A FRAMEWORK FOR COASTAL RESILIENCE

Networks and Strategies in the Envision Resilience Challenge

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Client Organization(s): Remain + Envision Resilience Challenge Program
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A project submitted in partial fulfillment of the requirements for the degree of Master of Science / Master of Landscape Architecture (Environment and Sustainability) in the University of Michigan.
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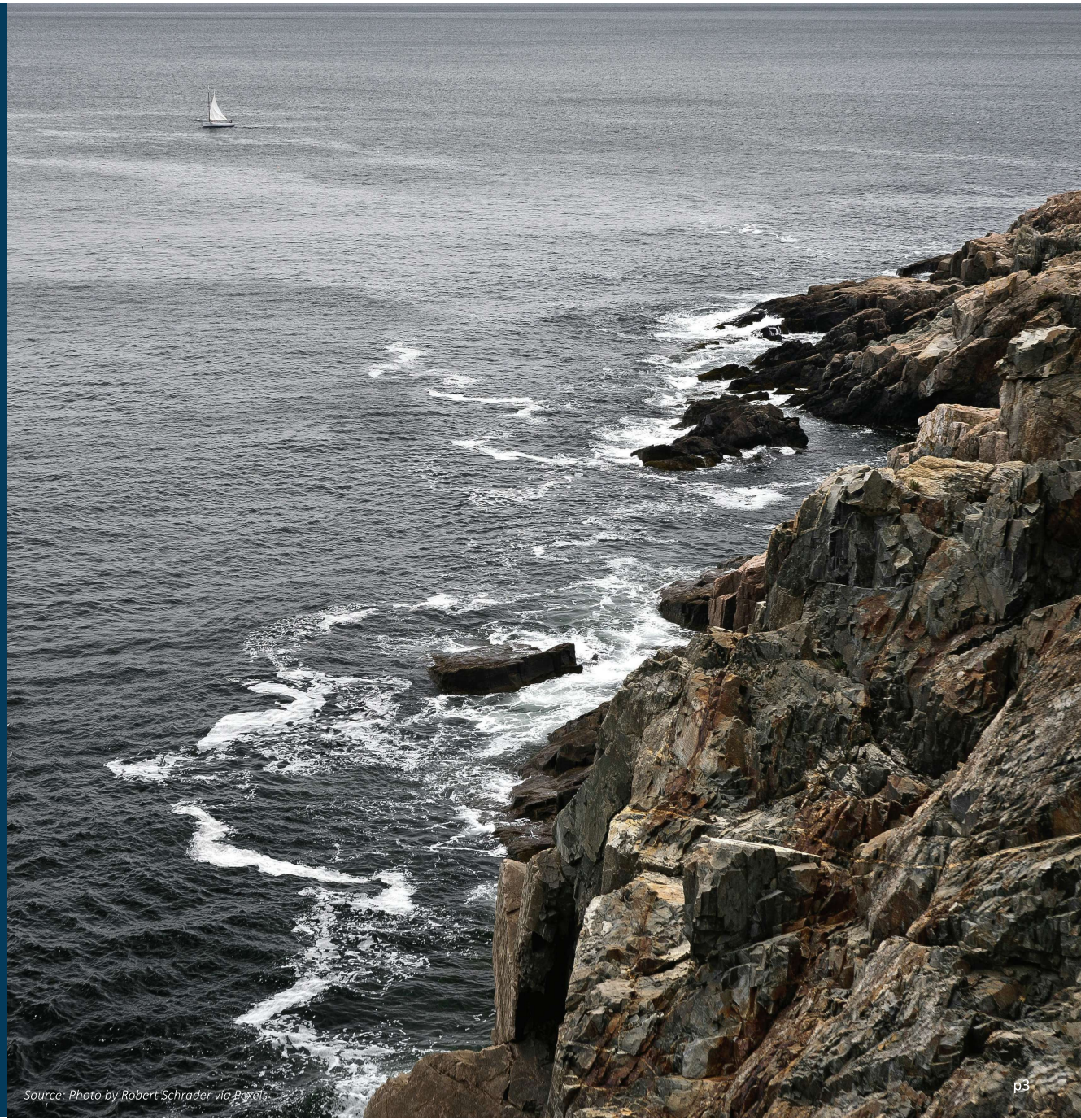
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PREFACE

Communities along the U.S. Northeast coast are facing multiple challenges posed by climate change, including rising sea levels, extreme weather, and frequent flooding. These constantly evolving and complex environments not only pose sustained challenges to ecosystems and infrastructure, but also pose increasing challenges to communities' long-term resilience. Relying solely on engineering or planning approaches is no longer sufficient to address uncertainty. Exploratory and interdisciplinary design methods are increasingly becoming key strategies for coastal resilience.

In this context, design studios and multi-stakeholder collaboration platforms serve as vital vehicles for testing different strategies and envisioning future scenarios.



Source: Photo by Robert Schrader via Pexels

ACKNOWLEDGEMENTS

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We are especially grateful to our faculty advisor, Lisa Du Russel, for her support, feedback, and encouragement throughout the research and design process. We also thank our project partners, reviewers, and all those who contributed ideas, questions, and insights during meetings and presentations.

Finally, we would like to acknowledge the many students, advisors, organizations, and community participants whose work shaped the Envision Resilience Challenge from 2021 to 2024. Their proposals, research, and engagement efforts form the foundation of this report.

SEAS SCHOOL FOR ENVIRONMENT AND SUSTAINABILITY UNIVERSITY OF MICHIGAN X ENVISION RESILIENCE

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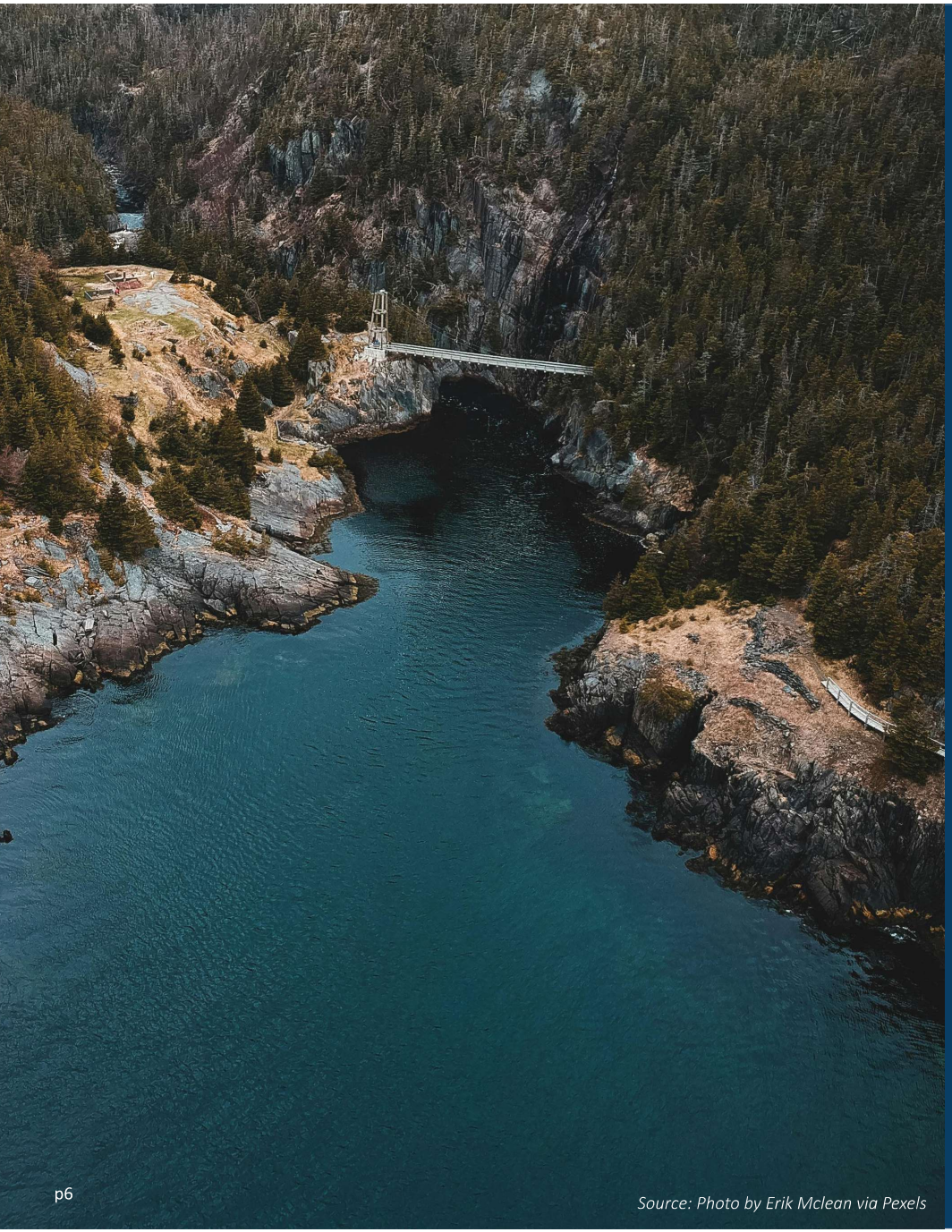
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INTRODUCTION

Against this backdrop, this study examines the outcomes of ERC projects from 2021 to 2024. Building on a review of existing design work, it further extracts valuable insights and conclusions from these strategies and translates them into analytical tools that can support future research and practice.

The research further aims to present its findings in a clearer and more accessible manner, thereby promoting public awareness and dialogue on coastal resilience. Focusing on multiple coastal sites, this study establishes a unified analytical framework to systematically classify and compare across years the three core elements of the ERC process: site-specific issues, community engagement networks, and student design strategies. Building on existing classification methods, this framework has been adapted and expanded to account for the specific characteristics of the ERC project, thereby forming a classification system suitable for this study.

The main outcome of this study integrates and presents the relationships among these factors through visualizations, data analysis, and cross-year comparisons. Rather than treating each annual project as a standalone case study, this collection focuses on identifying common patterns and evolving trends in ERC projects at the macro level, providing guidance and insights for future coastal resilience initiatives.

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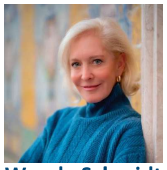
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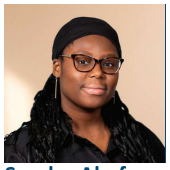
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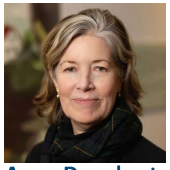
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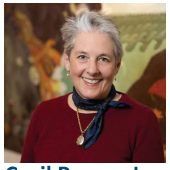
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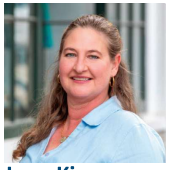
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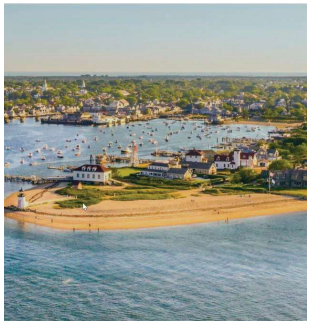
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ENVISION RESILIENCE

Envision Resilience works to advance innovative planning and design in the face of climate change through student and community partnerships.

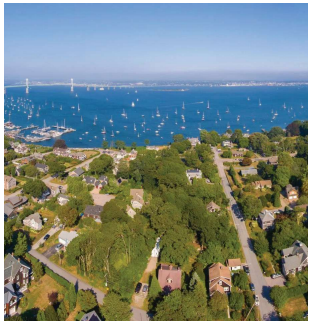
By connecting current and future professionals working across disciplines, the organization creates opportunities for communities to reimagine climate challenges and inspire resilient solutions. Envision Resilience, originally developed by Remain, is part of the philanthropic organizations and initiatives created and funded by Eric and Wendy Schmidt to work toward a healthy, resilient, secure world for all.

THE CHALLENGE



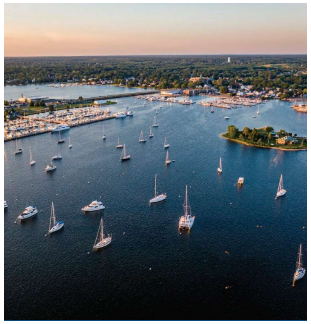
2021 NANTUCKET CHALLENGE

In 2021, the Envision Resilience Challenge focused on Nantucket Island, a historic coastal community facing increasing risks from sea level rise and flooding. Graduate design students from leading universities explored strategies to reimagine Nantucket Harbor and support the island's long-term climate resilience.



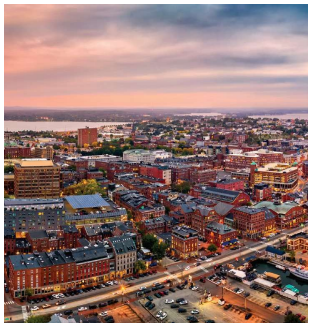
2022 NARRAGANSETT BAY CHALLENGE

The 2022 challenge focused on Narragansett Bay in Rhode Island, the largest estuary in New England and a region increasingly vulnerable to sea level rise. Students from six universities explored design strategies to help coastal communities adapt to future climate impacts.



2023 NEW BEDFORD AND FAIRHAVEN CHALLENGE

In 2023, the challenge shifted to the historic port communities of New Bedford and Fairhaven on the Massachusetts South Coast. Facing rising sea levels and climate pressures, students explored design strategies to support resilient waterfronts and help coastal communities adapt to future change.



2024 PORTLAND AND SOUTH PORTLAND CHALLENGE

The 2024 challenge focuses on Portland and South Portland, two coastal cities on Casco Bay in Maine. The Gulf of Maine is one of the fastest-warming ocean regions and faces increasing risks from sea level rise, flooding, and stronger storms. Students from eight universities explore strategies to support resilient waterfronts and help local communities adapt to climate change.

2021 PARTICIPATING SCHOOLS

University of Florida
Harvard University Graduate School of Design
Northeastern University
University of Miami
Yale School of Architecture

2022 PARTICIPATING SCHOOLS

Northeastern University
Rhode Island School of Design
Roger Williams University
Syracuse University
University of Florida
University of Rhode Island

2023 PARTICIPATING SCHOOLS

Howard University
Northeastern University
Rhode Island School of Design
University of Florida
University of Massachusetts Amherst
University of Massachusetts Dartmouth
University of Virginia

2024 PARTICIPATING SCHOOLS

Cornell University
University at Buffalo
Harvard University
University of Maine Augusta
University of Michigan
University of Toronto
University of Virginia
Yale University

ERC IMPACT MAP



According to inundation risk maps developed by National Oceanic and Atmospheric Administration (NOAA), coastal areas along the U.S. East Coast are increasingly exposed to concentrated inundation risks driven by sea-level rise. *(National Oceanic and Atmospheric Administration n.d.)* In this context, the Envision Resilience Challenge (ERC) collaborates with coastal communities and engages university students in design competitions. Since 2021, students from diverse disciplinary backgrounds have proposed a wide range of innovative design strategies addressing site-specific challenges.

However, the large volume of projects and the multiple influences shaping the design process—including organizational frameworks, advisor guidance, and individual preferences—make systematic evaluation highly complex. This study therefore examines two interrelated dimensions: (1) the extent to which design strategies respond to site-specific issues, and (2) the organizational influence of ERC throughout the design process. Based on this framework, the research conducts a multi-dimensional analysis grounded in systematic data collection and organization.

APPROACH

Phase 1

Understanding How Envision Resilience Works

Understand how ERC operates, including its structure, workflow, and participants.





Phase 2

Data Collection and Organization

Collect and organize project data, including design strategies, site issues, and student findings.



Phase 3

Framework Development for Strategy Classification

Develop a classification framework to systematically organize design strategies based on key dimensions such as scale, time, and thematic focus.



Phase 4

Problem–Participant–Strategy Loop

Conduct surveys to gather stakeholder feedback and integrate findings with previous analysis to generate insights.



Phase 5

Comparative and Analytical Study

Analyze relationships between site issues, student-identified problems, and design strategies to identify patterns and gaps.



Survey and Synthesis

Conduct surveys to gather stakeholder feedback and integrate findings with previous analysis to generate insights.

Phase 1

Understanding How Envision Resilience Works

Understand how ERC operates, including its structure, workflow, and participants.

ENGAGEMENT ANALYSIS

The Envision Resilience Challenge (ERC) operates as a continuous and structured process that unfolds across three stages: pre-challenge, challenge, and post-challenge. This framework helps coordinate different participants and supports the development of design proposals over time.

PRE-CHALLENGE STAGE

In the pre-challenge stage, ERC primarily acts as a connector. It brings together community members, organizations, and advisors through regular meetings and informal discussions. Some advisors become the key connectors, connecting students and the organization. These interactions help identify local issues and establish a shared understanding of site-specific needs. The knowledge gathered during this stage provides an important foundation for the design process.

CHALLENGE STAGE

During the challenge stage, student teams begin developing design proposals through site visits, workshops, and iterative design work. At the same time, advisors remain actively involved. They provide feedback at key moments, including the midterm review and final review. This ongoing guidance allows ideas to be tested, refined, and strengthened.

POST-CHALLENGE STAGE

In the post-challenge stage, final deliverables are completed and shared beyond the studio. The outcomes may influence stakeholders such as organizations and decision-makers. In addition, exhibitions and public presentations help communicate design ideas to a broader audience. Through this process, ERC extends its impact beyond academic settings and connects design with real-world contexts.

CONNECTION STRUCTURE

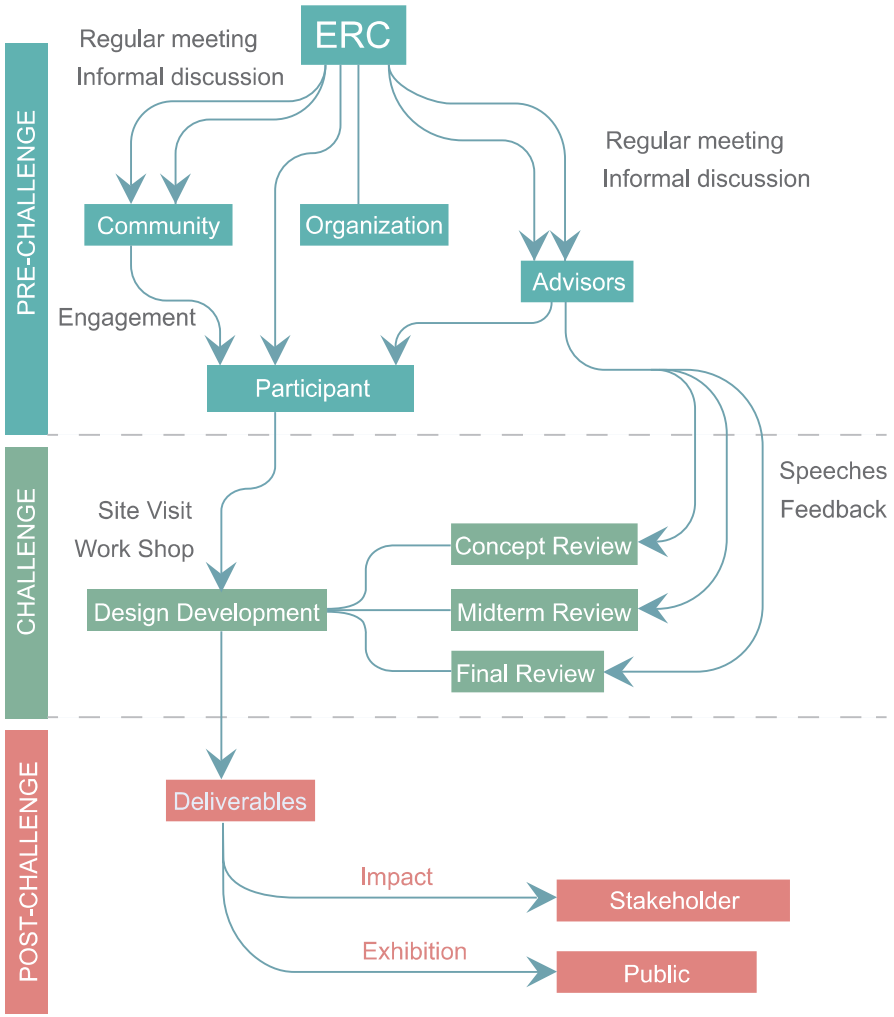


Fig 1-1. Engagement structure

Phase 2

Data Collection and Organization

Collect and organize project data, including design strategies, site issues, and student findings.

DATA STRUCTURING AND CODING

1. DATA COLLECTION
First, we reviewed project presentation videos from previous years published on the official ERC website. Subtitles were extracted using automated transcription tools and converted into text files for subsequent analysis.

2. MANUAL DATA EXTRACTION AND STRUCTURING
The extracted text files were manually reviewed and filtered to identify student design strategies. Each strategy was recorded as an individual data entry and organized into a structured table. In addition to forming the initial dataset, each entry was labeled according to project year and participating institution.

3. MACHINE LEARNING-BASED CLASSIFICATION
Because the number of strategies is large, manual classification alone is inefficient. Therefore, we introduced a machine learning workflow to make the process faster and more consistent.
First, we organized the raw strategy data into a structured table using a library called pandas. In this table, each row represents one strategy, including information such as year, school, and text description.
Next, we manually labeled the 2021 strategies into five predefined categories. This served as the training data for the model. At the same time, we converted the text descriptions into numerical data that a computer can understand (for example, using a method called TF-IDF).
During model training, we split the data into two parts: one for training and one for testing. We used a model called Logistic Regression to perform the classification task.

We chose this model for several reasons:
a. Works well with text data, which is often high-dimensional and sparse
b. Fast to train and computationally efficient
c. Easy to interpret (we can see which keywords influence the results)
d. Performs reliably in similar text classification tasks

After training, we evaluated the model's performance (such as accuracy) to ensure the results are reliable. Once the model performs well, we applied it to strategies from 2022–2024.These new data went through the same processing steps, and the model automatically assigned categories to each strategy.
Finally, we added the predicted categories back into the dataset and exported it as a complete file for further analysis and visualization.

