hydrology

Review

Social Barriers and the Hiatus from Successful Green Stormwater Infrastructure Implementation across the US

Jingyi Qi [1,*] and Nicole Barclay [2]

[1] Infrastructure and Environmental Systems Program, University of North Carolina at Charlotte, Charlotte, NC 28262, USA
[2] Department of Engineering Technology and Construction Management, University of North Carolina at Charlotte, Charlotte, NC 28262, USA; nbarclay@uncc.edu
* Correspondence: jqi1@uncc.edu

Abstract: Green stormwater infrastructure (GSI), a nature-inspired, engineered stormwater management approach, has been increasingly implemented and studied especially over the last two decades. Though recent studies have elucidated the social benefits of GSI implementation in addition to its environmental and economic benefits, the social factors that influence its implementation remain under-explored thus, there remains a need to understand social barriers on decisions for GSI. This review draws interdisciplinary research attention to the connections between such social barriers and the potentially underlying cognitive biases that can influence rational decision making. Subsequently, this study reviewed the agent-based modeling (ABM) approach in decision support for promoting innovative strategies in water management for long-term resilience at an individual level. It is suggested that a collaborative and simultaneous effort in governance transitioning, public engagement, and adequate considerations of demographic constraints are crucial to successful GSI acceptance and implementation in the US.

Keywords: stormwater management; social factors; green stormwater infrastructure

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1. Introduction

Urbanization can affect the hydrologic functions of urban watersheds and precipitation patterns [1–5]. The consequential increased use of impervious surfaces results in substantial increments of stormwater runoff volume and peak flow [6]. Thus, the transition from the conventional approach into a more sustainable stormwater management paradigm which includes green stormwater infrastructure (GSI), is indispensable to reducing substantial environmental, economic, and social damage [7–9]. Hence, there is also a need to understand the hindrances and limitations in GSI implementation.

GSI offers a promising solution to stormwater management by mimicking natural hydrological processes to reduce localized flooding events and water quality improvement through decentralized natural or engineered processes to treat stormwater runoff at its source [10]. In the US (United States), awareness of GSI has slowly increased over the past two decades. Its historical progress in stormwater management and background knowledge is documented in several in-depth publications [11–14]. Research teams across nations have developed various GSI practices and in addition, retrofits and hybrid measures on different spatial scales (such as watershed scale and site scale, etc.) with diverse primary purposes have been developed [15–20]. The details on these practices are well documented in the literature [21–28].

Numerous studies have evaluated the performance of GSI, particularly in economic and technical aspects [14,29–32]. GSI provides extra benefits to the community, such as raising property values, enriching life quality, and providing adaptable climate resilience [33–35]. Urban stormwater management has advanced gradually over the last two decades, thus various terminologies are used to define new principles and practices, where the concepts behind them often overlap [14,36]. Using these different terms may reduce effective communication in certain circumstances, such as when documenting all the alternative stormwater practices used in the US to assess their performance in general [36]. To avoid confusion, the term GSI was used throughout this work in referring to all types of multi-purpose structural stormwater management practices that involve natural processes for runoff volume and water quality control.

Despite the progress, there are limited study efforts on non-technical factors, such as public perceptions and knowledge, that could explain the slow advancement in the wide adaptation of GSI to the desired level for stormwater management and sustainability capacity building [37]. The contradiction between the low implementation rate of GSI in major regions of the US and the actual demand to address climate change impacts suggests that certain factors are hindering the relevant decision-making processes [38,39]. Furthermore, a study discovered the mismatch in the percentage of their survey participants that expressed an intention to support GSI and the number of those who actually adopted GSI [40]. This result is in agreement with the findings in an exhaustive review [41]. Irrational decision-making behaviors in energy-related decisions have been interpreted through the cognitive bias perspective [42,43], where cognitive biases can be defined as a belief that hampers one's ability to make rational decisions given the facts and evidence [44]. It has been supported by various studies that cognitive biases are influential in decision making and planning [44]. Yet, little attention has been given to the potential influence of cognitive biases in GSI implementation, despite numerous studies on perceptions of various GSI stakeholder groups [45–47]. This study aims to bridge this knowledge gap.

Historically, quantitative decision support tools have been developed with the main aim to maximize GSI performance to control runoff and water pollution and to be cost-effective [48–52]. On the other hand, despite the extensive attempts made to expand the assessment work to include the social aspect of decision support [17,48,53–64], they lack a deeper understanding of the public perceptions and associated cognitive bias perspective to resolve the implementation dilemma from a bottom-up approach [65] as examined in other environmental issues [43,44]. This shortcoming can affect the expected outcomes envisioned by major decision-makers [42,66]. This study focuses on the barriers that could be linked to biased perceptions due to social factors in GSI development and implementation.

This work was conducted to examine the relevant social factors through the lens of cognitive biases, which may lead to implementation barriers during GSI adoption processes. The scope of social factors can vary significantly as they are commonly assessed in combination with factors from other dimensions, such as socio-ecological, social-cultural, socio-economic, and socio-technical factors [10,67–70]. We use a concept adapted from Gifford and Nilsson [71] to define social factors as the internal differences among people and the contextual factors that define them in this study. This study aims to understand the potential connections of cognitive biases with these barriers, and to recommend an approach to analyze and address the associated problems. Studies have been conducted to analyze cognitive biases with agent-based modeling (ABM) in various contexts [72–74]. However, no study has done a similar analysis in the context of GSI implementation. ABM is a methodology that can incorporate the autonomy, heterogeneity, and adaptability of individuals in a social system to study the resulting global patterns through a bottom-up approach [75,76]. It is also an approach that can carry exploratory simulations for a deeper understanding of the underlying adaptive behaviors and interactions that could lead to the emergence of phenomena that was previously overlooked [40]. However, the models developed solely based on social and physical science are usually fragmented in their fields, rely on qualitative analysis, or are difficult to incorporate into quantitative models [77]. This work was conducted to answer the following questions:

1. What social factors have been identified as barriers to GSI implementation?
2. How do these social factors connect to cognitive biases?
3. How can ABM accommodate these cognitive biases for better quantitative decision support?

