AI-Enhanced Stakeholder Engagement for Climate Adaptation: Evidence from Lithuania

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Abstract. Civil engineering faces the dual challenge of decarbonisation and resilience under increasing threat of climate change. While artificial intelligence (AI), machine learning, and digital twins are increasingly applied to optimise design, material reuse, and hazard modelling, most systems remain techno-centric and overlook the human dimensions of adaptation. This article addresses this gap by combining a nationally representative survey of Lithuanian residents (n = 1,013, 2023) with the design of an AI-enabled platform for civil engineering adaptation. The survey captured six domains (hazard experiences, adaptation behaviours, motivational drivers, preparedness levels, institutional linkages, and climate attitudes) providing a behavioural evidence base that reveals how climate concerns and motivations translate into action. The results highlight differentiated motivational pathways, moderate levels of preparedness, uneven institutional communication, and four distinct citizen profiles with specific adaptation probabilities. Building on these insights, the article proposes the Citizen-informed AI for Climate Adaptation (CiA-CA) framework, which systematically maps citizen evidence onto AI system design variables. The framework informs the development of the Lithuanian Construction Materials Reuse Optimization (LSEPO) platform, created under the Civil Engineering Research Centre (CIMC), by integrating hazard-prioritised digital twins, recommender systems with motivational weighting, clustering for personalisation, and preparedness-aware interfaces. Conceptually, CiA-CA advances the integration of behavioural adaptation evidence with socio-technical AI design. Empirically, it provides one of the first nationally representative datasets on climate adaptation behaviours in the Baltic region. Practically, it offers a blueprint for municipalities and industry partners in Lithuania to embed citizen evidence into AI-enabled platforms, with potential transferability to similar European contexts.

Keywords: Artificial intelligence, Climate adaptation, Civil engineering, Civil engineering adaptation, Stakeholder engagement, Behavioural evidence, Human-centred AI, Circular economy

1. Introduction

Climate change is redefining the conditions under which civil engineering systems are designed, built, and maintained. According to the Global Status Report for Buildings and Construction 2024/2025, the sector is responsible for approximately 32% of global final energy consumption and 34% of energy-related CO_2 emissions (UNEP & GlobalABC, 2025). Beyond operational energy, the rapid growth of demolition waste and embodied carbon from construction materials creates systemic pressures that demand new circular solutions (Kovacic et al., 2020; Wynn & Jones, 2022). In response, artificial intelligence (AI), machine learning, and digital twin technologies are increasingly deployed to optimize resource flows, predict hazards, and model resilient infrastructure futures (Rodrigo et al., 2024; Therias & Rafiee, 2023; Iranshahi et al., 2025). Initiatives such as the "D5 digital circular workflow" for material reuse (De Wolf et al., 2024), infrastructure digital twins spanning design through operations (Moshood et al., 2024), and policies incorporating material passports and circular construction material flows exemplify how AI and digital twins are being mobilized globally to optimize resource reuse and reduce waste across the construction lifecycle. While technically sophisticated, current AI tools often omit the human dimensions of adaptation. Several recent studies document these gaps: AI systems for climate evaluation frequently neglect local social-ecological variables and community values (Adaptation Fund, 2025); organizational readiness is shaped not just by capability, but by how individuals perceive limitations, risk, and trust (Übellacker, 2025); and psychological barriers such as transparency, fairness and perceived risk strongly mediate adoption even when technical performance is high (De Freitas et al., 2021; Ghosh et al., 2025).