4. DATA VISUALIZATION
To explore patterns within the classified dataset, multiple visualization methods were used. First, bar charts were generated using Matplotlib to illustrate the distribution of strategy types across different years and institutions, providing a preliminary understanding of temporal and organizational trends.
After preprocessing in Python, the dataset was exported to the Flourish platform to generate Sankey diagrams, which were used to visualize overlaps across multiple classification dimensions.

5. WORKFLOW AND REPRODUCIBILITY
The entire workflow, including text processing, classification, and visualization, was implemented in a modular Python pipeline and organized in a GitHub repository. This structure ensures that the data processing steps are transparent and reproducible.

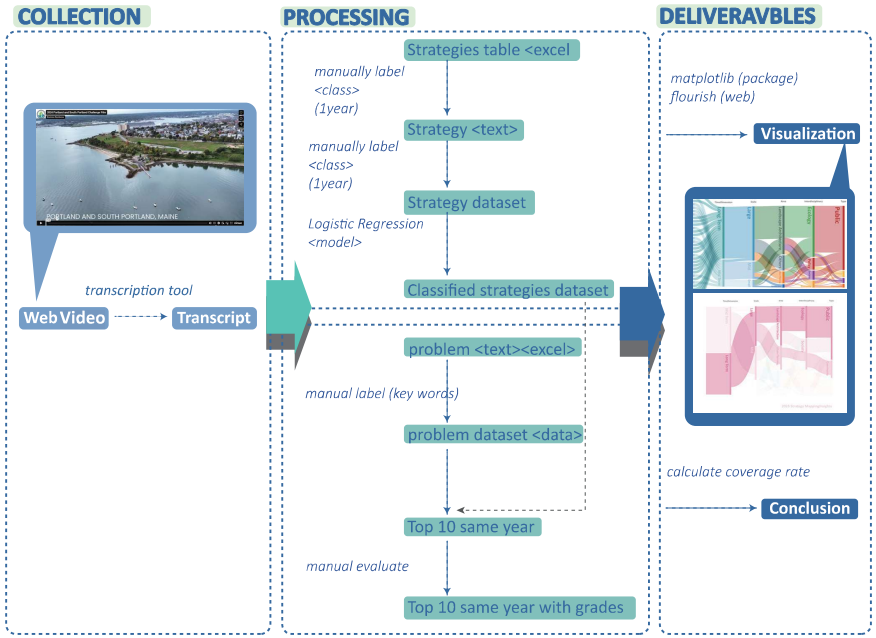


Fig 2-1. Data Processing and Classification Workflow

Phase 3

Framework Development for Strategy Classification

Develop a classification framework to systematically organize design strategies based on key dimensions such as scale, time, and thematic focus.

In the early stages of organizing ERC projects, the team first attempted to categorize design strategies along a single dimension, such as grouping, site, or theme type. However, in practice, it has been found that these single-category approaches are unable to effectively account for the differences between projects. Since design strategies are embedded within broader proposals, comparing projects as a whole makes it difficult to identify similarities and differences systematically.

Further analysis show that ERC projects exhibit significant variations across multiple dimensions, including disciplinary backgrounds (such as landscape architecture, architecture, and urban planning), spatial scales (ranging from local nodes to regional systems), temporal scales (short-term interventions versus long-term transformations), and the areas of impact addressed by the strategies (ecological, social, economic, and others). This indicates that design strategies are multidimensional, and a single classification method cannot fully capture their complexity.

Related research also supports this conclusion. Studies on Nature-based Solutions (NBS) indicate that design interventions often have simultaneous impacts across multiple dimensions, including environmental, social, economic, and governance aspects. *(Kabisch et al. 2016)* Meanwhile, the Landscape Performance resources developed by the Landscape Architecture Foundation use case studies to link design strategies with multiple benefits, highlighting the multifaceted nature of design outcomes. *(Landscape Architecture Foundation n.d.)* Furthermore, research on ecological and environmental systems shows that complex systems involve many interrelated factors. In this context, multidimensional classification methods are more effective for organizing information and revealing relationships between variables.

The team shifted to a multidimensional classification approach. Through repeated refinement and comparison of specific strategies, common characteristics were gradually identified.

This framework draws to some extent on the categorization of “benefit types” and “impact dimensions” found in existing research, while incorporating adjustments and reorganizations to reflect the specific characteristics of ERC projects. It primarily comprises the following five dimensions:

a. Area of Specialization: Reflects the disciplinary background and knowledge framework underpinning the strategy
b. Time Horizon: Describes the strategy’s implementation cycle and its short-term and long-term impact pathways
c. Scale: Defines the spatial scope of the strategy’s impact
d. Interdisciplinary Theme: Identifies the primary domains of impact (ecological, economic, social, or cultural)
e. Project Type: Describes the strategy’s application context and functional attributes

The five dimensions mentioned above are not mutually exclusive; rather, they function collectively as a multidimensional analytical matrix. A single strategy can be categorized under multiple dimensions simultaneously, thereby providing a comprehensive representation of its multifaceted attributes. This structure allows strategies from different projects to be organized and compared within a unified framework. It also lays the groundwork for subsequent visualization and pattern recognition.

Phase 4

Problem–Participant–Strategy Loop

Conduct surveys to gather stakeholder feedback and integrate findings with previous analysis to generate insights.

RESILIENCE CYCLE

Coastal communities in the northeastern United States are facing growing risks from sea-level rise, stronger storms, and more frequent flooding. These changes have made it harder for traditional infrastructure and planning tools to keep up. In response, many designers and planners are now focusing on adaptive and resilient approaches that combine ecological systems, social needs, and long-term thinking.

The ERC works within this context. ERC brings together interdisciplinary student teams to collaborate with local communities and explores design responses to climate-related challenges. Over the past several years, the program has produced a wide range of design proposals across different sites, scales, and disciplines.

While these projects show strong creativity and ambition, ERC has not previously had a clear way to look across all years and understand how strategies relate to one another. It has been difficult to see which ideas repeat, which gaps remain, and how different disciplines approach similar problems. This project addresses that gap.

This study, conducted within the framework of the ERC project, systematically reviews and analyzes existing ERC project outcomes to establish an analytical and visualization framework for design strategies. It aims to provide reference and support for future ERC research and project implementation.

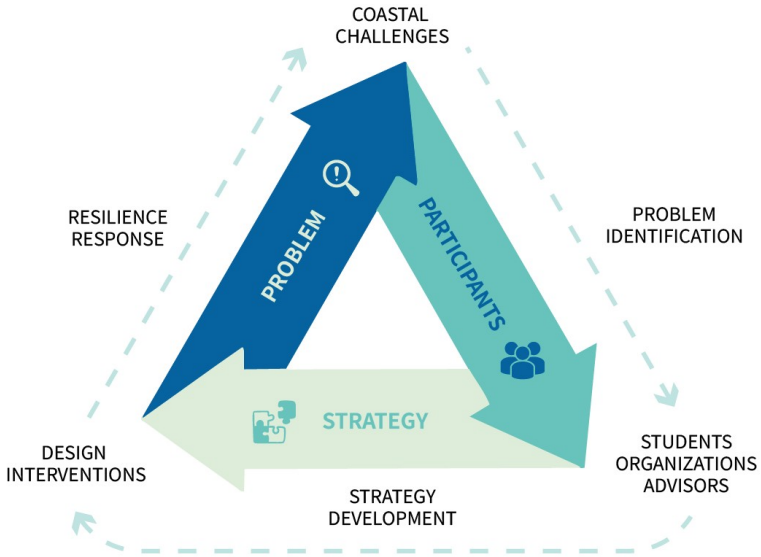


Fig 4-1. ERC Resilience Cycle Framework

Phase 5

Survey and Synthesis

Conduct surveys to gather stakeholder feedback and integrate findings with previous analysis to generate insights.

INTERNAL SURVEY

To better understand how the Envision Resilience Challenge (ERC) operates between 2021 and 2024, we conducted a survey with ERC organizers and organized the results by year for comparison. Rather than treating each year as an independent project, this approach allows us to read ERC as an evolving system, and to track how it develops and changes over time.

The survey focuses on several key aspects of ERC's operation. These include how different roles interact (engagement structure), how participants' backgrounds influence project direction (participant background), how advisors contribute to decision-making (advisor influence), and what works well or needs improvement in the overall process (process feedback). Through this framework, we are able to understand not only who is involved, but also how design ideas are formed, how decisions are made, and how projects move forward across different stages.

By comparing multiple years instead of looking at a single moment, we are able to identify recurring patterns as well as gradual shifts over time. As ERC is a multi-phase process—including community engagement, design studios, reviews, and final deliverables—this analysis also helps reveal how different stages are connected, and where transitions or gaps may occur. It also highlights how the focus of each year shifts in response to different contexts.

The goal of this survey is not only to document participation, but to better understand how ERC functions as a system. By analyzing the data, we can see how different participants, collaboration structures, and decision-making processes collectively shape design outcomes. At the same time, the findings help identify existing challenges within the process and point toward potential directions for future improvement.

INSIGHT

Phase 6

Engagement Network Analysis

Examine how different participants are connected and collaborate within ERC projects, shaping the design process.





Site Problem and Analysis

Analyze site-specific challenges across projects to reveal patterns of environmental, social, and spatial issues.

Phase 7

Phase 8

Flow Mapping and Visualization

Map and visualize how different elements are interconnected across projects through dynamic flows.



Closing the Loop: Returning to the Problem

Conduct surveys to gather stakeholder feedback and integrate findings with previous analysis to generate insights.

Phase 9





Phase 6

Engagement Network Analysis

Examine how different participants are connected and collaborate within ERC projects, shaping the design process.

ERC CONNECTION

Building on the overall engagement process outlined above, it is important to consider who sustains these connections over time and how their roles influence the structure of ERC.

Advisor involvement can be understood across **three main stages:**
a. **Pre-Challenge**: agenda setting and early direction
b. **During Challenge**: design development and decision-making
c. **Post-Challenge**: feedback and reflection

To understand patterns of influence, a survey was conducted with ERC staff members. Respondents were asked to identify individuals they considered most important in each stage. By comparing these responses, it became possible to track which names appeared repeatedly across phases and years. These recurring mentions were used as an indicator of influence and later visualized in the diagrams.

Mapping participation across stages highlights differences in influence. Some advisors are involved across multiple phases, suggesting deeper engagement, while others contribute at specific moments with more targeted input.

The diagrams in next page show how influence is unevenly distributed across individuals. In several cases, a small number of advisors appear repeatedly and occupy more prominent positions. These advisors are recognized as the key connectors.

Overall, this pattern suggests that ERC operates as a collaborative network. Participation is not evenly distributed, and key connectors play an important role in shaping project direction over time.

ERC CONNECTION (SINGLE YEAR)

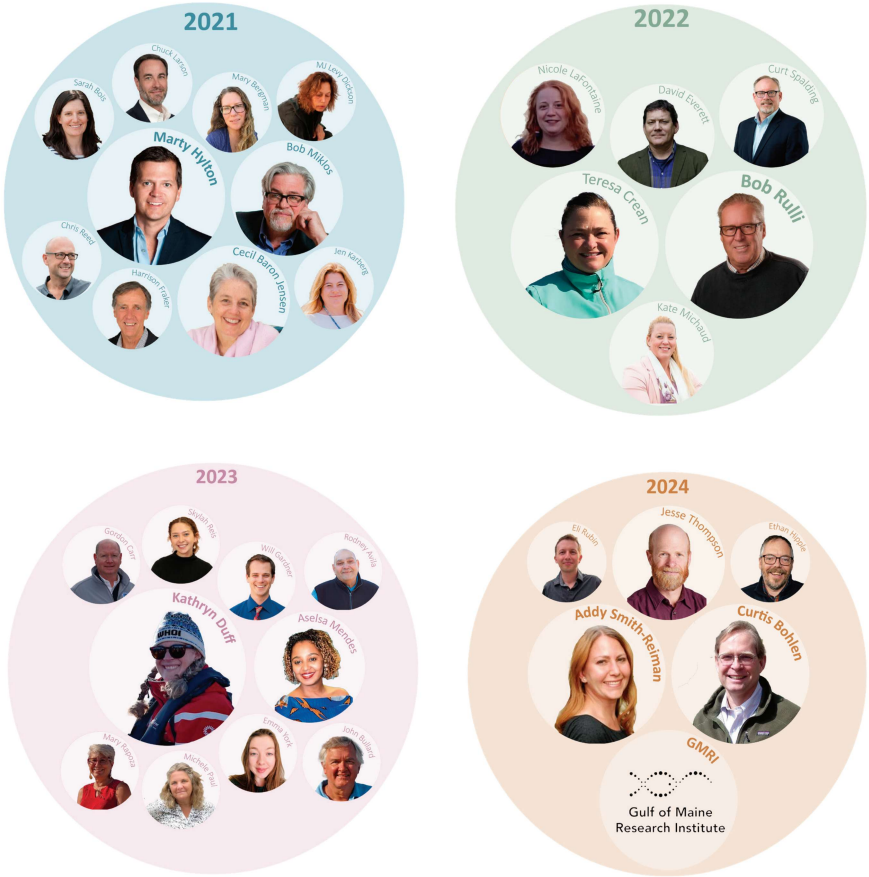


Fig 6-2. ERC Connection Network

ERC CONNECTION (CROSS YEAR)

A cross-year perspective provides further insight into how these networks develop over time.

When viewed collectively, the ERC network appears fragmented. Most advisors participate only one year, and relatively few remain involved across multiple years. As a result, each challenge year tends to form a largely independent network rather than contributing to a continuous structure.

This pattern has several implications. Knowledge and experience are not consistently carried forward, and each year often operates with limited continuity from previous efforts. In this sense, the process can resemble a series of isolated cycles rather than a cumulative system. At the same time, this fragmentation highlights a potential opportunity. It suggests the need for a more structured framework that can connect these otherwise separate networks and support longer-term knowledge transfer.

Addressing this gap becomes an important direction for this project, which aims to better organize and link information across different ERC years.

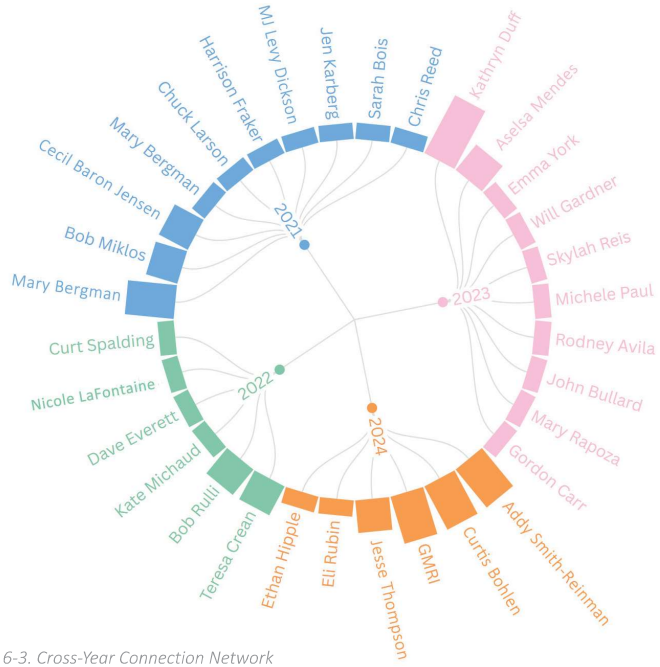


Fig 6-3. Cross-Year Connection Network

BACKGROUND ANALYSIS

Examining disciplinary backgrounds provides additional context for understanding variations in design approaches across different ERC years.

STUDENT BACKGROUND

Student backgrounds vary noticeably from year to year.
2021: Architecture and Landscape Architecture are relatively balanced
2022: Architecture becomes dominant
2023: Greater diversity emerges, including Art & Design
2024: Landscape Architecture regains dominance

These shifts suggest that differences in disciplinary training may contribute to variations in design strategies. Rather than indicating a consistent trend, the composition appears to respond to external factors such as site conditions, project themes, and the types of participants attracted each year.

ADVISOR BACKGROUND

In contrast, advisor backgrounds show a clearer directional shift.
2021: Landscape Architecture has the largest share
2022–2024: Urban Planning becomes the dominant background

This transition reflects a change in project scale and focus. As challenge sites become larger and more complex, the emphasis moves from site-specific design toward regional and system-level thinking. As a result, there is an increased need for expertise in planning, policy, and large-scale coordination.

At the same time, this pattern suggests that ERC actively aligns advisor expertise with project needs. Advisors are not randomly distributed but are selected in response to the scale and complexity of each challenge.

Taken together, these patterns highlight how both student and advisor backgrounds may influence design outcomes. Differences in disciplinary composition can shape ways of thinking, while shifts in advisor expertise may guide projects toward broader, more systemic approaches. Understanding this relationship becomes an important step in the project.

In later analysis, these background patterns will be compared with design strategies to examine how disciplinary differences are reflected in design outcomes.

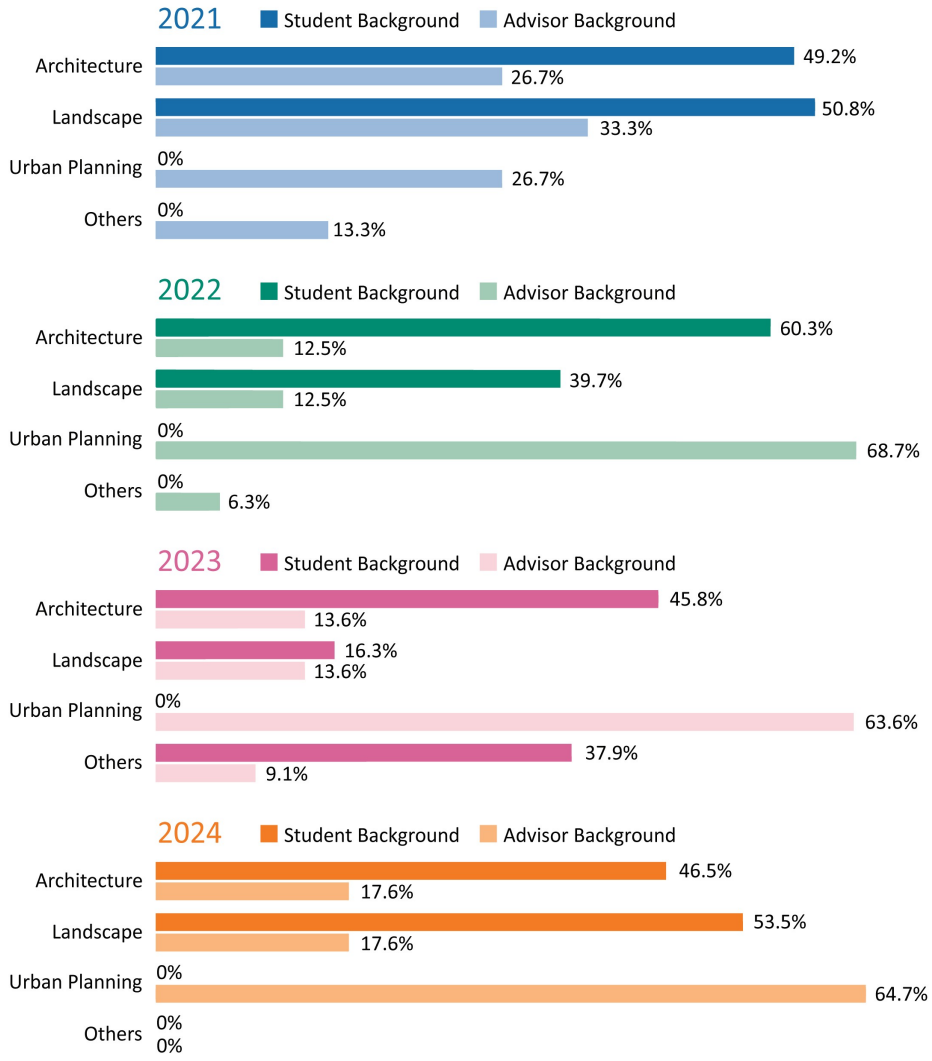


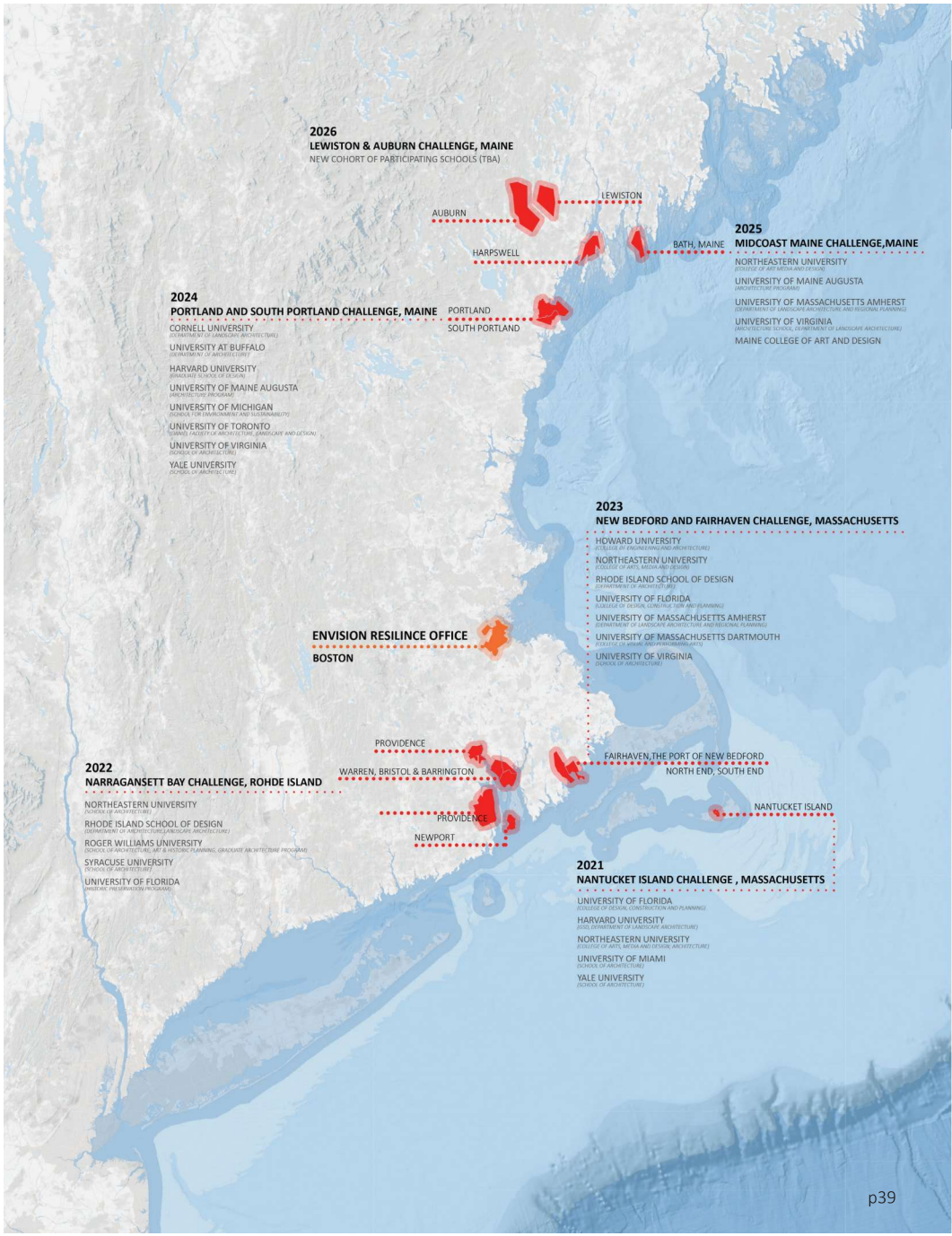
Fig 6-1. Participant Background Analysis (2021–2024)

IMPACT MAP

This section focuses on project analysis, examining how site-specific problems and design strategies are connected across different ERC challenge years. Building on the Resilience Cycle framework, it shifts from understanding participation to analyzing how challenges are identified and addressed through design.