To address these research questions, we reviewed the literature on GSI implementation barriers that arise from social aspects and on the connections between cognitive bias with these barriers. Subsequently, we reviewed the literature to show and assess the applicability of ABM in addressing the issue of social factors' hindrances to GSI adoption and implementation.

2. Materials and Methods

A literature review was conducted on two main topics in this study using a combination of platforms, including literature search engine Web of Science (WoS) and relevant referenced articles in the papers collected through the means mentioned above. Firstly, studies that were conducted to understand the restraints to wider/efficient/effective GSI adoption were examined. Reported barriers to GSI implementation that may link to social factors in the literature were identified using the search terms: 'social', 'barrier* OR challenge* OR difficult*', 'stormwater OR storm water', and 'infrastructure' as the primary screening criteria. Only peer-reviewed papers written in English published between 1900 to 2020 were considered. Seven records were first excluded prior to the screening due to lack of access to the full text. Four book chapters and 20 articles that were not directly relevant to the social barriers in GSI were eliminated. Finally, because the social context that could contribute to barriers that are dependent on local governmental regulations and governance practices [48,64,78] and socio-ecological context [64,79], the records that did not explicitly study the social barriers in the US were excluded from the final results. As a result, the search within the scope of this study yielded 34 papers in total (Figure 1). The final results are further divided into two groups, where one (20) is the collection of empirical-based studies that examined the barriers, and another (14) is the collection of studies that developed qualitative frameworks to incorporate social factors to reduce such barriers as decision support tools (the works focused solely on qualitative post-construction performance evaluations were excluded). Note that analytical simulation-based works found through this search were rearranged to the second part of the review. These barriers were reviewed through the concepts of cognitive biases proposed by Haselton, et al. [80]: Biases resulted from heuristics, artifacts, and error management.

In their article, Bukszar Jr [81] provided strong evidence that failing to address cognitive biases among decision-makers can cause strategic heuristics and biases, thus hampering the strategy's adaptability. They argued for the need for a higher capability to accommodate such cognitive biases for greater strategy success. Thus, the second part of this review was conducted using the same search platforms of records written in English and published between 1900 and 2020 to evaluate the potential applicability of ABM in addressing the issues studied in the first review topic. Due to the limited studies conducted within stormwater management, research that analyzed innovation diffusion in water infrastructure, in general, were also considered in this review. Thus, a total of 10 results were finalized (Figure 2). The key search terms used were 'agent based OR agent-based', 'infrastructure', 'perception* OR cogniti*', 'model*', and 'water'. This yielded 6 outcomes with 11 additional articles from external references. Additionally, the Institute of Electrical and Electronics Engineers (IEEE) was employed due to its particular research focus on computational simulations using a combination of key search terms of 'water', 'infrastructure', 'percept*', 'cogniti*', and 'agent-based'. It yielded 34 additional results. One record was eliminated from the WoS results because it was a conference proceeding. A total of 38 additional studies were excluded after abstract screening because they were not directly relevant to the interpretation of cognitive biases or perceptions of innovative water management strategies simulated through ABM. It was noted that all search outcomes from IEEE were not within the scope of the search objectives for this review.

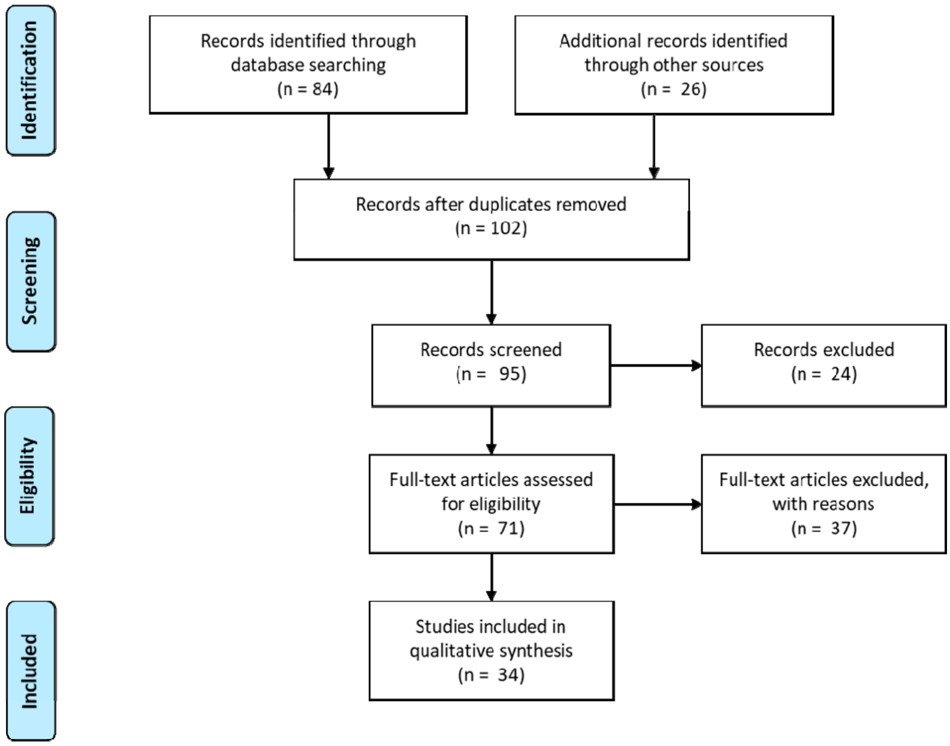

Figure 1. Flow diagram of the search results of the first topic following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol [82].

