An Ethical Decision-Making Framework with Serious Gaming: Smart Water Case Study on Flooding

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Abstract:
Sensors and control technologies are being deployed extensively in both urban and rural water environments, leading to unprecedented ability to sense and control. Because these sensor networks and control systems allow for higher resolution monitoring and decision making in both time and space, greater discretization of control will allow for an unprecedented precision of impacts, positive and negative. Likewise, due to growth in system complexity, humans will continue to cede direct decision-making powers to decision-support technologies, e.g. data algorithms. Systems will have ever-greater potential to effect human lives and yet humans will be insulated from direct decisions. Combined, these trends present a challenge for water resources management decision support tools to incorporate concepts ethical and normative expectations. Towards this end, we propose the Water Ethics Web Engine, $(WE)^2$, an integrated and generalized web framework to incorporate voting-based ethical and normative preferences into water resources decision-support schemes. We then demonstrate the framework with a proof-of-concept use case where decision models are learned and deployed to respond to flooding scenarios. Results indicate the framework can capture group "wisdom" in learned models and use this to make decisions. We share our generalized framework and its cyber components openly with the research community.

Keywords: Ethics, Decision Support, Flooding, Smart Water Systems, Human-Centered AI

Highlights:

1. Water Ethics Web Engine, $(WE)^2$, is a generalized, open, and integrated web framework to incorporate voting-based ethical and normative preferences into water resources decision support schemes. We share $(WE)^2$ openly at our project repository: https://github.com/uihilab/WaterEthicsWebEngine.
2. Water professionals and researchers can use $(WE)^2$ to investigate how algorithmic components of smart water systems or disaster response perform in relation to people's normative expectations of right and wrong.
3. We demonstrate the framework with a proof-of-concept use case where decision models are learned and deployed to respond to flooding scenarios. Results indicate the framework can capture group "wisdom" in learned models and use this to make decisions.

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1 Introduction

Sensor networks, built on the backs of the latest digital communication technologies, are increasingly being deployed in urban sewer networks and at regional scales to monitor flooding and water quality of rivers (Habibi *et al.*, 2017; Mullapudi *et al.*, 2017; Jones *et al.*, 2018; Yildirim and Demir 2019). Concurrently, control technologies are being deployed alongside sensors which allow for operators to actively manipulate these systems in places and in a way that was previously inconceivable (Kerkez *et al.*, 2016; Mullapudi *et al.*, 2018). Further, the continued adoption of control technologies also introduces new stakeholders by which our water environment is *actively* manipulated (Rentsch 2019). These new technologies allow for higher resolution monitoring via novel sensors (Sermet *et al.*, 2019), social media (Sit *et al.*, 2019) and decision making (Demir *et al.*, 2018; Sermet *et al.*, 2020) both in time and space. Where historically our water infrastructure, such as stormwater ponds, were designed as passive structures there is now the capability to control releases *actively* and *precisely* from a growing, distributed amount of water infrastructure, oftentimes as small as stormwater ponds.

A proliferation of new sensing and control locations means massively more complex systems to address persistent water resources challenges such as flooding and water quality. Yet, to do so requires harnessing the unprecedented complexity of these new systems. Toward this end, there is a growing body of research on control schemes for water systems (Overloop 2006; Mollerup *et al.*, 2017; Schütze *et al.*, 2018). Recent studies mainly focus on the challenges of controller design to meet objectives of physically-based water *quantity* (flooding) (Sadler *et al.*, 2019; Mullapudi *et al.*, 2020; Sun *et al.*, 2020), and sometimes *quality* (total suspended solids or different "indicator" pollutants) (Muschalla *et al.*, 2014; Sharior *et al.*, 2019; Troutman *et al.*, 2020). The collective work demonstrates the potential for improved system performance with a coordinated, and increasingly automated, control approach; the promise of the new, "smart" water paradigm.

However, little work exists to determine whether control schemes with physically based objectives are consistent with socially normative expectations of "right" and "wrong" actions. Because the primary objective of these control studies is to investigate the performance of control strategies, many experimental designs use toy networks or simplified, abstractions of real networks. One consequence of this experimental design is that the social and economic variations within and across the network are not considered in development of control schemes, nor in determining the impact of the controller performance. Yet, when considering the deployment of these distributed technologies across an entire city or region, these demographic factors become relevant. Consider the case, for example, where some flooding is an inevitable outcome within the catchment area of a stormwater network with dynamic control capabilities; how *ought* a controller act to consider the societal implications of such flooding? Or, if a control scheme consistently recommends distributing damages in poor neighborhoods and benefits in richer neighborhoods, *ought* its directives be followed? These normative questions of *ought* – across populations, landscapes, communities, etc. – pose serious ethical and moral dilemmas, especially where negative impacts are unavoidable and uneven.

While ethical questions of civil infrastructure are as old as the infrastructure itself, the challenge to incorporate moral and ethical preferences into the automated, algorithmic decision-making tools that water resources management will rely upon are, indeed, new. The novelty of this challenge is supported by two trends. First, because sensor networks and control systems allow for higher resolution monitoring and decision making in both time and space, it follows that greater discretization of control will allow for an unprecedented precision of impacts, both positive and negative. A second and complimentary trend is as the complexity of systems grow, humans will continue to cede direct decision-making powers to decision-support technologies such as data algorithms (Sermet and Demir 2018; 2019). Systems will have ever-greater potential to effect human lives and yet humans will be insulated from these direct decisions. An important topic to explore is whether decision support tools for water resources management can integrate socially normative expectations with physically based objectives.

1.1 Individual to Institutional: Ethics, Morality, and Machines

The challenge to consider social concepts into what are seemingly technical problems is non-trivial. The social and the technical are intertwined to make a sociotechnical problem (Jonoski 2002; Vojinović and Abbott 2012). This understanding motivates our review of both social and technical work as it relates to our efforts. Generally, we can consider ethics and morality along a spectrum that spans from the individual to the institutional. At the individual level, "normative" ethics considers theories and schema to determine appropriate actions of an individual, or agent. At the institutional level, studies of ethics and morals consider power structures that shape norms, their compliance, and their impact on individuals and groups. Work in biology, philosophy, psychology, and sociology investigate questions along this spectrum. The field of machine ethics complements the efforts from the natural and social sciences by developing methods to incorporate decision making into artificial technologies that are consistent with human's (society's,) normative expectations of their behavior (Moor 2006). Here we provide a brief background on these fields and how they relate to incorporating normative ethics into smart water systems. Though some disciplines make distinctions between ethics and morality, we use them as interchangeable in the context of this effort. For consistency within various disciplines, we defer to their respective terminology when referencing their work.