This article addresses that gap by combining a nationally representative survey of Lithuanian residents (n = 1,013; 2023) with a design blueprint for AI-enabled adaptation support that will be operationalised in the Lithuanian Construction Materials Reuse Optimization (LSEPO) platform under the Civil Engineering Research Centre (CIMC). The survey systematically captured six domains (hazard experiences, adaptation actions, motivational drivers, preparedness levels, institutional linkages, and climate attitudes) providing a behavioural evidence base that explains how concerns and motivations translate (or fail to translate) into action. Crucially, these domains map to design variables (hazard priorities, motivational weights, preparedness-aware interfaces, and user profiles) that can be embedded in decision-support for municipal partners and industry stakeholders in Lithuania, with portability to similar Baltic and Northern-Central European contexts. Guided by research in adaptation psychology and technology adoption, we address four research questions: RQ1: How do citizens' experiences of climate hazards relate to their concerns and reported adaptation actions?; RQ2: Which motivational and perceptual factors are most strongly associated with different types of adaptation behaviours?; RQ3: How do preparedness and institutional contact influence the translation of concern into action?; and RQ4: In what ways can these behavioural insights be operationalised as features and profiles for AI-enabled adaptation platforms?

The remainder of the article proceeds as follows. Section 2 reviews the literature on AI and digital twins in civil engineering, behavioural adaptation, sustainability-oriented recommender systems, and trustworthy/ participatory AI. Section 3 outlines the survey design and analytical approach. Section 4 reports results aligned with RQ1-RQ4. Section 5 situates the findings in the international literature and develops the CiA-CA framework into a concrete blueprint for LSEPO deployment. Section 6 concludes with contributions, limitations, and directions for longitudinal validation and live pilots with municipal and industry partners.

2. Literature Review

Recent scholarship has explored how AI and digital twin technologies can advance civil engineering by improving predictive modelling, optimising material flows, and supporting transitions to circular construction systems. Applications range from hazard simulation and resilience planning to life-cycle analysis and secondary material markets (Iranshahi, Zhang, & Xu, 2025; Therias & Rafiee, 2023; Wynn & Jones, 2022). These tools are noted for their ability to generate multiple alternatives, balance objectives (e.g., cost and carbon), and support decisions at scales beyond human capacity (Rodrigo, Omrany, Chang, & Zuo, 2024). However, most of this work has concentrated on technical optimisation, with comparatively limited attention to the behavioural and social conditions that shape adoption.

Behavioural research has consistently shown that citizens' responses to climate risks depend not only on technical feasibility but also on perceptions, motivations, and institutional trust. Theories such as the *Theory of Planned Behaviour* and the *Value-Belief-Norm framework* underline the role of attitudes, perceived control, and normative values in shaping adaptation choices (Ajzen, 2020; Stern, Dietz, Abel, Guagnano, & Kalof, 1999). Empirical studies confirm that risk perception and efficacy beliefs are key predictors of whether individuals act on climate concern (Van Valkengoed, Perlaviciute, & Steg, 2024). Psychological distance and climate anxiety further influence outcomes: climate change is often seen to affect "others" or future generations, while anxiety can either mobilise or inhibit action depending on efficacy and preparedness (Clayton, 2020; Kühner, Schäfer, & Wamsler, 2025). Longitudinal studies also highlight the mediating role of institutional trust and perceived preparedness in the concern-action link (Wong-Parodi & Rubin, 2024). Together, this evidence shows that adaptation behaviour is contingent on socio-cognitive factors. Yet these insights are rarely operationalised into data structures that could inform AI-enabled civil engineering platforms, leaving a gap between behavioural evidence and system design.

In parallel, recommender systems research demonstrates the value of personalisation in promoting sustainable choices. Personalised decision support has been shown to increase the acceptance of pro-environmental actions compared to generic campaigns, particularly when recommendations align with user motivations and values (Debnath, Chattopadhyay, & Ray, 2025; Sander, 2025). Multi-objective optimisation approaches allow such systems to balance criteria such as adoption probability, carbon reduction, financial savings, and equity (Satinet, De Wolf, & Reisch, 2025). However, most implementations stop short of linking behavioural survey data to computational pipelines. While conceptual calls for personalised sustainability tools are common, few blueprints exist for translating motivational profiles or preparedness gaps into feature vectors and objective functions in civil engineering contexts. In addition, trust and participation are also central to the AI adoption in public-facing systems. Scholars and policymakers emphasise that for AI to gain legitimacy it must be transparent, explainable, and accountable (Albahri et al., 2024; Agbabiaka, Haque, & Afolabi, 2025). OECD guidance similarly stresses citizen engagement and governance mechanisms that ensure fairness and accountability (OECD, 2025). Research in human-centred AI shows that uptake depends not only on accuracy but also on alignment with user values and well-being (Sebestyén, 2025; Shin & Lee, 2025). Yet much of this literature remains normative, offering principles without empirically grounded variables that platforms can use to adapt interfaces and recommendations.