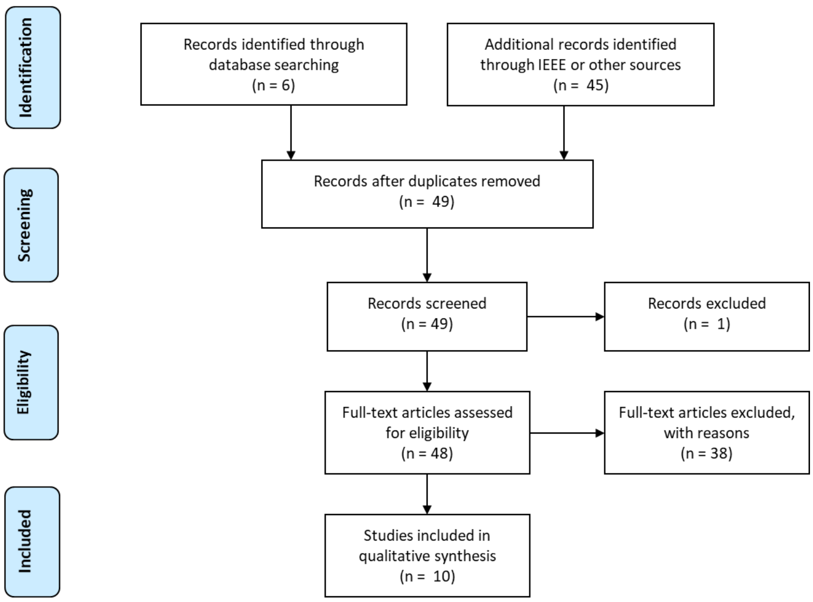

Figure 2. Flow diagram of the search results of the second topic following the PRISMA protocol [82].

3. Results and Discussion

3.1. Identified Social Barriers to GSI Implementation

The barriers to GSI have been studied by numerous international research teams, ranging from individual perceptions and attitudes, financial burdens, resource allocations, and governance rigidity to conflicts across institutions [45,67,79,83–86]. Barriers originating from social factors may be harder to address, as the values of which are usually difficult to quantify yet should not be overlooked [55,58,65]. Barriers primarily identified as associated with social factors, in terms of their potential influence on the implementation of GSI, are attributed to three main categories from the literature. They mostly cover governance discord, public participation, and demographic constraints (Table 1). Governance refers to the inconsistent strategies among or within governance entities; public participation refers to the involvement of the public in the decision-making of GSI regulations and collaborations; and demographic constraints refers to the general demographic factors, social norms, and perceived environmental concerns. However, there always is a possibility of unrecognized social factors in the published studies. For example, though not directly addressing the issues in stormwater management adaptation, a study brought forth the dilemma in regenerating historical cities of which preserving the historical cores were paramount [87]. It is thinkable that advancing GSI in such areas may encompass greater complexities than others. Additionally, the underlying interrelations across infrastructure sectors and even industries are also likely to influence sustainable decision-making in general [88,89].

Table 1. Relevant social factors that could influence the implementation of GSI in the US.

Social Barriers	Barrier Subcategories	GSI Types	Spatial Scales	Location	Stakeholder	Study Methods	Source
Demographic constraints & public engagement	Race, ownership status, relevant knowledge of GSI, knowledge dissemination platform	Rainwater harvesting, pervious paving, rain gardens, lawn depression	Sub-watershed	Two sub-watersheds in Chesapeake Bay watershed	Private landowners	Knowledge, attitude, and practice question-naire	[90]
	Age, education, homeownership, prior experience of floods, lack of awareness, underuse of social capital	Rain barrels, rain gardens, and permeable pavement	Region	Knoxville, TN	Private landowners (households)	Survey	[91]
Governance	Limited focus on the multifactional of GSI to respond to local needs, lack of interdepartmental collaboration, and private-public partnership	Green alleys with various GSI features	Region	Various locations in the US	Government agencies, non-governmental organizations (NGOs), community groups	Narrative analysis	[34]
	Conflicting visions in hydro-social relations	GSI in general	Region	Chicago, IL, and Los Angeles, CA	Government entities, NGOs	Interviews, participant observa-tion, literature review, survey	[92]
	Leadership in transitioning governance (informal, multiorganizational)	GSI in general	Region	Ohio	Community NGOs, environmental NGOs/land trust, federal government, local govern-ment/regional authority, university /contractor	Social network analysis survey	[93]
	Departmental silos (stakeholders' multiple and competing social perspectives)	GSI in general	Region	Chicago, IL	NGOs, governmental entities	Q-methodology	[94]
	Tensions and convergences among different management strategies	GSI in general	Region	Pittsburgh, PA	Community organizations, municipalities, advocacy groups	Interviews, participant observa-tion	[95]

Table 1. *Cont.*

Social Barriers	Barrier Subcategories	GSI Types	Spatial Scales	Location	Stakeholder	Study Methods	Source
	Conflicting perceptions, implementation priority, limited focus on the multifunctionality during planning	GSI in general	Region	New York, NY	Agencies, city departments, national and local nonprofits, research institutions	Spatial analyses, survey, interview, participant observation	[78]
	Inequity for disadvantaged communities	GSI in general	Sub-watershed	Los Angeles, CA	Government agencies, non-profits, community organizations, and others	Statistical analyses	[96]
Public engagement	Failing to recognize the values of social capitals for long-term productivity	Rain gardens, rain barrels	Household site	Cincinnati, OH	Landowners	Experimental reverse auction	[97]
	Perception (status quo bias)	Rain gardens, bio-swales, green alleys with permeable pavement	Region	Cincinnati, OH, and Seattle, WA	Engineering graduate students	Functional near-infrared spectroscopy	[38,97]
	Ineffective information dissemination, underuse of social capital	Rain barrels, rain gardens, permeable pavement	Region	Washington DC	Homeowners	Voluntary stormwater retrofit program with statistical analyses	[98]
	Stormwater context (perception of neighborhood-level challenges, town-level stormwater regulation)	Rainwater harvesting, rain gardens, permeable pavers, infiltration trenches, and tree box filters	Cross-scale	Vermont	Residents	Statewide survey	[79]
	Depreciation of community involvement (expertise, education)	GSI in general	Region	Houston, TX	Researchers, community	Participatory action research	[99]
Governance & public engagement	Lack of awareness and responsibility for maintenance, education programs not aligned with local preferences	Stormwater ponds	Community	Southwest Florida	Homeowners, governmental entities	Survey, interviews	[100]
	Lack of awareness, ineffective regulation enforcement	Stormwater ponds	Region	Manatee County, FL	Landscape professionals, residents, government agents	Interviews, surveys, participant observation, and literature review	[101]
	Lack of awareness, understanding, and sense of responsibility; geographic disconnection between watersheds and governing entities; fragmentation of responsibility among stakeholder groups	GSI in general	Region	Cleveland, OH, and Milwaukee, WI	Practitioners (regional sewer districts, local governments, community development organizations)	Interviews	[28]