The map on the right provides an overview of the four study sites along the U.S. Northeast coast, offering a shared geographic context. While each site has unique conditions, they are connected through similar coastal risks such as sea level rise and flooding.

Based on this foundation, the following pages compare how site problems are defined and how design strategies respond to them across different years.



Phase 7

Site Problem and Analysis

Analyze site-specific challenges across projects to reveal patterns of environmental, social, and spatial issues.









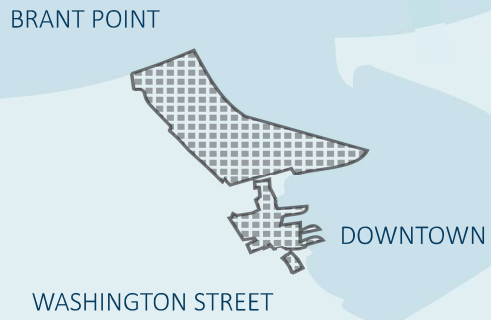




Source: Envision Resilience, Envision Resilience, accessed April 20, 2026.

NARRAGANSETT BAY- 2021

PROBLEM MAPPING



ISSUE INSIGHTS

HIDDEN ECOLOGICAL RISK



ENVIRONMENTAL VULNERABILITY

Low-lying terrain combined with sea level rise puts the core area of Nantucket at long-term flood risk.

ECONOMIC ADAPTATION

The shift from the whaling industry to tourism and real estate has made the waterfront more economically important, but also more exposed to climate risks.

CULTURAL CONTINUITY

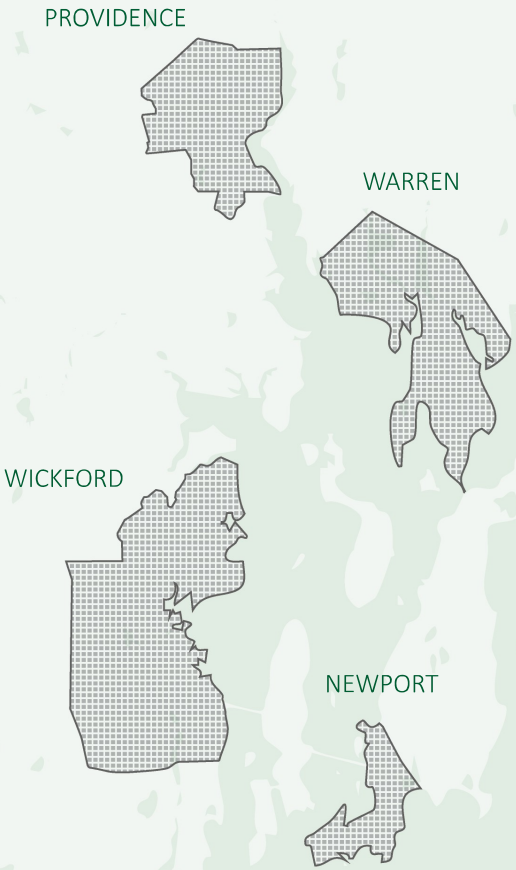
Historic districts and cultural assets along the waterfront face a dual challenge: preservation and climate adaptation.

In this year's study, when identifying problems, students did not focus much on historic preservation. However, the ERC, in its site analysis, emphasized historic buildings and the unique economic transition over time.

The ERC's background information included wetland ecosystems related problems. Although students did not highlight this in their early research, some of the students' strategies responded to these ecological issues later in the process.

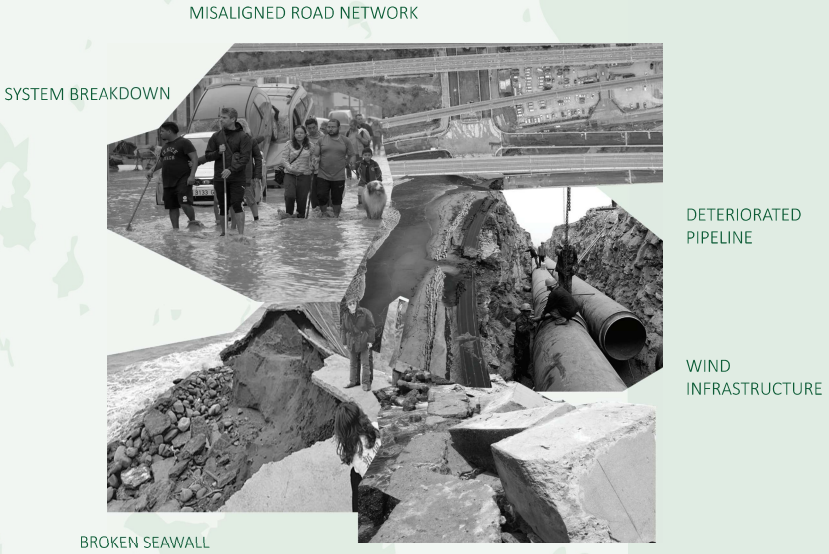
NARRAGANSETT BAY- 2022

PROBLEM MAPPING



ISSUE INSIGHTS

BROKEN SYSTEM



TOPOGRAPHIC EXPOSURE AND INFRASTRUCTURE VULNERABILITY
Low elevation and weak integration of flood control infrastructure make the site highly exposed to risk.

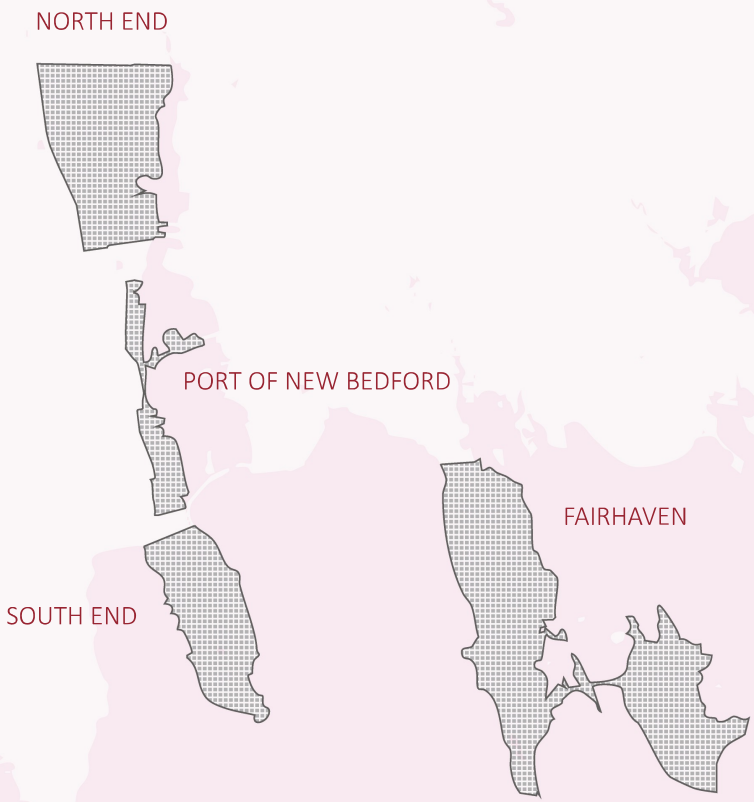
POLICY AND GOVERNANCE CONSTRAINTS
Resilience planning is shaped not only by physical risks, but also by policies, regulations, and governance systems.

TENSION BETWEEN HISTORIC PRESERVATION AND ECONOMIC ADAPTATION
With increasing climate risks, conflicts between historic value and economic feasibility become more visible.

Students this year responded more deeply to ERC's challenges. They translated abstract topics, such as historic preservation and immigrant cultural identity, into spatial analysis problems. These were then addressed through site-specific design strategies.

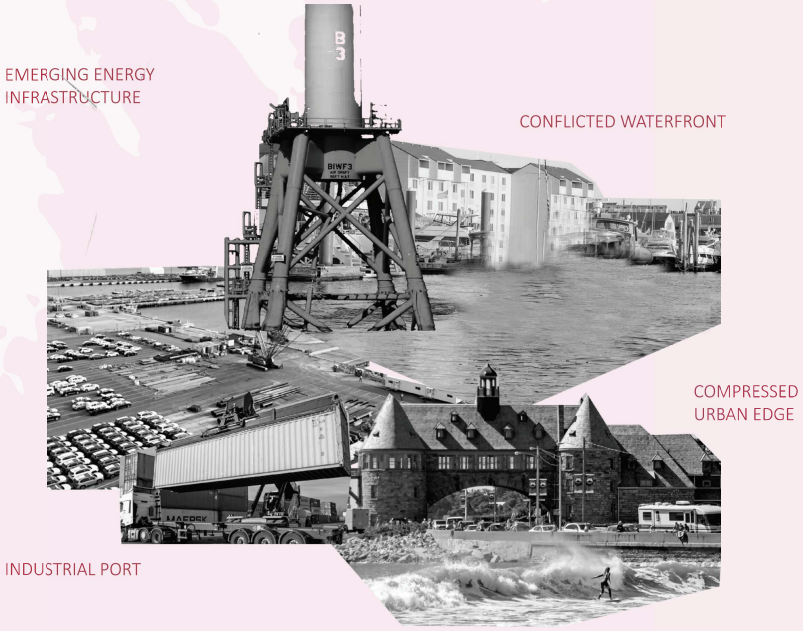
NEW BEDFORD AND FAIRHAVEN- 2023

PROBLEM MAPPING



ISSUE INSIGHTS

SPATIAL CONFLICT



FLOOD RISK FROM INSUFFICIENT INFRASTRUCTURE
With rising sea levels and stronger storms, aging and inadequate coastal infrastructure increases flood risk.

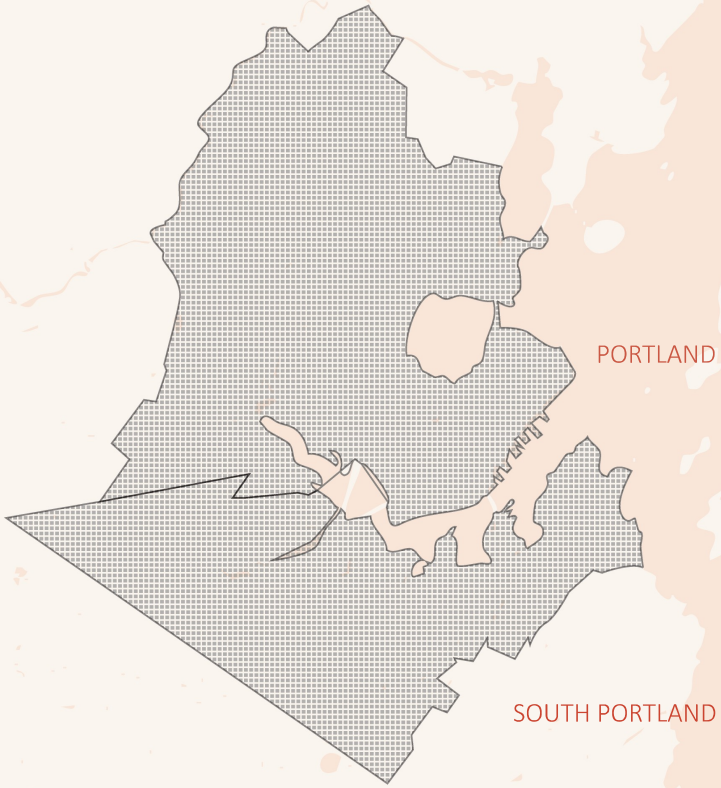
INDUSTRIAL TRANSITION AND ECONOMIC RESTRUCTURING
The region is going through a complex economic shift. Traditional marine industries must coexist and compete with emerging offshore wind energy.

URBAN LAND USE AND SPATIAL REORGANIZATION
Ongoing land use changes and fragmented infrastructure are reshaping the urban structure and weakening spatial coherence.

Students mainly responded to the challenges identified by ERC. Their site analysis largely aligned with ERC's problem framing.

PORTLAND AND SOUTH PORTLAND- 2024

PROBLEM MAPPING



URBAN TRANSITION UNDER CLIMATE RISK



TOPOGRAPHY-DRIVEN FLOOD RISK
Low elevation and coastal exposure make flooding the primary long-term challenge.

URBAN RENEWAL AND WATERFRONT REVITALIZATION
Urban renewal needs to balance economic development, climate resilience, and institutional constraints.

ENERGY TRANSITION
As the city moves away from fossil fuel infrastructure, its future depends on redefining its identity and development path.

Students approached ERC's urban renewal goals through housing and transportation. They also paid attention to challenges related to energy transition.

PROBLEM MAPPING 2021 - 2024

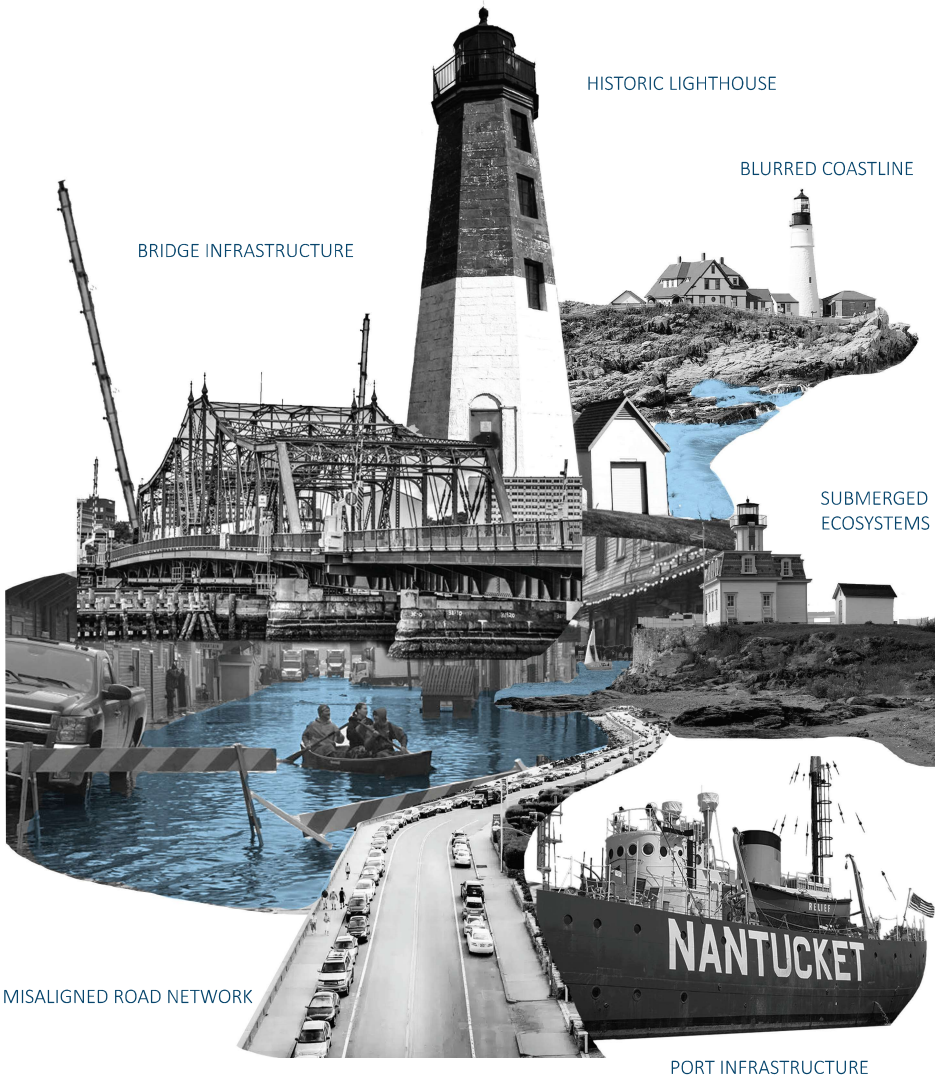


Fig 7-1. Cross-Year Problem Mapping (2021–2024)

Although each site has its own conditions, several core conflicts appear repeatedly in coastal areas. These include long-term flooding caused by sea level rise, ecological degradation, and the structural conflict between economic activities and flood risk.

In places focused on fisheries, ports, or waterfront industries, production activities often overlap with high-risk zones. This creates ongoing tension between development and safety. As a result, design strategies have clearly evolved over the years.

Social equity and housing pressure were frequently mentioned. Students began to realize that flood risk is not evenly distributed. It often affects vulnerable and low-income communities more.

Because of this, some strategies started to include relocation policies, affordable housing, and community engagement. Resilience is no longer only about the environment or technology. It is also closely connected to social structures.Cultural identity and local memory were also discussed repeatedly across projects.

After reviewing strategies from all four years, we found that ERC shows a design tendency that is different from typical practice.
In real projects, design is often limited by budgets, regulations, and timelines. In contrast, ERC provides a more open space for exploration. Teams can test future scenarios without immediate implementation pressure.

Many strategies are highly experimental. Some are even idealized or ambitious, such as large-scale landform changes, industry relocation, or complete spatial reorganization. These proposals are not always meant for short-term implementation. Instead, they explore possible futures.
For this reason, the ERC is not just a competition. It works more like a platform for thought experiments.

Design here is not only about solving problems. It is also about raising questions, building scenarios, and testing ideas. This creates a space where reality and imagination can interact. That experimental nature may be one of the key values of the ERC.

Phase 8

Flow Mapping and Visualization

Map and visualize how different elements are interconnected across projects through dynamic flows.

STRATEGY MAPPING WORKFLOW

After the student presentation videos and boards were reviewed, extracted, and classified, strategy data tables were compiled in Excel for all four years. To make this information more legible and visually comparable, the dataset was further translated into a series of visual diagrams.

RAWGraphs was initially used as the primary platform for data visualization. However, repeated testing showed that the platform could not reliably interpret multiple parallel category selections contained within a single Excel cell, and instead required CSV-formatted input with comma-separated values. As a result, each annual Excel dataset required additional processing before visualization. This involved expanding the combined category entries and assuming a uniform distribution across the five strategy dimensions and their corresponding subcategories, so that the data could be converted into a CSV structure readable by RAWGraphs.

Once the base diagrams were generated, the exported graphics were further refined in Adobe Illustrator and Adobe Photoshop. These post-processing steps included adjustments to layout, color, labeling, and overall visual composition, resulting in the final strategy diagrams used for analysis and presentation.

STRATEGY MAP - 2021

The diagram is read from left to right. Each flow represents a grouped strategy, and the width of each band indicates the relative concentration of strategies within each category.

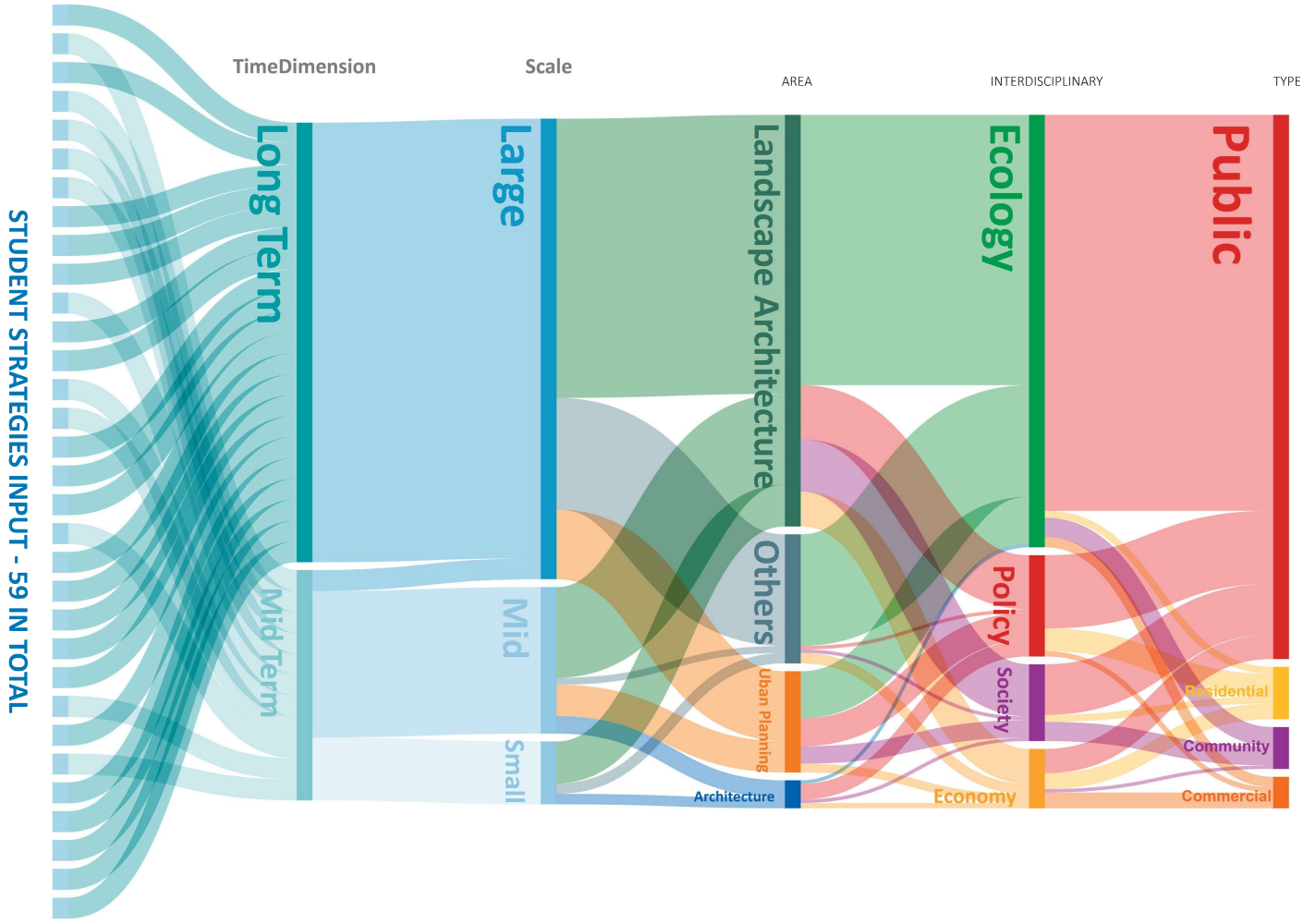


Fig 8-1. Strategy Classification Sankey Diagram (2021)

STRATEGY MAP - 2022

The diagram is read from left to right. Each line represents a strategy, and wider flows indicate a larger number of strategies moving through that category.