Finally, existing participatory AI frameworks face well-documented limitations. Many remain confined to small-scale pilots or experimental case studies, raising questions about scalability when applied across national or international contexts (Bryson & Theodorou, 2019; Jasanoff, 2020). Others encounter inclusivity gaps, since engagement processes often attract digitally literate or already motivated participants, while more vulnerable or less-connected populations (those typically most at risk from climate impacts) are underrepresented (Birhane et al., 2022). Furthermore, these frameworks often emphasise aspirational principles such as transparency, fairness, and accountability, but provide limited methodological guidance on how behavioural variables such as motivations, preparedness, or trust can be systematically translated into system design logics (Shneiderman, 2020; Rahwan, 2018). This results in a persistent gap between what participatory AI advocates in theory and what can be operationalised in practice.

Together, these strands of literature underscore the need for socio-technical approaches to civil engineering adaptation, which this study develops through empirical survey evidence and AI design.

3. Methods

3.1 Study Design, Sample and Data Collection

This study was designed to address four research questions (RQ1-RQ4) on how citizens' hazard experiences, motivations, preparedness, and institutional contact relate to adaptation behaviors and how these insights can inform AI-enabled civil engineering design. To generate the necessary evidence, a nationally representative survey of Lithuanian residents (n = 1,013) was conducted in October-November 2023. The questionnaire, originally developed by Brink and Wamsler (2019), was adapted to the Lithuanian context using a back-translation procedure to ensure conceptual equivalence. The analysis focuses on six domains that provide direct inputs for AI-supported adaptation: (i) Hazard experiences: self-reported exposure to storms, floods, heatwaves, cold spells, mould, or coastal flooding (measured as Yes/No); (ii) Adaptation actions: grouped into four categories: *technical* (e.g., installing flood barriers, retrofitting windows/roofs), *social/organisational* (e.g., helping neighbours, joining community preparedness initiatives), *institutional* (e.g., contacting municipalities, participating in public meetings), and *ecosystem-based* (e.g., tree planting, garden adaptation).

Each reported adaptation action was recorded in binary form, distinguishing between those who had undertaken the measure (coded as 1) and those who had not (coded as 0). From these items, indices were constructed for each domain (technical, social, institutional, ecosystem-based) by calculating the proportion of actions undertaken within that category. In addition to actions, several attitudinal and contextual measures were included. Motivational drivers were captured across four dimensions: economic ("I act because it saves money"), ecological ("to protect nature"), social ("to help the community"), and ethical ("because it is the right thing to do"). All were measured using five-point Likert scales ranging from low to high importance. Preparedness was assessed through a single item asking respondents to rate their ability to cope with climate hazards, also on a five-point scale (1 = not at all prepared, 5 = very prepared). Institutional contact was measured by whether respondents reported having received information on climate risks from municipalities or other public bodies (Yes/No). Finally, climate attitudes were measured using two indices: general concern about climate change and climate-related anxiety, both rated on five-point scales. To account for heterogeneity in the population, the survey also collected socio-demographic variables including age, gender, education, income, and place of residence. These variables provided the basis for examining group-level differences in adaptation behaviour and for informing AI-driven segmentation and personalisation.

The survey used a multistage stratified random sampling method, ensuring representation by geography (urban/rural), gender, age, education, and occupation. Data were collected through face-to-face interviews across 31 cities and 43 villages. The sample was balanced by gender (54% women, 46% men) and broadly reflected national population structures in age, income, and education. All fieldwork was conducted by *Baltijos tyrimai*, following ESOMAR guidelines and EU standards for survey research. Participation was voluntary, informed consent was obtained, and all responses were anonymized and securely stored.