Table 1. *Cont.*

Social Barriers	Barrier Subcategories	GSI Types	Spatial Scales	Location	Stakeholder	Study Methods	Source
	Lack of awareness and adaptivity in policies to prioritize GSI measures to align with local values	Bioswales, green roofs, street trees, parks & natural areas, community gardens, and permeable playgrounds	Region	New York, NY	Residents and practitioners (individual sprofessionally engaged in the siting, design, maintenance, public engagement, and/or monitoring of GSI programs)	Preference assess-ment survey and semi-structured interviews	[46]
	Outdated regulatory constructs, conflicted views among gray and green advocates, jurisdictional overlap, influences of social media coverage, leadership gaps or influence of lobbying	GSI in general	\	USA	Residents, governmental entities, engineers	Narrative analysis	[102]

The unclear distribution of responsibilities among stakeholders can impede the decision-making processes associated with GSI implementation. Particularly, the general public's involvement is the fundamental building block that could be influential in shaping the direction of GSI implementation [17,28,47]. Dhakal and Chevalier [83] stated in their study that, above all challenges, cognitive barriers and socio-institutional factors should be the primary issue to focus on. Furthermore, the multi-sector benefits will only be nuanced if the public is not willing to implement GSI [103]. Similarly, one study stated that sustainable GSI implementation would necessitate the need for structured public participation and local partnerships. They emphasized that, in addition to putting more reach effort onto comprehensive cost-benefit evaluations on GSI, such needed engagement would fortress the networks of non-governmental organizations, county and state agencies, municipal sewer districts, and federal research support, which could lead to a faster adaptation of GSI on larger scales [104]. Therefore, the barriers to the general public to accept GSI are crucial to dissect these aforementioned disconnections and provide practical yet effective decision support. To date, there is a limited number of conceptual frameworks that capture social factors in GSI implementation processes (Table 2). Yet there still is a need for quantitative analysis measures for better decision support for case-based GSI adoption using standardized methods that could assist in horizontal comparison and further knowledge transfer. The frameworks listed in Table 2 were categorized based on their main purpose: Classification scheme (proposed to enhance terminology clarity), planning strategy (suggesting new approaches to be adopted in current management regimes), process conceptualization (promoting a better understanding of complex socio-infrastructure systems), and framework efficacy assessment (evaluating the existing frameworks' usefulness in promoting GSI implementation).

Table 2. Conceptual frameworks that consider social factors in GSI implementation processes.

Framework Nature	Social Factors	Sub-Categories	Stakeholders	Method	Scale	Source
Classification Scheme	Governance, stakeholder engagement	Stakeholder interactions, governance, political contexts	Individuals and groups involved in rule-making processes, property owners	Social-ecological services framework	Cross-scale	[54]
	Public engagement, governance	Policy instrument assessment	Citizens	Policy instrumentations scheme	Region	[56]
	Public engagement, governance	Ownership status, political power	Governmental entities	Topology framework	Region	[64]
Planning Strategy	Governance, demographic constraints	Equitable GSI distribution, age, income, education, ownership status	Governmental entities, residents	Green infrastructure equity index	Region	[60]
	Public engagement, governance	Multifunctional strategy, multisectoral communication	All involved in decision-making processes	Millennium ecosystem assessment classification-based framework	Cross-scale	[105]
	Governance, public engagement, demographic restraints	Adaptive governance, stakeholder participation, inclusion	Governance, nongovernmental organizations, communities, academia, industry	Adaptive socio-hydrology framework	Cross-scale	[106]
	Public engagement	Interdisciplinary collaboration, university-stakeholder partnership, institutional capacity	Universities	Integrated framework combining social-ecological dynamics, knowledge to action processes, organizational innovation	Region	[63]
Process Conceptualization	Public engagement	Community participation in three themes (context, participation processes and outputs, and implementation results)	City, federal government agencies, community residents, and community NGOs	Public participation conceptual model	Watershed	[61]
	Public engagement, governance	Low stakeholder buy-in, discoordination in management objectives and goal among stakeholders, lack of awareness	Government researchers, stormwater managers, and community organizers	Adaptive management framework	Site	[62]

Table 2. *Cont.*

Framework Nature	Social Factors	Sub-Categories	Stakeholders	Method	Scale	Source
	Governance, public engagement, demographic restraints	Stakeholder interactions, governance and political contexts	All that are involved in stormwater management	Integrated structure-actor-water framework	Cross-scale	[55]
	Public engagement, governance	Hybrid governance envisioning (management and monetary responsibilities)	Regulatory agencies, residents	Multi-criteria governance framework	Cross-scale	[17]
	Public engagement, governance	Perceptions, stewardship, human-environment interactions	Residents	Coupled human and natural systems framework	Region	[58]
Existing Framework Efficacy Assessment	Governance	Governance, capacity, urbanization rate, burden of disease, education rate, political instability	Government agencies, NGOs	City Blueprint® Approach	Region	[53]
	Public engagement, governance	Community education and awareness campaign, multifunctional strategy	Residents, governmental entities	Socio-ecological framework	Watershed	[107]

3.2. Interpretations through Cognitive Biases

Kahneman and Tversky [108] pointed out that human decision making can be subjected to cognitive biases (or cognitive illusions) especially when under uncertainty, which infers that an erroneous judgment may be formed subjectively (as judgmental heuristics). It is particularly profound when forming judgment based on certainty and probability under uncertainty [109]. Over the past several decades, research efforts have been made to study cognitive biases and how they can influence decision making [41,44,66,110,111]. A deeper understanding of cognitive biases can assist in effective debiasing and re-biasing measures for better decision making [112–114]. Cognitive biases have been studied extensively in the sociological and psychological fields, yet these intellectual outputs have rarely been considered in other research domains [112], such as in the stormwater management sector. In the context of governance strategy primarily for managing complex systems, such as natural resources, hazards, and the environment, one review study pointed out that there was a need to enhance participatory processes connecting scientists with stakeholders and policy-makers to propel successful governance and policy enforcement, in which biases, beliefs, heuristics, and values were the critical influencing factors [111]. The authors believe that, despite being intrinsic to a certain extent [110], cognitive biases are shaped by surrounding contextual factors, such as social factors. Hence, this work is an early attempt to connect these two pieces in the context of GSI implementation with an envision of advancing quantitative insights on the slow progress in GSI adoption in the majority of the US territories. Only a limited number of studies have explored the social factors involved in the decision-making process of stakeholders at various levels in the context of stormwater management, and they tend to be based on simplified concepts to interpret the information transfer tarnished by cognitive biases [40,115,116].