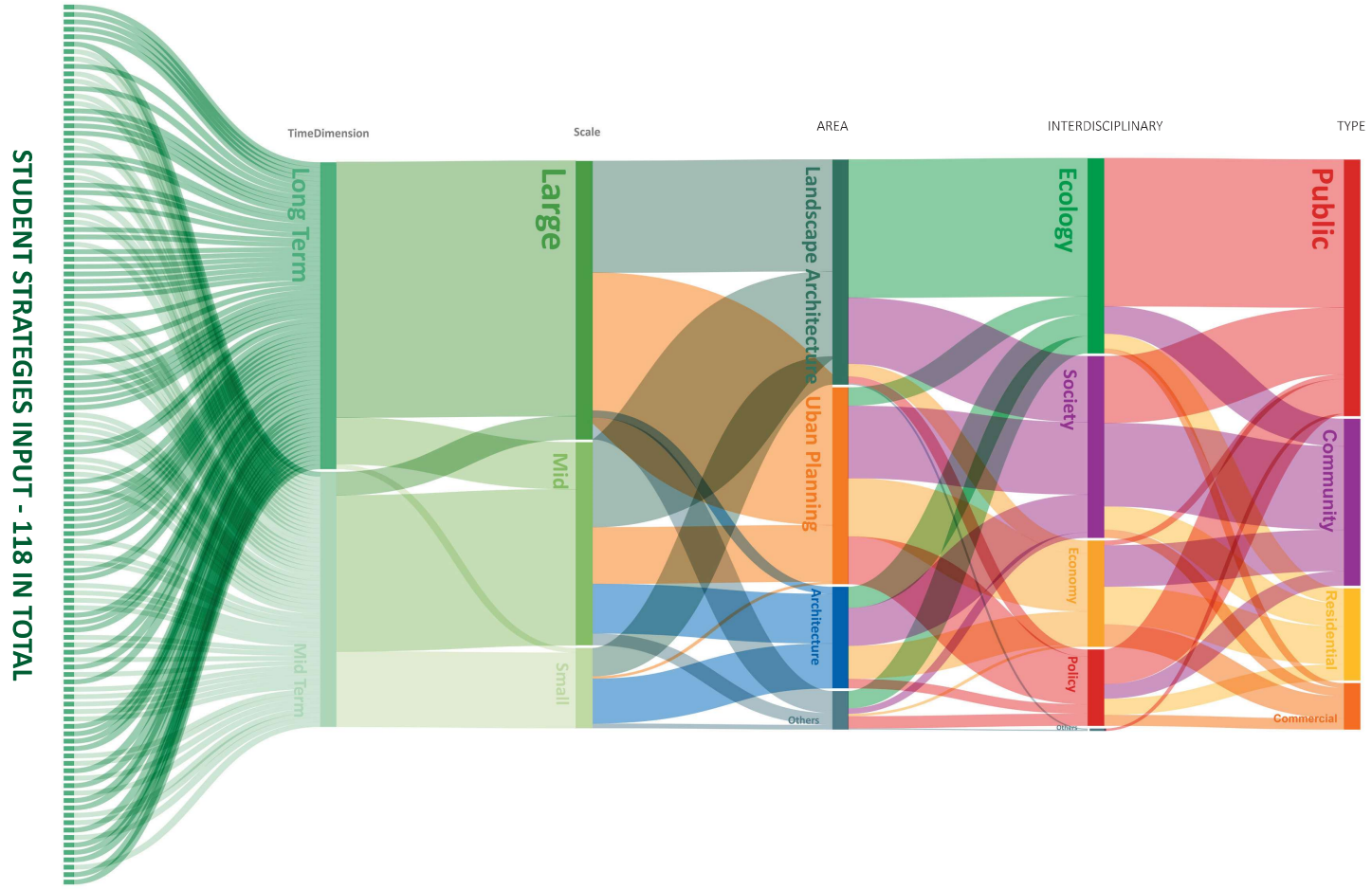


Fig 8-2. Strategy Classification Sankey Diagram (2022)

STRATEGY MAP - 2023

The diagram is read from left to right. Each line represents a strategy, and wider flows indicate a larger number of strategies moving through that category.

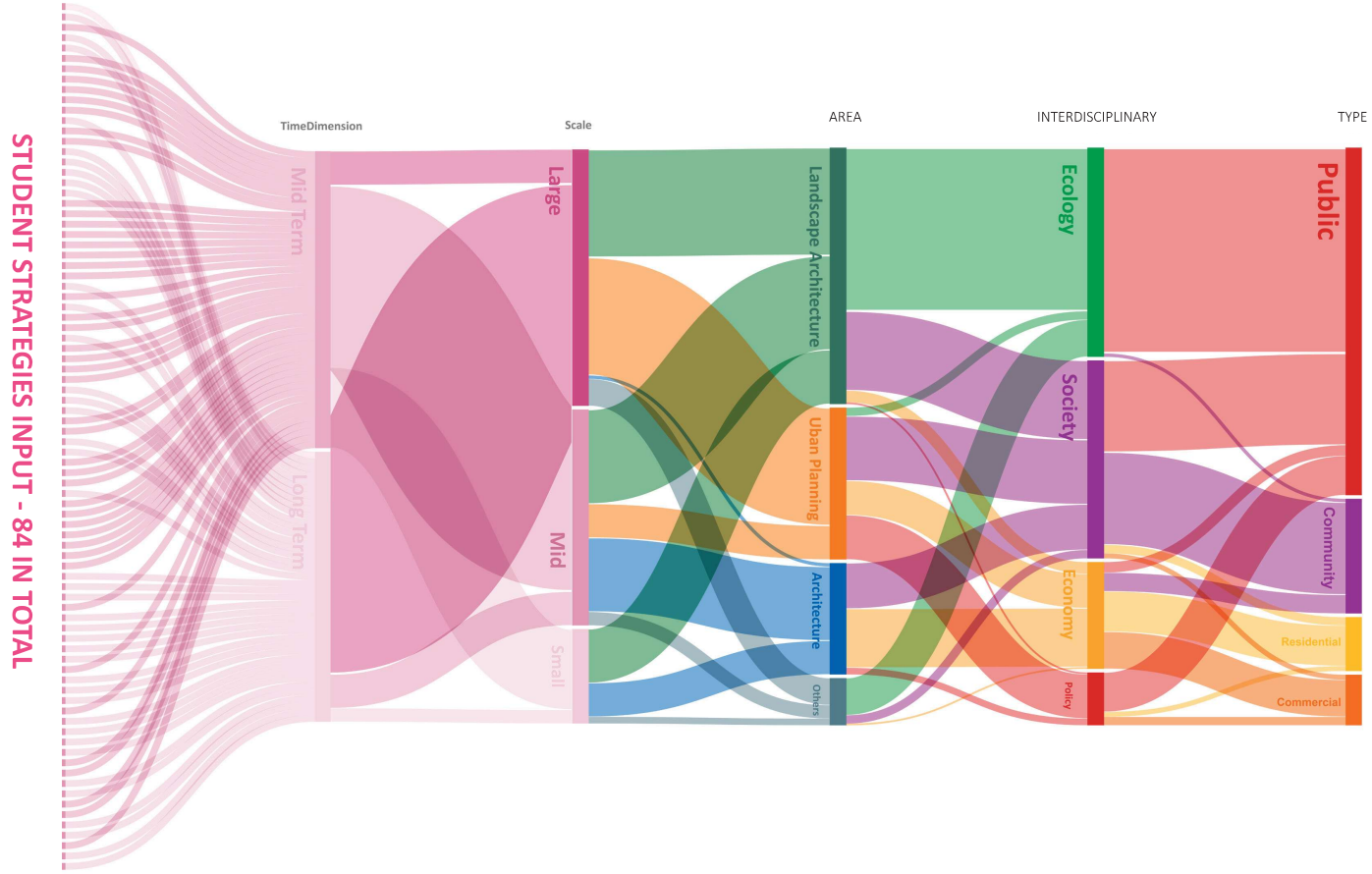


Fig 8-3. Strategy Classification Sankey Diagram (2023)

STRATEGY MAP - 2024

The diagram is read from left to right. Each line represents a strategy, and wider flows indicate a larger number of strategie moving through that category.



Fig 8-4. Strategy Classification Sankey Diagram (2024)

STRATEGY INSIGHTS - 2021

The diagram is read by following the flow from left to right. Darker and wider bands indicate stronger strategy patterns, while lighter and narrower bands indicate secondary ones.

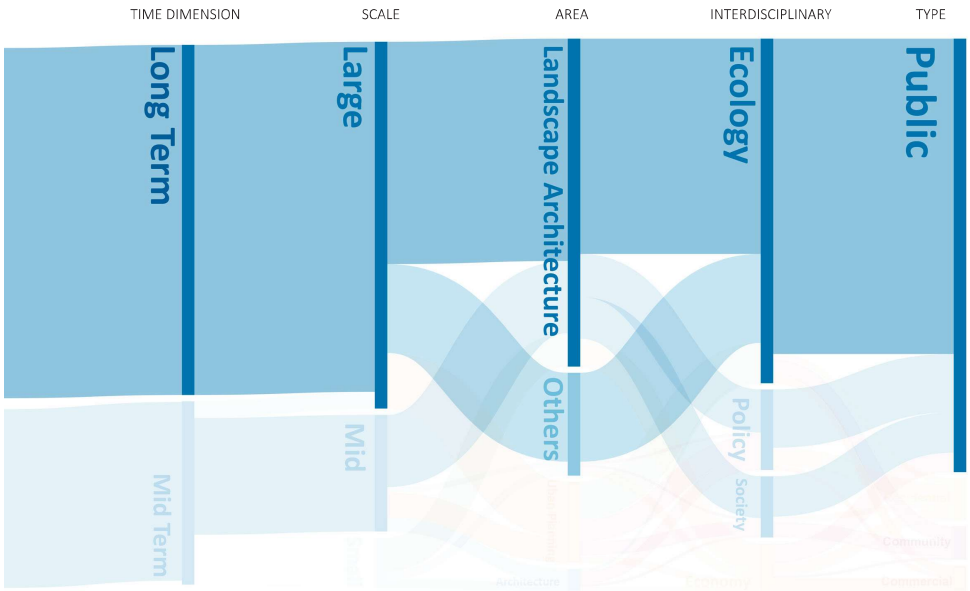


Fig 8-5. Strategy Insights from Sankey Diagram (2021)

The diagram is read by following the flow from left to right. Darker and wider bands indicate stronger strategy patterns, while lighter and narrower bands indicate secondary ones.

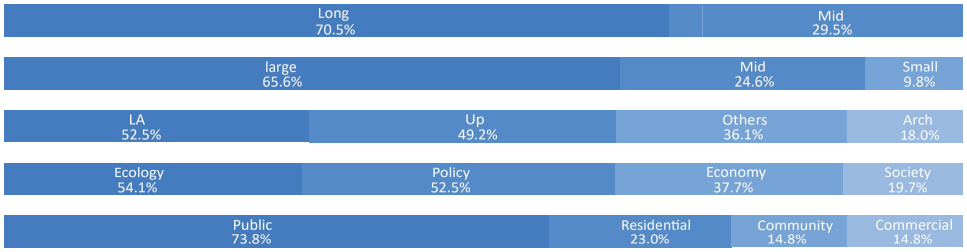


Fig 8-6. Strategy Distribution Summary (2021)

In the 2021 Envision Resilience Challenge, student teams developed a wide range of design responses to coastal resilience challenges. Through systematic classification and consolidation, a total of 59 strategies were identified. Overall, the strategic structure in this year is relatively concentrated, with most proposals centered on long-term, large-scale interventions and characterized by a strong ecological priority.

The most prominent trend is the concentration of long-term, large-scale strategies within the field of landscape architecture, guided by both ecological value and public benefit. Representative strategies include ecological shoreline design, wetland restoration, and deployable or floodable public landscapes. These approaches emphasize foundational ecological interventions as the primary means of addressing coastal resilience, working with natural processes while enhancing the performance and accessibility of public space.

A second major trend follows a similar long-term, large-scale logic, but shifts toward the “Others” category, primarily involving civil engineering and infrastructural systems. Strategies in this group include hybrid hard–soft waterfront edge conditions, adjustable or adaptable piers, and structural systems informed by hydrodynamic processes. These approaches suggest that ecological performance is not achieved through landscape systems alone, but is reinforced through the integration of engineered infrastructure, providing technical support and operational stability for broader resilience frameworks.

The third, less dominant trend consists of mid-term, mid-scale interventions, still largely rooted in landscape architecture, but extending into policy and social dimensions. Representative strategies include incentive-based mechanisms to encourage ecological transformation of private properties, as well as the integration of public education into environmental infrastructure systems. This indicates that, alongside the emphasis on long-term ecological systems, there is an emerging effort to incorporate policy tools and social engagement as implementation pathways, supporting project realization while increasing public awareness and participation.

STRATEGY INSIGHTS - 2022

The diagram is read by following the flow from left to right. Darker and wider bands indicate stronger strategy patterns, while lighter and narrower bands indicate secondary ones.

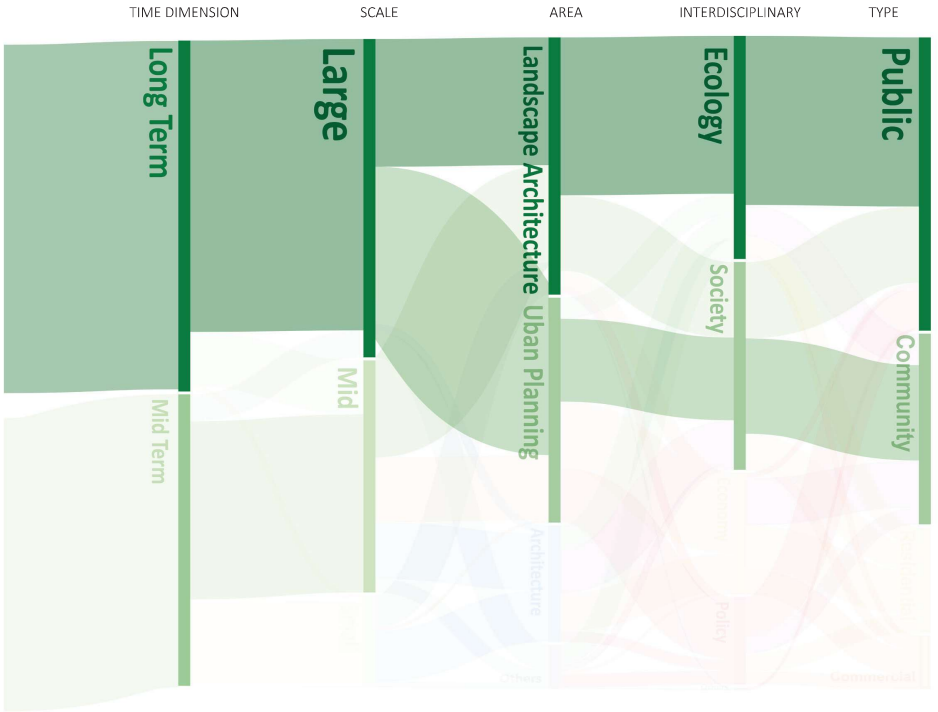


Fig 8-7. Strategy Insights from Sankey Diagram (2022)

The diagram is read by following the flow from left to right. Darker and wider bands indicate stronger strategy patterns, while lighter and narrower bands indicate secondary ones.

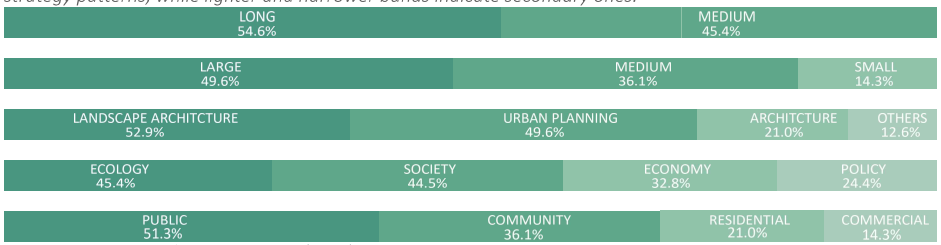


Fig 8-8. Strategy Distribution Summary (2022)

In the 2022 Envision Resilience Challenge, student teams responded to issues of coastal adaptation, community transformation, and spatial restructuring through a wide range of design strategies. Through consolidation and classification, a total of 118 strategies were identified. Overall, while long-term, large-scale interventions remained dominant, the distribution of strategies became more dispersed, reflecting a parallel development of ecological and planning-oriented approaches.

The most prominent trend continues to be the concentration of long-term, large-scale strategies within the field of landscape architecture, guided by ecological performance and public benefit. Similar to 2021, representative strategies include ecological shoreline systems, wetland construction, and floodable public landscapes. This continuity indicates that ecological approaches remain a foundational component of coastal resilience, with landscape-scale interventions widely used to address environmental risks while positioning public space as a primary medium for resilience.

A second major trend follows a similar temporal and spatial logic, but shifts more explicitly toward urban planning, with stronger connections to social and community dimensions. Strategies in this group include the organization of mixed-use communities in safer areas, phased coastal retreat, and broader spatial restructuring. This suggests that resilience design is extending beyond environmental response into the realm of spatial governance and social structure, using planning as a tool to guide long-term transformation and community adaptation.

The third, less dominant trend consists of mid-term, mid-scale interventions, still largely grounded in landscape architecture but increasingly oriented toward public space and community use. Representative strategies include improving waterfront accessibility, promoting community-oriented adaptive reuse, and enhancing pedestrian and slow mobility networks. These approaches indicate a growing emphasis on more implementable, everyday spatial interventions that complement the larger strategic frameworks and strengthen their impact at the community scale.

Compared to 2021, the number of strategies increased significantly, and the disciplinary structure shifted from a landscape architecture–dominated framework to a more balanced relationship between landscape architecture and urban planning. In addition to addressing ecological systems, strategies increasingly engage with community conditions and the improvement of public space.

STRATEGY INSIGHTS - 2023

The diagram is read by following the flow from left to right. Darker and wider bands indicate stronger strategy patterns, while lighter and narrower bands indicate secondary ones.

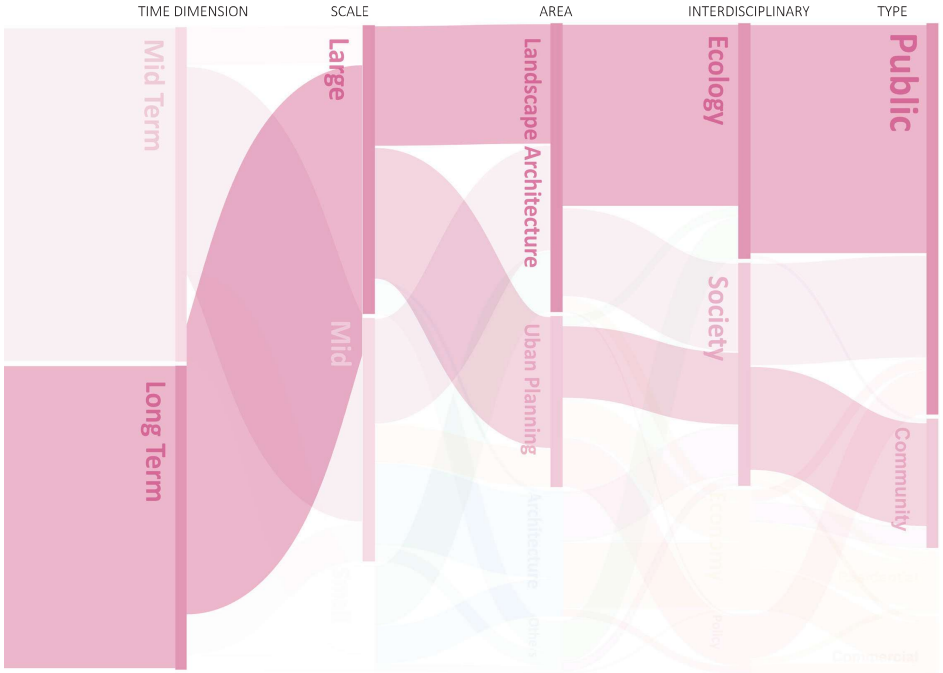


Fig 8-9. Strategy Insights from Sankey Diagram (2023)

The diagram is read by following the flow from left to right. Darker and wider bands indicate stronger strategy patterns, while lighter and narrower bands indicate secondary ones.