3.2 Analytical Approach

Survey data were analysed using Python (pandas, numpy, scipy.stats). Analyses were organised around the four research questions. For RQ1, descriptive statistics were used to summarise the proportion of respondents reporting exposure to storms, heatwaves, flooding, and other hazards, and regression models tested whether hazard experience was associated with higher concern and a greater likelihood of adaptation actions. For RQ2, adaptation behaviours were examined by calculating the frequencies of technical, social, institutional, and ecosystem-based measures, and regression models estimated how different motivational dimensions (economic, social, ecological, ethical/other) predicted these behaviours. For RQ3, preparedness was analysed as an intermediate variable linking motivations to actions, and municipal information was examined as a potential moderator of the concern-action relationship. These associations were tested using mean comparisons, ANOVA, and regression models with interaction terms. For RQ4, population heterogeneity was explored through clustering analysis. A four-class solution was selected based on fit statistics and interpretability, and predicted probabilities of each adaptation action were calculated for each class to identify distinct citizen profiles relevant for AI personalisation.

Instrument reliability was confirmed with Cronbach's alpha (overall $\alpha = 0.92$; subscales 0.76-0.80). Missing data were minimal (<2% per item) and addressed using multiple imputation by chained equations, with listwise deletion applied as a robustness check. Survey weights were applied to correct for small deviations from national population distributions. These procedures ensured that the analyses rested on a validated and representative evidence base suitable for translating behavioural patterns into AI design features.

4. Results

The results are presented in line with the four research questions (RQ1-RQ4), moving from hazard exposure, through motivational drivers and mechanisms, to population profiles that inform AI personalisation.

RQ1. Hazard exposure and adaptation responses*. A significant minority of Lithuanian households has already been affected by climate hazards. The most frequently reported experiences were storms and strong winds (11.4%) and temperature extremes (8.3%), with smaller proportions reporting flooding (4.6%) or humidity-related mould (3.7%), and coastal flooding virtually absent (0.1%). Table 1 summarises these findings. Respondents who had experienced any hazard reported slightly higher climate concern (average score 3.23 vs. 3.14 on a five-point scale) and far higher adaptation activity (average of 34% vs. 12% of actions taken). The difference in behaviour was statistically large ($\Delta = 0.225$; $t \approx 14.8$), confirming that direct experience is a strong driver of action.*

Table 1: Hazard exposure among Lithuanian households

Hazard type	Respondents (%)
Storms/wind/hail	11.4
Heatwaves/cold spells	8.3
Heavy rain/flooding	4.6
Mould/humidity	3.7
Coastal flooding	0.1

***RQ2. Motivations associated with different adaptation behaviours.** Four categories of motivation were analysed: economic, social, ecological, and ethical/other. All scored relatively high (mean values between 3.5 and 4.0 on a five-point scale), but they were associated with behaviour in different ways. Regression models showed that economic motives were the strongest predictors of technical measures (e.g., retrofitting, protective investments). By contrast, social and ethical motives were most strongly linked to community-oriented and ecosystem-based actions (e.g., helping neighbours, planting trees). Ecological concern correlated positively with overall action levels but lost significance once other motivations were included, suggesting its effect is mediated by more immediate drivers.*

Table 2: Motivations predicting adaptation behaviour

Motivation type	Effect on action (β)	Significance
Economic	0.027	$p < .01$
Social	0.040	$p < .01$
Ecological	0.012	n.s.
Ethical/Other	0.022	$p < .05$

These relationships are visualised in Figure 1, which plots respondents' mean motivation scores against the number of adaptation actions undertaken. The scatter shows that while most individuals report high motivation (≈4/5), the majority cluster at low to moderate action counts (0-4 actions). The positive trendline indicates that greater motivation is indeed associated with more actions, but the spread of points highlights a persistent "concern–action gap." This gap is particularly visible among respondents with high motivation but very few reported actions.