Historically, there has been an ongoing debate on the definition and categorization of cognitive biases across different scientific domains. Furthermore, according to Caverni, et al. [117], cognitive biases is an evolving topic. Thus, this review is based on the theory developed by Haselton, Nettle, and Murray [80] based on its wide acceptance among scholars, how suitable it is to interpret social factors-related barriers to GSI implementation, and its year of publication. Through a literature search of the social barriers mentioned in the literature, three are salient in the context of stormwater management that may be associated with cognitive biases (Table 1). However, the authors acknowledge the limitation on the selection of the theory due to its novelty in the context of GSI adoption, particularly the three biases chosen in this review. Furthermore, interdisciplinary discussions are encouraged to strengthen research efforts in this topic for practical decision support.

3.2.1. Uncoordinated Regulations and Governance—Biases Resulted from Heuristics

People tend to rely on rules of thumb to simplify problems at hand that may deviate from the optimum range of decisions, which can be considered heuristics [80]. The most commonly studied bias based on heuristics is the status quo bias which can be seen in regulation adaptation progresses. The status quo bias first received a greater level of scientific attention through the work of Fernandez and Rodrik [118], which can be used to explain the resistance to change within a group of people where the beneficiaries of the status quo have a stronger influence than the other group, which they referred to as the non-neutrality. This can be considered a bias due to human's insensitivity to make predictions under the influence of representative heuristics where people predict future events based on the intuition under uncertainty [119,120]. Hu and Shealy [38] conducted a study to illustrate how setting up GSI resolutions can overcome the status quo bias which limits its adoption. They demonstrated that simple public engagement strategies using factual endorsement in a municipal resolution by regulatory organizations could favor GSI over conventional practices.

Status quo bias can also be observed among the key professionals whose preferences may largely set the direction of the reform. One study identified five typical types of decision-making patterns of students in civil engineering, which include risky, social, conflicted, purchasing, and influenced by built-environment decision making [121]. By carefully examining these thinking patterns, it could contribute to overcoming potential cognitive biases among stormwater engineers. On the other hand, biases might be amplified if the role of the GSI-related implementation processes is heavily played by one stakeholder group, such as the contractor company, which takes the responsibility from the design to the construction phase. This might limit their scopes, such as potential risks or alternatives. Rather, they could distribute the workload to a third-party design company, allowing further discussions on the optimal plan. A study found that professionals who had hands-on experience favored GSI [39].

The general situation of stormwater management in the US has been depicted as lacking clear guidance and regulation [12,83]. Stormwater management was not brought into the National Pollutant Discharge Elimination System (NPDES) program until 1987 [13]. Further challenges lie in the adaption of drainage system management when facing climate change and anthropogenic stressors, which has propelled the use of GSI [122]. Attempts made through the established federal regulations often conflict with the existing rules set on state and local levels, which have more discretions on primary goals and responsibility distributions. This has resulted in the current dilemma that, even though private sources count for a greater percentage of the flow generation or have a higher potential in fortifying stormwater storage capacity, NPDES and municipalities cannot enforce regulations in these areas [13,19]. In summary, the major weaknesses and gaps in these regulation-related issues are poor coordination across institutions due to land use as private properties and not prioritizing the control and storage capacity of the discharge volume [13]. Several other studies listed in Table 1 have also observed such barriers.

3.2.2. Low Public Engagement and Inefficient Knowledge Transferring—Biases Resulted from Artifacts

Artifact biases intentionally form unrealistic conditions on which people make decisions, for instance, framing and anchoring biases [80]. It could suggest that if the information was not translated into a language that is appropriate to a specific audience, the efficiency in the transfer of such knowledge could be reduced, even causing the generation of erroneous interpretation. The framing effect occurs when a person changes their decision based on how the information is presented [123]. A study has demonstrated that the biases can be prevented in the early stage during education by using the sustainability-conscious teaching approach to assist in decision making for sustainable infrastructure like GSI, such as by using the Envision rating system [124]. On the other hand, it may lead to an anchoring effect if the parameters used in said rating systems are not properly determined [42], where a biased estimate toward the set arbitrary values will be formed even though they are far from rational estimations [125].

Even though it can bring forth multi-sector benefits, GSI implementation still faces a range of practical barriers, including the poorly perceived necessity of effective stormwater management [126]. In addition, miscommunication due to terminology confusion or ineffective knowledge transfer can also hinder the progression of GSI development to the optimum level [36,127]. These miscommunications might link to the conservative mindset about gray infrastructure, risk aversion attitude toward the related cost and performance of GSI, confusion between GSI and the gray option, and fear of taking maintenance responsibility as identified in the literature [45,79,83–85]. It was also pointed out by the U.S. Environmental Protection Agency (US EPA) that many of the barriers could be overcome if sufficient efforts were made as the policies and regulations evolved on a need basis. Given that, these aforementioned efforts need to be initiated first in order to achieve the expected outcome. The results from a study demonstrated that solely relying on GSI implementation was not adequate if public education and social learning were not enforced at the same time [85]. The authors suggested the diversity of perspectives could not be omitted to encourage the successful transitioning of this stormwater management regime. To attract more financial support to advance and accelerate research on gathering reliable GSI performance data, inadequate public (especially the major stakeholders') awareness needs to be appropriately addressed [128,129].

