

Exploring the influential factors of residents' attitudes toward implementing green infrastructures for stormwater management in the US

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ABSTRACT

Although green infrastructures (GIs) have been gaining increasing popularity, their widespread adoption in the US has been limited. To encourage wider implementation, understanding residents' attitudes toward GIs and the factors influencing their decisions in implementing such measures is crucial. This study employed a systematic review approach and a regional survey to identify these influential factors (IFs) and investigate their spatial patterns over the past 20 years. The systematic review targeted previous US survey studies to summarize the IFs at the national and regional scales. The e-survey was conducted in the Northeastern US to further investigate residents' willingness to adopt GIs regarding different types and cost settings. The systematic review highlighted age, homeownership, and annual income were key IFs at the national scale. Furthermore, environmental awareness and flood risk perception were additional IFs on the East Coast. Our e-survey revealed that these factors had varying effects across different types of GIs and cost settings. For instance, "flood experience" is more significant when GIs are provided for free, and "employment status" is more significant when GIs are not provided for free. These findings provide comprehensive insights for governments in developing stormwater management policies that consider residents' perceptions and adoption of GIs.

1. Introduction

Green infrastructures (GIs) comprise a network of natural, semi-natural, and engineered components that are designed and managed to provide multiple ecological, social, and environmental benefits (Choi, Coyner, Kalpathy-Cramer, Chiang & Campbell, 2020; Kim & Song, 2019; Tzoulas et al., 2007). These benefits include, for instance, reducing the runoff amount by integrating GIs with existing infrastructures (Damodaram et al., 2010; Hood, Clausen & Warner, 2007), especially in urban areas, providing recreation and greenery areas (Cinderby & Bagwell, 2018), fostering physical and psychological benefits among people (Kim & Miller, 2019), and enhancing the air and water quality (Jayasooriya, Ng, Muthukumaran & Perera, 2017).

Implementing GIs in both public (e.g., parks and streets) and private spaces (e.g., residential areas) is vital to obtain broader benefits from GIs in stormwater management (Federal Emergency Management Agency [FEMA], 2022). Since 80 % of the land in the US is owned by private individuals (Eno, Dyche & Mass, 2006), the ways in which the government encourages residents to utilize their lands for implementing GIs become critical. Over the past decade, there have been many efforts

from different levels of the government to increase GI implementation in the US (Meerow, Helmrich, Andrade & Larson, 2021). For example, in terms of public spaces, the Environmental Protection Agency (EPA) collaborated with communities in 2011 at the federal and state levels and provided technical assistance and grants to support GI implementation within communities in Maryland and Washington, DC (EPA, 2011; EPA, 2013). Similarly, city governments have undertaken endeavors at the local level. For instance, New York City's NYC Green Infrastructure Plan has created initiatives such as the Bluebelt Program to enhance the water quality and reduce the effects of the combined sewer system in the city via bioswales (New York City Department of Environmental Protection, 2021). There have also been some initiatives for implementing GIs in private places. For instance, the City of Philadelphia launched the Green City, Clean Water program in 2011 to reduce the runoff volume entering the combined sewer system and enhance stormwater management by encouraging the implementation of GIs on residents' properties (Philadelphia Water Department, 2023). In Chicago, the West Chicago Environmental Commission provides discounted rain barrels to residents as part of its initiative to promote rain barrel implementation on private properties (Environmental

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Commission, 2023).

Several previous studies have highlighted one key aspect of these programs that can successfully encourage GI implementation on private lands: a better understanding of residents' perceptions toward GIs (e.g., Ando & Freitas, 2011; Montalto et al., 2013; Shandas, 2015). Venkataramanan et al. (2020) conducted a systematic review by focusing on the knowledge, attitudes, and intentions of residents, government workers, and other experts about GIs. The authors advocated the importance of performing further studies to investigate residents' perceptions toward GI implementation at a global scale. To this end, several studies have evaluated the statistical relationship between different socioeconomic, demographic, and environmental influential factors that might affect residents' perceptions toward GIs and their decisions to implement them. Different methodologies have been adopted in these previous studies, such as the interval data model (Newburn & Alberini, 2016), the ordered logit model (Ureta, Motallebi, Scaroni, Lovelace & Ureta, 2021), principal component analysis, and logistic regression (Baptiste, Foley & Smardon, 2015). Usually, GIs with different cost settings, such as free, at a cost, and with or without a government rebate, have been one of the research focuses in the literature (e.g., Ando, Cadavid, Netusil & Parthum, 2020; Bowman, Tyndall, Thompson, Kliebenstein & Colletti, 2012; Newburn & Alberini, 2016; Ren, Zia, Rizzo & Mathews, 2020). In addition, assessing residents' willingness to pay (WTP) to support or participate in GI programs (Hunter, 2011; Wong-Parodi & Klima, 2017), exploring the perceived value of GI benefits from the perspective of residents (Brown et al., 2020; Miller & Montalto, 2019), and investigating the spatial difference of residents' perceptions toward GIs (Conway et al., 2021; Spahr, Smith, McCray & Hogue, 2021) have also been popular research topics in the literature. However, there was no systematic summary of spatial pattern of these influential factors at the national scale. Also, whether there is a spatial scale effect in these influential factors (i.e., the same pattern might exist at the national, regional, and local levels) is still unexplored.

To address these knowledge gaps and advance our understanding of the human dimension of GI implementation, this study aimed to investigate patterns of regional socioeconomic factors and other factors (e.g., flood experience) that might affect residents' perceptions and decisions toward GIs implementation. We first conducted a systematic review of the previous survey studies in the Contiguous US regarding residents' perceptions toward GIs and then used the results to identify spatial (ten regions in the Contiguous US) patterns and distribution of influential factors that affect residents' willingness to adopt GIs and temporal (2011–2021) pattern of the studies' number that conducted on this topic. We then distributed an e-survey that included other influential factors (e.g., flood risk preparedness) within the Greater Lehigh Valley (GLV) area, located in Eastern Pennsylvania and Western New Jersey, to investigate residents' perceptions toward GI implementation and compare our results with those of other survey studies that have been conducted in the same or nearby regions to explore the spatial scale effect.

The rest of the paper is organized as follows. In Section 2, we describe the methods and procedures used for the systematic review, including article identification, screening, and inspection processes. In Section 3, we outline the e-survey structure and the methods used to analyze our survey data and examine the significant factors that play a role in residents' decisions to adopt GIs. In Section 4, we discuss the factors that influence residents' decisions to adopt GIs at the national scale (resulting from the systematic review) and discuss the significant regional factors (resulting from both our e-survey and the systematic review). We discuss the policy implementation at two scales (national and regional) in Section 5 and draw conclusions in Section 6.

2. Systematic review on survey studies for the contiguous US

We conducted a systematic review of survey studies that have attempted to explore residents' perceptions toward GI implementation

based on journal articles published in the Web of Science database between January 1990 and February 2022. Three steps were used in the systematic review process: identification, screening, and inspection (Staples & Niazi, 2007). First, our search primarily used three terms related to GIs and their synonyms: green infrastructure, low-impact development, and sustainable stormwater management. In addition, we used three words to describe the methods used to evaluate residents' perceptions toward GIs: survey, interview, and questionnaire. By combining these two groups of keywords, we used nine phrases for the article identification step: "green infrastructure" & "survey"; "green infrastructure" & "interview"; "green infrastructure" & "questionnaire"; "low impact development" & "survey"; "low impact development" & "interview"; "low impact development" & "questionnaire"; "sustainable stormwater management" & "survey"; "sustainable stormwater management" & "interview"; and "sustainable stormwater management" & "questionnaire". This first step, article identification, resulted in 470 articles.

