the interdisciplinary, deliberative, and compromise-oriented characteristics of decision-making.

Therefore, according to one interviewee, decision-making requires monitoring and adaptation in order to stay flexible, as diverse input from various stakeholders is added, and also as laws may change. Stern and Fineberg (1996, p. 96) also reflected the necessity for flexibility in the process "to allow for midcourse corrections", while Gregory et al. (2012, p. 10) explained further that it permits "to incorporate what is learned over time". Moreover, according to the interviewees, it necessitates governing activities facilitating deliberation through platforms to engage different stakeholders, like "*team-building processes*" (5). Planning meetings, or workshops, were explicitly cited by seven interviewees as such a platform. They enable brainstorming to gather and present ideas, to compare alternatives and results (e.g. from modelling), to renew plans, to go deeper in some proposals, and to physically engage different stakeholders for eventually finding "*compromises*" (11). This finding is consistent with Kvamsås (2021) and Leskens et al. (2014a) who mentioned various types of meetings engaging different stakeholders for the planning process. Nevertheless, platforms for stakeholder collaboration are not bound to formal physical meetings: Leskens et al. (2014b) enumerated more of them such as informal talk, telephone calls, and emails.

The interviewees emphasised the importance of stakeholder participation, especially in an interdisciplinary fashion. The latter was indicated by 10 interviewees, when emphasising the need for involving multiple stakeholders, such as green landscape planners, architects, policymakers and authorities, consultant companies (e.g. to do the modelling), the social department of the city planning, and in general any non-experts in water or sewer systems, including the citizens. Cross-sectoral collaboration is echoed by Hadjimichael et al. (2016, p. 4) as it "allows for the inclusion of a wide range of different perspectives rather than decision-making by specialists and experts in isolation – something that is particularly important in early design and planning stages". Moreover, Kvamsås (2021) stressed the importance of transdisciplinary cooperation as it supports the current shift from traditional approaches to more sustainable ones, such as NbS.

> "*We have a strategy to involve and include the strategies from the municipality with regards to recreational activities, health, biodiversity, and so on. So, in order to include those strategies, I often include different stakeholders from the municipalities, authorities, maintenance people, city planners, and so on. [...]. I think my perception is that, in order for my projects to be a success, the municipality and all the stakeholders have to have some sort of ownership of the project.*" (7)

> "*For us, it is very important to use different experiences, to have different occupations, to have their view on the matter, or on the risks, or on the challenges.*" (16)

Finally, it was found that decision-making implies the translation of information when communicating to non-experts, for example by sharing maps that are easy to understand as an output of modelling. In this matter, Leskens et al. (2014a) precised that this communication generally flows from modellers to decision-makers.

5.1.4. Technical aspect

The decision-making process was also described to rely a lot on technical considerations. Indeed, 12 interviewees mention this aspect when asked about their definition of decision-making. Likewise, Larsen et al. (2016, p. 928) stated that decisions "rely primarily on highly specialised technical expertise". Most of the professionals put emphasis on the conventional tools and software currently being utilised through the phases of decision-making, for modelling, generation, comparison, and evaluation of alternatives, as well as for presentation of the results. These include hydraulic models such as MIKE Urban, Scalgo, and GIS (QGIS), which are also widely cited in the literature as decision-making supports (Adhikari, 2020; Leskens et al., 2014a; Lombardi & Ferretti, 2015; Saraswat et al., 2016).

> "*These are tools that we are using for making a decision, they are not making these decisions for us. It is just a tool to address the problem.*" (12)

Thus, proper measurements, databases, parameters, and models are required to base the decisions on. One of the German interviewees, as a member of a city government, declared having free access to a pool of public data from the state, in addition to the database of their town. Another interviewee highlighted their extended rainwater system and the importance of the stormwater physics supported by the tools. However, three interviewees indicated that the tools used depend on the scale of the decision to implement, on the needs, as well as on the current knowledge and resources. For example, in smaller projects, an interviewee indicated that Excel matrix calculations are sufficient, in contrast to complex projects requiring detailed hydraulic modelling results.

Moreover, interviewee 15 stressed the importance of interdisciplinary collaboration for the use of DSS, which corroborates McIntosh et al.'s (2011) assertion that such tools necessitate stakeholder involvement. On another note, when successfully utilised, they are very valuable for fostering collaboration further.

> "*I think this is quite important that these tools actually provide the opportunity for cross-country or cross-department dialogue. [...]. Decision support tools need the actors, stakeholders from different areas [to] sit down together and look into the stuff. […]. [These are] the tools that have actors involved, instead of like monitoring tools, [with] one guy sitting [in front of] the computer.*" (15)

In order to incorporate more diverse input into the decision-making process, multi-criteria, utility value, or cost-benefit analyses can be combined with hydraulic models and GIS. As explained by Wang Yujing et al. (2011), it is necessary to select appropriate criteria to reduce subjectivity in decisions. Thus, "there will frequently be decisions made in stormwater management that reflect the economic, political, social, and aesthetic components that may not always be easily incorporated into a GIS analyses and modelling system" (Saraswat et al., 2016, p. 102). Contrarily, Gregory et al. (2012) motivated that such an approach could be too technocratic, thus limiting the required creativity for robust decisions. Still, with seven mentions, the financial criterion is the most cited as part of the evaluation of decisions. The latter is considered as expensive, for instance when having to bring all stakeholders together. Contrariwise, an interviewee cited the financial criterion at only the third rank of significance, below the safety and performance. This was the only time that the safety and performance criteria were acknowledged. Other criteria stressed were environmental, or ecological, and social.

5.2. Challenges and shortcomings potentially addressed by AI

In this section, the interviewees' perspective on the current challenges and shortcomings of the conventional stormwater management decision-making process are discussed together with the potential benefits of AI-tools, to analyse gaps that may be filled to some extent.

Two clusters of challenges were identified from the interviews, based on the complexity of the stormwater management field: technical and organisational challenges. Then, one cluster of shortcomings was recognised, displaying what is currently lacking in the conventional decision-making process. In parallel, the potential benefits of an AI-based tool for decision-making in stormwater management are discussed through the case study of InflowGo, according to the workshops' participants and developers. They are further consolidated by other stormwater professionals with no experience of InflowGo, reflecting upon AI tools in general and what they entail. It is however important to note again that the results concerning the potential benefits of AI present limitations. They concern a version of the InflowGo tool without AI being implemented, but only emulated by a numerical model, as previously mentioned.

5.2.1. Technical challenges

Expertise needed

Given the complexity of the field, interviewees are challenged by the importance of having "*sufficient knowledge and experience*" (1) to be able to understand the tools, parameters, models, systems, and to interpret results. Other interviewees mentioned that the complexity of the tools and specialised software in stormwater management make the expertise "*very isolated*" (14) and "*not very inclusive*" (11). The tools are "*created by experts for experts*" (1) and there is "*so much you need to know*" (11).