3.2.3. Perceived Demographic Constraints—Biases Resulted from Error Management

Error management bias occurs when people make decisions primarily to reduce consequential losses [80]. The typical bias that falls into this category is risk (or loss) aversion. As pointed out by Tversky and Kahneman [130], people tend to value any amount of loss greater than the same amount of gain, which infers that losses (or disadvantages) will be considered more than gains (or advantages). In the context of GSI implementation, one factor that hinders the decision-making process is the lack of convincing empirical data on multi-sector functionality in a life cycle [16,131,132]. This bias might emerge due to unfamiliarity with long-term GSI performance and with the demand for capital cost and maintenance fees, of which the payback has not been clearly quantified. A study found that the most salient barrier to adopting innovations is the perception of risks [39]. The authors suggested that extensive knowledge transfer in a combination of equal sharing of contractual risk through team collaborations could contribute to easing such perceptual barriers. Great progress has been made to minimize these barriers. Without enough perceived incentives, it would be difficult for any major stakeholder to bring forth the input, whereas other studies have shown some positive influence of GSI in the triple bottom line (i.e., economic, social, and environmental) [14,15,133–135].

In a study performed by Di Matteo, et al. [136], their results suggested that being able to review trade-offs among solutions can minimize biases at the decision-making stage. According to Coleman's finding [79], some private landowners favored small-scale GSI practices over community-wide alternatives, as they were more focused on addressing local issues rather than collective actions. On the other hand, some GSI practices are more likely to provide better performance if used in tandem [79,137], which could further complicate the multi-sector performance monitoring processes. Of particular note was that social performance was considered a critical factor for enhancing multi-sector funding opportunities and the adoption of GSI [68,138]. Further studies are needed on the influential social features that affect the development of GSI to resolve the knowledge gaps among the public and to elucidate major social restraints (e.g., demographics and ruling regulations). Demographic factors were regarded as the contextual background. Policy enforcement and revision according to the current GSI implementation situation were mainly the responsibility of governmental entities at federal, state, and county levels. The field experts were considered the leading personnel responsible for designs based on the built environment within the region and the outreach for knowledge diffusion. Compared to the households that prioritize individual benefits, the local community tracks the inter-connective components. Despite the efforts invested into understanding the influence of the social environment on GSI implementation, only limited research studied individual behaviors at the system level to identify the most potentially effective approach to increase social acceptance at a regional scale [139].

3.3. Applied Agent-Based Modeling in Quantitative Decision Support

Tremendous research has addressed the hydraulic and hydrological and economic uncertainties of GSI, yet social contextual factors remain under-studied given its complexity and challenges in quantitative analysis. Our work reviews and analyzes the most identified social barriers including governance inconsistency, low public participation, and demographic constraints from the consequential behavior patterns by incorporating knowledge in cognitive biases. Table 2 presents the most relevant frameworks that qualitatively assist in decision support for GSI implementation. They brought forth early attempts to solve the social dilemma identified in Table 1 through various degrees of active public engagement, collaborative governance regimes, and strengthened knowledge transfer among stakeholders. A new conceptual framework (Figure 3) was proposed to take into consideration such barriers on their potential impacts on the adoption of GSI.

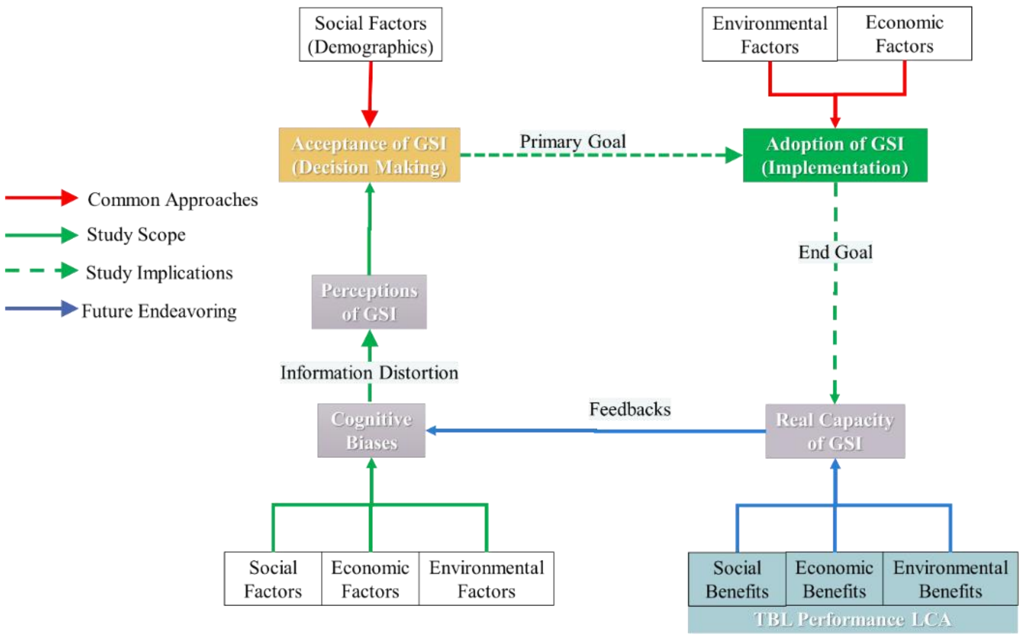

Figure 3. The conceptual framework proposed in this study.

Policymakers are usually required to make science-based decisions and actions by which they need to provide transparency in their prediction of the expected impacts of their decisions [111]. Hence, further efforts are needed to provide evidence-based quantitative analysis to gain advanced insights on practical decision support. Existing quantitative decision support tools used to simulate or evaluate GSI performance rely on the assumption of rationality, omitting the potential interference to the outcomes due to cognitive biases. For instance, several multi-criteria decision-making (MCDM) support systems made of decision support tools (DSTs or DSSs) have gradually incorporated as many relevant factors as possible [132].

Despite their capacity in being able to address multiple criteria, these decision support tools for GSI implementations have limited considerations on the potential cognitive biases, which could result in less effective strategies implementation. For instance, a study indicated that individual bias has various effects on the organization's objectivity in both positive and negative directions and distort individuals' process of creating, retaining, and transferring knowledge. Their study results suggested that for a system with high complexity, reducing individual bias may not necessarily enhance the objectivity of the organization. Thus, it is wise to examine specific social systems when developing cost-effective mediation strategies in case of simulating individual biases [74]. Psychological- and sociological-based behavioral rules have been adopted in ABM by macroeconomics since the 1960s [140]. As reviewed by Bharathy [77], the combination of an understanding of human behaviors and systems thinking is crucial for successful decision-making. Their study identified the research niche on human behavioral modeling with an emphasis on the coordination among stakeholder groups in different fields. Despite being unable to truly reflect on realistic situations, human behavioral models can still assist decision-makers in the understanding of social systems. However, the models that are developed solely based on social and physical science are usually fragmented in their fields, rely on qualitative analysis, or are difficult to incorporate into quantitative models. For models with agents to behave more realistically, one must expand their study scope to incorporate the models developed in social sciences (such as psychological and cultural studies). Limited research was able to accomplish this task [77].