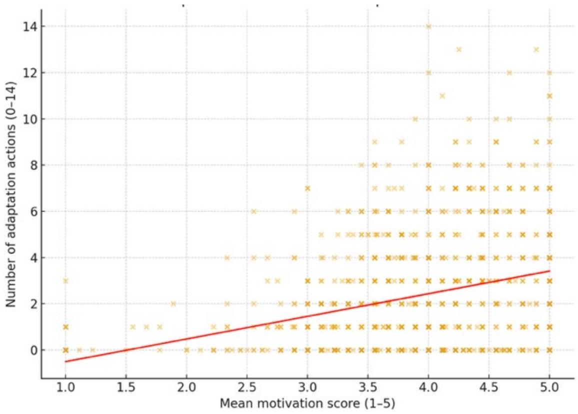

Figure 1: Motivation vs Adaptation Actions

Taken together, Table 2 and Figure 1 demonstrate that different adaptation actions are fuelled by different motives, and that motivation alone does not guarantee action. For AI-enabled platforms, this underscores the need for tailored recommendations: technical actions should be framed in terms of affordability and economic incentives, while community and ecosystem measures can be promoted through appeals to ethical responsibility and social solidarity.

RQ3. Preparedness and institutional contact. *On average, citizens rated themselves only moderately prepared for climate risks (mean = 2.9 on a five-point scale). Preparedness was positively correlated with all motivational drivers ($r \approx 0.44$-0.50), indicating that individuals with stronger economic, social, or ecological values also tended to feel more capable of responding. The results are consistent with a mediation pattern in which stronger motivational drivers are associated with higher perceived preparedness, which in turn predicts greater adaptation behaviour. Municipal information provided only a limited additional mechanism: respondents who reported receiving communication from municipalities were somewhat more likely to act, but the interaction between concern and municipal contact was small and statistically uncertain. These findings suggest that institutional information on its own is insufficient to generate behaviour change unless it is coupled with motivational and efficacy supports.*

RQ4. Adaptation profiles for AI personalisation. *To capture heterogeneity in the Lithuanian population, a clustering analysis was applied to motivational indices, concern, anxiety, preparedness, and institutional variables. A four-profile solution provided the clearest structure (Figure 2). The largest group, Baseline pragmatists (48%), were characterised by mid-level motivations and only average readiness. Their uptake of adaptation actions was modest, with relatively low shares across all categories (10% technical, 18% social, 8% institutional, 16% ecosystem). A smaller but broadly engaged group, High-motivation all-in adopters (31%), scored very high across all motives and reported strong readiness. They showed consistent action across categories, particularly in social (31%) and ecosystem measures (23%). Two minority profiles stood out. The Community & nature oriented (8%) group combined high ecological and social motives with high readiness but low municipal communication. They displayed the highest uptake of community and ecosystem measures (41% and 40%, respectively), alongside above-average technical (24%) and institutional (23%) actions. By contrast, the Low engagement group (13%) had the lowest motivations, concern, and readiness, translating into minimal action across all categories (4-9%).*

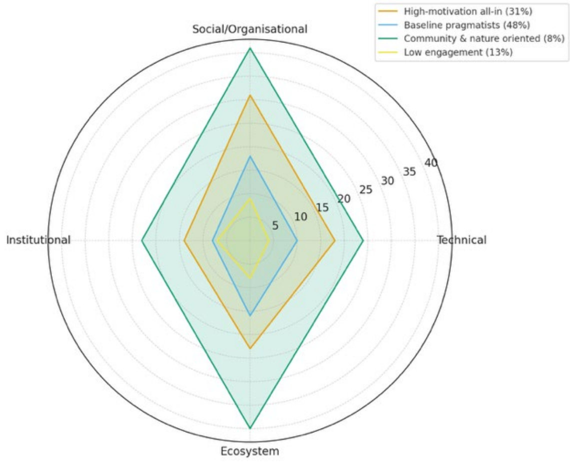

Figure 2: Motivations predicting adaptation behaviour

These profiles illustrate actionable levers for AI design: for example, emphasising cost savings for pragmatists, ecological/community benefits for the nature-oriented, and confidence-building tools for the low-engagement group. They provide a direct pathway from behavioural evidence to personalisation parameters for the conceptual framework discussed in Section 5.2.