Next, we used four screening criteria to select the candidate articles. In the first criterion, we focused on the articles that had study areas only inside the Contiguous US. Second, we removed articles that had used surveys and/or interview results for other purposes, such as reviews, modeling, and experimental studies. Third, we removed any duplicates or very similar articles published by the same group of authors for the same study areas. Finally, since we focused on residents' perceptions, we removed articles that had conducted surveys or interviews with government officials, experts, and engineering companies. This second step, article screening, resulted in 28 articles.

Finally, we conducted a detailed article inspection of these 28 articles to better understand the spatial distribution of the influential factors (e.g., age, income, and flood experience) on residents' decisions to adopt GIs. The basic information of these 28 articles, e.g., authors, titles, study areas, research purposes, and sample sizes, are available in Supplementary Material (Table S1). In these survey studies, we tried to identify the significant factors that were either positively or negatively correlated with GI implementation. To better organize our results, we grouped these common factors into five influential factor groups (IFGs). **IFG1: Demographic and socioeconomic status**, which included factors such as gender, age, and annual income. **IFG2: Flood experiences, losses, and risk perceptions**, which are influential factors related to the frequency (e.g., time) and magnitude (e.g., amount of loss) experienced by previous flood-affected residents and their future flood risk perceptions (e.g., a belief that a flood will have a negative impact in the future). It is a common practice in the literature to relate flood experiences and losses faced by residents with their changes in attitudes and intentions toward adopting mitigation measures (Ureta et al., 2021). Additionally, flood risk perception has a crucial effect on residents' behaviors, attitudes, and decisions to prepare for the next flood by adopting flood mitigation measures (Liu, Li, Li & Chen, 2022). **IFG3: Flood preparedness**, in which we investigated residents' preparedness for future floods by assessing elements such as their flood insurance status. **IFG4: Environmental awareness**, in which we investigated residents' beliefs in the importance of stormwater management and the responsibility of different entities. Environmental awareness has been assessed in several ways in the literature. These include identifying a flood as a problem in residents' cities (Ureta, Motallebi, Vassalos, Alhassan & Ureta, 2021), responsibility for reducing the runoff generated from residents' houses to protect streams (Newburn & Alberini, 2016), expressing concerns about flood issues on residents' properties (Conway et al., 2021), and expressing interest in stormwater management (Spahr et al., 2021). **IFG5: Knowledge about GIs and the effects of social norms**, in which we investigated residents' familiarity with GIs. This component was assessed by asking them the following example questions: "Had they seen GIs before?" (Ureta et al., 2021). "Had they had the opportunity to choose between GIs and gray infrastructure as the best solution to handle stormwater management?" (Spahr et al., 2021). Additionally, the effects of social norms, which examine the impacts of a

group's norms on others' feelings and behaviors, were investigated by examining how neighborhood behaviors in adopting GIs influenced others' perceptions of these measures (Farrow, Grolleau & Ibanez, 2017; Marmur, 2022).

In Section 4, the resulting significant factors on the residents' GI implementation decisions will be geographically visualized based on the FEMA regional distribution of the US (FEMA, 2022). FEMA divides the Contiguous US into ten regions: regions I, II, III, and IV represent the East Coast; regions V, VI, VII, and VIII represent the middle of the US; and regions IX and X represent the West Coast.

3. E-survey about residents' perceptions toward GIs in the Northeastern US

3.1. Study area and survey structure

The East Coast regions in the US are preparing for looming high-frequency and extreme rainfall patterns (Lewellyn & Wadzuk, 2019). Consequently, it is imperative to take the right steps and increase the region's resilience by implementing flood control measures. We thus conducted an e-survey study in the GLV to enrich the current literature that has examined residents' perceptions of these measures. The GLV region includes the Eastern part of Pennsylvania and the Western part of New Jersey in the US and is considered a typical "bedroom community" in the Northeastern US, where the majority of residents are white (83.6 %) and have their own houses (68 %) (US Census Bureau, 2021). A lot of residents in GLV commute to nearby big cities, such as New York and Philadelphia, for work daily (Lehigh Valley Contractors Association, 2023). Our survey's questions draw from one of our prior studies conducted by Cheng et al., 2017 in Michigan US that addressing residents' risk perception and preparedness for climate change (e.g., Q7 and Q9 in Table 1) and from previous studies to investigate the spatial distribution of the influential factors that affect the residents' decision to implement GIs (e.g., Q14 in Table 1). Additionally, we introduce questions to explore additional influential factors to provide a more comprehensive view (e.g., Q17, Q18, and Q31 in Table 1). In our study, we employ a stratified sampling technique where participants are randomly selected from predetermined categories. We collected a random sample while maintaining an equal representation of females (50 %) and males (50 %). This sampling method was previously utilized in a range of environmental surveys (e.g., Toftager et al., 2011 and Zhang et al., 2014). The e-survey was distributed via the Qualtrics platform, in January 2022, to 1414 residents in the study area. A total of 400 people completed the survey, with a 28.3 % response rate, close to the average response rate (33 %) for an e-survey (Shih & Fan, 2009). We removed 15 responses from the survey due to quality control issues (e.g., short response times and illogical responses) which resulted in 385 responses in our final analysis. This final sample size gave us a margin error of ± 5 % under a 95 % confidence level, given that the total population of GLV is about 825,000 (US Census Bureau, 2021).

Our survey questions (Supplemental Material, Text S1) were designed by following the IFGs summarized from the systematic review (Table 1). The first group (IFG1) included questions about respondents' demographic and socioeconomic information, such as their gender, age, educational attainment, annual income, employment status, and homeownership. This information allowed us to double-check whether our survey samples fit the overall demographic and socioeconomic patterns in our study area and provided the most fundamental characteristics of residents.

The second group (IFG2) included questions regarding residents' past flood experiences, losses, risk perceptions, and other general stormwater-related topics (e.g., the preferred method to receive flood warnings). We asked the respondents to indicate the most recent time they had experienced a flood. Those who had not experienced a flood were assigned the code 1, while those who had experienced the last flood less than a year ago were assigned the code 2. A progressively

Table 1

The influential factor groups, associated survey questions, and data types used in this study.

Influential factor group (IFG)	Individual influential factor description	Question number in the e-survey	Data type
IFG1-Demographic and socioeconomic status	Gender	Q37	Binary
	Age	Q38	Categorical
	Annual income	Q40	
	Educational attainment	Q41	Binary
	Homeownership	Q44	
IFG2-Flood experiences, losses, risk perceptions	Employment status	Q42	
	Flood experience	Q3, Q5	Categorical
	Flood losses	Q4, Q6	
	Flood risk perception in the next 10 years (house scale)	Q7	
	Flood risk perception in the next 10 years (city scale)	Q9	Binary
IFG3-Flood preparedness	Collecting stormwater fee (house scale)	Q17	
	Collecting stormwater fee (city scale)	Q18	
	Flood insurance	Q10	Categorical
IFG4-Environmental awareness	Weather forecast	Q11	
	Stormwater importance in their community	Q14	Binary
	Responsibility to cope with climate change	Q20	
IFG5-Knowledge about GIs and the effects of social norms	GIs vs. gray infrastructure to handle stormwater	Q15	Binary
	Having GIs already installed on the property	Q26	
	Trust in GIs in mitigating stormwater (house scale)	Q32	Categorical
	Trust in GIs in mitigating stormwater (city scale)	Q33	
	Effect of neighbors' behaviors (social norms)	Q31	

higher numerical value indicated a longer time since experiencing the last flood, with the highest code being 7, denoting the respondents who had experienced a flood 30 years ago. We evaluated the flood losses by asking the respondents to indicate the frequency of their loss exposure. The respondents who had not suffered from flood losses were assigned the code 1. Respondents with the highest frequency of loss exposure were assigned the code 6, indicating that they had suffered from flood losses seven or more times. Also, to assess the residents' flood risk perceptions, they were asked to indicate their answer to the following question on a seven-point Likert scale: "Did they expect to experience a flood in the next ten years at the house and city scales?" (extremely unlikely were coded as 1 and extremely likely as 7). This measure of flood risk perception was influenced by the definitions established in previous studies that have defined risk perception as the evaluation of the probability of a hazardous occurrence and its associated negative impacts (Becker, Aerts & Huitema, 2014; Grothmann & Reusswig, 2006). We asked these questions in two different spatial scales because the respondents' answers enabled us to not only examine the relationships between flood risk perceptions, residents' attitudes, and their willingness to adopt GI but also to investigate how residents' perceptions toward GIs change at the house and city scales.