In terms of complexity among available DST, ABM is more robust at detailed micro-level simulation than qualitative studies, yet less dependent on sophisticated mathematical logic than some quantitative models, such as system dynamics. This methodology can simulate global emergent patterns/social consequences by setting up only individuals' characteristics and behaviors. ABM is better at capturing the non-linear interactions between human behaviors based on various factors and the macro-environment through feedback effects and at explaining the collective outcomes resulted from a given set of interactions among individuals. So far, the primary use of ABM for policy decision support has primarily been in the fields of sociology, epidemiology, and urban planning [75,114,141–143].

The theory of innovation diffusion was developed to conceptualize innovation adoptions through communication channels over time, which are determined by individuals' personal and social characteristics in a social system, and the decision-making logic of individuals regarding the associated social changes [144]. ABM is advantageous at micro-level simulations that can account for the heterogeneity and autonomy of individuals during the innovation diffusion process to a greater extent in comparison to aggregate-level models. Kiesling, et al. [145] conducted an extensive review on ABM applied in this theory, which has been used for two main purposes: To advance the theoretical development, and to forecast outcomes for decision support using empirical data. Similar to other simulation models, ABM has its own limitations. To date, no ABM framework has been widely agreed on for innovation diffusion due to the diverse selections of sub-theories, parameters, and equations to interpret the adoption processes. The two major challenges are: The lack of capability in capturing opinion changes as models generally assume a binary decision switch from a non-adopter to an adopter with a presumption of global success as the final outcome [115]. Therefore, there is a research need to continue extending and revising the existing ABM framework to better simulate more realistic innovation diffusion, particularly water-related infrastructure due to the pressing issues highlighted in the background section of this article.

Though different in prior aims, the use of ABM to assist in decision support for diffusing innovative water-saving technologies shares similarity in the general concepts with GSI technology diffusion in terms of the simulations and behavior rules. Therefore, studies conducted on innovation diffusion of water conservation were reviewed in this section as well (Table 3).

A few studies have applied ABM to analyze isolated influences of certain demographic, household, social, and external factors on water conservation technology adoption. However, they failed to take into account the potential simultaneous influence of these attributes on agents' acceptance decision making. One empirical-data-driven study argued that ABM was favorable in simulating innovation diffusion than the Bass model and cellular automata for its greater capacity in incorporating heterogeneity of agents and explicit special relationships [146]. The statement was also supported by another study [40]. Another study discovered a research gap on the observed disagreement between the overall numbers of the households that indicated their wills to adopt certain water conservation technologies and the number of the populations that implemented said technologies. They suggested it could be due to the additional costs and motivation required to install these inventions into one's household. They used ABM to simulate the innovation diffusion process by the state transition approach as mentioned in the previous section. Their results shed light on the importance to consider various characteristics of the communities when developing intervention strategies for the effective adoption of water-saving technology by households such as income growth, water pricing structure, the cost of rebated programs compared to the affluence of the community, and social network connections [40].

One study based in Germany [146] adopted the integrated ABM approach to combine the theoretical aspects of innovation diffusion, social psychology, sociology, and decision theory to enhance the accuracy of realistic decision-making processes using an empirical study of diffusion of water-saving technologies. This model contributed to an advanced decision-making process during water-saving innovation diffusion. On a different aspect during the adoption process, few researchers have developed ABM models that are capable of incorporating the dynamics between public adoptions that are affected by changes in demands for resources and services and infrastructure expansion. A study [115] approached the issue through an ABM framework, which simulated the perception changes in risks/benefits of water reuse during the course of infrastructure expansion by incorporating the theory of risk publics to simulate the social networks. It overcomes several limitations of cognitive models and diffusion of innovation models because the risk publics theory is relatively more comprehensive in reflecting real decision making compared to other existing theories in that it assumes definitive connections among agents who held similar opinions about the risk/benefits of a technology based on a social psychology approach. This work is one of the few that applied social psychology-based ABM in innovation diffusion for water reclamation among households and has the potential to be adopted for decision support for GSI implementation.

Note that the review in this study is limited to the research works conducted solely through ABM. However, there have been several studies that used hybrid simulation models as a decision support tool in water infrastructure management. For instance, Faust, et al. [147] developed a hybrid quantitative system dynamics-ABM framework to investigate the water demand dynamics in shrinking cities. This type of hybrid model showed its advantages in capturing the sophisticated socio-technical interactions within the human-infrastructure system through feedback loops compared to using ABM. On the other hand, simulations of cognitive biases using ABM have been explored on various types of cognitive biases, such as risk aversion, confirmation bias, motivated reasoning, cognitive filtering within social science, and economy domains [148–152]. These scholarly contributions can be substantially beneficial in driving insightful decision support tools for GSI implementation that reflect realistic public opinions and actions.

Table 3. Innovative strategy diffusion in water management using ABM.