> "*They have a very steep learning curve, and before you are able to not only do some calculations, but also provide some results that you can show to non-experts… it takes quite some time in order to be able to do that. [...]. But in order to use them properly, in order to understand what you have to do, it just takes some experience and that means it takes some time and you have no chance to learn it. You can read a lot, but it does not help really*." (5)

This is also reflected by Haris et al. (2016) who described conventional hydraulic models as being of low accessibility, and highlights the need for user-friendliness within AI solutions to increase their application (Hadjimichael et al., 2016). In this regard, interviewee 12 also stressed the necessity for AI solutions to be easily dealt with, as solutions that are too technical are generally not appreciated. In the case of InflowGo, even though still in development, all eight workshops' participants agreed upon the user-friendliness of the tool. This was also noted by the two InflowGo developers, allowing non-experts to take part in the modelling.

In this regard, the interviews revealed that InflowGo and AI in general could have the potential to raise awareness and support educational purposes. The tool could help to learn from its application, to better understand stormwater management and the interaction between the water system's behaviour and the infrastructure planned. This aspect was stressed by eight interviewees.

> "*InflowGo, or tools like this, would also help in education very, very much. And also, probably in fields that are not directly related to the water sector. For example, for architects or for spatial development planners, or who are not engineers but who have to deal with these factors. Nevertheless, they can also try to understand how systems work. [...]. In my mind, I think it will also start forcing, and let's say helping others in their fields, to also probably get into tools like this in order to help us understand their points, and that is pretty important.*" (5)

> "*I see added knowledge to the participants in the workshop, so they know more why the solutions have been chosen. So that, in other projects, they know why water behaves as it does. They know why water is important to include in the projects they [have].*" (7)

> "*AI-based tools could explain even more to people who do not know the water or wastewater industry as well. [...]. On the other hand, I am not sure that people would fully understand or be able to question the results of that tool. But, it could help with the explanation or teaching, spreading knowledge.*" (16)

Furthermore, one interviewee explicitly mentioned that InflowGo could be regarded as a game, highlighting again the user-friendliness of the tool and its potential for learning by doing.

> "*It feels a little bit like a game, like SimCity. You just drag something in and out, and you click on something and change the value, and then you have another building there. So, that is something that I really liked from this tool, that things are kept very simple. I think that it is really important to keep it as simple as possible. [...]. You can play, you can change the variable and then you can see the results. So, it is kind of a learning tool, and as it is with games, you just learn without really noticing that you have just learnt something. I think that it is very, very important that you can see the differences when you do something here or do something there, immediately.*" (5)

Amount of data

Seven interviewees identified that data plays a significant role in the decision-making process in this field: "*[it] depends on the quality of the databases*" (4). This finding correlates with the fundamental principle of data analysis mentioned in the *Conceptual framework* chapter, 'garbage in – garbage out', which emphasises that the quality of input data fundamentally affects the quality of output data produced by the computing system, regardless of the methods used (Kilkenny & Robinson, 2018). Moreover, the amount of data in the field was mentioned as one of the biggest challenges: "*We use, of course, a lot of data from different areas, from different topics, to address the issue in the field of water. There is a lot of different data that we need to use to make good planning*" (12).

On the contrary, one interviewee emphasised that "*there is a lack of sufficient data and measurements*" (5). Moreover, it was mentioned that "*a lot of cities have different databases, they have different data types*" (12), which creates yet another obstacle to communication between stakeholders. Furthermore, one interviewee emphasised that "*there is a lack of data, especially when it comes to nature, or green-related, because the blue-green infrastructure, sustainable stormwater management, these concepts just emerged 20 years ago*" (15).

Thanks to ML, four interviewees see AI increasing the speed of the calibration of hydraulic models, allowing quicker preparation. Moreover, interviewee 4 sees AI as a support for gathering and combining data, and interviewee 11 for data quality control and patching.

> "*With the help of AI, we can manage to input more data into the algorithm behind it, that is beyond the capacity of the practitioner.*" (15)

Indeed, one of the main advantages of AI, that among others can speed up decision-making, is its ability to analyse large amounts of data in a shorter time, which is beyond the capability of humans (Habbal et al., 2024; Yigitcanlar et al., 2020).

Linked to the previous point, AI is for seven interviewees beneficial to the decision-making process in stormwater management due to its promising superior capacities, compared to the ones of humans. For instance, AI's potential was highlighted when it comes to identifying an area with the most impacts, to processing and summarising huge amounts of data (textual or technical), to automating conventionally heavy workloads, and overall to handling complexity.

> "*A normal situation could be that the human who calculates oversees this point, or does not recognise this, and I think that does not happen when the AI calculates.*" (3)
>
> "*I also think that an AI-based tool could handle a more complex question. I think so because our brains are limited.*" (16)

5.2.2. Organisational challenges

Number of stakeholders

Although, as previously mentioned, the interdisciplinary nature of the decision-making process in stormwater management is noted as a positive aspect, it also brings new challenges. Interviewees indicated that the number of stakeholders, depending on the size of the project, complexifies the decision-making process. Thus, since stormwater management is part of the urban planning process, most projects require the participation and input of various experts in the field, which influences project dynamics and communication. Bohman et al. (2020) emphasised in their work that cross-sectoral collaboration between different stakeholders is an important component of stormwater management and is critical to the development of holistic and flexible solutions. The same narrative was found in the works of Cettner et al. (2013) and

Skrydstrup et al. (2020), indicating the need for an interdisciplinary approach to urban water management involving many active stakeholders with their own objectives.

> "*Nowadays we have to consider a lot of stakeholders. […] The requirement is to involve every part of the city that [has to be] involved. For example, streets, sewer systems, green people who are responsible for the green area, the social part of the city.* [...]. *There are a lot of stakeholders who want to have their own opinion on these solutions, in this planning process. It also means that the communication we are using today is really different from 20-30 years ago. And we are dealing today more with the organisational challenges. We have complex communication between a lot of different stakeholders.*" (12)

However, although participation of diverse stakeholders is important, another interviewee noted how decision-making is first and foremost associated with the consideration of who to include or exclude from the start, and whose objectives to incorporate or not.

> "*In the same sector, [participation of stakeholders is] not so difficult because you do not need to spend so much time on setting up your results in a way that even someone who is not an expert can understand it [...]. You can use your typical vocabulary, which is pretty easy. [...]. First, you should think about who is not to be involved for sure in the process, and that is basically in the beginning of the project. But in most cases, you do not know who not to involve, and then you start talking to the people. But they will tell you pretty fast if they do not need to be involved. And then you come to the group that has to be involved, and you need to find out their objectives. So, it is just the same as for a single process, but just a multi-criteria process in this case.*" (5)

In addition, interviewee 8 noted that due to the workload of stakeholders, they are unable to hold additional meetings or workshops despite the value they could add to the decision-making process: "*They do not have the time. They have other things which have a high priority*." Moreover, it was emphasised that "*the problem is that we do not have so much time and we also have to focus on other things. I think that what we do right now is some kind of minimum… there are many more possibilities*" (8).