1.2 Normative Ethical Theories in Philosophy

In the study of ethics, or moral philosophy, there are three fundamental traditions: ***deontological***, ***consequential***, and ***virtue***. Respectively, these camps choose to inspect morality from three overlapping, but not identical, questions: "What is the right thing to do?", "How is the best possible state of affairs achieved?", and "What qualities make for a good person?" (Grayling 1995). Importantly, each of these questions, and the responses of the ethical theories, are posed for *individuals*.

The ***deontological approach***, or duty ethics, considers an action to be moral based upon *a set of rules* that deem an action permissible, impermissible, or obligatory (Alexander and Moore 2016). A strength of the deontological approach is the clarity of the rule to *direct* actions. However, multiple rules can require contradicting actions, which is a key weakness of a purely deontological approach.

In contrast the ***consequentialist*** tradition judges the correctness of an act on its *outcome* (Sinnott-Armstrong 2019), in that the correct action is the action which leads to the best outcome by some specified *objective function*, such as maximizing happiness or minimizing costs. Egalitarianism and utilitarianism are well-known consequentialist moral theories. A concern for consequential approaches is which factors should be included in determining the normative value of an outcome. Though both consequential in approach, utilitarian and egalitarian models can produce incompatible solutions due to which factors are given importance. This tension is referred to as the equality-efficiency or the fairness-efficiency dilemma (Binmore 1998).

In the ***virtue ethics*** tradition**,** virtues are the fundamental, irreducible unit by which to define normativity, meaning that they are derivative to neither the outcome of actions (consequential) nor duty to perform an action (deontological) (Hursthouse and Pettigrove 2018). In agent-based virtue ethics, agents' *motivations* ascribe the rightness and wrongness of an act and agents learn virtue from "exemplars of goodness" (Zagzebski 2004). This understanding buoys the concept of learning models of normative behavior by observing human performance of similar tasks.

1.3 Morality in the Sciences

Evolutionary biology tells us that morals are adaptations to social living; when prehistoric humans began to form larger groups, survival was dependent upon the group and therefore what was best for it could supersede the priorities of the individual (Krebs 2008). Psychology and disciplines of biology are interested in the mechanisms and processes of the human brain as they relate to developing and making moral judgements (Haidt 2007). As a distinction from other fields, sociology interrogates morality at scales beyond the individual. When sociology does focus on the morality of individuals, it is almost always in relation to a larger group. Contemporary sociology of morality includes both moral theorizing and experimental science to uncover moral truths (Bykov 2019). Work is not a shared substantive focus, but the recognition that moral evaluations and categorizations are an essential part of struggles in 'social fields' (Hitlin and Vaisey 2013).

When considering how to incorporate moral and normative sentiments into intelligent infrastructure, the sociological literature provides intriguing insights. The theory of "thick" and "thin" moral concepts contends that thin moral concepts are "methodologically tractable," through hypothetical, situational tests. Conversely, thick concepts – like dignity, integrity, humanness, etc. – do not lend themselves to parsimonious description or measurement, making it difficult to explore thick concepts by experiment (Abend 2011). Because there is a lack of theoretical evidence for how thin and thick concepts relate to each other, a holistic approach would incorporate exercises in which feedback on both thin and thick moral concepts can be collected. Further, other studies show that higher social class predicts increased unethical behavior (Piff *et al.*, 2012), that lower-class individuals are more likely to be compassionate to another's suffering (Stellar *et al.*, 2012), that different social classes use different criteria in anticipated cost benefit analyses (Trautmann *et al.*, 2013), and that lower-class individuals are more likely to perform an unethical act if the act was to the benefit of others (Dubois *et al.*, 2015). Together, these findings clarify the process and partners needed when operationalizing feedback on normative expectations of smart water systems.

1.4 Integrating Moral and Normative Sentiments into Intelligent Systems

Machine Learning (ML), Artificial Intelligence (AI), and data algorithms generally have been – and stand to be – applied in a wide range of scenarios from data augmentation (Demiray *et al.*, 2020) to forecasting (M. Sit and Demir 2019; Xiang *et al.*, 2020). There is, however, growing acknowledgement that, unexamined, these techniques can institutionalize the biases and structural prejudices that persist in the world, especially in decisions that directly affect humans such as in job hiring, evaluating credit scores, and predicting repeat offenders during parole processes (O'Neil 2016). Consequently, popular culture, industry, government, and academia have focused attention upon the intentional and ethical application of AI, creating a proliferation of AI Ethics frameworks (Hagendorff 2019; Jobin *et al.*, 2019). Two primary concerns of deploying these technologies in a complex world are: (1) their instantiated purpose and behavior may not be well understood and (2) the systems may take irrevocable acts before humans have the data to discern their error (Samuel 1960).

These concerns connect to questions of building frameworks and governance models to responsibly integrate algorithms into systems that affect humans. Towards this aim, the agenda of "society-in-the-loop" (SITL) proposes to build an *algorithmic social contract* where human-in-the-loop principles and general stakeholder values are integrated into an iterative development process (Rahwan 2017). In its proposal SITL forwards the tenets of *algorithmic regulation* (O'Reilly 2013). The algorithmic regulation proposed requires a deep understanding of the desired outcome, that outcomes are monitored, that the algorithm adjusts based on new data, and periodic deeper analysis on algorithm performance.

Recent work in machine ethics can be understood in the context of building methodologies and frameworks towards SITL and algorithmic regulation (Tolmeijer *et al.*, 2020). A crowdsourced, voting approach has been proposed as a flexible method to incorporate moral sentiments for AI applications (Conitzer *et al.*, 2015; 2017). Crowdsourced voting has already been tested on a massive scale to query preferences on resolving moral dilemmas of autonomous vehicles using a pairwise comparison experimental setup (Awad *et al.*, 2018). After data collection, concepts from computational social choice (Chevaleyre *et al.*, 2007) and ML classification techniques can be used together to build preferences models of individuals and groups (Noothigattu *et al.*, 2017). These preference models, which in theory represent the real sentiments of the participants, can then be used in decision-support algorithms. Two examples of this process are in the development of an algorithm to decide tiebreaks in a theoretical kidney exchange market (Freedman *et al.*, 2019) and an algorithm to support a fair and efficient dispatch of food donations (Lee *et al.*, 2018). Critically, these examples apply voting-based preference aggregation within a larger, participatory framework. We observe that such frameworks to generally be able to: a) Identify relevant belief features to base decisions upon; b) Assay preferences along each relevant belief feature using pairwise comparison testing; c) Learn a preference model from the preference assays; d) Use the learned preference model in experimental decision-making scenarios; e) Analyze the outcomes of the preference model and identify if / where model-driven outcomes are incongruous with stated values or objectives; and f) Iterate on and / or deploy the learned preference model. In the materials and methods section, we provide further details for this process.