Simulation Objectives	Agents	Behavior Rules	Social Networks	Time Step	Platform	Calibration, Verification & Validation	Novelty/Advantages	Limitations	Location	Source
Water consumption behaviors	Households	Reversible stochastic diffusion of opinions, Bass' model of innovation diffusion	Random graph	Three-month (10 years)	Java	Calibration with empirical data, face validation	Integrate geographical, cultural, and socioeconomic factors with ABM for decision support in water demand	Requires exhaustive efforts into interdisciplinary empirical validation, demands advanced expertise and computation power to embed GIS into ABM	Valladolid (Spain)	[153]
Flood risk communication strategies effectiveness	Households	Protection motivation theory	Stochastic with predefined connection rules	Yearly (7 years)	NetLogo	Calibration with empirical data and sensitivity analysis	Simulates micro-level diffusion of information for flood risk communication	Requires sufficient empirical data to minimize uncertainty	Rotterdam-Rijnmond (Netherlands)	[154]
Adoption of water reuse measures	Households	Risk publics ABM framework	Small-World	Yearly (30 years)	Not specified	Calibration with historical data and sensitivity analysis, validation through comparing results from another model	Captures opinion dynamics and adoption decisions on water reuse innovations under various infrastructure expansion scenarios	Assumes several parameters of fixed values, simulates at the unitary household level, limited capacity in capturing opinion dynamic resulted from external factors	Town of Cary, NC	[115,155]
Innovation processes in urban water infrastructure systems	Water supplier, water consumers, sewage system operator, technical components producer	Bounded rationality with utility functions	Simplified structured models	Yearly (50 years)	Not specified	Not specified (theoretical development only)	Captures the transition patterns of water supply infrastructure influenced by interactions of multiple stakeholder groups	Lacks of agent heterogeneity of simulated stakeholder groups, omits some relevant stakeholder groups	Not specified	[156]
Spatiotemporal emergence of GSI	Residential property owners	Probability-based GSI adoption rules	Simplified structured models	Monthly (30 years)	NetLogo	Calibration with historical data	Simulates micro-level spatiotemporal adoption rates of two GSI practices determined by physical compatibility and socio-economic factors	Requires expertise in collecting, characterizing, and modeling with the relevant data, the behavioral rules need further data collection to reflect the decisions made under various constraints and conditions	Philadelphia, PA	[139]
Effect of various factors on residential water conservation technology adoption	Households	Innovation diffusion, affordability theory, peer effect	Various (random, distance-based, ring lattice, small-world, and scale-free)	Yearly (20 years)	AnyLogic	Calibration with historical data, internal validation with sensitivity analysis, external validation through comparison with similar studies' results	Explored the influence of various social factors, social networks, and water policies on water conservation technology adoption under	Fails to capture all impactful demographic factors due to data limitations and potential feedback mechanisms through dynamic factors	City of Miami Beach, FL	[40]

Table 3. *Cont.*

Simulation Objectives	Agents	Behavior Rules	Social Networks	Time Step	Platform	Calibration, Verification & Validation	Novelty/Advantages	Limitations	Location	Source
Diffusion of water-saving innovations	Households	Innovation characteristics, Theory of Planned Behavior, lifestyles, decision theory	Small-World	Monthly (14 years)	Java	Calibration with empirical data, validation with independent empirical data	Simulates the diffusion of water conservation technology among households (heterogeneous agents) based on two decision algorithms and driven by empirical data	Sensitive to the values set to categorize households based on lifestyles, model accuracy can be improved by adding other economic factors	Southern Germany	[146]
GSI adoption optimization	Water utility, local community organizations, and property owners	Probability-based rules	\	Quarterly (30 years)	NetLogo	Calibration with historical data	Simulates multi-agent simulation of GSI adoption based on physical compatibility and socioeconomic factors with undergoing synergistic infrastructure transitioning and ownership scenarios	Relies on numerous yet reasonable assumptions	Pint Breeze, PA	[157]
Assessments of the long-term resilience of water supply infrastructure	Users, agencies, wells, stressors, wastewater treatment plant	Bounded rationality and regret aversion, stochastic processes, consequential impacts of the other two agents	\	Yearly (100 years)	AnyLogic	Internal verification through component verification assessment, external verification through tracing, calibration with empirical data, face validation	Provides insights on theoretical, computational, and practical decision support for water supply infrastructure resilience under various scenarios of sea-level rise and adaptation strategies	Omits the salinity fluctuation caused by overexploited freshwater aquafer, and other adaption solutions by households	Miami-Dade County, FL	[158, 159]

4. Conclusions and Recommendations

The burgeon urbanization and rapidly increased impervious surfaces have led to the increment of runoff volumes and peak flows casting burdens on existing stormwater management infrastructure. Conventional gray infrastructure utilizes a centralized management approach to control stormwater through treatment facilities or direct discharge into receiving water bodies bypassing the treatment process. It is environmentally inadequate in modern societies as climate change has gradually intensified its impacts worldwide. On the contrary, GSI exploits decentralized natural processes to treat stormwater runoff at its source, which also provides additional benefits to the community contributing to urban resilience and sustainability. However, it still faces various barriers to GSI implementation in the US mainly due to existing presumptions that can lead to a lack of funding allocation. Conceptual frameworks are directing tools that can be used to standardize GSI project planning. There is an urgent need for inclusive decision support tools to better evaluate the perceptions of private landowners (homeowners and renters) of GSI so as to devise effective intervention strategies for encouraging GSI implementation. This can minimize the erroneous perceptions of GSI of the stakeholders, compared to the existing gray infrastructure. This paper made the first attempt to bring forth the connections between such social barriers to GSI implementation in the US and the potentially linked cognitive biases that had hampered rational decision making, which few studies have set their research efforts on. The authors acknowledge the limitation of this review regarding the connections due to its novelty in relevant research fields applied in GSI adoption, particularly the three biases chosen in this review. Further interdisciplinary discussions are encouraged to strengthen the research efforts on this topic to drive evidence-based local data analysis in addition to systematic analyses of these cognitive biases among stakeholder groups.

On the other hand, despite their capacity in being able to address multiple criteria, the existing decision support tools omitted some common cognitive biases which could result in less effective strategy implementation as pointed out in an article [74]. Various scholarly publications reached an agreement on ABM's robusticity in simulating individual-level decision-making processes. Thus, this paper reviewed quantitative analysis for decision support to promote innovative strategies in water management for long-term resilience. Yet there have been no ABM models developed to approach the well recognized social factor-related biases in GSI adaptation using the social-psychological approach of innovation diffusion. Thus, we proposed a conceptual framework to bridge this disconnection as shown in Figure 3. In this framework, assumptions of the presence of biases could be safely made if differences are recognized between the empirical data on households' perceptions of GSI, thus the acceptance and adoption and simulated results using the common mathematic theories in a multi-agent model. To further advance the realistic simulation of socio-infrastructure systems such as GSI implementation processes, future efforts should be made to incorporate the complex opinion dynamics due to cognitive biases into advanced hybrid models to explore the interdisciplinary interactions on a broader scale that have not yet been well examined for implementing innovative strategies of water infrastructure systems.

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