In the third group (IFG3), we asked questions about residents' preparedness for the next flood event by checking whether they had or intended to buy flood insurance, whether they agreed to pay a stormwater fee at the house and city scales, and whether they paid attention to the weather forecast. The flood preparedness assessment encompassed

different factors, including whether the respondents already had or intended to buy flood insurance (coded as 1) or not (coded as 0). Also, we asked them to indicate their level of agreement on a seven-point agreement scale about paying a stormwater fee based on impervious areas to mitigate floods at the house and city scales and whether they paid attention to the weather forecast on a seven-point Likert scale (strongly disagree or extremely unlikely were coded as 1 and strongly agree or extremely likely were coded as 7).

The fourth group (IFG4) included questions about respondents' environmental awareness, such as their attitudes toward their responsibility to cope with climate change. This environmental awareness was determined by asking the respondents how important stormwater management was in their communities and their agreement on their communities' responsibilities to cope with climate change. The quantification of responses in this group was based on a seven-point importance scale and a seven-point agreement scale (extremely not important or strongly disagree were coded as 1 and extremely important or strongly agree were coded as 7).

The fifth group of questions (IFG5) was designed to assess respondents' knowledge of GI implementation and the effects of social norms. Since one of the goals of our study was to investigate the factors that affect residents' decisions to implement GIs in their properties, we asked the respondents whether they had already implemented GIs on their properties (coded as 1) or not (coded as 0). Additionally, we asked them to select the preferred infrastructure for stormwater management. If a respondent's answer was GIs or a combination of GIs and gray infrastructure, we coded it as 1, and if they only preferred gray infrastructure, we coded it as 0. Lastly, we asked the respondents to rate their confidence level in the effectiveness of GIs to handle stormwater at their house and city scales (extremely unlikely was coded as 1 and extremely likely was coded as 7). We also examined the effects of social norms by asking the respondents to rate their feelings, using a seven-point scale, based on the premise that their house was the only one without any GI implementation (very bad was coded as 1 and very good was coded as 7). Similar to the questions in IFG2, we asked the respondents to answer the question about the effectiveness of GIs across different scales to acquire more spatial information on their perceptions toward GIs.

Finally, to assess the residents' willingness to implement GIs on their properties, we asked the respondents to indicate their willingness to adopt two types of GIs (rain garden and rain barrel), given two cost settings (free or not free). When the GIs were provided for free, we used a seven-point Likert scale to quantify their willingness, and when they were not provided for free, we used cost ranges to quantify their WTP. The cost range of a rain garden was from below \$100 (coded as 1) to over \$2000 (coded as 7), and the cost range of a rain barrel was from below \$50 (coded as 1) to over \$200 (coded as 7). The answers to these questions were used as the dependent variables for the analysis and were linked to the influential factors in the five aforementioned IFGs.

Table 2 compares two GI types used in this study (i.e., rain garden and rain barrel). It outlines differences in scale of implementation, cost, and other characteristics. Moreover, these GIs showed notable stormwater reduction efficiency. For instance, Rezaei et al. (2019) found a 27 % runoff reduction from rain gardens for a 70 mm rainfall event, while Litofsky and Jennings (2014) reported up to a 40 % reduction using rain barrels. Among other GI types, Imran, Akib and Karim (2013) showed that permeable pavements significantly reduce both the volume and peak of runoff. Similarly, Woznicki, Hondula and Jarnagin (2018) reported that bioswales installed at a residential scale effectively lowered both runoff volume and peak flow rates. These studies underline the diverse capabilities of GI measures in stormwater management.

3.2. Survey data analysis

Our survey aimed to better understand residents' perceptions toward GI implementation and the relationship of such behaviors with influential factors. To this end, we adopted two methods: the ordered logit

Table 2
Comparison between rain gardens and rain barrels.

Feature	Rain gardens	Rain barrel
Definition	A management practice where a planted depression is used to soak up the stormwater runoff coming from impervious surfaces such as roofs and driveways. (Putri, Hidayah & Ma'ruf, 2023)	A storage container to collect and store the rainwater from the roofs. (Putri et al., 2023)
Implementation scale	House and community	House
Usage	No direct usage of the processed water	Potential direct usage of water stored
Benefits	-Reduce the stormwater quantity.(Kumar & Singh, 2021; Zhang, Xu, Liu & Zhou, 2021) - Improve the water quality.(Jeon et al., 2021) - Recharge the groundwater.(Austin, 2012) -Reduce the erosion. (Austin, 2012) -Other ecosystem and biodiversity benefits such as improving the habitat for wildlife and preserving natural vegetation. (Shafique & Kim, 2017)	- Reduce the stormwater quantity. (Litofsky & Jennings, 2014) - Provide a source of water for landscaping and gardening (Tamaddun, Kalra & Ahmad, 2018) - Reduce the erosion. (Steffen, Jensen, Pomeroy & Burian, 2013)
Cost	Depends on the complexity of the design (e.g., area and landscaping)	Generally, have lower cost and depends on the size of the barrel

regression model (OLR) and an artificial neural network (ANN) to develop models and predict the residents' behaviors concerning GI implementation using the most significant influential factors. These two methods have been commonly used in previous studies for similar tasks (Aditian, Kubota & Shinohara, 2018; Kalantar, Pradhan, Naghibi, Motevalli & Mansor, 2018). The OLR is considered the most appropriate statistical method if the outcome variable has ordinal order, such as the seven-point Likert scale used in our survey (Kramer, 1996; Pohlmann & Leitner, 2003). Furthermore, it has been demonstrated that ANNs show enhanced efficacy and increased accuracy when predicting human behavior (e.g., Lamb, Annetta, Hoston, Shapiro & Matthews, 2018; Weber, Weber, Goesele & Kabst, 2018). In this study, the dependent variables were the residents' intention or willingness to adopt/implement or not adopt/implement GIs on their properties, and the independent variables were 23 influential factors, as shown in Table 1. Additionally, a *t*-test is utilized to compare differences in the mean value between the same variable in two questions (e.g., residents' flood risk perception at the house scale vs city scale), whereas the Pearson correlation coefficient is employed to evaluate the linear correlation between the variables.

An ANN is a machine learning algorithm that has been inspired by the simplification of neurons in the brain (Choi et al., 2020). Compared to the OLR, an ANN assumes a nonlinear association between dependent and independent variables, enabling it to effectively capture complex relationships among the variables (Althubiti, Kumar, Goswami & Kumar, 2023). ANNs comprise units of input, hidden, and output layers, with each having many nodes. A shallow ANN usually encompasses one input layer, 1–2 hidden layers, and one output layer. The number of nodes depends on the input data and the number of predicted classes in the input and output layers (Aggarwal, 2018). The activation function in the hidden layer depends on the output range (West, Brockett & Golden, 1997). We used a shallow ANN model with one input layer and one hidden layer (i.e., this study used optimal hidden layers), and one output layer. Also, we had 23 nodes (corresponding to 23 pre-selected influential factors) in the input layer, six nodes in the hidden layer (i.e., the

optimal number of nodes in this study), and seven nodes in the output layer. We adopted Softmax activation in the hidden layer, which is a generalization of the logistic regression to predict the categorical output, such as the seven-Likert scale (Munkhdalai, Ryu, Namsrai & Theera-Umpon, 2021). We also applied the permutation importance technique for ANN analysis to estimate the variable importance by dropping one variable at a time and then computing the corresponding change in the model accuracy (Altmann, Tološi, Sander & Lengauer, 2010). The more significant the drop in model accuracy, the more important this variable becomes.