In this regard, it was recognised that the above-mentioned benefits associated with AI, namely faster simulations and user-friendliness, save time, and improve interdisciplinary collaboration among all stakeholders in the decision-making process, regardless of their level of experience in stormwater management.

Contextual differences and their consequences

Based on most of the interviews, it became clear that the difference in context, whether different countries or different municipalities within the same country, also plays an important role in assessing the decision-making process as well as the ability to integrate new technologies into existing systems. In this regard, budget limitations were mentioned as a problem for small municipalities. Indeed, they affect the development of in-house technical resources, thus small municipalities are forced to use third-party modelling services. One interviewee shared that they "*would preferably want more modelling to have in the decisions*", however, "*to do additional or extra modelling and simulations by the hired company will increase the budget expenses"* (16).

The speed of data analysis and its compilation provided by AI and the possible web-based nature of AI tools were identified as contributing success factors in addressing budgetary constraints. With faster computing, fewer workshops can be held as stakeholders' comments can be shared immediately, and accordingly changes can be made, and different models can be tested. Interviewee 3 emphasised that this makes it quicker and easier to obtain governmental approvals and therefore makes the process more cost-effective. Decision-making becomes more accessible due to the time gained, as two other interviewees pointed out that the loss of time increases costs. This is an important point given the importance of the financial criterion discussed earlier.

Different legislations and rapid changes in the regulations were also mentioned as challenges. The interviewees mentioned multiple times that their processes are heavily regulated: "*the legal framework in Germany has complex requirements*" (1). "*This field is complicated with regards to legislation. The legislation has changed four or five times over the last 10 years. And those changes, they affect the decision-making process*" (7). Moreover, it was noted that climate change is also increasing regulatory requirements. Due to climate change, many industries are changing their paradigms, including in stormwater management where the need to mitigate the effects of global warming is recognised (Johnson et al., 2022; Saraswat et al., 2016).

5.2.3. Miscellaneous shortcomings

Time-consuming process

Overall, 11 interviewees described the decision-making process as slow and time-consuming. This was associated with the lengthy process of conducting hydraulic simulations and modelling while using conventional tools, which can take several hours, as also displayed in the literature (Grum et al., 2023; Leskens et al., 2014b; Palmitessa et al., 2022). This is further problematic as finding solutions in this field was acknowledged as requiring a lot of calculations, especially when comparing all alternatives and proposals. As a result, "*the calculations and the evaluation of impacts of different scenarios is done not during workshops, but basically between workshops*" (11). In that sense, Leskens et al. (2014a, p. 1730) illustrated this point when highlighting that "model information is prepared prior to multi-stakeholder work sessions". The authors added that this is also due to the expertise needed to handle the modelling tools, which AI can potentially help with, as previously discussed.

AI/ML was also identified by eight InflowGo workshops' participants as having the potential to accelerate the decision-making process by increasing simulation speed of hydraulic models, thanks to faster calculations and display of results, as in the literature (Grum et al., 2023; Palmitessa et al., 2022; Shrestha et al., 2019). The interviews revealed that this benefit is also obtained due to the web-based nature of the tool, a contributing success factor for effective AI application. Due to this characteristic, the tool can quickly run without initial download, on multiple platforms (computers, tablets, smartphones), and even with little computational power. Therefore, this advancement in speed potentially grants the opportunity to test different alternatives and to incorporate more input as real-time simulations are undertaken, a significant feature found in Leskens et al. (2014a).

> "*It is so quick to change things and see what is happening. [...]. We can immediately decide [if] it is a good measurement, or [if] it does not work we can put it away.*" (2)

Moreover, another interviewee shared the concern that because of the lack of workshops due to lengthy simulations, "*not all options are always explored [as] some people's input arrives very late in the process, whereas it could have been more valuable earlier*" (11). Consequently, AI can play a role in addressing this shortcoming, as it was described as having the potential to "*compress five workshops into one*" (7). This would enable to quickly change plans and thus try different variations of scenarios to compare them more rapidly, to get "*the right solution faster*" (7).

Lack of flexibility

The interviewees also noted that the process of decision-making is not flexible enough. Interviewee 5 emphasised that "*when you go into a decision-making process, you usually have no chance to do some additional modelling or measurements during this decision-making process*". It is thus a "*linear*" (5) process where it is hard to adjust things easily as the modelling is too time-consuming. According to two interviewees, this leads practitioners to look only for solutions to decisions that had already been made in advance. Leskens et al. (2014a) explained further that even if stakeholders come up with new ideas along the process, it would most likely lead to technical information becoming quickly obsolete because of lengthy simulations, and thus to technical output not matching with decision-makers' expectations (Leskens et al., 2014b). In this regard, the modelling speed increase by AI is highlighted again as a potential benefit, to improve the flexibility of decision-making.

Furthermore, the application of AI showed potential in its easy integration in the conventional decision-making process. Eight interviewees mentioned that due to increased simulation speed, the AI tool accelerates decision-making by allowing the filtering of ideas and scenarios in the early stage of the process, which could in turn "*break up the linearity*" (5). For instance, in the conceptual planning phase, when designing "*a rough sketch of how the system looks*" (7), InflowGo was described as beneficial to make fast decisions by quickly providing an overview of the behaviour of the stormwater system when implementing different planning solutions. The tool was reported to be used as a guide, to preliminarily investigate solutions and sort them out, as already done by one workshop participant according to the CEO of InflowGo. This confirms the findings of Daalmans' (2023) thesis which identified InflowGo as a screening tool for the same reasons. However, to date, the tool was said to be too limited for detailed planning and to make the final decision and needs more development.

Building on these points, AI is a tool easily implementable with conventional tools, as mentioned by two interviewees. This is significant, as it was seen as an advantage for five other interviewees to be able to follow-up on the AI-based results giving an early overview with the conventional "*old-school planning*" (1) tools, to "*get into details*" (5). Indeed, it makes it possible to avoid wasting time in the beginning when making long-lasting simulations on conventional tools, thus also simplifying the collaboration with the consultancy firm making the modelling for some of the interviewees.

Lack of participation, ownership, and collaboration that create silos

Eight interviewees explained that the current low speed of the decision-making process is also due to the limited availability of stakeholders to participate in additional meetings, and by the complexity of communication between stakeholders. Moreover, two interviewees emphasised that there is a sense of detachment and a lack of ownership for some stakeholders due to the lack of additional workshops, although participation and ownership were identified as essential for decision-making by the interviewees and literature (Bohman et al., 2020; Kvamsås, 2021; Romano & Akhmouch, 2019).

> "*[it] can be quite long and frustrating for some because there is a limit to how many times I can invite people to a meeting about a certain project. So, I would like them to only maybe meet once and give all their ideas and their views on what solution we should choose.*" (7)

Fu et al. (2022) identified two ways to enable direct involvement of decision-makers: improve the flexibility of models and lower their present-day high computational time. As recognised so far, those are possible benefits of AI, showing its potential to address the current shortcomings in participation. The interviewees also mentioned the potential positive impact from increasing simulation speed, saying that "*it makes communication with others easier*" (1) and that "*the value of speed is that we can make a tool that is more inclusive*" (11). Furthermore, AI emulation was recognised as strengthening real-time collaboration, identified by interviewees as conventionally complex, with the potential of incorporating more input during simulations in workshops.