Currently, open frameworks which support all or part of the above workflow are limited (if any) in the literature. Previous studies have built custom web-voting applications, b), for their specific applications but did not share generalized source code. Other studies used proprietary web platforms to collect preference data. Furthermore, we are unaware of any framework that has shared analytical tools for post-play data processing and preference model development.

Towards this end, we propose an integrated and generalized framework to incorporate voting-based ethical and normative preferences into water resources decision-support schemes. We then demonstrate the framework with a proof-of-concept use case where decision models are learned and deployed to respond to flooding scenarios. Results indicate the framework can capture group “wisdom” in learned models and use this to make decisions. Further, we share our generalized framework openly with the research community.

The remaining sections are organized as follows. Materials and Methods provide details on the methodology of each step of the framework listed above, and cyber components used in handling the step. Results and Discussion demonstrates the framework with a proof-of-concept use case for decision-making for flood response with a discussion of the framework. Finally, Conclusion section presents the larger context of incorporating normative expectations into smart water systems.

2 Materials and Methods

In this section we describe the approach and technologies used to employ the methodological framework introduced previously. First, we describe how to identify relevant belief features. Next, we describe the process employed to collect people’s preferences. This subsection includes a description of the generalized web framework developed to collect voting-based preferences, its web architecture, gameplay, and database architecture. Finally, this section details the post-play data analysis to derive preference models, how to use them to make decisions, and the analytics toolbox developed to support this exercise.

2.1 Identifying and Assaying Relevant Belief Features

Example methodologies to identify relevant belief features for decision-making, step a), can be found in (Lee *et al.*, 2018; Freedman *et al.*, 2019) and include survey and interview techniques. Relevant belief features are those that someone would use to make a deliberative action. For example, in the case of choosing between two flooding outcomes, relevant belief features to be considered could be: public costs, private costs, injuries, deaths, and environmental impact. Once belief features have been established, different scenarios can be created that vary along the belief features. The scenarios are presented to individuals in pairs. Participants must choose which outcome they prefer from each pair presented to them. Their choices are recorded and used later to learn a preference model.

To collect preference data from participants, we built an integrated web-based serious gaming platform. Serious gaming is used in a variety of fields for training, decision-making, and education (Susi *et al.*, 2007). In water resources, serious gaming is used to explore the multifaceted challenges such as multi-hazard mitigation (Carson et al. 2018). Web-based serious gaming offers easily accessible and user-friendly interfaces with flexible architectures for various skill levels (Xu et al. 2020). In many serious gaming applications, gameplay offers the user an opportunity to explore real problems and strategies without the consequences of their actions impacting the real world. Instead, play informs a value system that guides behavior and action during a future, real world event. Play is recognized as an important feature in the development of value systems and morals in humans. Furthermore, actions within the context of play (i.e. games,) give rise to different value systems compared to a work context, even when considering the same topic (Bargheer 2018). These value systems result in different moral treatments of the same topic which can result from starting in the context of play or work. Gamification allows for parsimonious yet engaging descriptions of the ethical dilemmas at hand. More engaged users are more likely to play for longer and contribute more to the model development. The following subsections describe the web architecture, gameplay, and database architect of our serious game approach.

2.2 Water Ethics Web Engine, $(WE)^2$, Architecture

The Water Ethics Web Engine, $(WE)^2$, is an open and integrated framework that allows rapid deployment of web applications to investigate moral preferences via pairwise comparisons. The framework is comprised of a PHP-based application engine and use case web template, and includes a database architecture on the back end (Figure 1.) Full documentation of the framework and source code can be found on Github: https://github.com/uihilab/WaterEthicsWebEngine. Researchers provide their application and experimental information to the engine via two

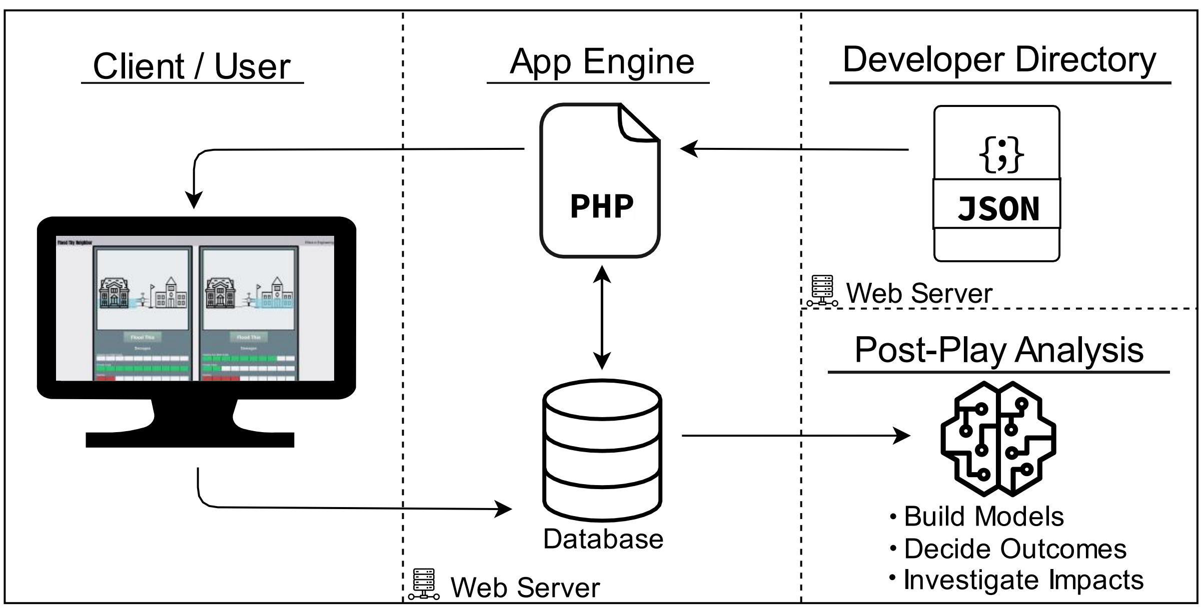

Figure 1. System architecture of the web-based decision-making framework. The application engine, database, and researcher-supplied data are located on a web server. When clients, or users, navigate to a project directory, the application engine builds the project using the information supplied in the static JSON files. After game play, researcher may use the post-play analytical tools to investigate results and learn preference models.

configuration files (site_meta.json and scenarios.json) using JavaScript Object Notation (JSON) format. These files, along with supplied images, are stored on a web server and accessed during game play by the application engine. Data generated during game play are logged in a web-accessible database. Once data are collected, researchers have access to analytics tools and a portal for data export.