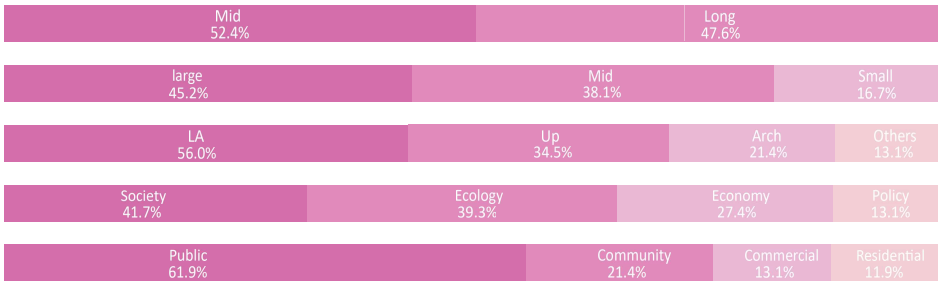


Fig 8-10. Strategy Distribution Summary (2023)

The diagram is read from left to right. Each flow represents a grouped set of strategies, and the width of each band reflects the relative concentration within each category.

In the 2023 Envision Resilience Challenge, student teams explored design responses to coastal resilience, industrial transition, and waterfront transformation. Through consolidation and classification, a total of 84 strategies were identified. Compared to previous years, disciplinary interactions became more integrated, and individual strategies increasingly operated across multiple dimensions, forming more interconnected and coordinated relationships.

The most prominent trend remains the concentration of long-term, large-scale strategies within the field of landscape architecture, guided by ecological performance and public benefit. Strategies in this category are further refined and include salt marsh restoration, constructed wetlands, living shorelines, oyster reef systems, and floodable public landscapes. These approaches suggest that ecological strategies are no longer treated as isolated environmental responses, but are increasingly incorporated into broader spatial and social frameworks.

A second major trend follows a similar long-term, large-scale logic, but shifts more clearly toward urban planning, with deeper integration of social and community dimensions. Strategies include phased coastal retreat, adaptive housing, mixed-use reconfiguration, community-support spaces, and industrial transition frameworks. This indicates a shift from addressing individual spatial or ecological conditions toward coordinating social structures, economic activities, and long-term urban transformation through planning. Urban planning is no longer positioned as a parallel discipline, but increasingly functions as an organizing framework that connects multiple systems.

The third, less dominant trend consists of mid-term, mid-scale interventions, still rooted in landscape architecture, but extending toward public space and community-oriented applications. These strategies focus on waterfront boardwalk systems, pedestrian and mobility networks, public access improvements, adaptive waterfront reuse, and community-oriented public space design. Such approaches reflect a growing emphasis on implementability and everyday spatial experience, translating resilience from large-scale systems into interventions that operate at the community and user level.

Compared to 2022, the total number of strategies decreased, and the overall disciplinary balance remained relatively consistent. However, strategies became more refined and internally complex, with individual proposals addressing multiple dimensions simultaneously and incorporating more specific and integrated content. This reflects a more advanced and nuanced understanding of coastal resilience as a multi-layered and interconnected challenge.

STRATEGY INSIGHTS - 2024

The diagram is read by following the flow from left to right. Darker and wider bands indicate stronger strategy patterns, while lighter and narrower bands indicate secondary ones.

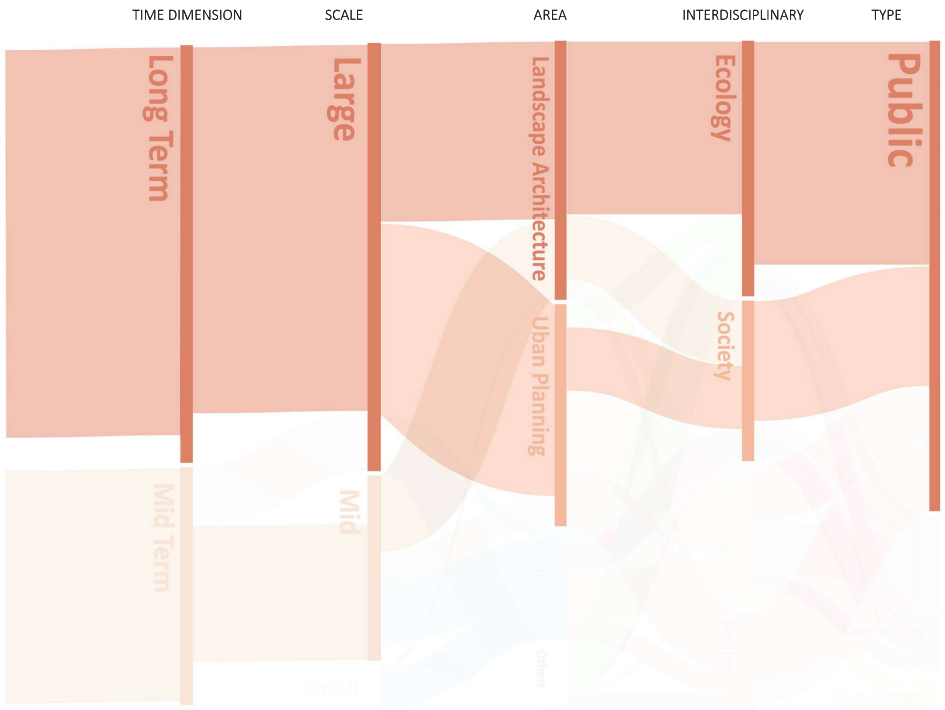


Fig 8-11. Strategy Insights from Sankey Diagram (2024)

The diagram is read by following the flow from left to right. Darker and wider bands indicate stronger strategy patterns, while lighter and narrower bands indicate secondary ones.

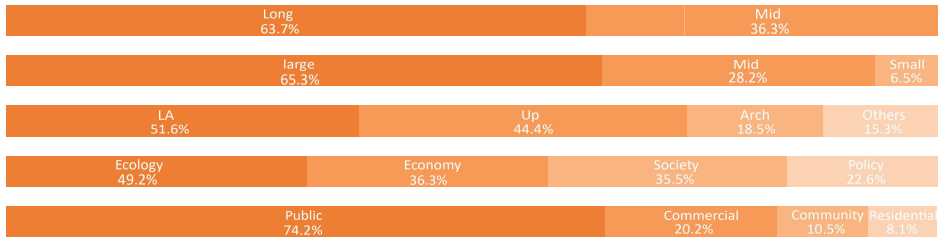


Fig 8-12. Strategy Distribution Summary (2024)

The 2024 Envision Resilience Challenge focused on issues of flood risk mitigation, waterfront restructuring, mobility, energy transition, and broader urban transformation. Through consolidation and classification, a total of 124 strategies were identified.

The most prominent trend remains the concentration of long-term, large-scale strategies within the field of landscape architecture, continuing to be guided by ecological performance and public benefit. Representative strategies include wetland migration, salt marsh expansion, ecological buffering systems, layered coastal defense frameworks, urban wetland networks, and floodable public landscapes. Compared to previous years, this trajectory not only reinforces the central role of ecological approaches, but also shows a clearer integration with infrastructure systems and spatial restructuring. Ecological strategies are no longer framed primarily as conceptual systems, but are increasingly developed as implementable spatial and engineering frameworks.

A second major trend follows a similar long-term, large-scale logic, but shifts more explicitly toward urban planning, with strong connections to social and public dimensions. Strategies in this category focus on mobility restructuring, mixed-use redevelopment, resilient housing, transportation integration, and phased urban adaptation. Representative approaches include multimodal transit hubs, water-based mobility systems, climate-responsive housing, and the reorganization of port and logistics systems. This indicates that strategies are no longer limited to improving spatial form or ecological systems alone, but increasingly operate through planning to coordinate urban processes, restructuring spatial organization and infrastructure systems under conditions of climate risk.

The third, less dominant trend consists of mid-term, mid-scale interventions, still grounded in landscape architecture, but extending toward public space and community-oriented applications. These include adaptive waterfront reuse, improvements in public accessibility, community facilities, and waterfront public space design, as well as smaller-scale resilience interventions such as maker spaces, community centers, and floodable micro-scale urban spaces. These strategies reflect a growing emphasis on implementation and everyday use, translating resilience into interventions that are perceptible and functional at the community scale.

Compared to 2023, the number of strategies increased significantly, reaching the highest level across the four years. More strategies are oriented toward public use while also addressing operational mechanisms and implementation pathways. Overall, the 2024 strategy structure no longer treats ecological, planning, and public-oriented approaches as parallel or independent trajectories. Instead, they are increasingly organized within a unified framework of spatial restructuring and infrastructural transformation, indicating a clear shift from system exploration toward implementation-oriented practice.

CROSS YEAR INSIGHTS(2021- 2024)

FLUCTUATIONS IN STRATEGY QUANTITY REFLECT EVOLVING MODES OF RESPONSE

The number of identified strategies increased from 59 in 2021 to 118 in 2022, declined to 84 in 2023, and rose again to 124 in 2024, forming a pattern of expansion, adjustment, and renewed growth. This variation is not only quantitative, but also relates to the expanding geographic scope, increased institutional participation, and a growing number of contributors. At the same time, these fluctuations indicate shifts in how student teams approached coastal resilience: some years emphasized broad exploration and diverse proposals, while others focused on integrating greater complexity and multiple dimensions within a more limited set of strategies.

CORE TRAJECTORIES PERSIST, WHILE ORGANIZATIONAL EMPHASIS SHIFTS ACROSS YEARS

Across all four years, several key trajectories remain consistent, including long-term, large-scale interventions, a landscape architecture perspective, ecological prioritization, and the use of public space as a primary medium for resilience. These recurring directions form a stable conceptual foundation, reflecting the Challenge's sustained focus on core coastal resilience issues. However, within this shared framework, each year exhibits distinct structural emphases. For example, strategies in 2021 demonstrate closer alignment with civil engineering and infrastructural systems, while 2022 shifts more explicitly toward urban planning, community transformation, and spatial restructuring. This suggests that rather than repeating a fixed model, the strategies evolve through continuous recalibration in response to site-specific conditions and thematic priorities.

STRATEGY LOGIC SHIFTS FROM DISCIPLINARY DOMINANCE TO INTERDISCIPLINARY INTEGRATION

In earlier phases, strategies were more clearly structured and discipline-led, with landscape architecture occupying a dominant role in 2021. Over time, the range of disciplinary involvement expanded, with increasing overlap among landscape architecture, urban planning, governance, economic systems, and infrastructure. As a result, strategies became less easily categorized within single disciplines and instead operated across multiple domains simultaneously. This shift reflects a broader change in how coastal resilience is understood—from a primarily environmental concern to a more complex, system-based condition. Within this evolution, urban planning moves beyond a parallel discipline and increasingly functions as an organizing framework, coordinating relationships among social, economic, and spatial systems.

STRATEGY DEVELOPMENT MOVES FROM CONCEPTUAL PROPOSITIONS TOWARD IMPLEMENTATION-ORIENTED APPROACHES

In the earlier years, many strategies were framed as high-level, conceptual, and system-oriented proposals, with a strong emphasis on vision and exploration. As the overall complexity of the challenge increased, particularly in 2023 and 2024, a growing number of strategies began to address implementation, phasing, and spatial adaptation to everyday use. Resilience is no longer approached solely at the scale of systems or master planning, but is increasingly translated into interventions at the community, infrastructural, and experiential levels. For example, strategies such as community participation, small-scale yard transformations, and rain gardens embed ecological resilience within daily life. This shift indicates a transition from proposing ideas to structuring pathways for implementation, with greater attention to use, participation, and real-world applicability.

Phase 9

Closing the Loop: Returning to the Problem

Conduct surveys to gather stakeholder feedback and integrate findings with previous analysis to generate insights.

VALIDATION

DATA PREPARATION

Two datasets were used: a strategy dataset and a problem dataset.
The strategy dataset consists of design strategies extracted from ERC projects from 2021 to 2024, where each record contains a textual description of the strategy.

The problem dataset is derived from issues identified in student site analysis, each accompanied by manually extracted keyword tags.

Both datasets were initially stored in separate sheets by year. To facilitate unified analysis, they were reorganized into a long-table format, with each record assigned a unique identifier (strategy_id and problem_id) along with its corresponding year.

To transform problems into retrievable textual representations, we applied text concatenation, combining the problem description with its associated keyword tags to form a unified query text.

This query text integrates both full semantic information and keyword-level features.
For the strategy dataset, only the textual description under Design Method was used for matching.

DATA PROCESS(TF-IDF RETRIEVAL)

A TF-IDF approach was adopted as a baseline model to measure lexical similarity between problems and strategies.

First, all strategy texts were transformed into TF-IDF vectors.
Then, the problem query texts were projected into the same vector space, and cosine similarity was computed between each problem and all strategies.

It is important to note that TF-IDF similarity is used only for ranking candidate strategies, and does not indicate the “correctness” or “quality” of a strategy.

The evaluation focuses on whether the retrieved strategies, as a set, can collectively provide an effective response to the problem.

Therefore, this study emphasizes the matching relationship between problems and strategies, rather than evaluating the intrinsic quality of design solutions.

For each problem, the top k (k = 10) most similar strategies were selected as candidate results.
Additionally, a same-year matching mechanism was applied, meaning each problem was only matched with strategies from the same year.

This was used to test whether problems identified in a given year could be effectively addressed by design strategies proposed in that same year.

MANUAL EVALUATION

Since there is no predefined ground-truth mapping between problems and strategies, manual evaluation was introduced.
For the top 10 retrieved strategies of each problem (210 pairs in total), relevance was assessed individually using the following scale:

1 = Highly relevant
0.5 = Partially relevant
0 = Not relevant

This step allows evaluation beyond lexical similarity, assessing whether a strategy semantically addresses the problem.
To quantify how well a problem is addressed by a set of strategies, a coverage metric was defined:

coverage = (1 × number of highly relevant + 0.5 × number of partially relevant) / total number

Here, the total number refers to the number of retrieved strategies per problem (k = 10).
The coverage value ranges from 0 to 1, indicating the degree to which a problem is addressed by the strategy set.

After calculating coverage at the individual problem level, the values were averaged by year to analyze trends in problem–strategy matching across different years.
This approach helps evaluate whether the ability of strategies to respond to problems evolves over time.

Overall, this method integrates text-based retrieval with manual evaluation to systematically analyze the matching relationship between problems and design strategies.
It reveals how design responses to problems vary across years and uncovers their evolutionary patterns over time.

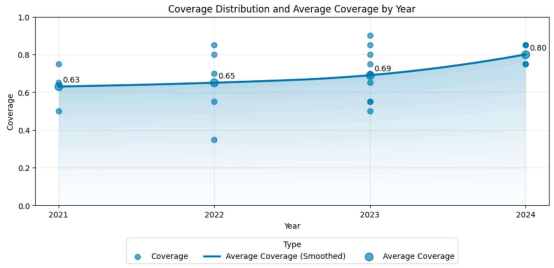


Fig 9-1. Coverage Distribution by Problem Type (Spatial vs Systemic)

OBSERVATION

Across the four years of data, the majority of problems show coverage values concentrated within the range of 0.3–0.6.

There're several outliers are noteworthy.

The problem labeled 2022_P004 (How can port-dependent economies overcome path dependency and lack of urban vitality?) has a coverage value of 0.35, which is significantly lower than the minimum range observed for most problems. This indicates that this issue is poorly addressed by existing strategies.

In contrast, 2023_P007 (How can conflicts between industrial development and urban cultural identity be mediated?) has a coverage value of 0.90, which is substantially higher than the upper range of most problems, suggesting a strong alignment between this issue and the strategies.
Conclusion

The coverage results indicate that, overall, design strategies are able to respond to most problems at a moderate to high level. Most problems have coverage values above 0.6, suggesting that at least half of the strategies are relevant to these issues to varying degrees.
At the aggregate level, the average coverage increases from 0.63 in 2021 to 0.80 in 2024, showing a steady upward trend. This suggests that the alignment between problem statements and design strategies has improved over time.

We argue that this trend is closely related to changes in ERC's organizational approach. In 2021, problem statements were relatively broad, providing students with a high degree of flexibility. From 2021 to 2024, as site information became more detailed and project requirements more specific, students were better able to address frequently observed issues identified during site analysis. Therefore, this trend aligns well with the evolution of the project structure.

At the level of individual years, considering both high and low values, we observe significant differences in how different types of problems are addressed by strategies.

Problems with higher coverage values (e.g., 0.85–0.90) tend to exhibit strong alignment with strategies. These problems are typically more specific and spatially explicit, such as flood management, shoreline adaptation, or ecological restoration.

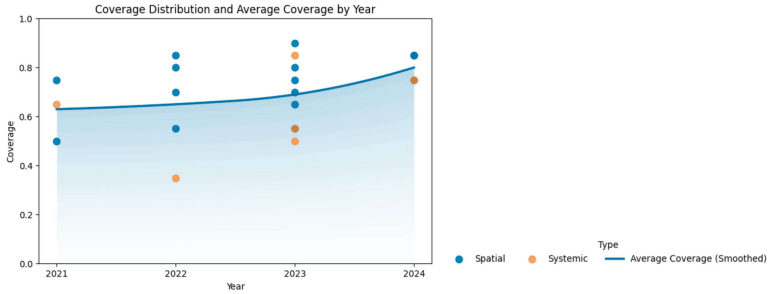


Fig 9-2. Coverage Distribution by Problem Type (Spatial vs Systemic)

In contrast, problems with lower coverage values (e.g., 0.35–0.50) tend to be more abstract or systemic, often involving governance structures, socio-economic relationships, or cross-scalar dynamics. These are less effectively addressed by design strategies.

Compared to physically grounded issues such as flooding and ecological restoration, problems related to social structures, governance systems, or multi-scalar relationships show a wider distribution of lower coverage values. This suggests that current design strategies are more effective in addressing spatially explicit and operational problems, while their capacity to respond to complex systemic issues remains limited.

Overall, the results demonstrate that design strategies are more effective when responding to problems with clear spatial attributes. When problems are framed around physical processes—such as flooding, erosion, or ecological degradation—strategies are more likely to provide direct responses.

However, for problems involving abstract relationships or systemic complexity, the degree of alignment decreases significantly. This reflects a partial mismatch between problem framing and design outputs across different types of issues.

Current design approaches tend to prioritize spatial and technical challenges, while their ability to address social and systemic issues remains comparatively limited. This highlights a potential limitation of design strategies in dealing with governance, social equity, and long-term transformation.

Improving this alignment may require the integration of broader interdisciplinary perspectives and an expansion of design interventions beyond the physical domain.

INSIGHTS

Respoding to the ERC Organization

Beyond methodological factors, the observed increase in coverage may also reflect organizational changes within ERC. According to the internal survey, the number of program organizers increased over time, including the addition of new members and the transition of participants into organizing roles.

Such changes suggest the formation of institutional knowledge and continuity within the program. This enhanced organizational capacity may have improved the clarity of problem framing and the precision of strategy formulation, thereby strengthening the alignment between problems and strategies and leading to higher coverage values.

The increasing fragmentation observed in the strategy maps corresponds closely with the rising coverage values. As the system evolves, strategies are no longer organized along a few dominant pathways but instead form a more interconnected network across multiple dimensions, including scale, disciplinary domains, and implementation types.

Responding to Strategy

This diversification expands the semantic and structural space of the strategy set, allowing a single problem to be addressed through multiple pathways. As a result, the likelihood of a problem being matched with at least one relevant strategy increases, leading to higher overall coverage.



Source: Photo by David Yu via Pexels

CONCLUSION

LOOKING BACK

This project systematically organizes the dispersed materials, abstract data, underlying patterns, and internal relationships found across the Envision Resilience Challenge from 2021 to 2024. Through classification, data analysis, and relational mapping, it transforms these materials into a coherent, readable, and reusable framework for presentation, communication, and future use. It is the first attempt to systematically reveal hidden connections and patterns across four years of ERC challenges, while also establishing a reusable knowledge structure and a basis for cross-year comparison. The result functions as both an initial database and a foundational framework, providing a starting point for the long-term documentation and comparative study of future challenges.

WHAT IT REVEALS

This study shows that the value of the Envision Resilience Challenge's annual studios and workshops lies not only in the final design proposals produced by students, but also in the broader process of interdisciplinary collaboration and multi-stakeholder participation. Viewed across multiple years, the Envision Resilience Challenge can be understood as a comparable and continuously evolving system. Site issues, participation structures, and design strategies also emerge as interconnected parts of the ERC process, shaping one another over time.

LOOKING AHEAD

The framework developed in this report can continue to be applied in future ERC challenge years. Its classification system, data coding logic, and visualization workflow provide a reusable process for future annual summaries, cross-year comparison, archive building, and communication. It may also help ERC identify recurring patterns, shifting priorities, and changes in disciplinary emphasis across challenge years. Looking ahead, ERC may benefit from more intentional planning in how problems are defined, how participation is structured, and how outcomes are interpreted. When future challenges address sites with different scales, levels of risk, and development priorities, it may also be useful to more strategically select participants from different disciplinary backgrounds and activity types that align with those conditions.

WHAT COMES NEXT

Future challenge years may also serve as important opportunities to test and further refine this framework. If its usefulness continues to be demonstrated over time, the framework may help build a more consistent and cumulative foundation for future ERC research, documentation, reflection, and communication.
continuously evolving system. Site issues, participation structures, and design strategies also emerge as interconnected parts of the ERC process, shaping one another over time.

RECOMMENDATIONS

1. STRENGTHENING COMMUNICATION AND LONG-TERM COLLABORATION

ERC can further enhance its impact by establishing more consistent communication channels with participating schools and long-term advisors. Sustained collaboration with advisors and partner organizations can help build continuity across successive challenge years and support knowledge accumulation over time.