> *"It is easier to incorporate more viewpoints earlier on. And, so, you have less of a risk to get lost or to take a path that is maybe not as helpful, less productive, and weaker.*" (14)

Additionally, two interviewees would like an AI tool to follow the meeting and gather the inputs of different live-prompting stakeholders, in order to come up with "*the best solution for the environment, for the economy, for the citizens, for the whole picture*" (9).

Regarding improved participation and collaboration, it is important to recall the two contributing success factors for the application of AI-based tools for decision-making: their user-friendliness and web-based nature. The former was shown to help address the current challenge of high expertise needed, thus in turn helping the participation and collaboration of more stakeholders in the modelling, and eventually decision-making. Moreover, the web-based nature of the tool makes it easy to collaborate with people without having to download anything, and in real time on the same model, by adding "sticky notes" (a feature to leave comments on all users' interfaces) in order to gather ideas, share information, and try various alternatives.

One of the current challenges is the lack of communication among professionals from different fields. It was stressed that the current collaboration process "*is not interdisciplinary enough*" (2) and "*very isolated*" (14), as professionals from different sectors of urban development (e.g. road department and green department) "*are not used to working together*" (2, 4). This corroborates Bohman et al.'s (2020) study identifying silo structures in stormwater management, as well as findings of Daalmans' (2023) thesis on the same case study. This can also be explained by the fact that professionals do not communicate in the same way, as "*everyone prepares their own information from a certain stand*" (5), leading to misunderstandings. Moreover, two interviewees mentioned that the large number of various tools, requirements, sets of units, and measurements that are used across departments makes it hard to convey a message in an intelligible way, and to visualise each other's solutions, as in Skrydstrup et al. (2020).

> "*In my whole education, I did not learn how to communicate with others. It was just communication inside your bubble, but not outside.*" (5)

This is problematic since interviewees agreed that the field of water is very complex and cannot be addressed in silo, as "*every planning decision-making process is unique*" (4) and "*there are always a lot of other fields that you have to think of*" (5).

In this matter, they also presented AI as potentially improving interdisciplinary collaboration and breaking silos for reasons previously discussed, namely its use for educational purposes and improving participation, ownership, and collaboration. It was indeed reported eight times that external stakeholders can be involved from the early stages (and not only later, as conventionally) to decide if the result satisfies them or not, allowing them to gain more ownership at the same time. Overall, "*the involvement of several departments seems to be easier*" (3) and "*it feels like a common decision that has been made*" (5). Moreover, due to its user-friendliness, the tool was said to facilitate the involvement of non-experts in the modelling by four interviewees.

5.3. Relevance of AI and expectations to fill more gaps

The capability of AI/ML is to increase the modelling speed, which in turn has the potential to overcome technical and organisational challenges, as well as to help tackling current shortcomings. The flexibility of the decision-making process, the involvement and ownership of stakeholders, as well as the interdisciplinary input received can be increased, which are all characteristics that were seen as essential for successful decision-making, both by the interviewees and the literature (Cettner et al., 2013; Gregory et al., 2012; Romano & Akhmouch, 2019; Skrydstrup et al., 2020). To illustrate, interviewee 14 sees AI as potentially making decision-making "*more efficient*", "*more robust, and sound*". Moreover, Hering et al. (2013) stated how the effective participation of actors can allow the establishment of an enabling environment, which facilitates the achievement of future societal needs.

Based on these potential benefits, some interviewees expressed their opinion on the relevance of AI in their profession. Five of them think that it will have a significant role to play in stormwater management, including three adding that AI tools are an opportunity that cannot be missed, as "*it is important for all civil engineers to take the next step*" (1). One of the InflowGo members considers that this technological advancement will enable the inclusion of stormwater management earlier in the general urban planning decision-making, whereas currently, water is only dealt with too late. Another interviewee agreed with this, saying that AI is a chance to give more focus to the field of stormwater, which importance has "*gained momentum*" (4).

> *"I think it is the only way we can go forward as humans, and as engineers, and students, and so on as people.*" (13)

This relevance could be echoed in the overarching field of disaster risk reduction and climate change adaptation, as positively indicated by 10 interviewees. AI tools such as InflowGo could be applied for flood management to compare different risk scenarios quickly and collaboratively "*with just slight changes in certain parameters*" (5), assess the sensitivity of elements and impacts of various return period floods, make predictions and verifications, and even grasp climate uncertainty better "*in order to find out which system is the most resilient one*" (5). Moreover, interviewees said that AI tools have the potential to foster the implementation of NbS and blue-green solutions, and thereby minimise flood risk (Faivre et al., 2018; Sowińska-Świerkosz & García, 2022). Finally, interviewees shared the point that it is difficult to assess all the possibilities of AI that there will be in the future.

5.4. AI's limitations and new challenges

Despite some potential benefits identified, it was found that AI is not able to address all the challenges and shortcomings of conventional decision-making, especially about the complexity of the world. Moreover, the application of AI comes with new challenges and shortcomings that are necessary to take into consideration to increase its potential.

5.4.1. Complexity of the world

As noted earlier, many factors influence the decision-making process. Interviewees indicated that compromises must be made as it is impossible to consider every aspect. There is no single solution and it is impossible to meet all needs, which leads to the complexity interviewees experience in their work. In addition, there are many uncertainties, ambiguities, non-linear interactions, and dynamic changes associated with climate change and adaptation processes, adding another layer of overall decision-making complexity (Becker, 2024).

"*I think it is especially this uncertainty. We do not know how the future will be, when we talk about climate change adaptation. If we build a structure today or a pipe today, then it will remain, or at least it is planned that it will remain for 80 years. So we have no idea now how the weather will be in 2100.*" (5)

"*Nowadays, you are trying to plan a lot of measures that are on the surface and are better for the climate resilience of the cities. In Germany the rules are changing, there are more standards to climate resilient planning. And also the topic is more and more complex. It is not enough to just consider the problem from the engineering part, but also the social part, and so on. Also the planning is also getting more complex, because the requirements are more complex.*" (12)

Despite the aforementioned benefits that AI can bring to the field, to date, interviewees do not see the opportunity to address the complexity and uncertainty of the world with AI. This may be due to the rapid but still emergent development of AI. In that respect, it was expected that in the future, an AI tool such as InflowGo will be applied to larger and more complex geographic systems in order to better reflect reality. Moreover, one interviewee hoped that AI will bring more holism to decision-making by incorporating qualitative data into quantitative data more easily.

5.4.2. New challenges and shortcomings

The results showed that despite the benefits that AI-based tools can bring to stormwater management decision-making, they also reveal new social and technical challenges that can hinder their adoption and implementation.