5. Discussion

5.1 Results in Context

The Lithuanian findings broadly align with international research on climate adaptation while also offering contextual nuances that sharpen their relevance for AI-enabled civil engineering. Hazard experience emerged as a strong driver of both concern and action, consistent with global evidence that lived experience intensifies perceived risk and motivates protective behaviour (Wong-Parodi & Rubin, 2024; Van Valkengoed et al., 2024). What the Lithuanian data add is specificity: storms and heatwaves were identified as the most influential triggers. This points to clear priorities for digital twin scenarios in mid-latitude contexts, where system design should emphasise, hazards already recognised as pressing by citizens.

The analysis of motivations similarly extends behavioural theory. Prior work highlights the importance of efficacy beliefs and value orientations (Ajzen, 2020; Stern et al., 1999) but often collapses these into a single "pro-environmental" dimension. Our results show instead that different motivations map onto different action types: economic concerns underpin technical measures, while social and ethical values drive community and ecosystem-based responses. This differentiation supports global findings that motivations matter (Clayton, 2020) while providing operational clarity for recommender systems, which can assign motivational weights to actions rather than assuming a universal driver. Preparedness reinforced these patterns by acting as an intermediate factor: stronger motivational orientations were associated with higher self-reported readiness, which in turn predicted greater behavioural uptake. This echoes international work linking efficacy and readiness to adaptation (Kühner et al., 2025), but the Lithuanian case also underscores limits to institutional influence. Municipal communication was only weakly associated with increased action, diverging from studies that stress trust in institutions as a primary driver (Albahri et al., 2024). The implication is that information campaigns alone are insufficient; without reinforcing motivation or building efficacy, institutional contact does little to convert concern into practice.

Finally, the clustering analysis confirmed international evidence on heterogeneity in sustainability adoption (Shin & Lee, 2025) while advancing it in two ways. First, it quantified the behavioural implications of different profiles across technical, social, institutional, and ecosystem domains. Second, it highlighted distinctive combinations (e.g., community- and nature-oriented citizens) were highly active in ecosystem measures despite limited municipal communication, while low-engagement citizens remained resistant across all domains. These findings suggest both opportunities and challenges: bottom-up ecological action can thrive even in the absence of institutional support, but low-readiness groups require new strategies if they are to be mobilised.

5.2 From Evidence to Conceptual Framework

A central contribution of this study is to show how empirical evidence on citizens' adaptation behaviours can directly inform the design of AI-enabled platforms. Prior research has noted that decision support must align not only with technical optimisation but also with user values, capacities, and institutional contexts (Baxter & Sommerville, 2011; Sander, 2025). By linking survey results to system design, this study demonstrates how behavioural data can serve as inputs rather than background context. Four design implications follow. First, hazard experience matters: citizens affected by storms or heatwaves were more active, suggesting digital twins should prioritise these hazards to increase salience and legitimacy (Therias & Rafiee, 2023). Second, motivations are diverse: economic motives drive technical measures, while social and ethical concerns support community and ecosystem actions, meaning recommender systems should weight recommendations according to user profiles (Ajzen, 2020; Sander, 2025). Third, preparedness shapes uptake: higher self-assessed readiness mediates between motivation and action. Interfaces should therefore adapt to user readiness, offering simple, confidence-building options to low-readiness users and more complex portfolios to high-readiness ones (Kühner, Schäfer, & Wamsler, 2025; Albahri et al., 2024). Finally, population heterogeneity enables personalisation: clustering revealed four citizen profiles with distinct probabilities of action, providing a natural basis for profile-based segmentation in human-centred AI (Shin & Lee, 2025).