Since the influential factors can vary based on whether GIs are provided for free or not (e.g., due to a government's incentive program), we conducted an analysis by considering two parallel GI cost settings: when GIs were provided for free and when GIs were not provided for free. In the second set (i.e., when GIs were not provided for free), the influential factors that affected the residents' WTP to adopt GIs were used as proxies for their decisions. Since we had two GI cost settings and two types of GIs (rain garden and rain barrel) and we used two methods to build the prediction models of residents' decisions to adopt GIs, in total, we developed eight (2^3) models to predict residents' decisions. In each

model, we used 70 % of the data as a training set and 30 % as a testing set. By comparing the results of these eight models, we could identify the most significant influential factors under different methods, GI cost settings, and GI types.

4. Results

4.1. Systematic review

4.1.1. Spatial and temporal patterns of survey studies in the US

Fig. 1 uses a bar chart to show the temporal pattern (Fig. 1a) and a map to show the spatial distribution (Fig. 1b) of the systematic review results. From Fig. 1a, we can observe that the interest in this topic (i.e., exploring residents' perceptions toward GI implementation) was sparked in 2011, in the middle of the US, and was then followed by the East Coast in 2014 and the West Coast in 2015. There has been an increasing trend in the amount of research conducted on this topic since 2011, indicating that scholars have been increasingly drawn to investigating residents' perceptions toward GIs and their willingness to adopt these measures in all regions. Fig. 1b shows the spatial distribution of the

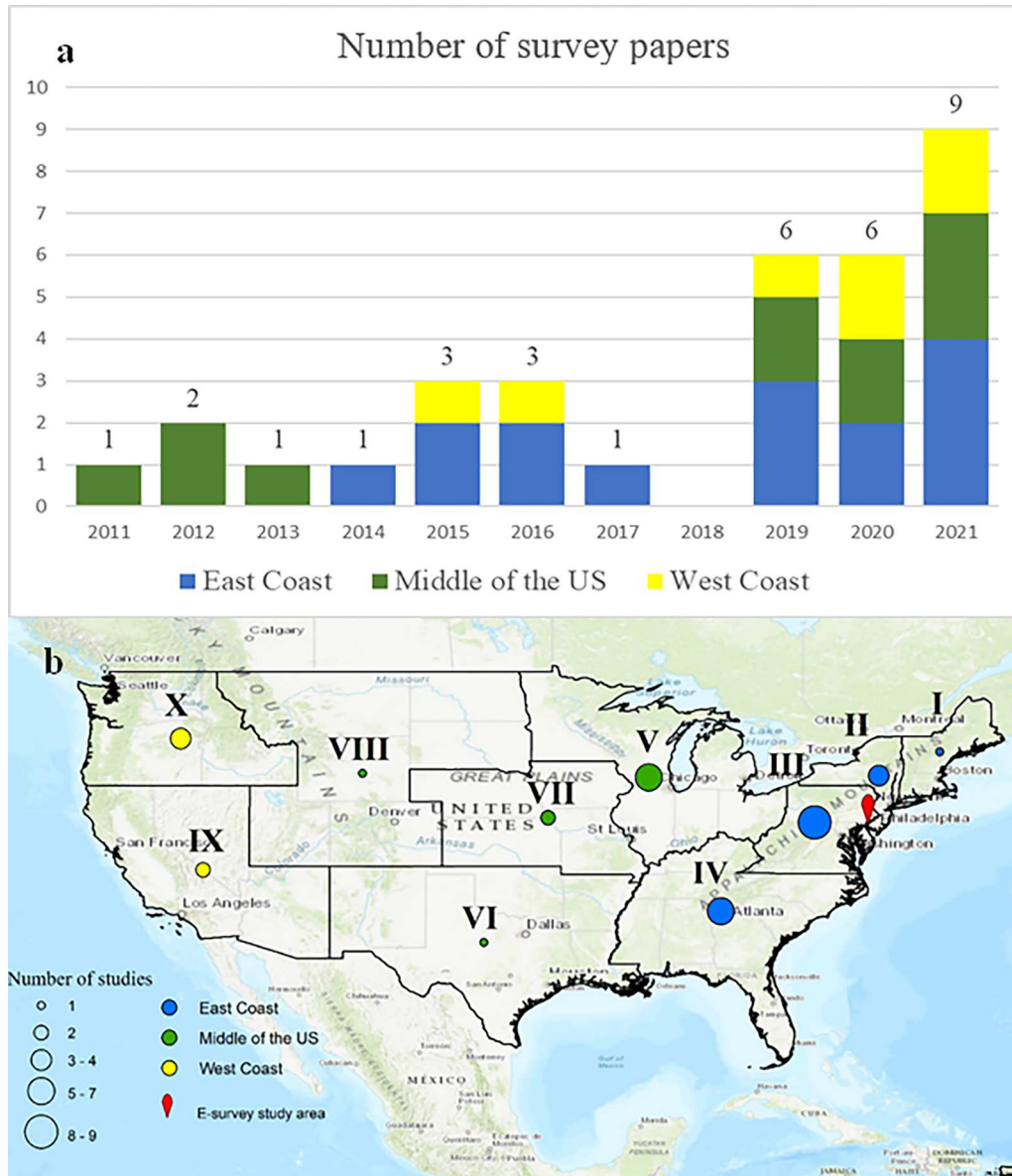


Fig. 1. (a) Temporal and (b) spatial distribution of the 28 reviewed studies that resulted from the systematic review.

28 articles, and the circle size in the map represents the number of studies in each region. The number of studies shown on the map is higher than 28 because some of these studies had conducted surveys in more than one study area. About half of the studies (45.5 %) were conducted in the East Coast (regions I–IV); this pattern implies that more attention was given by the governments and academic fields to these regions. This number is followed by the middle of the US (33.4 %, regions V–VIII) and the West Coast (21.1 %, regions IX and X). These spatial and temporal patterns are consistent with previous studies, which have concluded that urban flooding issues are more commonly observed on the East Coast (Lewellyn & Wadzuk, 2019). Therefore, it came as no surprise that almost half of the survey studies were conducted in these regions. However, due to the impacts of climate change, Midwest and West Coast have also encountered more urban flooding issues in recent years (Corringham, Ralph, Gershunov, Cayan & Talbot, 2019; Slater & Villarini, 2016). This could possibly be the reason why we see an increasing number of survey studies on residents' perceptions toward GI implementation, especially on the West Coast.

4.1.2. Common influential factors affecting residents' perceptions toward GI implementation

Fig. 2 summarizes the common influential factors from the 28 reviewed articles that affect residents' perceptions and willingness to implement GIs. As mentioned earlier, different methodologies, GI types, and cost-related settings have been used to examine the factors affecting residents' willingness to implement GIs through different survey studies. Fig. 2 summarizes the most significant factors from these survey studies regardless of their analysis methods used, GI type, or cost setting.