Case study information described above is stored on a web server in a unique directory. When a user navigates their browser to the specific game version, given to them by the researcher, the engine generates the web page from the content stored in case study files (i.e. the site metadata, scenario content, and the images.) Scenarios displayed to participants are chosen randomly from the total set supplied.

2.3 Game Play

Users are presented with a homepage that provides a brief mission statement on the purpose of the game and a button to start the game play. During gameplay, users are presented with two scenario windows displayed side-by-side. In each scenario windows are descriptions of the event and an action button with a user-defined decision, e.g. "Flood This" or "Save This." Descriptions come in some combination of three forms: an image, info bar, and written description. All description types are supplied by the researcher and are customizable. Users are instructed to use the descriptions to determine what outcome they prefer for the scenario. To choose the preferred decision, users click on the action button on which the decision is recorded, and a new scenario is displayed. Once the user has provided their preference for all scenarios, they will be guided to a results page which provides the user a description of their aggregate preferences in relation to all others who have played the game and to the absolute possible outcomes along the belief features provided in the descriptions.

2.4 Post-Play Analysis

In this section we describe the methods used in post-play analysis. This includes learning preference models, making decisions with these models, and the iterative process of improving and deploying them. We also describe our analytic toolkit to facilitate these efforts.

Learning Preference Models

By using the paired comparison experimental design, parsimonious random utility models can be leveraged to learn preference model for individuals or groups, c) (Tsukida and Gupta 2011). When a participant votes that they prefer one outcome over another, one can hypothesize that the outcome has, on average, a greater utility. It is assumed that the utility of a decision relies on weighing the tradeoffs of each option across the belief features that describe them. When participants provide decisions across a set of scenarios, they provide a classified dataset from which a preference model can be learned via classification techniques used in machine learning.

There are numerous methods of using pairwise comparison data to build preference models (Conitzer *et al.*, 2015; Noothigattu *et al.*, 2017; Lee *et al.*, 2018; Freedman *et al.*, 2019). Here we employ the Thurstone's Law of Comparative Judgement Case V model to convert paired comparisons into group quality scores (Tsukida and Gupta 2011). For a group of participants who have made judgements on the same scenarios, an estimate of the mean quality difference between option A and B, μ_{AB}, can be calculated for each scenario as:

$$\mu_{AB} = \Phi^{-1}\left(\frac{C_{A,B}}{C_{A,B} + C_{B,A}}\right) \quad \text{Eq. 1}$$

Where $\Phi^{-1}(x)$ is the inverse cumulative distribution function (CDF) of the standard normal distribution, and $C_{A,B}, C_{B,A}$ are the number of votes for each option received. For example, $C_{A,B} = 27$ would mean that 27 people prefer outcome A over outcome B.

Mean differences can be related to scenario belief features as:

$$\mu_{AB} = \beta^{T}(X_A - X_B) \quad \text{Eq. 2}$$

where X_A, X_B are vectors of the belief features for option A and option B, respectively. The learned preference model of the group is the estimate of the belief feature weighting factors of β^T and can be found using linear regression, or other classification techniques, given that:

$$\begin{bmatrix} \mu_{AB,1} \\ \mu_{AB,2} \\ \vdots \\ \mu_{AB,n} \end{bmatrix} = \beta^{T} \begin{bmatrix} (X_A - X_B)_1 \\ (X_A - X_B)_2 \\ \vdots \\ (X_A - X_B)_n \end{bmatrix} \quad \text{Eq. 3}$$

where $\mu_{AB,i}$ is the estimated mean utility difference of scenario *i* of the *n* shared scenarios and $(X_A - X_B)_i$ is the difference in belief features of *i* of the *n* shared scenarios.

After a preference model β^T is learned, we can investigate its behavior. To do so, we need to calculate μ_{AB} in Eq. 2 using belief features of new scenarios. If μ_{AB} is positive, then choice A is selected. If μ_{AB} is negative, then choice B is selected. Decisions generated using the preference model can then be compared against various benchmarks, such as the historical performance of a system or against some specified definition of fairness and efficiency. Committing to this activity will require a reflection on whether the algorithm is meeting its purpose. After interrogating the behavior of the learned preference model, the researcher has a clear choice as to continue to refine the preference model iteratively or incorporate the preference model into their operation. As a practical matter, one can choose to pursue both continuously and simultaneously.

To facilitate the workflow of data retrieval, learning preference models, and using them to make decisions on new scenarios, we developed a data analytics toolkit using the Python programming language. The toolkit includes a data service interface with a PostgreSQL database, data structures and methods to streamline the workflow. The toolkit and documentation of workflow are provided in the project repository.

3 Results and Discussion

In this section the web framework and methodology are applied in a proof-of-concept use case with a group of undergraduate engineering students at the University of Iowa (n=409.) The use case explores the preferences of individuals to flood scenarios, and the result of using their preference models to make decisions.

Between 1980 and 2018 Iowa experienced 26 flood disasters where damages exceeded $1 billion (Immerman and Immerman 2018). Most recently, damages due to the spring 2019 flooding events in Iowa are estimated at $1.6 billion (Hardy and Cannon 2019). Further, between 1988 and 2016 there were a total of 951 flood-related presidential disaster declarations in the state (Eller 2018). In total, the sum of damages over the last 40 years is estimated at $41 billion, or a little more than $1 billion per year. In response, the State of Iowa has supported flood mitigation and flood preparedness through the Iowa Flood Center (IFC) and the Iowa Watershed Approach (Weber *et al.*, 2018). Yet still, when floods occur the response requires lay people and decision makers alike to make fraught decisions which take on ethical and moral dimensions (Bosman *et al.*, 2019; Kelley 2019; Marso 2019). Further, actions taken in the lead up to and during a flood event can result in litigation from damaged parties which contributes to a fractured response. As such, decision support recommendations from a voting-based framework could increase confidence and coordination in a community's flood response.