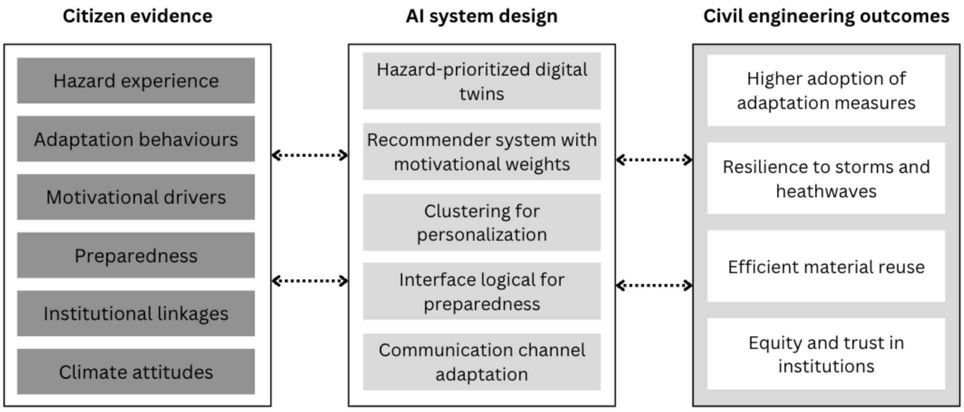

Figure 3: Citizen-informed AI for Climate Adaptation framework

Synthesising these insights, we propose a socio-technical design blueprint. At its centre is a recommender system that evaluates candidate measures against four objectives: adoption probability, expected CO_2 reduction, financial savings, and equity. The weight given to each objective is adjusted by citizen profile, ensuring that the system reflects the motivational and readiness patterns observed in the population. The pipeline unfolds in five stages: (i) profiling users into clusters, (ii) setting profile-specific priorities, (iii) generating candidate measures across technical, social, institutional, and ecosystem domains, (iv) scoring measures against weighted objectives, and (v) presenting tailored recommendations with transparent explanations. These design principles are brought together in the Citizen-informed AI for Climate Adaptation (CiA-CA) framework (Figure 1). The framework connects three layers: (i) Citizen evidence (hazard experiences, adaptation behaviours, motivations, preparedness, institutional linkages, and climate attitudes); (ii) AI system design (hazard-prioritised digital twins, recommender systems with motivational weighting, clustering for personalisation, and interfaces adapted to preparedness and communication channels); and (iii) Civil engineering outcomes (higher uptake of adaptation measures, greater resilience to storms and heatwaves, more efficient material reuse, and stronger equity and trust). By grounding system logic in behavioural evidence, the CiA-CA framework advances civil engineering adaptation as a socio-technical process. It responds to international calls for human-centred AI in sustainability (Debnath, Chattopadhyay, & Ray, 2025) and provides both a conceptual advance and a practical blueprint for platforms that are technically robust, socially resonant, and trusted by the citizens they aim to serve.

5.3 Integration Path: LSEPO Deployment

The CiA-CA framework will be implemented in the platform as a staged but continuous socio-technical integration. At the data layer, survey-based constructs (hazard exposure, motivational profiles, perceived preparedness, and institutional contact) are compacted into a LSEPO user model that can be elicited through a short onboarding module and, with consent, softly updated from in-platform interactions. On the modelling side, the digital-twin library will prioritise storms and heatwaves, reflecting the empirical salience of these hazards in Lithuania; scenario cards will render before/after material-reuse and household-adaptation outcomes parameterised by municipal and regional data where available. The recommender then operationalises the framework's behavioural logic by ranking technical, social, institutional, and ecosystem measures against four objectives (adoption likelihood, CO_2 reduction, cost savings, and equity) with profile-dependent weighting derived from the survey. Interfaces will be preparedness-aware: users who report lower readiness first encounter low-threshold, confidence-building steps and interactive simulations, whereas users with higher readiness are offered richer portfolios and bundled measures. To support legitimacy and governance, each recommendation is paired with a concise "why this?" explanation anchored in motivational fit and expected benefits; privacy, consent, and data minimisation are enforced, and model cards document data sources, assumptions, and equity checks. Technically, integration proceeds through an alpha phase in the CIMC lab (back-testing and expert review), followed by a beta with one or two municipalities (A/B testing of profile-aware explanations and preparedness-tailored flows), culminating in a pilot scale-up that incorporates market signals for secondary materials and municipal incentives. Although tuned for Lithuania, the same pipeline can be ported to Baltic and Northern-Central European contexts with minor recalibration of hazard priors and motivational weights, thereby providing a practical route from population-level evidence to operational decision support. At the same time, it should be noted that the underlying evidence base comes from self-reported survey data and a cross-sectional design. This may limit generalisability beyond Lithuania, as hazard recall, motivational reporting, and adaptation behaviours can vary across countries and over time. Accordingly, transfer to other contexts requires recalibration with locally validated data and, ideally, longitudinal evidence to capture how motivations and preparedness evolve.