2. EXPANDING DATA COLLECTION PROCESSES

a.Survey-based Feedback Collection

To better understand stakeholder perspectives, we suggest introducing structured survey processes at multiple stages:

Pre-challenge phase:

Conduct initial surveys targeting communities, advisors, and organizations to identify key concerns, needs, and perceptions of problems.

Post-challenge phase:

Survey participants and advisors to capture reflections on the design and collaboration process.
Survey community residents to understand how they perceive and evaluate the proposed design projects.
In addition, ERC could strengthen outreach before each challenge through:
Community lectures and events
YouTube videos for broader accessibility
Instagram campaigns for early-stage engagement and visibility

b. Collection of Student Strategy Lists

We recommend requiring students to submit a design strategy list as an appendix alongside their final projects. Each strategy should include a short description and 3–5 keywords, which would greatly improve consistency, clarity, and future analysis.

3. APPLYING OUR ANALYTICAL FRAMEWORK

Our proposed workflow can support ERC in building a structured and reusable analytical system in 5 steps:

Step 1: Data Preparation

Collect presentation transcripts from student reviews. Ideally, standardize strategy extraction by asking students to directly provide structured design strategy lists.

Step 2: Classification

Apply our classification system to categorize design strategies. For cross-year analysis or adjustments to classification criteria, our machine learning model can be used to scale and automate the labeling process, with outputs exported as CSV files.

Step 3: Visualization

Use Jupyter Notebook for single-dimension visualizations (e.g., Sankey diagrams).
Use platforms like the RAWGraphs website for multi-dimensional relationship analysis.

Step 4: Quantitative Analysis

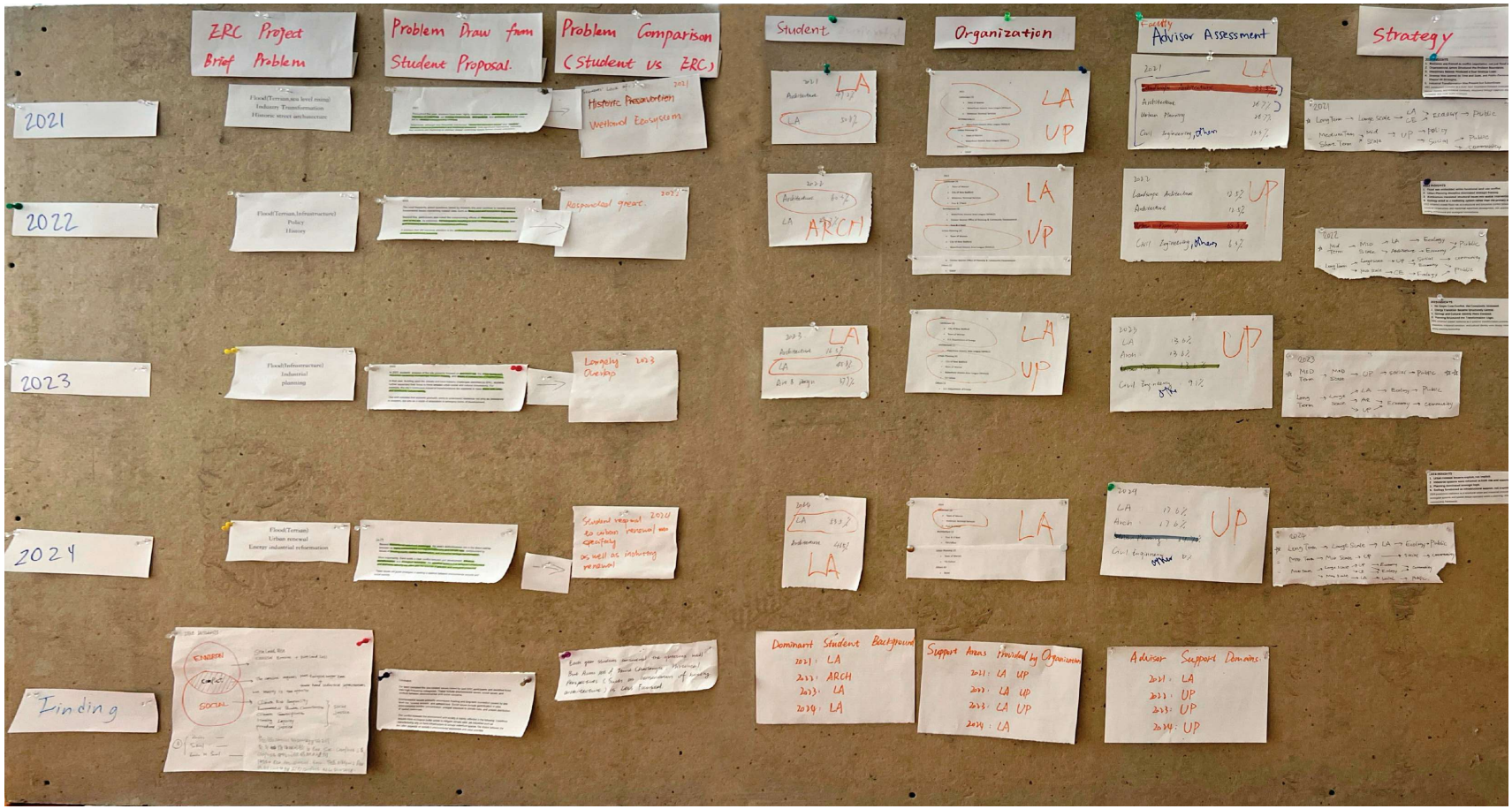
Prepare both problem lists and design strategy lists (CSV format), and apply our NLP pipeline to identify optimal problem-strategy matches.

Step 5: Advanced Visualization

Continue using our Jupyter-based tools to visualize matching results and reveal underlying patterns.
Overall, this process provides a scalable and systematic approach for ERC to better organize its data, evaluate design impacts, and support future cross-year comparisons and communication efforts.

APPENDIX

DATA ORGANIZATION MATRIX



We organized all ERC materials into a matrix. The matrix brings together project briefs, student proposals, organizations, advisors, and strategies from different years.This structure helps us compare the information and find key insights in the following analysis.

DATA VISUALIZATION(BAR-CHART)

ERC_Frame_Analysis-src\src\visualization\bar_chart.py

```python
import pandas as pd
import matplotlib.pyplot as plt

plt.rcParams["svg.fonttype"] = "none"

df = pd.read_csv("long_format_data.csv")

year = 2024

categories = [
    "Time Dimension",
    "Scale",
    "Specialization",
    "Interdisciplinary",
    "Type"
]

colors = [
    "#F58111",
    "#FFA34A",
    "#FFC080",
    "#FFDCBD"
]

fig, ax = plt.subplots(figsize=(12, 5), dpi=300)

total_width = 10
bar_height = 0.6

for i, cat in enumerate(categories):

    data = df[(df.year == year) & (df.category == cat)]
    data = data.sort_values("percentage", ascending=False)

    start_x = 0
    y_pos = 4 - i

    for j, row in enumerate(data.itertuples()):

        total_percent = data["percentage"].sum()
        width = row.percentage / total_percent * total_width

        ax.barh(
            y=y_pos,
            width=width,
            left=start_x,
            height=bar_height,
            color=colors[j],
            edgecolor="none"
        )

```



```python
        # if width > 1.2:   # ⭐ 关键阈值（可调）
        ax.text(
                    start_x + width/2,
                    y_pos,
                    f"{row.subcategory}\n{row.percentage}%",
                    ha="center",
                    va="center",
                    fontsize=9,
                    color="white"
                )

        start_x += width

ax.set_xlim(0, total_width)
ax.set_xticks([])
ax.set_yticks([])
ax.spines[:].set_visible(False)

plt.tight_layout()
plt.savefig("five_equal_bars.svg", transparent=True)
plt.show()

```

DATA ANALYSIS(ERC_SURVEYDEXPLOER)

In [62]:
```
import pandas as pd
import matplotlib.pyplot as plt
import os

os.getcwd()
```

Out[62]: '/Users/chenxinhe/26winter/capstone'

In [63]:
```
pd.read_csv('Envision Resilience Challenge Engagement and Network Mapping
```


Out[63]:

	Timestamp	Email Address	What is your name?	What was your role in this challenge?	Pleas sele whic phase(you we most acti i
0	11/4/2025 10:43:49	cxinhe@umich.edu	NaN	NaN	Na
1	11/4/2025 12:19:36	yunjiazo@umich.edu	NaN	NaN	Na
2	11/14/2025 16:11:00	cvanvoorhis@envisionresilience.org	Charlotte Van Voorhis	ERC program organizer	Pr challeng (planni and set-up Post-chal
3	11/17/2025 11:15:31	cjensen@remain.org	Cecil	staff/strategic advisor	Pr challeng (planni and set-up Challenge
4	11/17/2025 11:24:16	kdeans@envisionresilience.org	Kate Deans	ERC program organizer	Pr challeng (planni and set-up Challenge
5	11/23/2025 17:26:01	ccox.advisor@envisionresilience.org	Carolyn Cox	ERC program organizer	Pr challeng (planni and set-up Challenge
6	11/25/2025 13:55:34	cmartin@envisionresilience.org	Claire Martin	ERC program organizer	Pr challeng (planni and set-up Challenge
7	11/25/2025 16:03:53	sakufo@envisionresilience.org	Sandra Akufo	Student Participant in the 2023 New Bedford Ch...	Pr challeng (planni and set-up Challenge

8	11/26/2025 11:14:54	wjoseph@envisionresilience.org	Wendell T. Joseph	ERC program organizer	Challeng (design ar engageme perio	
9	12/3/2025 11:22:08	rjmiklos@gmail.com	Robert Miklos FAIA	Academic Advisor for the ERC program	Pr challeng (plannir and set-up Challenge	

10 rows × 45 columns

In [64]:
```
df = pd.read_csv('Envision Resilience Challenge Engagement and Network Ma
df.columns
```


Out[64]:
```
Index(['Timestamp', 'Email Address', 'What is your name?',
       'What was your role in this challenge?',
       'Please select which phase(s) you were most active in:',
       'Please select your year(s) of involvement (check all that appl
y):',
       'Were you involved in the 2021 Envision Resilience Challenge (ER
C) in Nantucket, Massachusetts?',
       'Approximately how many community participants or partners did yo
u involve in planning this challenge?',
       'Which methods did you use to engage with the local stakeholder
s?',
       'For your top three most influential collaborators overall, pleas
e list their name and three adjectives that best describe their contribu
tion or role:',
       'Based on your experience, which advisors acted as connectors or
bridges—either between groups within this challenge or across different
challenge years?',
       'Which types of key advisors were most influential in shaping thi
s challenge? Select up to three. ',
       'Is there anyone not listed who you believe played a significant
but less visible role in building or maintaining engagement networks in
this challenge?',
       'Were you involved in the 2022 Envision Resilience Challenge (ER
C) in Narragansett Bay, Rhode Island?',
       'Approximately how many community participants or partners did yo
u involve in planning this challenge?.1',
       'Which methods did you use to engage with the local stakeholder
s?.1',
       'For your top three most influential collaborators overall, pleas
e list their name and three adjectives that best describe their contribu
tion or role:.1',
       'Based on your experience, which advisors acted as connectors or
bridges—either between groups within this challenge or across different
challenge years?.1',
       'Which types of key advisors were most influential in shaping thi
s challenge? Select up to three. .1',
       'Is there anyone not listed who you believe played a significant
but less visible role in building or maintaining engagement networks in
this challenge?.1',
       'Were you involved in the 2023 Envision Resilience Challenge (ER
C) in New Bedford & Fairhaven, Massachusetts?',
       'Approximately how many community participants or partners did yo
u involve in planning this challenge?.2',
       'Which methods did you use to engage with the local stakeholder
s?.2',
       'For your top three most influential collaborators overall, pleas
e list their name and three adjectives that best describe their contribu
tion or role:.2',
       'Based on your experience, which advisors acted as connectors or
bridges—either between groups within this challenge or across different
challenge years?.2',
       'Which types of key advisors were most influential in shaping thi
s challenge? Select up to three. .2',
       'Is there anyone not listed who you believe played a significant
but less visible role in building or maintaining engagement networks in
this challenge?.2',
       'Were you involved in the 2024 Envision Resilience Challenge (ER
C) in Portland & South Portland, Maine?',
       'Approximately how many community participants or partners did yo
u involve in planning this challenge?.3',
```

```
       'Which methods did you use to engage with the local stakeholder
s?.3',
       'For your top three most influential collaborators overall, pleas
e list their name and three adjectives that best describe their contribu
tion or role:.3',
       'Based on your experience, which advisors acted as connectors or
bridges—either between groups within this challenge or across different
challenge years?.3',
       'Which types of key advisors were most influential in shaping thi
s challenge? Select up to three. .3',
       'Is there anyone not listed who you believe played a significant
but less visible role in building or maintaining engagement networks in
this challenge?.3',
       'Were you involved in the 2025 Envision Resilience Challenge (ER
C) in Midcoast Maine?',
       'Approximately how many community participants or partners did yo
u involve in planning this challenge?.4',
       'Which methods did you use to engage with the local stakeholder
s?.4',
       'For your top three most influential collaborators overall, pleas
e list their name and three adjectives that best describe their contribu
tion or role:.4',
       'Based on your experience, which advisors acted as connectors or
bridges—either between groups within this challenge or across different
challenge years?.4',
       'Which types of key advisors were most influential in shaping thi
s challenge? Select up to three. .4',
       'Is there anyone not listed who you believe played a significant
but less visible role in building or maintaining engagement networks in
this challenge?.4',
       'In which of the following areas do you think ERC has had the str
ongest community influence? (Select up to two)',
       'How do you personally define “impact” in the context of the Envi
sion Resilience Challenge? (This helps us understand how participants co
nceptualize success and influence.)',
       'Are there examples of lasting effects from any challenge you’ve
participated in (such as continued partnerships, implemented projects, c
urriculum changes, or new community initiatives?) If so, please describe
them.\n',
       'Any additional comments or reflections about engagement or netwo
rking during your ERC experience?'],
      dtype='str')
```

In [65]:
```
#Drop the first two rows which are nodata
df = df.iloc[2:].reset_index(drop=True)
```

In [66]:
```
raw_df = df.copy()
df = raw_df.copy()

#Extract the name and role columns for each respodent
analysis_df_id = df[[
    'What is your name?',
    'What was your role in this challenge?',
]]

analysis_df_id = analysis_df_id.rename(columns={
    "What is your name?": "name",
    "What was your role in this challenge?": "role",
})
print("analysis_df_id:")
```



```
print(analysis_df_id.head())
analysis_df_id.shape
```

```
analysis_df_id:
                    name                    role
0  Charlotte Van Voorhis    ERC program organizer
1                  Cecil   staff/strategic advisor
2             Kate Deans    ERC program organizer
3            Carolyn Cox    ERC program organizer
4          Claire Martin    ERC program organizer
```

Out[66]: (8, 2)

In [67]:
```
#Extract the participated duration
analysis_df_duration = df[[
    'Please select your year(s) of involvement (check all that apply):',
]]

analysis_df_duration = analysis_df_duration.rename(columns={
    'Please select your year(s) of involvement (check all that apply):':
})
print("analysis_df_duration:")
print(analysis_df_duration.head())
analysis_df_duration.shape
```

```
analysis_df_duration:
                                            duration
0  2023 (New Bedford & Fairhaven, Massachusetts),...
1  2021 (Nantucket, Massachusetts), 2022 (Narraga...
2                             2025 (Midcoast Maine)
3  2021 (Nantucket, Massachusetts), 2022 (Narraga...
4  2021 (Nantucket, Massachusetts), 2022 (Narraga...
```

Out[67]: (8, 1)

In [68]:
```
#Extract the community participation
analysis_df_community = df[[
    'Approximately how many community participants or partners did you in
    'Which methods did you use to engage with the local stakeholders?',
]]

analysis_df_community = analysis_df_community.rename(columns={
    'Approximately how many community participants or partners did you in
    'Which methods did you use to engage with the local stakeholders?': '
})
print("analysis_df_community:")
print(analysis_df_community.head())
for col in df.columns:
    if "Approximately how many community participants" in col:
        print(col)
analysis_df_community.shape
```

```
analysis_df_community:
    community_participants_number  \
0                              NaN
1                    25-30 people
2                              NaN
3                               50
4  ~15-25, with ~10 core partners

                     community_participants_methods
0                                               NaN
1  Regular meetings, Shared digital tools (like M...
2                                               NaN
3                                Informal discussions
4  Regular meetings, Shared digital tools (like M...
Approximately how many community participants or partners did you involve
in planning this challenge?
Approximately how many community participants or partners did you involve
in planning this challenge?.1
Approximately how many community participants or partners did you involve
in planning this challenge?.2
Approximately how many community participants or partners did you involve
in planning this challenge?.3
Approximately how many community participants or partners did you involve
in planning this challenge?.4
```

Out[68]: (8, 2)

In [69]:
```
#Extract the advisors
analysis_df_advisors = df[[
    'For your top three most influential collaborators overall, please li
    'Based on your experience, which advisors acted as connectors or brid
    'Which types of key advisors were most influential in shaping this ch
    'Is there anyone not listed who you believe played a significant but
]]

analysis_df_advisors = analysis_df_advisors.rename(columns={
    'For your top three most influential collaborators overall, please li
    'Based on your experience, which advisors acted as connectors or brid
    'Which types of key advisors were most influential in shaping this ch
    'Is there anyone not listed who you believe played a significant but
})
print("analysis_df_advisors:")
print(analysis_df_advisors.head())
analysis_df_advisors.shape
```



```
analysis_df_advisors:
                                 top3_advisors_list  \
0                                               NaN
1      Robert Miklos, Marty Hilton, Harrison Fraker
2                                               NaN
3  Cecil Barron Jenson, funder, nonprofit, connec...
4  Mary Bergman - historian, community-centric, i...

                                advisors_as_connectors  \
0                                               NaN
1                        Both connectors and bridges
2                                               NaN
3                           Marty Hylton, Bob Miklos
4  Mary Bergman, Marty Hylton, Cecil Barron Jense...

                                   inf_advisors_types  \
0                                               NaN
1  Nonprofit organizations, Municipal or governme...
2                                               NaN
3  Nonprofit organizations, Technical or scientif...
4  Nonprofit organizations, Technical or scientif...

                                      advisors_other
0                                               NaN
1                                      Anne Dougherty
2                                               NaN
3       Carolyn Cox and Claire Martin did the most
4  Vince Murphy, Tobias Glidden, Niles Parker, Ha...
```

Out[69]: (8, 4)

Merge ERC Staff and Duration

In [70]:
```
#Explode year list
analysis_df_duration["year_list"] = (
    analysis_df_duration["duration"]
    .str.findall(r"\d{4}")
)

analysis_df_duration_long = analysis_df_duration.explode("year_list")
```

In [71]:
```
analysis_df_duration_long.shape
```

Out[71]: (26, 2)

In [72]:
```
analysis_df_duration_long = analysis_df_duration_long.rename(
    columns={"year_list": "year"}
)

analysis_df_duration_long["year"] = analysis_df_duration_long["year"].ast
analysis_df_duration_long["year"].value_counts().sort_index()
```

Out[72]:
```
year
2021    4
2022    4
2023    6
2024    5

                  int64
```

- 2023年7人参与

(有个人干啥呢?