The primary goal of this use case was to demonstrate how voting-based preferences of specific flooding scenarios can be used to decide responses for a collection of flood scenarios. A secondary goal is to analyze the cumulative effect of these responses. To design flooding scenarios to use with the web-based ethics framework, we first determined relevant belief features. Belief features were chosen in an exploratory fashion based upon stated priorities of stakeholders as detailed in news publications and personal experience. Relevant belief features used to describe the impact of various flooding outcomes are *public costs, private costs, injuries, deaths, and environmental damage*. Given the proof-of-concept nature of our application, the process of identifying and clarifying relevant belief features is beyond the scope of this paper. Next, seventeen different scenarios were randomly generated. Scenarios present two options of flooding outcomes and consist of two assets with varying descriptors (e.g. flood national chain grocer in low income neighborhood or flood middle income multi-family home.) For each asset, unitless values were assigned for impact of flooding along each belief feature. Further each asset description includes an illustration and text (Figure 2.)

Figure 2. Example scenario and gameplay provided from the $(WE)^2$ framework. Participants are served multiple scenarios where they are provided two outcomes and their descriptions as photos, info bars, and text (displayed when information button, bottom is click.). Upon clicking the action button, e.g. "Flood This," the response is logged in the database and the participant is served another scenario.

To collect preference data, we had freshmen vote on a five-scenario subset of the seventeen scenarios during an ethics module in the University of Iowa, College of Engineering's Introduction to Engineering Problem Solving course. To build class-section specific preference models, all students within a section were served the same five scenarios (Table 1.) All responses were recorded in a web-accessible database and related to unique user ids and the class section keyword name.

Table 1. Each class section is referenced by a letter, Section Name. N details how many students provided preferences through gameplay. Scenarios column lists which five scenarios were served to each class section.

Section Name	N	Scenarios
a	103	2, 3, 10, 15, 16
b	111	2, 3, 4, 5, 6
c	106	8, 9, 10, 11, 12
d	89	13, 14, 15, 16, 17

To learn models from the collected data, votes were aggregated by class section. Participants who did not provide a vote for all 5 scenarios were not included in model generation. Preference models were learned using multiple linear regression. Five models were learned including one for each class section and one model that is the average of the four class sections. Five model parameters (β values) describe each model, one parameter for each belief feature provided in scenarios (Figure 3, Table 2.) A negative model parameter indicates the model's preference to minimize impact along the given dimension. A positive model parameter indicates the preference to maximize impact along the given dimension. This is due to the experimental design and our definition of marginal utility. For example, if it is preferred to minimize public costs then the difference in public cost between the preferred option and the undesired option would be negative; or, that the preferred option results in fewer public costs. This negative value is multiplied by a negative β value to result in a positive contribution to the utility of that choice. All learned models minimize public costs to some degree; model A gives the most priority to public cost minimization, model C give the least. However, no model gives minimizing public cost the highest utility against the other belief features. Models B, D, and Average give the highest utility to private cost minimization. Models A and C give the highest utility to the minimization of injuries. However, model A maximizes the minimization of public costs, private costs, and injuries almost equally.

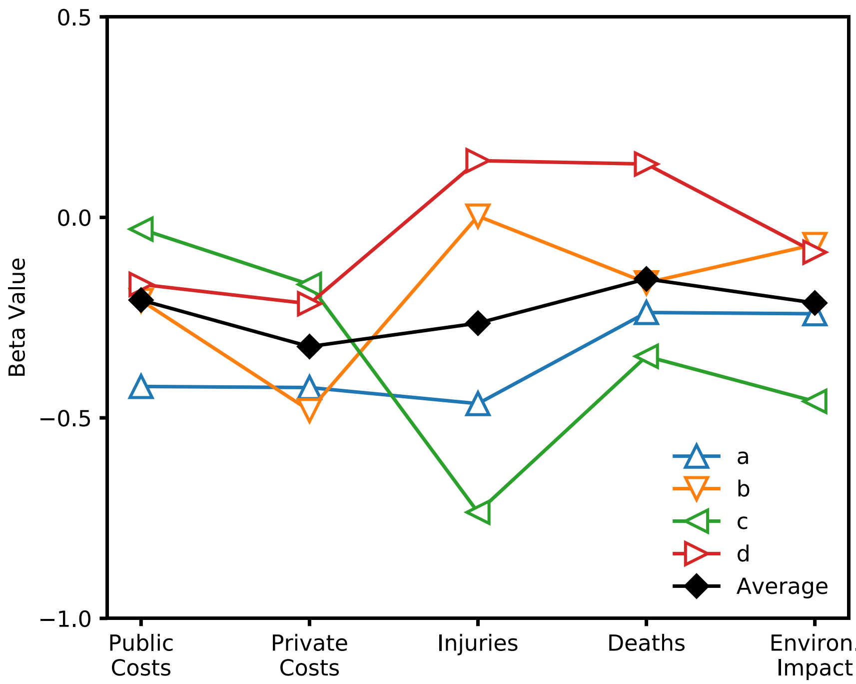

Figure 3. Learned preference models for each of the four class sections and their average. Negative beta values indicate a preference to minimize the impact for a category.

To analyze the impact of the learned models, we simulated decisions on all seventeen scenarios using the learned models. To add reference outcomes, we also simulated decisions of five models that, respectively, only prioritized one of the belief features. In effect, these reference models made decisions based on a single criterion instead of some combination of the five criteria of the learned models. Decisions, realizing the flood of the left or right scenario, for all seventeen scenarios were made by estimating the mean utility difference; negative difference, chose left, positive difference, chose right (Figure 4.) Ties, which only occurred with the reference models, were noted and interpreted as that outcome could go either way. In general, learned models voted similarly, showing agreement of vote on 11 of 17 scenarios.

To compare how the outcomes differed between the models, we calculated the total impact each model *avoided* along each belief feature and normalized them against the minimum and maximum possible avoidable damage (Figure 5a.) A score of one indicates that the maximum damage was avoided, while a score of zero indicates that the minimum damage was avoided. All learned models avoided high levels of death and environmental impacts, while showing less agreement and less ability to avoid public costs. The same exercise was performed for the reference models (Figure 5b.) Although each model scored maximally in their respective categories, it does not suggest with these example scenarios that it is a productive strategy to prioritize only one category over all others.