6. Conclusions

This study demonstrates how nationally representative behavioural evidence can be mobilised to design AI-enabled adaptation support in civil engineering. Using a Lithuanian survey (n = 1,013), we showed that lived hazard experience (especially storms and heatwaves) correlates with higher concern and substantially greater action uptake; that motivations are differentiated, with economic drivers linked to technical measures while social and ethical values underpin community and ecosystem actions; that perceived preparedness functions as an intermediate factor between motivation and behaviour; and that citizens cluster into distinct profiles with characteristic action probabilities. Taken together, these results move beyond descriptive analysis to provide design variables (hazard priorities, motivational weights, preparedness-informed interface rules, and user profiles) that can be directly operationalised in decision-support systems. Building on these insights, we proposed the CiA-CA framework. The framework connects behavioural adaptation research with socio-technical AI design; empirically, it introduces one of the first nationally representative datasets on adaptation in the Baltic region; and practically, it provides a blueprint for translating population-level evidence into implementable AI features for municipal and engineering platforms in Lithuania and beyond. Importantly, this framework is not abstract. It will be integrated into the LSEPO platform. This integration ensures that the behavioural insights gathered here will inform real-world digital twins, recommender logics, and municipal communication strategies. In this way, CiA-CA contributes not only to academic debate but also to the operationalisation of national and regional adaptation infrastructures.

Several limitations qualify these contributions. The data are self-reported and cross-sectional, which constrains causal inference and may over- or under-estimate real behaviours. Some constructs, such as preparedness, were measured parsimoniously, and institutional communication effects may depend on message quality and governance capacity not fully captured here. The framework itself remains design-oriented and requires prospective validation in live systems. Future work should therefore: (1) test CiA-CA in prototype deployments within LSEPO, evaluating offline accuracy and online outcomes such as adoption uplift, preparedness gains, and trust; (2) conduct longitudinal follow-ups to recalibrate motivational and preparedness weights as hazard experiences evolve; (3) expand explanation and governance layers, including profile-aware explanations, model cards, and equity auditing; and (4) assess transferability to other European contexts where hazard profiles and motivational structures may differ. By advancing adaptation support as a socio-technical endeavour (where optimisation is explicitly aligned with motivations, readiness, and institutional realities) this work outlines a path toward AI platforms that are technically robust, socially legitimate, and practically deployable. In doing so, it positions Lithuania, through CIMC and LSEPO, as a regional testbed for citizen-informed, AI-enabled climate adaptation that can inform broader European transitions.

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Ethics and AI declaration: This research was conducted in accordance with institutional and national guidelines for research involving human participants. Ethical clearance for the survey of Lithuanian residents was obtained from Ethical monitoring board at Citizen Science Hub at VILNIUS TECH No. CSH-2023-02. All participants provided informed consent prior to the interviews, and their responses were anonymised and stored in line with GDPR requirements. No vulnerable groups were specifically targeted in the study.

During the preparation of this manuscript, AI tools were used to support tasks such as drafting and refining sections of text, improving clarity and flow, checking consistency of terminology, and suggesting alternative formulations. All statistical analyses, interpretation of results, and conceptual contributions (including the design of the CiA-CA framework) were carried out by the authors. The authors reviewed and take full responsibility for the content of the final manuscript.

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