Three influential factors were commonly observed at the national scale: older residents usually (but not always) hesitated to implement GIs. Previous studies on elderly populations' pro-environmental behaviors (e.g., adopting GIs) have revealed conflicting results. Prokopy, Floress, Klotthor-Weinkauff and Baumgart-Getz (2008) found that elderly people were less likely to engage in these behaviors, while Wang, Hao and Liu (2021) found that they were more willing than younger people. The reasons for this difference could be attributed to older people's relatively fixed mindset and trust in gray infrastructure for stormwater management, higher trust in the industry than nature to solve the problem (Wright, Caserta & Lund, 2003), and the "attitude-behavior gap," where younger people may show higher willingness but not translate that into actions (Wang et al., 2021). A higher annual income and homeownership usually had a positive effect on GI implementation, which could be attributed to the homeowners' liberty in deciding whether to make changes to their properties and the financial security of those with a high annual income, which would have allowed them to afford GI implementation costs if needed. We also observed some regional differences from the results. Environmental awareness and future flood risk perception were two common positive influential factors in the East Coast. This result implies that outreach efforts from

the government or academia to educate the public about the negative effects of future flood hazards, including the residents' taking responsibility for mitigating floods, might prove more effective in promoting GI implementation in the East Coast. In addition, male residents seemed to have more positive attitudes in the East Coast compared to the other regions. Previous studies have presented conflicting results on the association between gender and pro-environmental behaviors. While some studies have suggested that females exhibit more pro-environmental behaviors than males (e.g., Kennedy & Kmec, 2018; McMillan, Hoban, Clifford & Brant, 1997), others have suggested the opposite (e.g., Kollmuss & Agyeman, 2002). The socialization theory suggests that women are more environmentally concerned due to socialization processes, whereas men prioritize economic growth over environmental issues (Zelezny, Chua & Aldrich, 2000). Some influential factors were only identified in one or two regions from previous studies. For example, education level only affected the residents in regions VII (Great Plains) and IX (Pacific Southwest). This could be because higher education levels contribute to more educated people with greater knowledge about environmental issues (Shandas, 2015; Meyer, 2015; Wang et al., 2022). Previous flood experiences affected residents' perceptions in regions IV (Atlantic Southeast) and V (Upper Midwest). This may be due to the fact that respondents in these regions reported a higher frequency of flood experience compared to the other regions (Londono Cadavid & Ando, 2013).

These results contribute to a better understanding of the national and regional trends regarding the influential factors. They also highlight specific regions, such as VI, VIII, and X, that require targeted research to gain further insights into residents' perceptions toward GIs, thus addressing a national knowledge gap. Moreover, this study identifies factors that have not yet been extensively studied, such as flood loss and flood experience, indicating the need for further investigation into these aspects.

4.2. E-survey

4.2.1. Survey result summary

Fig. 3 shows the demographic characteristics and socioeconomic status of the final 385 responses, which is a summary of IFG1. Almost an equal number of responses were received from both females and males. The mean age in our sample was 47–48 years, and the mean annual income among the respondents was \$67,000–\$68,000. Most of the respondents (about 85 %) were white. Furthermore, about 60 % of the respondents were employed, and about 70 % owned homes (with or without a mortgage or loan). Regarding the education level, about 37 % had high school diplomas, 26.4 % had a college or associated degree, 23.7 % were bachelor's degree holders, and 11.1 % had a graduate degree. According to the latest census data, these results were more or less comparable with the general demographic characteristics and socioeconomic status in the GLV (US Census Bureau, 2021). However, we

Region	Influential factors	Flood loss	Annual income
I	 (18)  (18)  (18)		
II	 (16)  (16)  (16)  (8)  (16)		
III	 (10,16) (23)  (10,16,23) (16)  (16)  (10)  (12)  (12)		
IV	 (16,24)  (16,24) (16)  (16,24)  (24)  (24)  (24)  (22)		
V	 (16)  (16)  (16)  (16)  (16)		
VII	 (2)  (2)  (2)  (2)  (2)		
IX	 (7)  (7,26)  (26)  (7)  (26)		

Fig. 2. Systematic review results of common influential factors on residents' GI implementation perception in different regions. "+" means a positive effect and "-" means a negative effect. The superscripts correspond to the ID column of Table S1 in Supplementary Material.

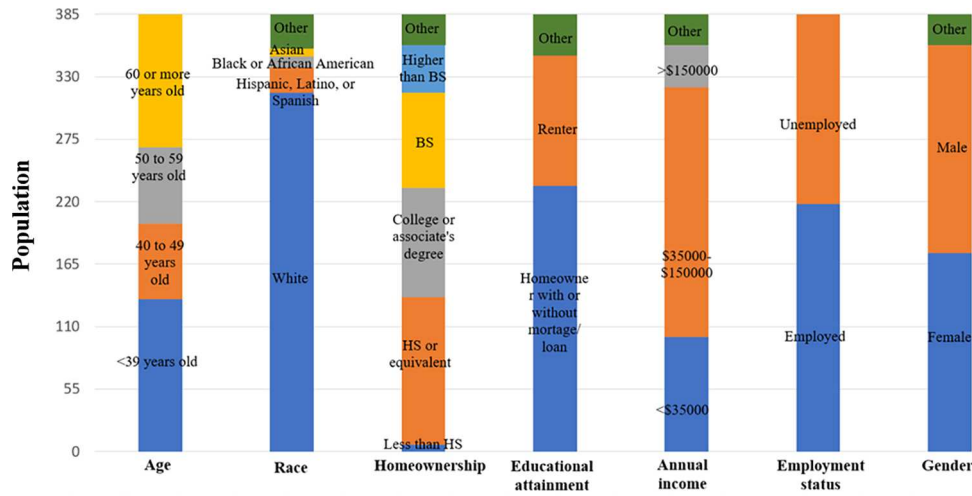


Fig. 3. Demographic characteristics and socioeconomic status of the 385 survey samples in the GLV (HS denotes high school degree holders and BS bachelor's degree holders).

did observe some differences. For example, our sample overrepresented the respondents between 30 and 39 years (i.e., 24.8 % compared to 13.2 % from the census data). Additionally, we slightly overestimated the proportion of the white population (i.e., 82.2 % compared to 68.5 % from the census data) and underestimated the percentages of Hispanic, Latino, and Spanish populations (i.e., 2.5 % compared to 9.1 % from the census data). Finally, our samples also overrepresented the number of bachelor's degree holders (i.e., 23.5 % compared to the census data). Nevertheless, these minor discrepancies did not have a significant impact on our subsequent analyses, as we did not focus on any particular race or education level for our findings.

Regarding IFG2, our survey results showed that 44.2 % of the respondents had never experienced floods at their properties. Moreover, about 23.8 % experienced floods less than a year ago, and 21.2 % experienced floods 1–5 years ago. Most of the respondents (73.2 %) had not suffered from flood losses because they did not always cause damage to their properties. About 22.3 % and 3.4 % had suffered from flood losses 1–2 times and 3–4 times, respectively. Results also show that respondents' flood risk perception has a spatial scale discrepancy at the house and in the city. According to the *t*-test result, Fig. 4a indicated that the respondents had a significantly ($p < 0.01$) higher expectation of having a flood in their cities (mean value from the seven-point Likert scale: $M = 4.58$) compared to their houses ($M = 3.52$) in the next 10 years. This can be explained by the spatial optimism phenomenon, which causes people to underestimate the hazard risk occurrence at a small scale, such as their house, and overestimate the risk at a larger scale, such as their city (Milfont, Abrahamse & McCarthy, 2011). The same pattern has been captured by many studies at different scales for

different environmental hazards (Fleury-Bahi, 2008; Gifford et al., 2009).

In terms of flood preparedness (IFG3), 54 % of the respondents did not have flood insurance. While 23 % were planning to purchase one in the future, 13.7 % had flood insurance and were planning to keep it. Moreover, 2.6 % had flood insurance and were planning to stop it, with 6.7 % being uncertain about their insurance status. The mean and standard deviation values regarding paying attention to the weather forecast on the seven-point Likert scale were 5.27 and 1.59, respectively, indicating that the residents paid greater than average attention to the weather forecast when there was a chance of flooding. Regarding the residents' agreement level to pay stormwater fees, Fig. 4b shows that the residents have a low willingness to pay a stormwater fee based on the impervious areas to reduce floods at either the house scale ($M = 3.34$, $SD = 1.73$) and city scale ($M = 3.39$, $SD = 1.73$). Also, we do not find any significant difference between the residents' willingness to pay a stormwater fee at these two spatial scales.