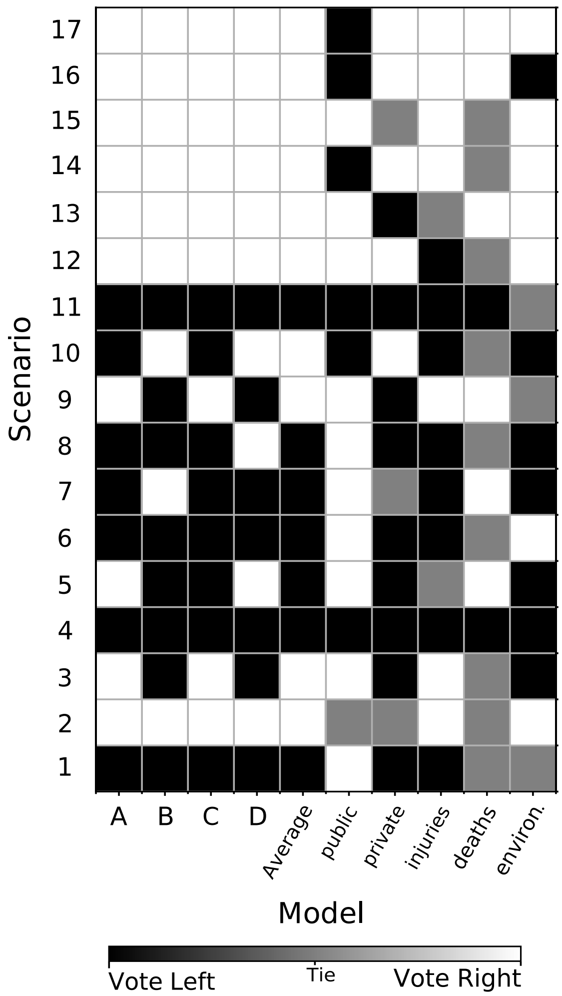

Figure 4. (above) Voting results from each of the five learned models and five reference models. Each model was used to vote, left or right, on the outcome of all scenarios generated for the flooding use case.

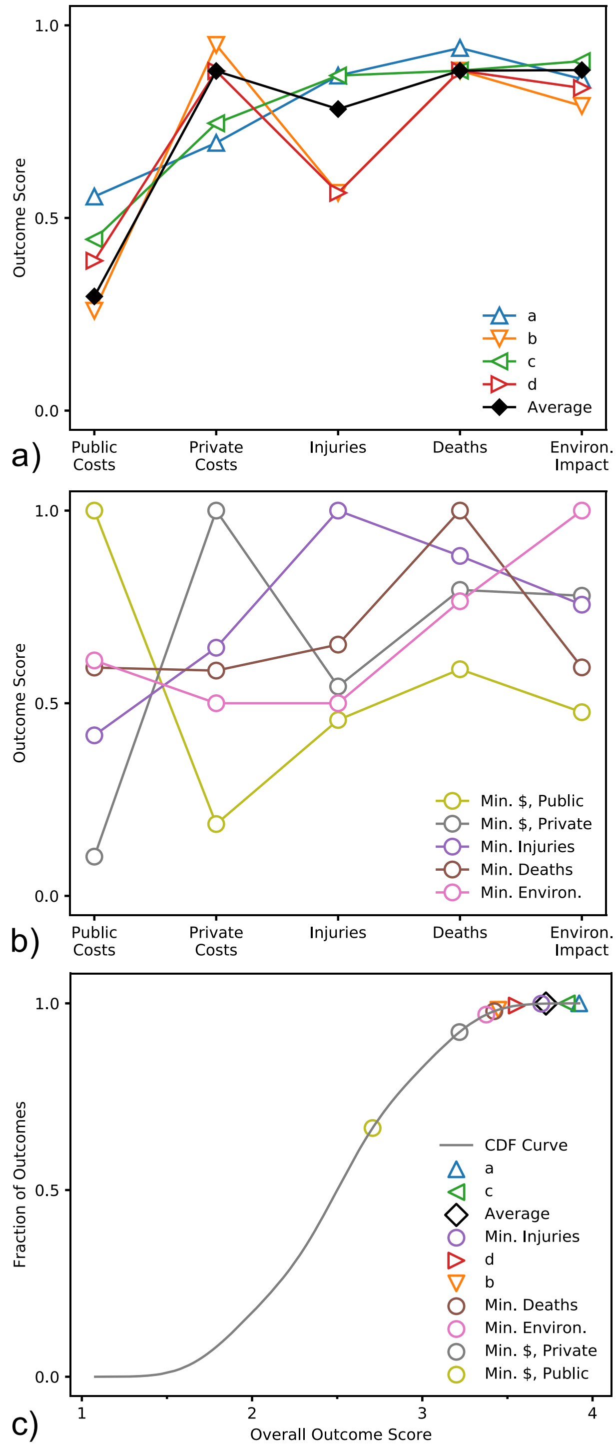

Figure 5. (right) Outcome scores are calculated as the avoided damage along a belief feature normalized by the maximum possible avoidance. Outcome scores were calculated for the learned models (a) and reference models (b). A model's cumulative outcome score is calculated as the sum of all outcome scores. Each model's cumulative score is ranked against all possible cumulative outcomes (c). Model a performed achieved the highest possible overall outcome score of 3.92 and rank of 1 in 2^{17}.

Because each of the seventeen scenarios have only two options, flood left or flood right, there are 2^{17} – or 131,072 – unique decision combinations. We normalized and ranked all outcomes along each category, allowing us to build percentile curves (Figure 6.) Only model A scored above the 50th percentile in all categories. The remaining four learned models performed above the 50th percentile in all but one category, public costs. Across the five categories and five models, 17 of the 25 outcome scores ranked above the 90th percentile, which indicates strong performance for all learned models.

To compute an overall outcome score for each of the 2^{17} voting possibilities, we performed a simple summation of the normalized outcome scores of each category for each model. These overall scores, too, were ranked and percentile scores calculated (

Table *3*, Figure 5c.) Shockingly, model A achieved the highest possible overall score of 3.922 (out of a maximum of 5) for rank 1 of 2^{17}. Model C achieved a cumulative outcome score of 3.849 for a rank of 6 of 2^{17}. All learned models achieved scores which put them in the 98th percentile of all outcomes in avoiding damages. Interestingly, only one of the single objectives, reference models performed better than any of the learned models.