Ethical concerns

During each interview, interviewees were also asked whether they see any ethical concerns associated with the use of the AI. Seven interviewees, who are acquainted with the InflowGo tool, admitted that they do not have any ethical concerns regarding the application of this tool in particular. In this regard, it was emphasised that the type of ML implemented in InflowGo does not imply the same ethical challenges as generative AI, such as ChatGPT. "*InflowGo is based on the same calculations as our hydraulic tools*" (3), thus it produces mathematical results derived from the known data put as input and from which it was trained on. Moreover, the developers shared that they are "*not using personal data, [and] not doing live video streaming analysis*" (11), but only accelerating calculations.

Additionally, in terms of the general application of AI in this field, two interviewees stated that they do not see any associated ethical concerns as long as the decision is made by humans and not by AI: "*if you let the AI-based tool make all the decisions without questioning, that would be problematic*" (16). In this regard, seven interviewees noted that they would not allow AI to make a decision for them but would use it as an assistant to help prepare arguments for a decision, since the responsibility for making a decision lies with a person. This can be explained by the fact that professionals are generally not willing to blindly believe in results just because they are generated by a computer, with or without an AI, taking into consideration that as "*every modelling software has its uncertainties [...], artificial intelligence also has uncertainties*" (5). Similar findings were identified in other studies, where the loss of control and power over decision-making appears to be a common obstacle to the implementation of AI (Bianco, 2021; Booyse & Scheepers, 2024). This social aspect is also related to the understanding of technology, the lack of which leading to distrust and rejection of the technological solution, as also reflected in the following findings.

On a side note, one interviewee believes that "*AI-based models will replace the standard modelling tools within the next 10 years fully*" and that "*what InflowGo does now will become the standard*" (5). In contrast, three interviewees do not see this change happening soon, or even at all, because there are currently too many conventional tools needed to make the decision safely.

Resistance to change

Despite the interviewees' openness to AI, they noted that there is some reluctance among stormwater professionals to embrace new technologies or software, including AI. The basic idea is that people get used to a way of working using certain tools, and they may find it difficult to adapt to alternatives because "*change is always challenging*" (2) and "*a lot of people are tired of being brought to new software they have to work with*" (4). To illustrate this point, interviewee 4 shared that out of 12 colleagues invited to InflowGo's workshops, only two agreed to participate.

> "*For the cities it is more valuable if you use these common software solutions because they are known and they know what is behind it.*" (12)

Daniel and Pettit (2021) emphasised that one of the reasons for resistance to change is the simple unwillingness of people to learn new ways of doing things. Individuals perceive change differently depending on many factors, "some thrive on change while others dislike it and prefer maintaining the status quo" (Warrick, 2023, p. 435). A status quo bias was also identified by Oschinsky et al. (2021) as they stressed that people may not be ready to adapt to new circumstances due to the tendency to maintain habits.

Another finding revealed that time is an important indicator when adopting new technologies, and that people need to gain some experience with the tool to be able to assess its applicability in the field. It was also identified by two interviewees that stormwater professionals may want to start using AI-based tools later, after they are better developed, and others provide "*good examples*" (13) of their application with clear benefits. Moreover, three interviewees emphasised that it also depends on how successful developers and pioneers will be in convincing other professionals to try new tools.

> *"There are some people who will never be the first to make changes to something new. They want to see it be used by someone else first.*" (11)

The results also showed that due to the emerging nature of AI-based tools, their potential has not been recognised in the field yet, which is also interrelated with users' awareness of the technology. Thus, interviewee 4 shared their opinion on colleagues' perception of AI: "*They are generally not interested because they do not see the benefits".* This correlates with Warrick's (2023) assertion that change is likely to be resisted due to insufficient reasoning for change. This finding is also supported by Bianco (2021) who argued that lack of adequate knowledge about AI or misunderstanding of the scope of its application among potential users leads to polarisation of their views on the benefits of the technology. Interviewees also emphasised that in order to see the benefits of and accept AI solutions, the system must be transparent and understandable to users. Moreover, the logic and argumentation of such suggestions should be unequivocal: "*When it comes to engineering stuff, I do not see any problem as long as it is very clear on how the AI is looking at the certain problem*" (10).

Furthermore, interviewee 11 emphasised that "*there is a big difference whether the technology is catering to a problem (to a pain) or whether it is catering to a gain*". This means that sometimes technology solutions are proactive and more focused on improving existing processes or experiences rather than solving a specific problem. Thus, some people may not even perceive existing processes as problematic or necessary for improvement and therefore be reluctant to adopt new technologies. For example, it might not be perceived as a problem that modelling is done between rather than during meetings because it has always been done this way. This is where technology adoption is seen as problematic: "*it has nothing to do with the AI, that is more to do with the fact that improving collaboration is a gain, and it is not a pain*" (11). This confirms Kahneman and Tversky's (1979) prospect theory presented earlier that depicts the asymmetry between gains and losses.

Need to understand AI

When talking about AI perception, interviewees noted that the biggest barrier to its acceptance is the fear of the unknown. Lack of understanding of internal working algorithms and of AI's complex essence leads to distrust and resistance. Interviewees shared that "*often, AI is a big scary cloud that nobody knows what is inside*" (12) and that "*people do not understand how AI works. It is like a black box.*" (13). They also noted that in order to start applying AI, the system must be transparent and comprehensible for users. It was emphasised that AI solutions can be accepted if the logic and reasoning behind it can be understood. This concern is also linked to the responsibility that decision-makers have, and supports Daalmans' (2023) findings on the same case study.

> "*I have to be 100% sure [about] what the system is doing. And with AI at this point, now I cannot say that. So I cannot give the responsibility to the online tool. Because it can cause damage. So at every point, I have to be sure about everything in the background.*" (1)
>
> *"If I really use decision-making AI, I really want to know exactly how it works to consider if I can agree with the AI.*" (2)
>
> "*If people do not understand how it works, the acceptance will not be very high.*" (8)

Many scholars have emphasised the lack of transparency and 'black box' nature of AI as its major challenges (Arun et al., 2020, as cited in Bianco, 2021; Booyse & Scheepers, 2024; Wagner & De Vries, 2019). Transparency and trust are universally identified as a key element for successful AI integration and a core value of its ethical use (Habbal et al., 2024; Olsen et al., 2024). The AI 'black box' effect and AI illiteracy lead to misunderstanding of where data comes from and how results are created, which in turn leads to deep mistrust (American Planning Association, 2022; Booyse & Scheepers, 2024). Practitioners must be informed about how AI-based tools work to be able to build personal trust in its outcomes, and to communicate and justify the results to stakeholders (Shrestha et al., 2019).

Legal aspects

It was stated by the interviewees that the legal aspect also plays a significant role in the implementation of AI applications. Interviewees noted that in order to adopt and use AI in their work, they would need approval, general guidance, or legal frameworks from authorities: "*if the government would say 'you may use this AI we have approved', then it is okay for me*" (1). Moreover, it was emphasised that "*the legal part of using AI solutions is not really clear*" (12) and "*there is currently no framework or law that can help me with that [(legitimacy of using data created by AI)]*" (15).