In terms of environmental awareness (IFG4), our survey results showed that most of the GLV residents believe that stormwater management is a crucial issue and needs to be addressed in their cities. About 56.6 % of the respondents answered 6 and 7 on the seven-point Likert scale to the question, and the mean value and standard deviation were 5.49 and 1.31, respectively. Similarly, 61.2 % of the respondents recognized their responsibility for coping with climate change (i.e., they answered 6 and 7 to the question), with mean and standard deviations values of 5.6 and 1.45, respectively, on the seven-point Likert scale. These results indicate that most of the respondents in the GLV showed high environmental awareness.

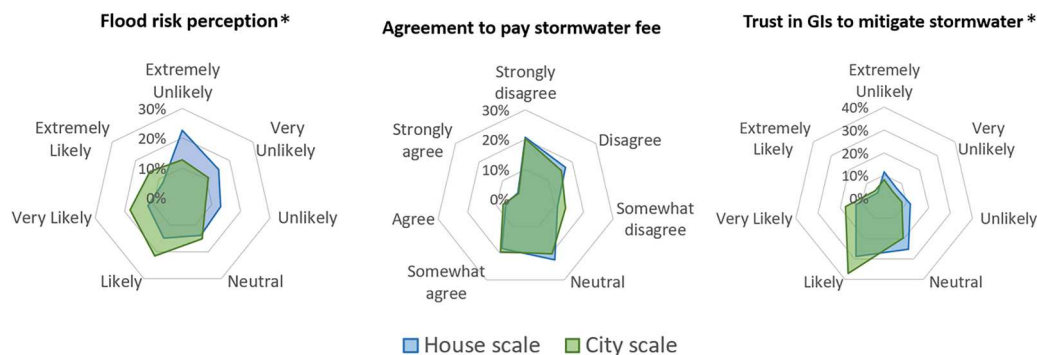


Fig. 4. Discrepancy in spatial scales (house vs city) regarding the residents' responses in (a) flood risk perception; (b) agreement to pay stormwater fee; and (c) trust in GIs to mitigate stormwater. “*” indicates a significant difference ($p < 0.01$).

Regarding IFG5, our survey results showed that about 43.8 % of the respondents trust that gray infrastructures are good solutions for addressing stormwater management issues. While 37.9 % considered a combination of gray infrastructure and GIs as a good solution, 2.4 % had other responses (e.g., “nothing” and “I don’t know”), and 15.9 % of the respondents preferred GIs for stormwater management. This result indicates that at least half ($37.9\% + 15.9\% = 53.8\%$) of the respondents think GIs can help in stormwater management. However, our *t*-test results also find a spatial scale discrepancy in respondents’ trust in the efficacy of GIs in mitigating stormwater at their house and at the city scale. Fig. 4c shows that respondents’ trust on GIs efficacy is significantly higher at the city scale than at the house scale ($p < 0.001$). Given that about half (43.8 %) of the respondents still believe that gray infrastructure is adequate for managing flood and stormwater issues and that most residents think GIs are more effective in mitigating stormwater impact somewhere else in the city rather than on their properties, it was not surprising to discover that most of the respondents (79.5 %) had not installed any GIs. Among those who had already installed GIs (20.5 %) on their properties, the majority had rain barrels (accounting for 7.8 % of the total response), followed by rain gardens (at 6.2 %). Additionally, 2.1 % of the total respondents had both rain gardens and rain barrels on their properties, and other types of GIs made up 4.4 % of the total response. Regarding the social norms effect, our survey found that 11.43 % of the total respondents had positive feelings if they were the only households in the community without any GIs installed. About half of the respondents (53.77 %) were indifferent, and about 34.8 % of the total respondents had negative feelings. These results indicate that while it is not a very strong influential factor, social norms do have some impact in promoting GI implementation.

Before developing the predictive models of residents’ behavior on GI implementation, we explored the correlation among the influential factors in these IFGs. Fig. 5 shows the correlation coefficient values (−1 to +1) of all the 23 influential factors that were compared to each other. Some very clear correlations were found between the influential factors targeting the same topic (e.g., flood experience) but with different details, such as flood experience and loss caused by different sources (i.e., thunderstorm or snowstorm), flood risk perceptions at different spatial scales (i.e., city and house scales), and attitudes toward stormwater fee at different scales. We also observed some correlations between the influential factors either within (i.e., the same question but at different spatial scales) or among the different IFGs. For example, previous flood losses (Q4 and Q6 in IFG2) had a positive correlation with flood risk

perception at the house scale (Q7 in IFG2) and the willingness to buy flood insurance (Q10 in IFG3), implying that those who had experienced flood losses before at their properties were more likely to have a higher flood risk perception and consider flood insurance in the future. Higher flood risk perception (Q7 and Q9 in IFG 2) had a positive correlation with buying flood insurance (Q10 in IFG3), paying additional attention to the weather forecast (Q11 in IFG3), and believing in the importance of stormwater management in their community (Q14 in IFG4). These results might indicate those with a higher flood risk perception were more prepared and more likely to cooperate with the city’s stormwater policy than those with a low flood risk perception. Unsurprisingly, residents’ agreement to pay a stormwater fee (Q17 and Q18 in IFG3) and their belief in their responsibility to cope with climate change effects (Q20 in IFG4) had a positive correlation with their trust in the efficacy of GIs at the household and city scales (Q32 and Q33 in IFG5). Despite these observations, the r^2 value of these correlations was not particularly high (the greatest value was $r^2 = 0.87$ between the stormwater fee agreement at different scales (i.e., city and house scales); therefore, we will be using all 23 influential factors for our statistical analysis in the next section.

4.2.2. Survey results—statistical analysis with the OLR and ANN

As described in the methodology section, we used the OLR and ANN to develop prediction models and predict the residents’ behaviors regarding GI implementation. Fig. 6 shows the results of the OLR and ANN, demonstrating the impacts of the influential factors on the two types of GI implementation (rain garden and rain barrel) under two different cost settings: when GIs were provided for free (Free) or not (WTP). The comprehensive statistical results of the OLR can be found in Supplementary Material (Tables S2 and S3).

The first result we observed was that regardless of the cost setting and analysis method adopted, the influential factors affecting the implementation decisions on the two GI types were very similar. This means that once the residents decided to implement GIs, the choice of GI type was not affected by most of the influential factors we considered in the survey, except for homeownership (IFG1) and social norms (IFG5) that positively affected rain barrels implementation. Thus, understanding the importance of stormwater management and climate change responsibility (IFG4) might have a positive effect among residents on rain garden implementation. Among the 13 common influential factors shared by the two GI types, previous flood experience (IFG2) was positively correlated with both types of GI implementation.

Although these results align with previous studies showing a positive

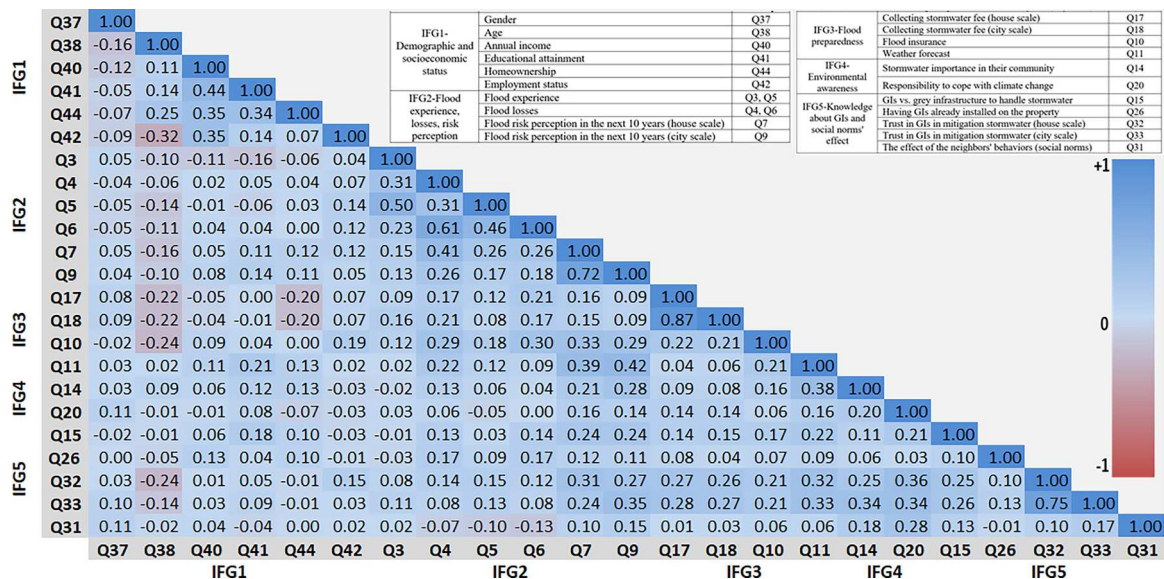


Fig. 5. Correlation coefficient of the 23 influential factors among the five IFGs.