In [73]:
```
analysis_df_duration = analysis_df_duration.reset_index(drop=True)
analysis_df_duration["respondent_id"] = analysis_df_duration.index
```

In [74]:
```
analysis_df_duration["year_list"] = analysis_df_duration["duration"].str.
analysis_df_duration_long = (
    analysis_df_duration
    .explode("year_list")
    .rename(columns={"year_list": "year"})
    .drop(columns=["duration"])
    .reset_index(drop=True)
)

analysis_df_duration_long["year"] = analysis_df_duration_long["year"].ast
```

In [75]:
```
analysis_df_id = analysis_df_id.reset_index(drop=True)
analysis_df_id["respondent_id"] = analysis_df_id.index
```

In [76]:
```
analysis_df_duration_long .columns
```

Out[76]:
```
Index(['year', 'respondent_id'], dtype='str')
```

In [77]:
```
analysis_df_duration_long = analysis_df_duration_long.merge(
    analysis_df_id[["respondent_id", "name", "role"]],
    on="respondent_id",
    how="left")
analysis_df_duration_long.columns
```

Out[77]:
```
Index(['year', 'respondent_id', 'name', 'role'], dtype='str')
```

In [78]:
```
analysis_df_duration_long
```


Out[78]:

	year	respondent_id	name	role
0	2023	0	Charlotte Van Voorhis	ERC program organizer
1	2024	0	Charlotte Van Voorhis	ERC program organizer
2	2025	0	Charlotte Van Voorhis	ERC program organizer
3	2021	1	Cecil	staff/strategic advisor
4	2022	1	Cecil	staff/strategic advisor
5	2023	1	Cecil	staff/strategic advisor
6	2024	1	Cecil	staff/strategic advisor
7	2025	2	Kate Deans	ERC program organizer
8	2021	3	Carolyn Cox	ERC program organizer
9	2022	3	Carolyn Cox	ERC program organizer
10	2023	3	Carolyn Cox	ERC program organizer
11	2024	3	Carolyn Cox	ERC program organizer
12	2025	3	Carolyn Cox	ERC program organizer
13	2021	4	Claire Martin	ERC program organizer
14	2022	4	Claire Martin	ERC program organizer
15	2023	4	Claire Martin	ERC program organizer
16	2024	4	Claire Martin	ERC program organizer
17	2025	4	Claire Martin	ERC program organizer
18	2023	5	Sandra Akufo	Student Participant in the 2023 New Bedford Ch...
19	2025	5	Sandra Akufo	Student Participant in the 2023 New Bedford Ch...
20	2025	6	Wendell T. Joseph	ERC program organizer
21	2021	7	Robert Miklos FAIA	Academic Advisor for the ERC program
22	2022	7	Robert Miklos FAIA	Academic Advisor for the ERC program
23	2023	7	Robert Miklos FAIA	Academic Advisor for the ERC program
24	2024	7	Robert Miklos FAIA	Academic Advisor for the ERC program
25	2025	7	Robert Miklos FAIA	Academic Advisor for the ERC program

Add index to Community

In [79]:
```
base_col = "Approximately how many community participants or partners did

year_map = {
    base_col: 2021,
    base_col + ".1": 2022,
    base_col + ".2": 2023,
    base_col + ".3": 2024,
    base_col + ".4": 2025,
}

community_cols = list(year_map.keys())
community_cols
```

Out[79]:
```
['Approximately how many community participants or partners did you invo
lve in planning this challenge?',
 'Approximately how many community participants or partners did you invo
lve in planning this challenge?.1',
 'Approximately how many community participants or partners did you invo
lve in planning this challenge?.2',
 'Approximately how many community participants or partners did you invo
lve in planning this challenge?.3',
 'Approximately how many community participants or partners did you invo
lve in planning this challenge?.4']
```

In [80]:
```
missing = [c for c in community_cols if c not in df.columns]
missing
```

Out[80]:
```
[]
```

In [81]:
```
community_wide = df[community_cols].copy()
community_wide = community_wide.reset_index(drop=True)
community_wide["respondent_id"] = community_wide.index

community_wide
```


Out[81]:

	Approximately how many community participants or partners did you involve in planning this challenge?	Approximately how many community participants or partners did you involve in planning this challenge?.1	Approximately how many community participants or partners did you involve in planning this challenge?.2	Approximately how many community participants or partners did you involve in planning this challenge?.3	Approximately how many community participants or partners did you involve in planning this challenge?.4	re
0	NaN	NaN	100	50	75	
1	25-30 people	10-15	5-10	5	NaN	
2	NaN	NaN	NaN	NaN	My role does not directly interface with the c...	
3	50	50	50	40	30	
4	~15-25, with ~10 core partners	NaN	40-50	40-50	20-30	
5	NaN	NaN	3 (I was a student in this challenge)	NaN	I mainly write challenge briefs before the stu...	
6	NaN	NaN	NaN	NaN	NaN	
7	50 or more	15	20	25	25	

为了以防万一我还是统一下id列

In [82]:
```
df = df.reset_index(drop=True)
df["respondent_id"] = df.index
```

In [83]:
```
community_long = df[["respondent_id"] + community_cols].melt(
    id_vars="respondent_id",
    value_vars=community_cols,
    var_name="question_version",
    value_name="community_participants_number"
)
community_long
```

Out[83]:

	respondent_id	question_version	community_participants_number
0	0	Approximately how many community participants ...	NaN
1	1	Approximately how many community participants ...	25-30 people
2	2	Approximately how many community participants ...	NaN
3	3	Approximately how many community participants ...	50
4	4	Approximately how many community participants ...	~15-25, with ~10 core partners
5	5	Approximately how many community participants ...	NaN
6	6	Approximately how many community participants ...	NaN
7	7	Approximately how many community participants ...	50 or more
8	0	Approximately how many community participants ...	NaN
9	1	Approximately how many community participants ...	10-15
10	2	Approximately how many community participants ...	NaN
11	3	Approximately how many community participants ...	50
12	4	Approximately how many community participants ...	NaN
13	5	Approximately how many community participants ...	NaN
14	6	Approximately how many community participants ...	NaN
15	7	Approximately how many community participants ...	15
16	0	Approximately how many community participants ...	100
17	1	Approximately how many community participants ...	5-10
18	2	Approximately how many community participants ...	NaN
19	3	Approximately how many community participants ...	50
20	4	Approximately how many community participants ...	40-50
21	5	Approximately how many community participants ...	3 (I was a student in this challenge)

	respondent_id	question_version	community_participants_number
22	6	Approximately how many community participants ...	NaN
23	7	Approximately how many community participants ...	20
24	0	Approximately how many community participants ...	50
25	1	Approximately how many community participants ...	5
26	2	Approximately how many community participants ...	NaN
27	3	Approximately how many community participants ...	40
28	4	Approximately how many community participants ...	40-50
29	5	Approximately how many community participants ...	NaN
30	6	Approximately how many community participants ...	NaN
31	7	Approximately how many community participants ...	25
32	0	Approximately how many community participants ...	75
33	1	Approximately how many community participants ...	NaN
34	2	Approximately how many community participants ...	My role does not directly interface with the c...
35	3	Approximately how many community participants ...	30
36	4	Approximately how many community participants ...	20-30
37	5	Approximately how many community participants ...	I mainly write challenge briefs before the stu...
38	6	Approximately how many community participants ...	NaN
39	7	Approximately how many community participants ...	25

In [84]:
```
community_long["year"] = community_long["question_version"].map(year_map)
community_long[["respondent_id", "year", "community_participants_number"]
```

Out[84]:

	respondent_id	year	community_participants_number
0	0	2021	NaN
1	1	2021	25-30 people
2	2	2021	NaN
3	3	2021	50
4	4	2021	~15-25, with ~10 core partners

In [85]:
```
community_long_clean = (
    community_long
    .drop(columns=["question_version"])
    .dropna(subset=["community_participants_number"])
    .reset_index(drop=True)
)
community_long_clean.head(15)
```

Out[85]:

	respondent_id	community_participants_number	year
0	1	25-30 people	2021
1	3	50	2021
2	4	~15-25, with ~10 core partners	2021
3	7	50 or more	2021
4	1	10-15	2022
5	3	50	2022
6	7	15	2022
7	0	100	2023
8	1	5-10	2023
9	3	50	2023
10	4	40-50	2023
11	5	3 (I was a student in this challenge)	2023
12	7	20	2023
13	0	50	2024
14	1	5	2024

In [86]:
```
methods_base = "Which methods did you use to engage with the local stakeh

methods_cols = [
    c for c in df.columns
    if c.startswith(methods_base)
]

methods_cols
```


Out[86]:
```
['Which methods did you use to engage with the local stakeholders?',
 'Which methods did you use to engage with the local stakeholders?.1',
 'Which methods did you use to engage with the local stakeholders?.2',
 'Which methods did you use to engage with the local stakeholders?.3',
 'Which methods did you use to engage with the local stakeholders?.4']
```

In [87]:
```
methods_year_map = {
    methods_base: 2021,
    methods_base + ".1": 2022,
    methods_base + ".2": 2023,
    methods_base + ".3": 2024,
    methods_base + ".4": 2025,
}
```

In [88]:
```
methods_wide = df[["respondent_id"] + methods_cols].copy()
methods_wide.head()
```

Out[88]:

	respondent_id	Which methods did you use to engage with the local stakeholders?	Which methods did you use to engage with the local stakeholders?.1	Which methods did you use to engage with the local stakeholders?.2	Which methods did you use to engage with the local stakeholders?.3
0	0	NaN	NaN	Regular meetings, Workshops, Informal discussions	Regular meetings, Informal discussions
1	1	Regular meetings, Shared digital tools (like M...	Regular meetings, Co-design sessions, Informal...	Regular meetings, Informal discussions	Regular meetings, Co-design sessions, Informal...
2	2	NaN	NaN	NaN	NaN
3	3	Informal discussions	Regular meetings, Informal discussions	Regular meetings, Workshops, Informal discussions	Regular meetings, Informal discussions
4	4	Regular meetings, Shared digital tools (like M...	Shared digital tools (like Miro), Workshops, I...	Regular meetings, Shared digital tools (like M...	Regular meetings, Shared digital tools (like M...

In [89]:
```
methods_long = methods_wide.melt(
    id_vars="respondent_id",
    value_vars=methods_cols,
    var_name="question_version",
    value_name="community_participants_methods"
)
methods_long.head(5)
```

Out[89]:

	respondent_id	question_version	community_participants_methods
0	0	Which methods did you use to engage with the l...	NaN
1	1	Which methods did you use to engage with the l...	Regular meetings, Shared digital tools (like M...
2	2	Which methods did you use to engage with the l...	NaN
3	3	Which methods did you use to engage with the l...	Informal discussions
4	4	Which methods did you use to engage with the l...	Regular meetings, Shared digital tools (like M...

In [90]:
```
methods_long["year"] = methods_long["question_version"].map(methods_year_

methods_long_clean = (
    methods_long
    .drop(columns=["question_version"])
    .dropna(subset=["community_participants_methods"])
    .reset_index(drop=True)
)

methods_long_clean.head(15), methods_long_clean.shape
```


Out[90]:
```
(    respondent_id                    community_participants_methods  y
ear
 0              1  Regular meetings, Shared digital tools (like M...  2
021
 1              3                              Informal discussions  2
021
 2              4  Regular meetings, Shared digital tools (like M...  2
021
 3              7                    Workshops, Informal discussions  2
021
 4              1  Regular meetings, Co-design sessions, Informal...  2
022
 5              3             Regular meetings, Informal discussions  2
022
 6              4  Shared digital tools (like Miro), Workshops, I...  2
022
 7              7  Regular meetings, Workshops, Informal discussions  2
022
 8              0  Regular meetings, Workshops, Informal discussions  2
023
 9              1             Regular meetings, Informal discussions  2
023
 10             3  Regular meetings, Workshops, Informal discussions  2
023
 11             4  Regular meetings, Shared digital tools (like M...  2
023
 12             5             Regular meetings, Informal discussions  2
023
 13             7  Regular meetings, Co-design sessions, Workshop...  2
023
 14             0             Regular meetings, Informal discussions  2
024,
 (25, 3))
```

In [91]:
```
community_panel = community_long_clean.merge(
    methods_long_clean,
    on=["respondent_id", "year"],
    how="outer"
)

community_panel.head(20)
```

Out[91]:

	respondent_id	community_participants_number	year	community_participants_
0	0	100	2023	Regular meetings, W Informal d
1	0	50	2024	Regular meeting d
2	0	75	2025	Regular meetings, W Informal d
3	1	25-30 people	2021	Regular meetings, Sha tool
4	1	10-15	2022	Regular meetings, sessions,
5	1	5-10	2023	Regular meeting d
6	1	5	2024	Regular meetings, sessions,
7	2	My role does not directly interface with the c...	2025	
8	3	50	2021	Informal d
9	3	50	2022	Regular meeting d
10	3	50	2023	Regular meetings, W Informal d
11	3	40	2024	Regular meeting d
12	3	30	2025	Regular meeting d
13	4	~15-25, with ~10 core partners	2021	Regular meetings, Sha tool
14	4	NaN	2022	Shared digital tools Worl
15	4	40-50	2023	Regular meetings, Sha tool
16	4	40-50	2024	Regular meetings, Sha tool
17	4	20-30	2025	Regular meetings, Sha tool
18	5	3 (I was a student in this challenge)	2023	Regular meeting d

In [92]:

```
community_panel = community_panel.merge(
    analysis_df_duration_long[["respondent_id", "year", "name", "role"]],
    on=["respondent_id", "year"],
    how="left"
)

community_panel.head(20)
```

Out[92]:

	respondent_id	community_participants_number	year	community_participants_
0	0	100	2023	Regular meetings, W Informal d
1	0	50	2024	Regular meeting d
2	0	75	2025	Regular meetings, W Informal d
3	1	25-30 people	2021	Regular meetings, Sha tool
4	1	10-15	2022	Regular meetings, sessions,
5	1	5-10	2023	Regular meeting d
6	1	5	2024	Regular meetings, sessions,
7	2	My role does not directly interface with the c...	2025	
8	3	50	2021	Informal d
9	3	50	2022	Regular meeting d
10	3	50	2023	Regular meetings, W Informal d
11	3	40	2024	Regular meeting d
12	3	30	2025	Regular meeting d
13	4	~15-25, with ~10 core partners	2021	Regular meetings, Sha tool
14	4	NaN	2022	Shared digital tools Worl
15	4	40-50	2023	Regular meetings, Sha tool
16	4	40-50	2024	Regular meetings, Sha tool
17	4	20-30	2025	Regular meetings, Sha tool
18	5	3 (I was a student in this challenge)	2023	Regular meeting d
19	5	I mainly write challenge briefs before the stu...	2025	Informal d

	respondent_id	community_participants_number	year	community_participants_

In [93]:
```
#方法使用频率分析
community_panel["community_participants_methods"].str.split(",").explode(
```

Out[93]:
```
community_participants_methods
 Informal discussions                22
Regular meetings                     21
 Workshops                           12
 Co-design sessions                   7
 Shared digital tools (like Miro)     5
Informal discussions                  2
Shared digital tools (like Miro)      1
Workshops                             1
                    nt64
```

In [ ]:
```
#这有异常值咋整''
```

不管了先写出吧

In [95]:
```
analysis_df_duration_long.to_excel("staff_duration_long.xlsx", index=Fals
community_panel.to_excel("community_panel.xlsx", index=False)
```

Merge Advisors and Duration

In [96]:
```
df = df.reset_index(drop=True)
if "respondent_id" not in df.columns:
    df["respondent_id"] = df.index
```

In [97]:
```
advisor_cols = [c for c in df.columns if "advisor" in c.lower()]
advisor_cols
```

Out[97]:
```
['Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?',
 'Which types of key advisors were most influential in shaping this challenge? Select up to three. ',
 'Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?.1',
 'Which types of key advisors were most influential in shaping this challenge? Select up to three. .1',
 'Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?.2',
 'Which types of key advisors were most influential in shaping this challenge? Select up to three. .2',
 'Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?.3',
 'Which types of key advisors were most influential in shaping this challenge? Select up to three. .3',
 'Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?.4',
 'Which types of key advisors were most influential in shaping this challenge? Select up to three. .4']
```

In [98]:
```
connectors_base = "Based on your experience, which advisors acted as conn
types_base = "Which types of key advisors were most influential in shapin
```

In [99]:
```
connectors_cols = [c for c in df.columns if c.startswith(connectors_base)]
types_cols = [c for c in df.columns if c.startswith(types_base)]

connectors_cols, types_cols
```

Out[99]:
```
(['Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?',
  'Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?.1',
  'Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?.2',
  'Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?.3',
  'Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?.4'],
 ['Which types of key advisors were most influential in shaping this challenge? Select up to three. ',
  'Which types of key advisors were most influential in shaping this challenge? Select up to three. .1',
  'Which types of key advisors were most influential in shaping this challenge? Select up to three. .2',
  'Which types of key advisors were most influential in shaping this challenge? Select up to three. .3',
  'Which types of key advisors were most influential in shaping this challenge? Select up to three. .4'])
```


In [100…
```
def make_year_map(base):
    return {
        base: 2021,
        base + ".1": 2022,
        base + ".2": 2023,
        base + ".3": 2024,
        base + ".4": 2025,
    }

connectors_year_map = make_year_map(connectors_base)
types_year_map = make_year_map(types_base)
```

In [107…
```
connectors_long = df[["respondent_id"] + connectors_cols].melt(
    id_vars="respondent_id",
    value_vars=connectors_cols,
    var_name="col",
    value_name="advisors_as_connectors"
)
connectors_long["year"] = connectors_long["col"].map(connectors_year_map)

connectors_long = (
    connectors_long
    .drop(columns="col")
    .dropna(subset=["advisors_as_connectors"])
    .reset_index(drop=True)
)

connectors_long.head(), connectors_long.shape
```

Out[107…
```
(   respondent_id                          advisors_as_connectors  year
 0              1                      Both connectors and bridges  2021
 1              3                         Marty Hylton, Bob Miklos  2021
 2              4  Mary Bergman, Marty Hylton, Cecil Barron Jense...  2021
 3              7                  Cecil Baron Jensen, Marty Hylton  2021
 4              3                        Bob Rulli and Teresa Crean  2022,
 (22, 3))
```

In [108…
```
connectors_long = connectors_long.merge(
    analysis_df_id[["respondent_id", "name"]],
    on="respondent_id",
    how="left"
)
connectors_long.head()
```

Out[108…

	respondent_id	advisors_as_connectors	year	name
0	1	Both connectors and bridges	2021	Cecil
1	3	Marty Hylton, Bob Miklos	2021	Carolyn Cox
2	4	Mary Bergman, Marty Hylton, Cecil Barron Jense...	2021	Claire Martin
3	7	Cecil Baron Jensen, Marty Hylton	2021	Robert Miklos FAIA
4	3	Bob Rulli and Teresa Crean	2022	Carolyn Cox

In [109…

```
connectors_long.to_excel("advisors_as_connectors.xlsx", index=False)
```


DATA ANALYSIS(ERC_TYPOLOGY_ML)

ERC_Frame_Analysis-src\src\classification\typology_ml.py

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

def read_csv():
  df = pd.read_excel("update 0223.xlsx")
  train_df = df[df["Category"].notna()]
  df_2022 = pd.read_excel("update 0223.xlsx", sheet_name="2022")
  df_2023 = pd.read_excel("update 0223.xlsx", sheet_name="2023")
  df_2024 = pd.read_excel("update 0223.xlsx", sheet_name="2024")
  return

def

train_df = train_df[train_df["Category"].notna()]

X_train_text = train_df["Design Method"]
y_train = train_df["Category"]

from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer(
    stop_words="english",
    ngram_range=(1,2)
)

X_train = vectorizer.fit_transform(X_train_text)

from sklearn.linear_model import LogisticRegression

model = LogisticRegression(
    max_iter=500,
    class_weight="balanced"
```



```

    return df, df_2022, df_2023, df_2024


# ----------------------------
# Training preparation
# ----------------------------
def prepare_training_data(df: pd.DataFrame) -> tuple[pd.DataFrame, pd.Series, pd.Series]:
    """Keep only labeled rows and extract training text and labels."""
    train_df = df[df["Category"].notna()].copy()

    # Fill missing text values to avoid vectorizer errors.
    train_df["Design Method"] = train_df["Design Method"].fillna("")

    x_train_text = train_df["Design Method"]
    y_train = train_df["Category"]

    return train_df, x_train_text, y_train


# ----------------------------
# Model training
# ----------------------------
def train_text_classifier(x_train_text: pd.Series, y_train: pd.Series) -> tuple[TfidfVectorizer, LogisticRegression]:
    """Vectorize text and train a Logistic Regression classifier."""
    vectorizer = TfidfVectorizer(
        stop_words="english",
        ngram_range=(1, 2),
    )
    x_train = vectorizer.fit_transform(x_train_text)

    model = LogisticRegression(
        max_iter=500,
        class_weight="balanced",
    )
    model.fit(x_train, y_train)

```

```python
    return vectorizer, model


# ------------------------------
# Prediction
# ------------------------------
def predict_category(df: pd.DataFrame, vectorizer: TfidfVectorizer, model: LogisticRegression) -> pd.DataFrame:
    """Predict categories for a dataframe using the trained model."""
    df = df.copy()
    df["Design Method"] = df["Design Method"].fillna("")

    x_text = df["Design Method"]
    x_vec = vectorizer.transform(x_text)
    df["Category_pred"] = model.predict(x_vec)

    return df


# ------------------------------
# Evaluation helper
# ------------------------------
def make_training_crosstab(
    train_df: pd.DataFrame,
    vectorizer: TfidfVectorizer,
    model: LogisticRegression,
) -> pd.DataFrame:
    """Return the notebook-style crosstab of actual vs predicted training labels."""
    x_train = vectorizer.transform(train_df["Design Method"].fillna(""))
    train_pred = model.predict(x_train)
    return pd.crosstab(train_df["Category"], train_pred)


# ------------------------------
# Output
# ------------------------------
def save_predictions(
    output_path: str | Path,
```



```python
    train_df: pd.DataFrame,
    df_2022: pd.DataFrame,
    df_2023: pd.DataFrame,
    df_2024: pd.DataFrame,
    training_crosstab: pd.DataFrame | None = None,
) -> None:
    """Write predictions to an Excel workbook."""
    output_path = Path(output_path)

    with pd.ExcelWriter(output_path) as writer:
        train_df.to_excel(writer, sheet_name="2021", index=False)
        df_2022.to_excel(writer, sheet_name="2022", index=False)
        df_2023.to_excel(writer, sheet_name="2023", index=False)
        df_2024.to_excel(writer, sheet_name="2024", index=False)
        if training_crosstab is not None:
            training_crosstab.to_excel(writer, sheet_name="train_crosstab")


# ------------------------------
# Main workflow
# ------------------------------
def main(input_path: str | Path, output_path: str | Path) -> None:
    df, df_2022, df_2023, df_2024 = load_workbook(input_path)

    train_df, x_train_text, y_train = prepare_training_data(df)
    vectorizer, model = train_text_classifier(x_train_text, y_train)

    training_crosstab = make_training_crosstab(train_df, vectorizer, model)
    print("Training label distribution:")
    print(train_df["Category"].value_counts())
    print("\nTraining crosstab:")
    print(training_crosstab)

    df_2022 = predict_category(df_2022, vectorizer, model)
    df_2023 = predict_category(df_2023, vectorizer, model)
    df_2024 = predict_category(df_2024, vectorizer, model)

```



```python
    save_predictions(
        output_path=output_path,
        train_df=train_df,
        df_2022=df_2022,
        df_2023=df_2023,
        df_2024=df_2024,
        training_crosstab=training_crosstab,
    )
    print(f"\nSaved prediction workbook to: {Path(output_path).resolve()}")


if __name__ == "__main__":
    parser = argparse.ArgumentParser(description="Train ERC typology classifier and predict categories.")
    parser.add_argument(
        "--input",
        default="update 0223.xlsx",
        help="Path to the input Excel workbook. Default: update 0223.xlsx",
    )
    parser.add_argument(
        "--output",
        default="strategy_prediction.xlsx",
        help="Path to the output Excel workbook. Default: strategy_prediction.xlsx",
    )
    args = parser.parse_args()

    main(args.input, args.output)

```

DATA ANALYSIS(TF-IDF EVALUATE COVERAGE)

ERC_Frame_Analysis-src\src\Validation\TF-IDF evaluate coverage