As the rapidly emerging and controversial nature of AI raises ethical, legal, and social issues, it is crucial to develop and implement new regulations for its development and application. Thus, in the European Commission's (2020) White Paper, *Artificial Intelligence:*

A European Approach to Excellence and Trust, it is stated that both citizens and companies are concerned about the legal uncertainty surrounding the application of AI technologies, which is holding back their wider adoption.

Since this study is conducted in a European context, it is worth mentioning two regulations recently adopted by the European Union (EU) to address challenges with AI adoption. In 2018, the General Data Protection Regulation (GDPR) came into force in the EU, which requires, among other things, transparency in the field of AI. Thus, according to the GDPR, in order to remove the ambiguity around AI, developers are required to provide information in an accessible form about the logic behind the automated solution, without necessarily disclosing the full algorithm (European Commission, 2018). Moreover, in March 2024, the EU adopted a pioneering legislative measure, the *Artificial Intelligence Act*, which aims to provide a comprehensive framework for the development and application of AI. It aims to empower end-users, individuals, and organisations through its core principles of transparency, accountability, and data protection (Musch et al., 2023).

Cybersecurity

Five interviewees expressed their concerns regarding cybersecurity. One of the aspects of this challenge is that "*the data that you have to transfer to the InflowGo service is potentially sensitive data. It is critical infrastructure. So it might be a problem*" (5). This is related to another issue not directly linked to AI, but rather to the web-based nature of the tool, namely the physical location and access to the servers on which the tool runs: "*There is always a data security issue once you are using the web*" (11) and *"all cities have different guidelines because web security is still a new topic*" (14). Thus, interviewees from Germany emphasised that *"it is important that the service which runs the programme, where it is hosted, is in Europe*" (1) and "*to make sure that you, as a provider of the InflowGo system, know where your data is stored, always*" (5). The representatives of InflowGo shared how they plan to prevent such concerns, for example by having in-house servers, and by training the AI on general data, or potentially on the municipalities' data with a clause permitting it.

6. Conclusion

The pressing issues of climate change and urban development that humanity is currently facing underline the importance of this study. By identifying new opportunities and challenges from the case study of the InflowGo tool – a model for stormwater management based on AI – the research contributes to the emerging knowledge in potential effects that AI application in urban stormwater management decision-making can have. Moreover, it helps to appraise contributing factors to the successful application of an AI-based tool in this specific context.

The results of the study were obtained by analysing 16 semi-structured interviews with urban stormwater professionals from Germany, Denmark, and Sweden. Some of the interviewees were participants in WaterZerv's workshops on the development of the InflowGo tool. The InflowGo case study provided feedback from practical knowledge and hands-on experience.

The research identified that the decision-making process in stormwater management is complex and depends on many factors. It is driven by the legislation and institutional rules of urban planning, and requires close interaction between different stakeholders, as stormwater management is an integral part of urban development. Moreover, an effective decision-making process requires specific technical expertise to analyse and model different scenarios, evaluate alternatives, and process large amounts of data using specialised tools and software.

It was found that stormwater professionals are challenged in the conventional decision-making process by several issues. Experience and significant expertise with complex software and tools are needed to understand their operation and interpret the outputs. Extensive amounts of data need to be analysed and their quality assessed during the process. Additionally, the number and variety of stakeholders that need to be included, collaboration and communication constraints associated, as well as the slowness due to time-consuming conventional tools and stakeholders' involvement further complicate the process. Moreover, the linearity of the process hinders flexible adjustments. Other limiting factors are the high dependency on the context and the consequences related to different resources available and changing legislation.

The research showed that the main potential benefit of AI/ML in stormwater management is to accelerate decision-making, by increasing the speed of data processing and hydraulic simulations compared to the conventional tools, and by suggesting capabilities superior to those of humans. Due to these abilities, AI/ML also shows potential in fostering collaboration between different stakeholders, breaking silos, enabling real-time adjustments, and improving ownership. Subsequently, these advantages can support educational purposes for non-experts' participation. Consequently, the application of AI/ML in stormwater management decision-making appears to be relevant for this field, and thereby for disaster risk management and climate change adaptation.

Furthermore, the InflowGo tool case study made it possible to identify key success factors for the application of AI-based tools: user-friendliness and web-based support. The user-friendliness of the tool plays a crucial role in its accessibility and seems to enable the involvement of all stakeholders in the decision-making process, regardless of their level of experience in stormwater management. Thus, improved interdisciplinary cooperation and the ability to incorporate inputs from different stakeholders at an early stage of the decision-making process have the potential to make decisions more effective. The web-based nature of the tool, paired with AI, allows to accelerate decision-making, which eases the budget constraints and makes the tool available with little computational power for increased and easier collaboration.

While AI-based tools can solve and alleviate most of the identified challenges and shortcomings associated with current decision-making approaches, the complexity of the world and uncertainty associated with climate change were identified by the research participants as impossible to currently solve with AI. Moreover, AI-based tools also create new challenges and disadvantages. These include concerns about: ethics, decision control, and responsibility; resistance to change and lack of openness to new technologies; transparency and perception of AI as a 'black box'; legal aspects of AI applications; and cybersecurity issues. The listed challenges and shortcomings are limited by the scope of the study and the methodological approach and are thus not exhaustive. Nevertheless, these results can be considered as a source of feedback for further development, which sheds light and raises awareness on challenges of AI in decision-making that are important to address for general application.

Given the limits of the case study, more investigation dealing with the context of AI application would be valuable to add on to this research. In that respect, it is worth testing the replicability of its findings by examining the application of an AI-based tool within different geographical and development settings with various enabling environments, as well as within different professional sectors of urban planning and decision-making. Evaluating the application of a fully developed AI-based tool is also considered as valuable, in order to compare it with this research where the tool is still in development.

Further research could also explore more in depth the added value of decision support AI tools for educational functions. This study's finding deserves further attention in order to delve into the training and learning outcomes that such tools can have for practitioners, students, and non-experts, to potentially foster further engagement, interaction, as well as multi- and transdisciplinary decision-making. In this regard, further research could explore the concepts of 'collaborative learning' (Voinov & Bousquet, 2010), 'learning-by-doing' (Hung & Hobbs, 2019), as well as 'serious game' and 'gamification' (Fox et al., 2022; Mittal et al., 2022; Teague et al., 2021) in relation to AI tools' application.

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Appendices

Appendix 1. Consent form

We, Sofia Bilmes and Antoine Berment, are two students from the Faculty of Engineering of Lund University, studying the last year of our Master programme Disaster Risk Management and Climate Change Adaptation (DRMCCA). We are writing a Master thesis titled *Artificial Intelligence based tool for decision-making in urban stormwater management*, which purpose is to *identify and appraise the potential opportunities and challenges that an AI-based tool can provide to decision-making in urban stormwater management*.

For InflowGo's workshops participants:

> In this regard, we are planning to conduct semi-structured interviews with cities or utilities which members are participating in workshops with InflowGo, to investigate the implementation of the tool by different users within its real-life context. With this approach, we are going to focus on the process of the application of the tool in the decision-making process and reflect on the outcomes of its implementation. We are aiming to investigate how the application of this tool alters the decision-making process.