Group	OLR				ANN				 Flood loss  Flood experience  Responsibility to cope with climate change  Stormwater importance  Trust in GIs efficacy at a city scale  Flood insurance  Social norm  Pay stormwater fee to reduce flood at house scale  Pay stormwater fee to reduce flood at city scale	 Paying attention to the weather forecast  Selecting GIs as a solution to solve stormwater management  Flood risk perception at a house scale  Having GIs  Gender  Elder participant  Annual income  Education attainment  Homeowner  Employment status
	Rain garden		Rain barrel		Rain garden		Rain barrel			
	Free	WTP	Free	WTP	Free	WTP	Free	WTP		
IFG1-Demographic and socioeconomic status	 -	 +	 -	 +		 -  +  +		 -  +  +		
IFG2-Flood experience, loss, and risk perception	 +		 +		 +		 +  +	 +  +		
IFG3-Flood preparedness		 +		 +  +		 +  +		 +		
IFG4-Environmental awareness					 +  +	 +  +				
IFG5-Knowledge about GIs, and social norms' effect	 +  +  +	 +	 +  +  +	 +  +	 +  +	 +	 +  +	 +  +  +		

Fig. 6. The OLR and ANN results show the factors influencing residents' decisions to implement two types of GIs on their properties, given two different cost settings: GIs were provided for free (Free) or not (WTP).

relationship between flood experiences and the adoption of GIs (Londono Cadavid & Ando, 2013; Ureta et al., 2021), a study by Ando and Freitas (2011) reported an exception, where flood experience did not significantly increase GI implementation in Chicago, potentially due to regional climatic variations affecting flood patterns and severity.

The second result we observed was the effect of cost settings on GI implementation. We found that many factors significantly influenced residents' decisions to adopt GIs regardless of the cost setting; for instance, recognizing the responsibility to cope with climate change (IFG4) and installing existing GIs on their properties (IFG5). We also observed that different influential factors became significant when different GI cost settings were used. When GIs were provided for free, choosing between GIs or a mix of GIs and gray infrastructure to handle stormwater issues (IFG5) became an additional significant factor; on the other hand, when GIs were not provided for free, annual income (IFG1), employment status (IFG1), and educational level (IFG1) became additional significant factors. These results make good sense because when cost is a concern, residents' financial status affects their GI implementation decision; however, when cost is not a concern, other factors such as choosing GIs to handle stormwater become significant. Our findings align with studies in the literature (e.g., Wang et al., 2022 and Newburn & Alberini, 2016), revealing that homeowners and those earning middle income levels show a higher WTP for GIs.

The influential factors identified by different methods were compared to obtain the third set of results. We observed that the most influential factors identified by the OLR also showed up in the ANN results. However, some additional influential factors were only identified by the ANN. In the ANN results, previous flood loss (IFG2) was the common influential factor across different GI cost settings and GI types. Also, flood risk perception at the house scale (IFG2) had a positive effect on the implementation of both types of GIs when they were provided for free. It was discovered that environmental awareness (IFG4) had a positive impact on rain gardens; social norms (IFG5) had a positive effect on rain barrels; and the education level (IFG1) had a positive effect when GIs were not provided for free. These results are in line with those reported by Marmur (2022), who found that the implementation of permeable driveways, another type of GI, saw a 60 % increase among residents with neighbors who had adopted similar measures, highlighting the strong influence of social norms on GI adoption.

4.3. Comparison between the systematic review results and the e-survey results

Since the systematic review results (Fig. 2 in Section 4.1.2) show that

almost half of the previous survey studies were conducted on the East Coast and mainly located in regions II and III, which is our study area, it provides us with an opportunity to compare our own survey results (i.e., influential factors from either the OLR and ANN in Fig. 6) with these previous results and evaluate whether there a spatial scale effect exist in these influential factors regarding residents' perceptions toward GI implementation (i.e., similar or different patterns at the national, regional and local level). Fig. 7 shows the common influential factors based on both the systematic review and our e-survey at three different spatial scales.

First, our e-survey results showed the same three influential factors (age, annual income, and homeownership) as the national pattern (Fig. 7, US national scale). The alignment further highlights the significance of these factors in influencing GI implementation, implying that any federal efforts on outreach and education to promote GIs that target the elderly, high-income individuals, and homeowners should also be effective in the GLV. When we only focused on regions II and III, where the GLV was precisely located, two additional common influential factors were identified: environmental awareness and trust in GI efficacy (Fig. 7, Mid-Atlantic scale). These results imply that state and local governments in these regions (e.g., Pennsylvania, New Jersey, New York, and Maryland) can put additional efforts into raising residents' environmental awareness, such as distribution of brochures to raise awareness of the impacts of climate change and organizing townhall meetings about how GI can facilitate stormwater management in the municipality to expedite its implementation and progress. We also observed a different pattern in our survey in the GLV compared to other survey studies in regions II and III, which was the gender difference. Our survey results did not show any significant difference in male and female perceptions toward GI. Unsurprisingly, previous studies could also not identify a universal pattern in gender differences toward GI implementation, as we have summarized in Section 4.2 already. Lastly, when we expanded the comparison to the rest of the East Coast (regions I and VI), we identified three additional common influential factors: flood risk perception, flood experience, and employment status (Fig. 7, East Coast scale). According to FEMA's report (FEMA, 2023), region IV is the most flood-prone region on the East Coast. Therefore, it is reasonable that past flood experiences and future flood perceptions will affect residents' perceptions toward GIs. Similarly, several municipalities in the GLV, such as Bethlehem and Easton, have suffered from the impacts of frequent historic flooding due to hurricanes and have been identified by the Pennsylvania Department of Environmental Protection as the highest flood risk municipalities in Commonwealth. Therefore, we observed the same influential factors in the GLV as in region IV.

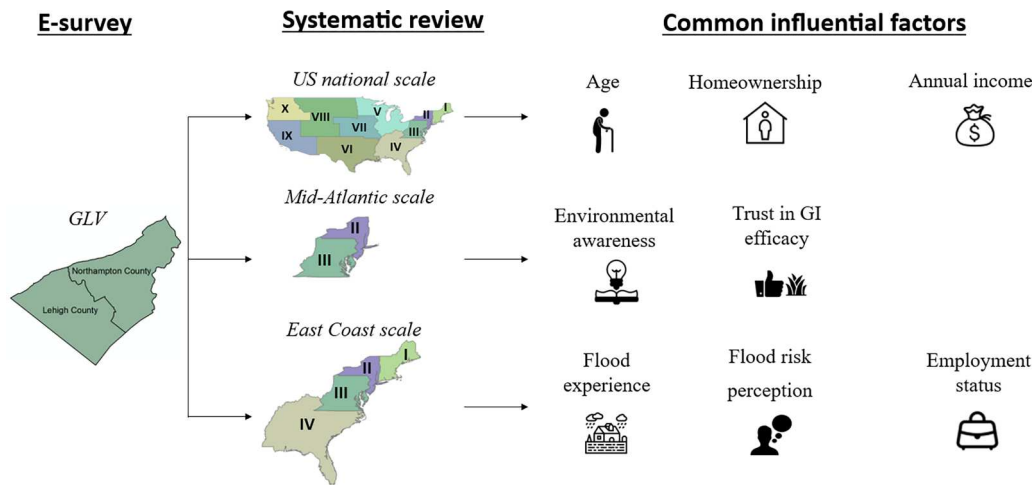


Fig. 7. The common influential factors identified by the e-survey in the GLV compared with results from systematic review at the US national, Mid-Atlantic, and East Coast regions scale.