Table 2 Beta values for each preference model used to make decisions. Models a, b, c, d are the learned models from each class section, and *Average* is the average of each of these learned models. These models weigh multidimensional effects to determine a decision. These models contrast with the reference models, which only consider the impact along a single category.

	Beta Values				
Experimental Model	**Public Costs**	**Private Costs**	**Injuries**	**Deaths**	**Env. Impact**
a	-0.42	-0.42	-0.46	-0.24	-0.24
b	-0.21	-0.48	0.00	-0.16	-0.07
c	-0.03	-0.17	-0.74	-0.35	-0.46
d	-0.17	-0.22	0.14	0.13	-0.09
Average	-0.21	-0.32	-0.26	-0.15	-0.21
Minimize Public Costs	-1	-	-	-	-
Minimize Private Costs	-	-1	-	-	-
Minimize Injuries	-	-	-1	-	-
Minimize Deaths	-	-	-	-1	-
Minimize Env. Damages	-	-	-	-	-1

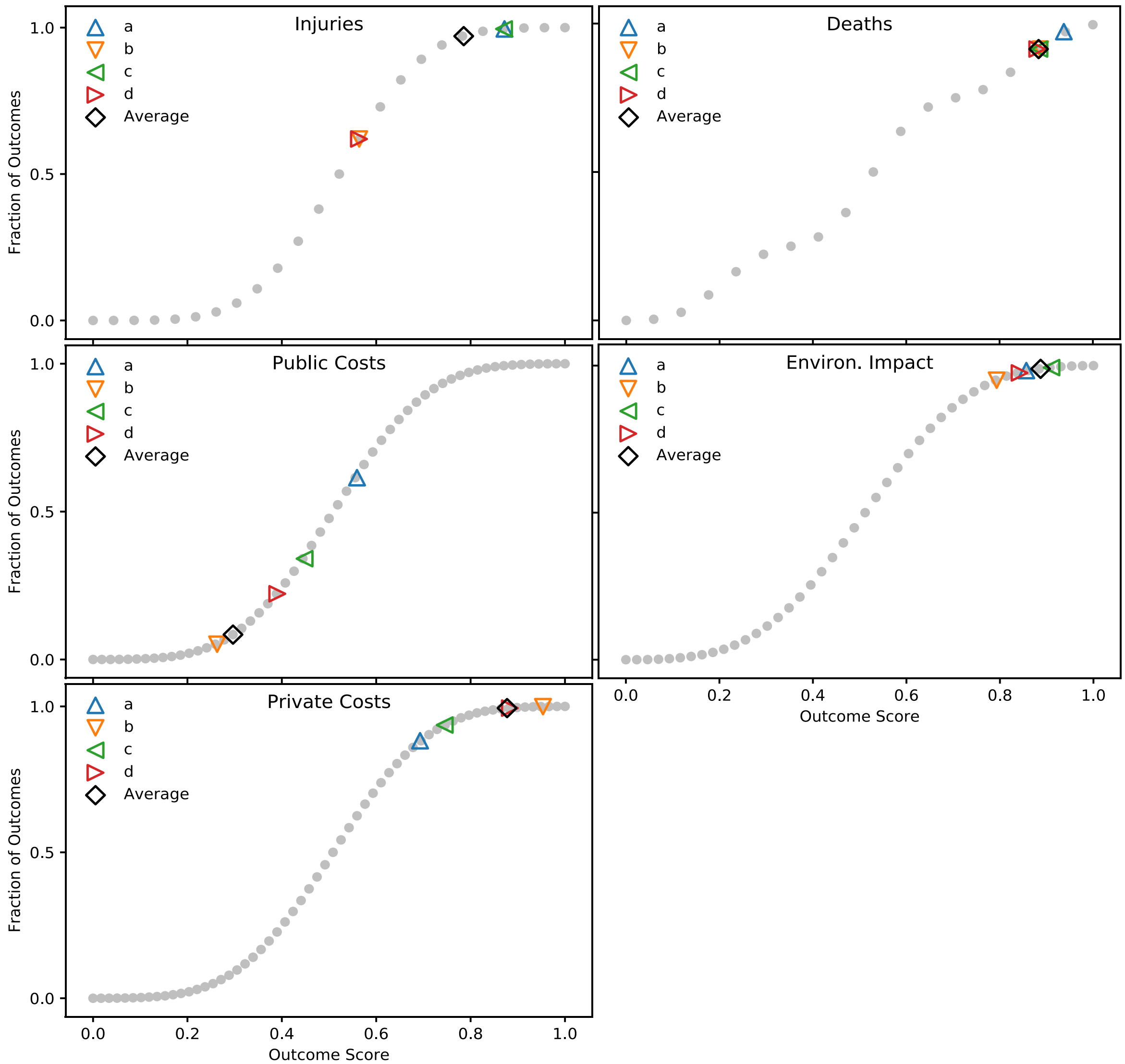

Figure 6. Ranking curves for each of the five learned models along each of the five relevant belief features. Overall, the learned models performed well. Model a, which had the highest cumulative score when considering minimization of damages, scored highest among the models in three categories: deaths, injuries, public costs. Yet, it also performed the worst in minimizing private costs and was third in environmental impact minimization.

Table 3 Cumulative impact scores for each learned and reference model in rank order. Total of 2^{17} possible outcomes.

Experimental Model	Cumulative Outcome	Percentile	Rank
a	3.922	0.99999	1
c	3.849	0.99995	6
Average	3.726	0.99944	73
Minimize Injuries	3.699	0.99911	117
d	3.555	0.99406	779
b	3.447	0.98280	2254
Minimize Deaths	3.423	0.97894	2760
Minimize Env. Damages	3.376	0.96988	3948
Minimize Private Costs	3.219	0.92303	10089
Minimize Public Costs	2.708	0.66605	43772

4 Discussion

The framework presented here demonstrates the ability to use a voting-based system to aggregate human preferences to ethical decisions in smart water systems. Collected data can be used to learn models of preferred behavior which can then be used to make decisions on new scenarios. This data driven approach is novel in helping researchers *learn* the utility function from a large, potentially massive, cohort of people and not assume an understanding of the utility function to be used to judge outcomes a priori. To this end, water professionals and researchers can investigate how algorithmic components of smart water systems or disaster response perform in relation to people's normative expectations of right and wrong.