For InflowGo developers:

> In this regard, we are planning to conduct semi-structured interviews with InflowGo members, to investigate the development of the tool. With this approach, we are going to focus on the process of the application of the tool in the decision-making process and reflect on the outcomes of its implementation. We are aiming to investigate how the application of this tool alters the decision-making process.

For other urban water professionals:

> In this regard, we are planning to conduct semi-structured interviews with urban stormwater management professionals. Our objective is to gather firsthand insights into the existing conventional decision-making processes in urban stormwater management, distinct from AI-driven approaches. Additionally, we seek to understand professionals' perception of the future of the field.

For ethical reasons in academic research, you as an interviewee must explicitly approve the conditions of your involvement and how the data collected will be used. Kindly read and sign this consent form to assure that you understand and agree with the following:

- I agree to participate in an online 45-60 minute interview to share my professional experience and knowledge.
- I understand that my participation is voluntary, thus I can withdraw from the project at any time and refuse answering any question without any consequence.
- I agree to my interview being audio-recorded and fully transcribed.
- I understand that the data collected is used for research purposes in this thesis project and possible future publications.
- I understand that all information provided is treated confidentially, except the profession / sector and country of exercise, as cross-sector collaboration for decision-making is an essential aspect under study.
- I understand that my identity remains anonymous, even when being quoted.

- I agree that I understand the purpose of this research and that I can ask questions about it.
- I understand that I can request access to the information provided and to the published article.

Signature of research participant: *Date:*

……………………………………… ……………………………………...

In case of questions, please contact us:

Sofia Bilmes, sofia.bilmes@gmail.com; Antoine Berment, bermentantoine@gmail.com

Our supervisor, Mo Hamza, mo.hamza@risk.lth.se

Appendix 2. Interview guides

Appendix 2.1. Interview guide for InflowGo's workshops participants

A. <u>The interviewee:</u>

1. What is your job/field of profession, described generally?
2. What is your role in urban planning, and more precisely in urban stormwater management?
3. Can you provide an overview of your role in InflowGo's seminars and workshops?

B. <u>The conventional (non-AI) decision-making process:</u>

1. What do you understand about the process of decision-making?
   - ➢ different steps, objectives, success factors / pre-conditions needed, challenges
2. What conventional processes (methods and tools) are currently being used/prevalent for decision-making without the use of Artificial Intelligence / Machine Learning (AI/ML) in the field of urban stormwater management?
3. How are these processes conducted?
   - ➢ short description (e.g. about length, time pressure, complexity, uncertainty and making assumptions, available means and resources…)
   - ➢ do decision-makers need to receive information from multiple various stakeholders?
4. Have you had any experience with decision-making/planning tools in stormwater management? If yes, could you provide examples?
5. To sum up, what are your views on the current situation of decision-making (without AI/ML) in the field of urban stormwater management? *(Can you describe it with 1-3 adjectives?)*
   - ➢ contributions to decision-making in stormwater management; advantages; shortcomings and limitations for addressing current challenges
   - ➢ how are the following: participation of stakeholders (and what type?), collaboration (intra- and inter-sector), social learning and/or tangible outcomes of a workshop, etc.

C. <u>The AI-based decision-making process:</u>

1. Have you had any experience with AI/ML-based tools for decision-making in this field? If yes, could you provide examples?
2. How do you see AI/ML (generally) supporting the process of decision-making? (its potential)
   - ➢ proactively, during workshops and the decision-making process, and after
   - ➢ what do you think you can do with AI-based tools for decision-making? (e.g. simulations, scenario comparisons, mapping, identifying the resources for implementation, planning and/or response?…)
3. How has the introduction of AI impacted the overall decision-making process in stormwater management? *(Can you describe it with 1-3 adjectives?)*

4. What gaps or challenges in the current decision-making tools do you think an AI-based tool can address effectively? What is the added value?

D. The InflowGo tool:

1. Do you find InflowGo user-friendly?
2. In your opinion, how easily can this tool be integrated into the existing stormwater management decision system?
3. How do you see change in the process of decision-making with InflowGo? Does it make the process of decision-making easier or more complex?
    - ➢ how are the following: participation of stakeholders (and what type?), collaboration (intra- and inter-sector), social learning and/or tangible outcomes of a workshop, etc.
4. Have you observed any challenges that, with the aid of InflowGo, became solvable or significantly easier to address, compared to when they were previously deemed impossible or highly challenging with conventional methods?
5. Is the information produced with InflowGo reliable for practical decision-making? (e.g. to implement urban projects like Nature-based solutions, disaster risk reduction and climate change adaptation measures, urban planning…)
    - ➢ are predictions realistic? is the information accurate? how is uncertainty quantified?
    - ➢ are the outputs obtained through the application of the tool clear and easily translatable/understandable to all stakeholders?
    - ➢ what criteria for decision-making are evaluated? only physical/technical or also societal values?
6. While addressing certain gaps, have you noticed any new shortcoming or challenges introduced by the utilisation of this tool? Do you have any recommendations for improving the integration or utilisation of this tool?

E. Perception of AI:

1. How do other colleagues in your field perceive AI/ML and a tool such as InflowGo? Have you heard about a similar tool already being used?
2. Are there any ethical considerations or social implications associated with the use of AI and InflowGo you have encountered? Do you have any concerns?

F. The future of the field:

1. How do you see the future of AI in stormwater management decision-making evolving, considering the current advancements and challenges?
2. Do you think this tool is important for future issues with decision-making and why?
    - ➢ with stormwater management and more generally urban planning?
    - ➢ with disaster risk reduction and climate change adaptation?

Appendix 2.2. Interview guide for InflowGo developers

A. The interviewee:
   1. What is your job, and role in InflowGo?
   2. What was your role in urban planning, and more precisely in urban stormwater management, before InflowGo?

B. The conventional (non-AI) decision-making process:
   1. What do you understand about the process of decision-making?
      - ➢ different steps, objectives, success factors / pre-conditions needed, challenges
   2. What conventional processes (methods and tools) are currently being used for decision-making without the use of Artificial Intelligence / Machine Learning (AI/ML) in the field of urban stormwater management?
   3. How are these processes conducted?
      - ➢ short description (e.g. about length, time pressure, complexity, uncertainty and making assumptions, available means and resources…)
      - ➢ do decision-makers need to receive information from multiple various stakeholders?
   4. Have you had any experience with decision-making/planning tools in stormwater management? If yes, could you provide examples?
   5. To sum up, what are your views on the current situation of decision-making (without AI/ML) in the field of urban stormwater management? (*Can you describe it with 1-3 adjectives?*)
      - ➢ contributions to decision-making in stormwater management; advantages; shortcomings and limitations for addressing current challenges
      - ➢ how are the following: participation of stakeholders (and what type?), collaboration (intra- and inter-sector), social learning and/or tangible outcomes of a workshop, etc.