5. Discussion

5.1. Policy implementation at different scales

The systematic review results provided insights into common influential factors that affect residents' GI implementation decisions at the national scale in different regions, and our e-survey results offered more detailed information on GLV in the Northeastern US. In this section, some policy suggestions on comprehensive GI implementation at different scales will be provided.

The three common influential factors (age, annual income, and homeownership) can provide policymakers with a better understanding of residents' attitudes toward GIs and help increase GI implementation at the national scale. For instance, policymakers might encourage landlords to adopt more GI on their properties by demonstrating how it can raise property values. For example, the addition of 100–200 square feet of rain gardens or swales could increase a property's value by \$950–\$1725, especially in urban areas like Philadelphia where a property is valued at \$250,000 (SB Friedman Development Advisors, 2022).

For Mid-Atlantic, our e-survey results identified additional influential factors that have not been previously identified in region III but in other East Coast regions, such as future flood risk perception and past flood experience and loss. These results enable policymakers to engage with community organizations or utilize flood insurance programs to reach individuals affected by floods. Providing these individuals with sufficient educational materials about GIs could raise their awareness and potentially lead to increase GI installation on their properties.

Additionally, our e-survey results showed two interesting patterns related to two spatial scales: property (house) and city scales. First, residents' flood risk perceptions at the city scale were significantly higher than the risk perceptions at the house scale. Moreover, only flood risk perception at the house scale positively correlated with GI implementation. This might indicate that residents will not adopt GI measures unless they have a high flood risk perception at the scale of their houses. Second, the residents believed that GIs were more effective in mitigating flood impacts when implemented at the city scale but not at their household scale. The observed discrepancies might reflect a gap in understanding regarding the dynamics of stormwater concentration in urban drainage systems. Additionally, there's a potential lack of awareness about the efficacy of small-scale GIs in contributing to the mitigation of city-wide flooding issues. With this information, policymakers can provide residents with maps and educational materials to clarify flood occurrences at their houses and other flood-prone areas in the city and how distributed efforts like GIs can facilitate city-scale

stormwater management through basic hydrologic concepts.

5.2. Limitation and future research

We identify several limitations that can be addressed through future research on related topics in this section. First, future studies can examine survey results conducted by governments (which are usually more comprehensive and at a larger scale) and obtain a better understanding of the public sector's point of view on this topic. Second, the demographic results of our survey samples had some discrepancies compared to the census data (e.g., we underestimated the proportion of Hispanic, Latino, or Spanish populations). This did not affect our results; however, if we need to devise a policy by bearing in mind a specific race, another survey needs to be conducted, which can be addressed by further studies. Third, the influential factors we used in this survey (which are the dependent variables that affect residents' GI implementation) primarily focus on the benefit of GIs as a flood management measure and ignore all other GI benefits such as improving water quality, air quality, and increase the property values (Spahr et al., 2021). As a result, the pattern we observed from the survey outcomes might be biased and missing those residents who want to implement GI but not for flood management purposes. Future studies can conduct a more comprehensive survey and include GIs' benefits from all aspects. Furthermore, we did not employ a validation process to ensure the accuracy of our survey results or to gain a deeper understanding of the reasons behind the residents' responses. Usually, follow-up focus group discussions with a sample of residents after the survey can help us achieve this goal. However, we were not able to do that due to our funding limitations.

In addition to the above limitations, our study only focuses on the US. However, by comparing the findings of our results (Fig. 2 and Fig. 6) with studies conducted worldwide, we can pinpoint the dominant influential factors that significantly impact GIs implementation in different countries. For instance, Yu et al. (2019) revealed that individuals with higher levels of education exhibit a greater willingness to adopt GIs in China. Pagliacci, Defrancesco, Bettella and D'Agostino (2020) summarized that elderly individuals tend to be less inclined to adopt GIs in Italy. Greene, Millward and Ceh (2011) and Ordóñez Barona, Conway and Roman (2021) concluded that higher income levels are associated with a higher likelihood of GI adoption in Canada and the Netherlands, respectively. Moreover, the methodology that we presented in this paper (i.e., literature review compared with a local survey) has the potential to be generalized and can help other countries to identify influential factors at the national, regional, and local levels.

Finally, to further expand on our work in this study, we plan to utilize the survey results to create a coupled agent-based model in the study area (Hung & Yang, 2021; Hyun, Huang, Yang, Tidwell & Macknick, 2019; Lin, Yang, Malek & Adam, 2022) to target stormwater management issues. Since many influential factors affect property owners' decisions to implement GIs, the survey results can help build the coupled model in two aspects. First, we can categorize property owners based on their income levels because, from the survey, we found that income is one of the most significant demographic properties that influence GI implementation. Second, the survey results indicated that flood experiences affected residents' willingness to implement GIs. Therefore, we will simulate the flood frequency that residents encounter in the coupled model, which will affect their GI implementation. The coupled model can help the municipality determine the portion of the funding that should be used to incentivize property owners and meet their specific stormwater reduction goals.

6. Conclusions

Given the multiple benefits of GI for urban stormwater management, governments at different levels have expressed a desire to expedite GI implementation. This study investigated the spatial pattern of the demographic, socioeconomic, and other influential factors (e.g., flood perception and flood experience) that might affect residents' perceptions toward GI implementation at the US national, regional, and local scale. We conducted a systematic review of previous studies that have surveyed residents' perceptions toward GIs over the past 20 years in the US. We also conducted our own e-survey in the GLV, located in the Northeastern US to explore the regional distribution of these factors by comparing them with the systematic review results.

Our systematic review highlights an increasing number of studies on this topic in the US, with the majority concentrated on the East Coast. Additionally, we've identified a consistent trend in the factors that influence the adoption of GIs nationwide. Homeowners and those with higher incomes are generally more likely to adopt GIs, while older adults tend to be more hesitant. Specific patterns are observed across different regions. For instance, on the East Coast, factors like environmental awareness, flood risk perception, and flood experience were common influential factors. This is because East Coast areas, in comparison to other regions, tend to be more susceptible to flooding. The results of our e-survey equipped us with additional details about the influential factors that affect residents' decisions to implement GIs based on the cost settings and GI types in our study area. For example, when GIs were provided for free, a mix of GIs and gray infrastructure to handle stormwater issues was deemed a significant influential factor; however, when GIs were not provided for free, annual income, employment status, and educational level significantly influenced residents' perceptions toward GI implementation. Additionally, e-survey has illustrated the spatial discrepancy in the flood risk perception and trust in GI at house and city scales. These results can be used to understand more how the influential factors can differ across different spatial scales.

Finally, our analysis comparing the systematic review with our e-survey findings indicates that the same three common influential factors identified nationally are also occurred in the GLV. In addition, regional-specific common influential factors were also identified, which can inform targeted stormwater outreach and education policies. The findings of this paper will be expanded in an immediate follow-up study that will attempt to leverage these results to develop an agent-based stormwater management model to quantify residents' GI implementation decisions. This newly developed model is expected to further advance our understanding of urban flooding issues and evaluate distributed flood mitigation efforts, such as GIs, from resident and government perspectives, and guide municipal funding strategies to encourage the property owners to implement GIs to meet the stormwater reduction goals.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.scs.2023.105067](https://doi.org/10.1016/j.scs.2023.105067).

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