The framework follows a consequentialist ethical theory, as the definitions of utility and performance rankings are based upon the *outcomes* of each scenario. However, learning of utility functions without any a priori knowledge mitigates for the limitations of traditional consequentialist approaches. As discussed earlier, consequentialist approaches come with limitations such as what factors (belief features,) to use to describe outcomes and the fairness-efficiency tradeoffs between following different moral theories (utilitarian vs. egalitarian strategies.) One strength of this approach is that belief features may also be crowdsourced, which allows many people to define an inclusive list of important belief features. Another strength is that by learning the models of action from people's decision, it is unnecessary to proclaim beforehand what fairness-efficiency tradeoffs should be made. Instead the fairness-efficiency priorities are captured within the learned models. However, these learned models may not agree with institutional understanding of rights or justice. Further effort may be required to integrate learned preference models with our ideals and aspirational sense of justice and fairness. Finally, this approach currently does not address the difficulty of decision making under uncertainty. This is an area of future work. Overall, we identify the inability for a single person, namely the researcher, to insert bias into the calculations as a positive outcome of using this framework.

Results from the experiment show the remarkable possibility for the models to choose outcomes that rank highly when considering cumulative outcome. Models A and C appear to achieve their astonishingly high ranking because they chose outcomes which did not favor private cost minimization at the expense of public costs. This observation is supported by the β values for public and private costs are equal for model A. These findings are relevant only within the context of our theoretical proof-of-concept. More robust studies are required to make that claim generally. Further, the cumulative scores and ranking method used here communicate only a single concept of "success." It is reasonable to justify other performance metrics beyond summing the normalized results of each category. Rather, the cumulative outcome score analysis can be instructive as a first step towards an application-specific evaluation technique.

Critiques of paired comparison for modeling moral preferences follow two forms: misplaced moral subject and lack of meaning of dilemmas descriptors. The first form states that the subject, or the moral actor, in the dilemma should move from the individual to the institutional. Consider the Trolley Problem, a classic philosophical dilemma in which the subject, the trolley driver, must choose between two bad decisions (Thomson 1985). One could ask: How did society fail to enforce safety standards such that an individual must intervene in a life and death scenario? Or, why has society allowed public infrastructure to be so underfunded that it poses the risk of catastrophic failure? Broadly, this critique emphasizes that moral and ethical dilemmas should be interrogated from an institutional or societal level and not exclusively at the individual. As such, a goal of smart water research and institutional design may ask: how can organizations be structured such that moral decisions made by an autonomous agent are minimized?

The second criticism is that the characteristic classifiers used in the moral dilemmas under describe scenarios and, in doing so, elicit not a users' moral ideas but their biases along the dimension of the classifiers (Everett Jaques 2019). Put another way, if an experimental setup provides only information on the age or race of a candidate to receive medical treatment what is the experiment doing but forcing participants to display their ageist and racist biases to make healthcare decisions? And, by extension, if we use these data to learn a model of "ethical" decision-making, are we not simply training a model to be biased just like us?

These criticisms are addressed in the methodological design. Contextually, pairwise comparison preference testing should not possess deep ethical or normative meaning independently of all the exercises in the stated framework. Next, because it is not well understood how thin moral concepts relate to thick moral concepts (Abend 2011), we cannot a priori assume that these thin normative preferences collected in pairwise comparison tests translate to thicker concepts. As such, thicker moral and ethical concepts can be incorporated via activities beyond pairwise comparison testing, such as numerous rounds of interviews with stakeholders (Lee *et al.*, 2018). Finally, strong reaction to an action or a method derived from the framework is itself a measure of normative values and can be integrated via the iterative process; collect data and act upon both thin and thick concepts of morality to improve system performance.

In practice, it is unlikely that a strictly consequentialist framework would be operational in real-world scenarios. Instead a hybrid decision-making process would be employed. For example, a system could trigger automatic human oversight if a decision is anticipated to reach a specified damage threshold. Likewise, because the learned models predict whether one outcome is better than another, a mean utility difference between two outcomes close to zero suggests there is a very weak preference. Thus, in these cases a human review could also be triggered. These rule-based heuristics can set guardrails on the strictly consequentialist models, while also providing further opportunity for society-in-the-loop principles.

5 Conclusion

Societal values are embedded into our built world – water systems are no exception – but these values are rarely inspected as part of the scoping of technical solutions. Instead, values are treated as priors – immutable, unstated and implicit as they relate to the objectives of infrastructure. Yet, our infrastructure itself evolves. Increasing resolution in sensing and control of our water environment will allow for unprecedented precision of impacts, both positive and negative. At the same, humans will continue to cede direct decision-making powers to decision-support technologies such as data algorithms. This new paradigm of smart and autonomous water systems will create new operational capabilities and new opportunities to [re]evaluate these values and explicitly incorporate them into operations.

The methodology and "proof-of-concept" presented here are a first step towards building a framework for engaging people in algorithmic decision-making in cases where normative and ethical preferences are considered. We developed the web based $(WE)^2$, a generalized framework with serious gaming to collect normative preferences through paired comparison testing. Although our framework was designed for water applications, the framework is generalizable and can be used for any paired comparison exercise in any field. Preferences collected using $(WE)^2$ can then be used with our data analytics toolbox to build decision support preference models and investigate their behavior. These resources are shared openly and can be found on the project repository.

We observe that the strength of this framework is that it can prime conversations on values and system expectations at every step of the process, forwarding an iterative process. By doing so, practitioners can work to unobscure AI, ML, and data-driven techniques from behind jargon and demystify the "black box" processes of decision-support algorithms. We anticipate benefits in deploying our integrated framework in education, operational, and outreach contexts.

Efforts towards incorporating ethics and norms into smart systems must be considered in a sociotechnical context. Importantly, this means that the solution to the development of a technology that is faithful to a society's values may not necessarily be technical in nature at all. Instead, findings from studies could support a structural, social solution as opposed to a solution reliant upon a technological artifice. Though aspects of the work can be technological, it should not preclude results finding that a structural or institutional solution is preferred. The application of AI, ML, and data-driven techniques to water sector problems does not alone make a system "smart". Instead, "smart" water should be conceived as the use of these tools to forward an explicitly recognized objective of the society.

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