C. The AI-based decision-making process:
   1. Have you had any experience with AI/ML-based tools for decision-making in this field other than InflowGo? If yes, could you provide examples?
   2. How do you see AI/ML (generally) supporting the process of decision-making? (its potential)
      - ➢ proactively, during workshops and the decision-making process, and after
      - ➢ what do you think you can do with AI-based tools for decision-making? (e.g. simulations, scenario comparisons, mapping, identifying the resources for implementation, planning and/or response?…)
   3. How has the introduction of AI impacted the overall decision-making process in stormwater management? (*Can you describe it with 1-3 adjectives?*)
   4. What gaps or challenges in the current decision-making tools do you think an AI-based tool can address effectively? What is the added value?

D. The InflowGo tool:

1. Why was InflowGo founded?
    - ➢ solve a problem/meet a certain need? increasing development of AI?
2. How complex is it to train the algorithm for ML? And to add new information or change it if required?
    - ➢ During workshops, was the tool found to be user-friendly?
3. In your opinion, and based on the feedback, how easily can this tool be integrated into the existing stormwater management decision system?
4. How do you see change in the process of decision-making with InflowGo? Does it make the process of decision-making easier or more complex?
    - ➢ how are the following: participation of stakeholders (and what type?), collaboration (intra- and inter-sector), social learning and/or tangible outcomes of a workshop or exchange, etc.
5. Have you observed any challenges that, with the aid of InflowGo, became solvable or significantly easier to address compared to conventional methods?
6. How do you perceive the validity of InflowGo?
    - ➢ According to the feedback, is the information produced with InflowGo reliable for practical decision-making? (e.g. to implement urban projects like Nature-based solutions, disaster risk reduction and climate change adaptation measures, urban planning…)
    - ➢ are predictions realistic? is the information accurate? how is uncertainty quantified?
    - ➢ are the outputs obtained through the application of the tool clear and easily translatable/understandable to all stakeholders?
    - ➢ what criteria for decision-making are evaluated? only physical/technical or also societal values?
7. Have you noticed any new shortcomings or challenges introduced by the utilisation of this tool?
8. What are the next development steps/objectives for InflowGo?
    - ➢ actual integration of AI, flood management…
9. What are your hopes and expectations for the tool in the future?

E. <u>Perception of AI:</u>

1. How do other colleagues in your field perceive AI/ML and a tool such as InflowGo? Have you heard about a similar tool already being used?
2. Are there any ethical considerations or social implications associated with the use of AI and InflowGo you have encountered? Do you have any concerns?
3. Can you identify obstacles to the development and application of AI?

F. <u>The future of the field:</u>

1. How do you see the future of AI in stormwater management decision-making evolving, considering the current advancements and challenges? What are your expectations?

2. Do you think this tool is important for future issues with decision-making and why?
    - ➢ with stormwater management and more generally urban planning?
    - ➢ with disaster risk reduction and climate change adaptation?

Appendix 2.3. Interview guide for other urban water professionals

A. The interviewee:
   1. What is your job/field of profession, described generally?
   2. What is your role in urban planning, and more precisely in urban stormwater management?

B. The conventional (non-AI) decision-making process:
   1. What do you understand about the process of decision-making?
      - ➢ different steps, objectives, success factors / pre-conditions needed, challenges
   2. What conventional processes (methods and tools) are currently being used/prevalent for decision-making without the use of Artificial Intelligence / Machine Learning (AI/ML) in the field of urban stormwater management?
   3. How are these processes conducted?
      - ➢ short description (e.g. about length, time pressure, complexity, uncertainty and making assumptions, available means and resources…)
      - ➢ do decision-makers need to receive information from multiple various stakeholders?
   4. Have you had any experience with decision-making/planning tools in stormwater management? If yes, could you provide examples?
   5. To sum up, what are your views on the current situation of decision-making (without AI/ML) in the field of urban stormwater management? (*Can you describe it with 1-3 adjectives?*)
      - ➢ contributions to decision-making in stormwater management; advantages; shortcomings and limitations for addressing current challenges
      - ➢ how are the following: participation of stakeholders (and what type?), collaboration (intra- and inter-sector), social learning and/or tangible outcomes of a workshop, etc.

C. The AI-based decision-making process:
   1. Have you had any experience with AI/ML-based tools for decision-making in this field? If yes, could you provide examples?
   2. How do you see AI/ML (generally) supporting and changing the process of decision-making? (its potential)
      - ➢ proactively *(e.g. to pre-calculate overflow/flood scenarios)*, during workshops and the decision-making process *(e.g. increase exchange of information and its speed…)*, and after *(i.e. evaluation of the decision)*.
      - ➢ what do you think you can do with AI-based tools for decision-making? (e.g. simulations, scenario comparisons, mapping, identifying the resources for implementation, planning and/or response?…)
   3. In your opinion, how easily can AI be integrated into the existing stormwater management decision system?
      - ➢ Would it make it easier or more complex?

4. How has the introduction of AI impacted the overall decision-making process in stormwater management? (*Can you describe it with 1-3 adjectives?*)
5. What gaps or challenges in the current decision-making tools do you think an AI-based tool can address effectively? What is the added value?

D. Perception of AI:

1. What is your perception of AI? Do you feel ready to use AI more in your work?
2. What do you need to accept and trust a tool based on AI for decision-making?
    - ➢ reliability and validity of the results, uncertainty, user-friendliness, approval by influential or public stakeholder…
3. How do other colleagues in your field perceive AI/ML?
4. Are the legislation and public authorities allowing the development and application of AI?
5. Are there any ethical considerations or social implications associated with the use of AI you have encountered? Do you have any concerns?

E. The future of the field:

1. How do you see the future of AI in stormwater management decision-making evolving, considering the current advancements and challenges? Your expectations?
2. Do you think AI is important for future issues with decision-making and why?
    - ➢ with stormwater management and more generally urban planning?
    - ➢ with disaster risk reduction and climate change adaptation?

Appendix 3: List of interviewees

#	Profile	Country	Date	Duration (min)
1	InflowGo's workshops participant	Germany	23/02/2024	57
2	InflowGo's workshops participant	Germany	27/02/2024	42
3	InflowGo's workshops participant	Germany	29/02/2024	33
4	InflowGo's workshops participant	Germany	01/03/2024	33
5	InflowGo's workshops participant	Germany	04/03/2024	50
6	InflowGo's workshops participant	Germany	08/03/2024	18
7	InflowGo's workshops participant	Denmark	13/03/2024	35
8	Other urban water professional	Germany	21/03/2024	31
9	InflowGo's workshops participant	Denmark	21/03/2024	18
10	Other urban water professional	Sweden	21/03/2024	30
11	InflowGo developer	Denmark	22/03/2024	60
12	Other urban water professional	Germany	25/03/2024	33
13	Other urban water professional	Germany	25/03/2024	32
14	InflowGo developer	Denmark	26/03/2024	36
15	Other urban water professional	Sweden	26/03/2024	32
16	Other urban water professional	Sweden	26/03/2024	26