```python
# Part 1: Data Preparation

import pandas as pd

strategies_file = "stradegies.xlsx"
problems_file = "Problem_from_studentsurvey.xlsx"

years = ["2021", "2022", "2023", "2024"]

strategy_dfs = []

for year in years:
    df = pd.read_excel(strategies_file, sheet_name=year)
    df["year"] = year
    df["strategy_id"] = [f"{year}_S{i+1:03d}" for i in range(len(df))]
    strategy_dfs.append(df)

strategies_long = pd.concat(strategy_dfs, ignore_index=True)

problem_dfs = []

for year in years:
    df = pd.read_excel(problems_file, sheet_name=year)
    df["year"] = year
    df["problem_id"] = [f"{year}_P{i+1:03d}" for i in range(len(df))]
    problem_dfs.append(df)

problems_long = pd.concat(problem_dfs, ignore_index=True)

print("strategies_long shape:", strategies_long.shape)
print("problems_long shape:", problems_long.shape)

print("\n--- strategies_long preview ---")
print(strategies_long.head())

print("\n--- problems_long preview ---")
print(problems_long.head())

strategies_long = strategies_long.rename(columns={
    "Design Method": "strategy_text",
    "Time Dimension": "time_dimension",
    "Scale": "scale",
    "Area of Specialization": "area_of_specialization",
    "Interdisciplinary": "interdisciplinary",
    "Type": "type"
})

strategies_long = strategies_long[
    [
        "strategy_id",
        "year",
        "strategy_text",
        "time_dimension",
        "scale",
        "area_of_specialization",
        "interdisciplinary",
        "type"
    ]
]

problems_long = problems_long[
    [
        "problem_id",
        "problem",
        "tags"
    ]
]

print("\n--- renamed strategies_long ---")
print(strategies_long.head())

print("\n--- renamed problems_long ---")
print(problems_long.head())

problems_long["year"] = problems_long["problem_id"].str.split("_").str[0].astype(int)
strategies_long["strategy_text"] = strategies_long["strategy_text"].fillna("").astype(str)
problems_long["problem"] = problems_long["problem"].fillna("").astype(str)
problems_long["tags"] = problems_long["tags"].fillna("").astype(str)

for col in ["time_dimension", "scale", "area_of_specialization", "interdisciplinary",
"type"]:
    strategies_long[col] = strategies_long[col].fillna("").astype(str)

print("\nMissing values check:")
print(strategies_long.isna().sum())
print(problems_long.isna().sum())


problems_long["tag_list"] = problems_long["tags"].apply(
    lambda x: [tag.strip() for tag in x.split(";") if tag.strip()]
)

print("\n--- tag_list preview ---")
print(problems_long[["problem_id", "tags", "tag_list"]].head())


problems_long["query_text"] = problems_long.apply(
    lambda row: row["problem"] + " " + " ".join(row["tag_list"]),
    axis=1
)

print("\n--- query_text preview ---")
print(problems_long[["problem_id", "query_text"]].head())
```


2026/4/5 19:57 TF-IDF evaluate coverage

```
strategies_long.to_csv("strategies_long.csv", index=False)
problems_long.to_csv("problems_long.csv", index=False)

print("\nFiles saved:")
print("- strategies_long.csv")
print("- problems_long.csv")

### Part 2: NLP Validation (to be implemented) ###

import re
import numpy as np
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity

# ========= Step 2.1: clean text =========
def clean_text(text):
    text = str(text).lower()
    text = re.sub(r"[^\w\s]", " ", text)
    text = re.sub(r"\s+", " ", text).strip()
    return text

strategies_long["strategy_text_clean"] =
strategies_long["strategy_text"].apply(clean_text)
problems_long["query_text_clean"] = problems_long["query_text"].apply(clean_text)

print("\n--- cleaned strategy text preview ---")
print(strategies_long[["strategy_id", "strategy_text", "strategy_text_clean"]].head())

print("\n--- cleaned query text preview ---")
print(problems_long[["problem_id", "query_text", "query_text_clean"]].head())

# ========= Step 2.2: TF-IDF =========
strategy_corpus = strategies_long["strategy_text_clean"].tolist()
problem_queries = problems_long["query_text_clean"].tolist()

vectorizer = TfidfVectorizer(stop_words="english")
strategy_matrix = vectorizer.fit_transform(strategy_corpus)
problem_matrix = vectorizer.transform(problem_queries)

similarity_matrix = cosine_similarity(problem_matrix, strategy_matrix)
print("\nsimilarity_matrix shape:", similarity_matrix.shape)

# ========= Step 2.3: retrieve top 5 =========
top_k = 5
results = []

for i, problem_row in problems_long.iterrows():
    scores = similarity_matrix[i]
    top_indices = np.argsort(scores)[::-1][:top_k]

    for rank, idx in enumerate(top_indices, start=1):
        results.append({
            "problem_id": problem_row["problem_id"],
```



```
            "problem": problem_row["problem"],
            "query_text": problem_row["query_text"],
            "rank": rank,
            "strategy_id": strategies_long.iloc[idx]["strategy_id"],
            "strategy_text": strategies_long.iloc[idx]["strategy_text"],
            "tfidf_score": scores[idx],
            "problem_year": problem_row["year"],
            "strategy_year": strategies_long.iloc[idx]["year"]
        })

tfidf_results = pd.DataFrame(results)

print("\n--- tfidf_results preview ---")
print(tfidf_results.head(10))

# ========= Step 2.4: save =========
tfidf_results.to_csv("tfidf_top5_results.csv", index=False)
print("\nSaved: tfidf_top5_results.csv")

# ========= Step 2.5: inspect one problem =========
sample_problem_id = "2021_P001"
sample_results = tfidf_results[tfidf_results["problem_id"] == sample_problem_id].copy()
print(sample_results[["problem_id", "rank", "strategy_id", "strategy_text",
"tfidf_score"]])

print("\n--- sample problem results ---")
print(sample_results[["problem_id", "rank", "strategy_id", "strategy_text",
"tfidf_score"]])

# ========= Step 3: same-year TF-IDF top 5 =========
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
import numpy as np
import pandas as pd

same_year_results = []
top_k = 10

years = ["2021", "2022", "2023", "2024"]
# unify year type
problems_long["year"] = problems_long["year"].astype(str)
strategies_long["year"] = strategies_long["year"].astype(str)

for year in years:
    # 只取当年的 problems 和 strategies
    year_problems = problems_long[problems_long["year"] == year].copy()
    year_strategies = strategies_long[strategies_long["year"] == year].copy()

    # 文本列表
    strategy_corpus = year_strategies["strategy_text_clean"].tolist()
    problem_queries = year_problems["query_text_clean"].tolist()

    # TF-IDF
    vectorizer = TfidfVectorizer(stop_words="english")
```

```
    strategy_matrix = vectorizer.fit_transform(strategy_corpus)
    problem_matrix = vectorizer.transform(problem_queries)

    similarity_matrix = cosine_similarity(problem_matrix, strategy_matrix)

    # 取 top k
    for i, problem_row in year_problems.reset_index(drop=True).iterrows():
        scores = similarity_matrix[i]
        top_indices = np.argsort(scores)[::-1][:top_k]

        for rank, idx in enumerate(top_indices, start=1):
            same_year_results.append({
                "problem_id": problem_row["problem_id"],
                "problem": problem_row["problem"],
                "query_text": problem_row["query_text"],
                "rank": rank,
                "strategy_id": year_strategies.iloc[idx]["strategy_id"],
                "strategy_text": year_strategies.iloc[idx]["strategy_text"],
                "tfidf_score": scores[idx],
                "problem_year": problem_row["year"],
                "strategy_year": year_strategies.iloc[idx]["year"]
            })


same_year_tfidf_results = pd.DataFrame(same_year_results)
same_year_tfidf_results["manual_relevance"] = ""
same_year_tfidf_results["notes"] = ""

print(same_year_tfidf_results.head(10))
print("\nshape:", same_year_tfidf_results.shape)

same_year_tfidf_results.to_csv("tfidf_top10_same_year_results.csv", index=False)
print("Saved: tfidf_top10_same_year_results.csv")

```


DATA ANALYSIS(TYPOLOGY_ML)

ERC_Frame_Analysis-src\src\classification\typology_ml.py

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

def read_csv():
  df = pd.read_excel("update 0223.xlsx")
  train_df = df[df["Category"].notna()]
  df_2022 = pd.read_excel("update 0223.xlsx", sheet_name="2022")
  df_2023 = pd.read_excel("update 0223.xlsx", sheet_name="2023")
  df_2024 = pd.read_excel("update 0223.xlsx", sheet_name="2024")
  return

def

train_df = train_df[train_df["Category"].notna()]

X_train_text = train_df["Design Method"]
y_train = train_df["Category"]

from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer(
    stop_words="english",
    ngram_range=(1,2)
)

X_train = vectorizer.fit_transform(X_train_text)

from sklearn.linear_model import LogisticRegression

model = LogisticRegression(
    max_iter=500,
    class_weight="balanced"
```



```
)

model.fit(X_train, y_train)

train_pred = model.predict(X_train)

pd.crosstab(train_df["Category"], train_pred)

def predict_category(df):

    X_text = df["Design Method"]

    X_vec = vectorizer.transform(X_text)

    df["Category_pred"] = model.predict(X_vec)

    return df

df_2022 = predict_category(df_2022)
df_2023 = predict_category(df_2023)
df_2024 = predict_category(df_2024)

with pd.ExcelWriter("strategy_prediction.xlsx") as writer:

    train_df.to_excel(writer, sheet_name="2021", index=False)
    df_2022.to_excel(writer, sheet_name="2022", index=False)
    df_2023.to_excel(writer, sheet_name="2023", index=False)
    df_2024.to_excel(writer, sheet_name="2024", index=False)

```

DATA ANALYSIS(VALIDATION_VISUAL)

In [ ]:
```
import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_excel("做图用表格.xlsx", sheet_name="Sheet2")

df.columns = df.columns.str.strip()
```

In [38]:
```
print(df.head())
```

```
    Problem  Year  Coverage  Avg Coverage Problem_Type
0  2021_P001  2021      0.50          0.63      Spatial
1  2021_P002  2021      0.75           NaN      Spatial
2  2021_P003  2021      0.65           NaN     Systemic
3  2022_P001  2022      0.80          0.65      Spatial
4  2022_P002  2022      0.70           NaN      Spatial
```

In [ ]:
```
df["Year"] = pd.to_numeric(df["Year"], errors="coerce")
df["Coverage"] = pd.to_numeric(df["Coverage"], errors="coerce")

df["Avg Coverage"] = pd.to_numeric(df["Avg Coverage"], errors="coerce")
```

In [ ]:
```
df = df.dropna(subset=["Year", "Coverage"])

df["Avg Coverage"] = df.groupby("Year")["Avg Coverage"].transform(lambda
```

In [ ]:
```
avg_df = (
    df.groupby("Year", as_index=False)["Avg Coverage"]
    .first()
    .sort_values("Year")
)


plt.figure(figsize=(8, 5))


plt.scatter(
    df["Year"],
    df["Coverage"],
    alpha=0.4,
    s=50,
    label="Coverage"
)

plt.plot(
    avg_df["Year"],
    avg_df["Avg Coverage"],
    linewidth=2.5,
    marker="o",
    label="Average Coverage"
)



for x, y in zip(avg_df["Year"], avg_df["Avg Coverage"]):
    plt.annotate(
    "x",
    (x, y),
    textcoords="offset points",
```



```
    xytext=(12,-10),
    ha='center',
)

base_color = "#1f77b4"

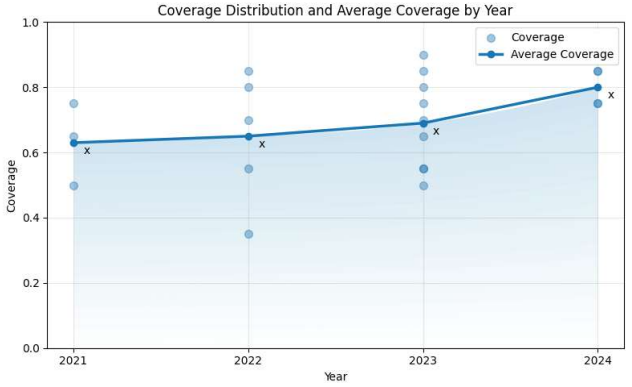
n_layers = 20

for i in range(n_layers):
    alpha = 0.01 + 0.2 * (i / n_layers)
    y_lower = y_smooth * (i / n_layers)
    y_upper = y_smooth * ((i + 1) / n_layers)

    plt.fill_between(
        x_smooth,
        y_lower,
        y_upper,
        color=base_color,
        alpha=alpha,
        linewidth=0
    )

plt.xlabel("Year")
plt.ylabel("Coverage")
plt.grid(axis='x', alpha=0.3)
plt.title("Coverage Distribution and Average Coverage by Year")
plt.xticks(sorted(df["Year"].dropna().unique()))
plt.ylim(0, 1)
plt.legend()
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()
```



In [ ]:
```
import numpy as np
from scipy.interpolate import make_interp_spline
```

```
x = avg_df["Year"].values
y = avg_df["Avg Coverage"].values

plt.figure(figsize=(10, 5))


plt.scatter(
    df["Year"],
    df["Coverage"],
    alpha=0.6,
    s=50,
    label="Coverage"
)


x_smooth = np.linspace(x.min(),


spline = make_interp_spline(x, y, k=2)  # k=2 比较稳（你数据点少）
y_smooth = spline(x_smooth)


plt.plot(
    x_smooth,
    y_smooth,
    linewidth=2.5,
    label="Average Coverage (Smoothed)"
)


plt.scatter(
    avg_df["Year"],
    avg_df["Avg Coverage"],
    marker="o",
    s=100,
    facecolors="#1f77b4",
    linewidth=1.5,
    zorder=4,
    alpha=0.6,
    label="Average Coverage"
)


for _, row in avg_df.iterrows():
    plt.text(
        row["Year"] + 0.08,
        row["Avg Coverage"] + 0.015,
        f"{row['Avg Coverage']:.2f}",
        ha="center",
        va="bottom",
        fontsize=10
    )


n_layers = 20
base_color = "#1f77b4"

for i in range(n_layers):
    alpha = 0.02 + 0.25 * (i / n_layers)**1.5
    y_lower = y_smooth * (i / n_layers)
```

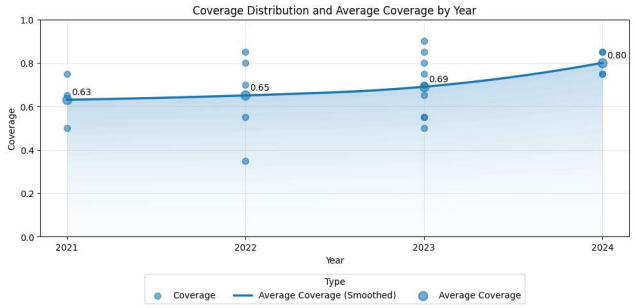


```
    y_upper = y_smooth * ((i + 1) / n_layers)

    plt.fill_between(
        x_smooth,
        y_lower,
        y_upper,
        color=base_color,
        alpha=alpha,
        linewidth=0
    )

plt.xlabel("Year")
plt.ylabel("Coverage")
plt.grid(axis='x', alpha=0.3)
plt.title("Coverage Distribution and Average Coverage by Year")
plt.xticks(sorted(df["Year"].dropna().unique()))
plt.ylim(0, 1)
plt.legend(
    title="Type",
    loc="upper center",
    bbox_to_anchor=(0.5, -0.15),
    ncol=3
)
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()
```



In [43]:
```
print(df["Problem_Type"].unique())

for v in df["Problem_Type"].unique():
    print(repr(v))
```

```
<StringArray>
['Spatial', 'Systemic']
Length: 2, dtype: str
'Spatial'
'Systemic'
```

In [44]:
```
df["Problem_Type"] = (
    df["Problem_Type"]
    .astype(str)
    .str.strip()
```

```
x_smooth = np.linspace(x.min(), x.max(), 200)


spline = make_interp_spline(x, y, k=2)
y_smooth = spline(x_smooth)

plt.plot(
    x_smooth,
    y_smooth,
    linewidth=2.5,
    label="Average Coverage (Smoothed)"
)


n_layers = 20
base_color = "#1f77b4"

for i in range(n_layers):
    alpha = 0.02 + 0.25 * (i / n_layers)**1.5
    y_lower = y_smooth * (i / n_layers)
    y_upper = y_smooth * ((i + 1) / n_layers)

    plt.fill_between(
        x_smooth,
        y_lower,
        y_upper,
        color=base_color,
        alpha=alpha,
        linewidth=0
    )

#for xi, yi in zip(x, y):
#    plt.text(xi, yi, f"{yi:.2f}", ha="center", va="bottom")

plt.title("Coverage Distribution and Average Coverage by Year")
plt.xlabel("Year")
plt.ylabel("Coverage")
plt.xticks(x)
plt.ylim(0, 1)
plt.legend(
    title="Type",
    loc="upper center",
    bbox_to_anchor=(0.5, -0.15),
    ncol=3
)
plt.show()
```

```
Spatial: 15
Systemic: 6
```


2026/4/5 20:42 validation_visual

x_smooth = np.linspace(x.min(), x.max(), 200)

spline = make_interp_spline(x, y, k=2)
y_smooth = spline(x_smooth)

plt.plot(
    x_smooth,
    y_smooth,
    linewidth=2.5,
    label="Average Coverage (Smoothed)"
)

n_layers = 20
base_color = "#1f77b4"

for i in range(n_layers):
    alpha = 0.02 + 0.25 * (i / n_layers)**1.5
    y_lower = y_smooth * (i / n_layers)
    y_upper = y_smooth * ((i + 1) / n_layers)

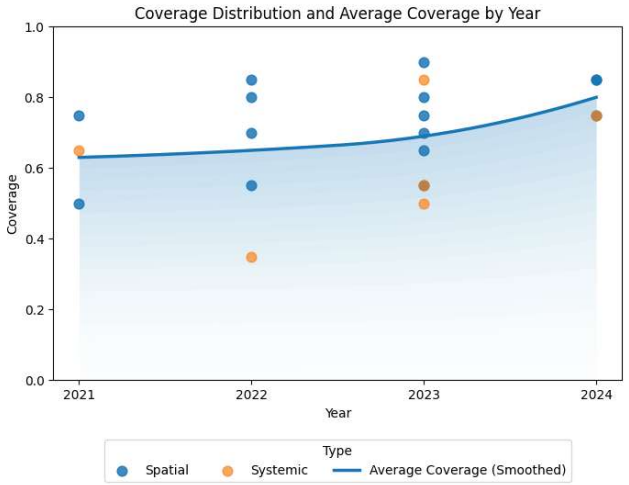
    plt.fill_between(
        x_smooth,
        y_lower,
        y_upper,
        color=base_color,
        alpha=alpha,
        linewidth=0
)

#for xi, yi in zip(x, y):
plt.text(xi, yi, f"{yi:.2f}", ha="center", va="bottom")

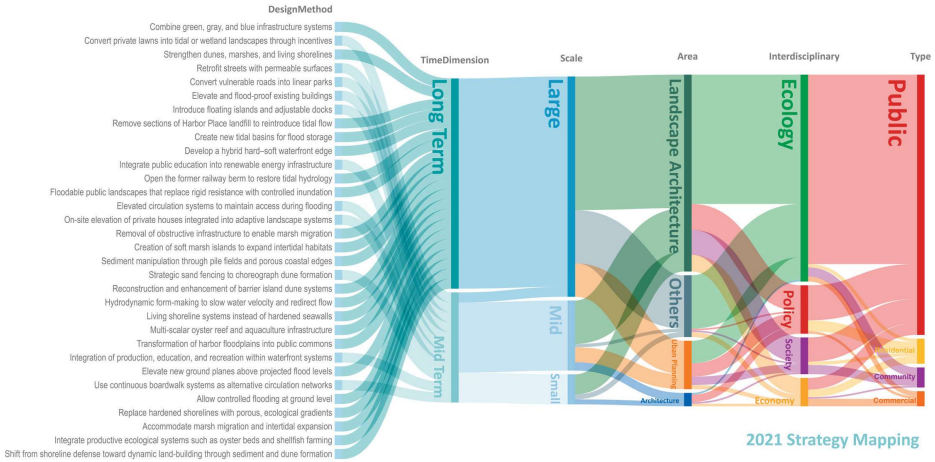
plt.title("Coverage Distribution and Average Coverage by Year")
plt.xlabel("Year")
plt.ylabel("Coverage")
plt.xticks(x)
plt.ylim(0, 1)
plt.legend(
    title="Type",
    loc="upper center",
    bbox_to_anchor=(0.5, -0.15),
    ncol=3
)
plt.show()

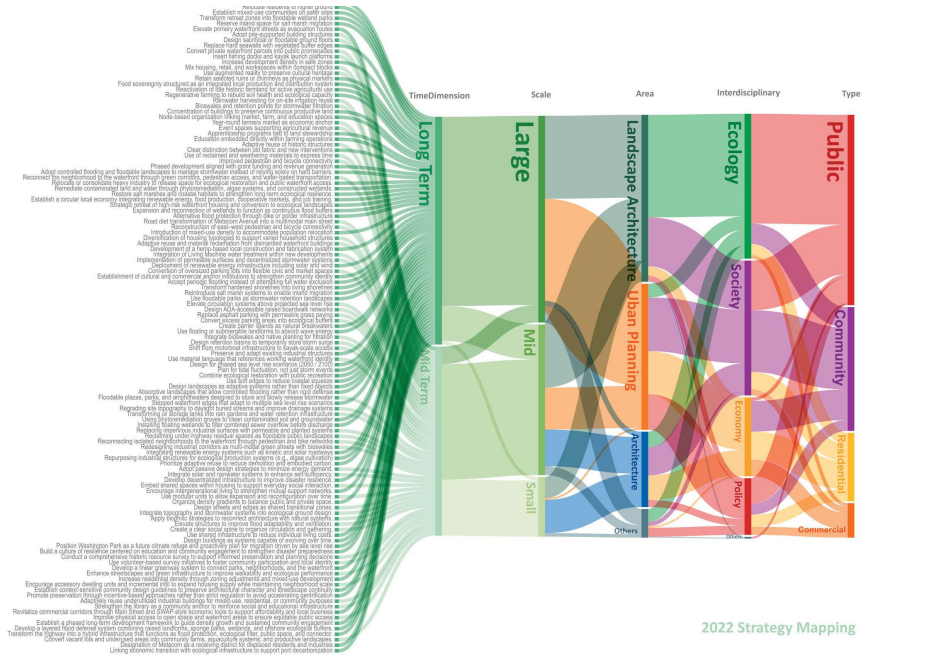
Spatial: 15
Systemic: 6

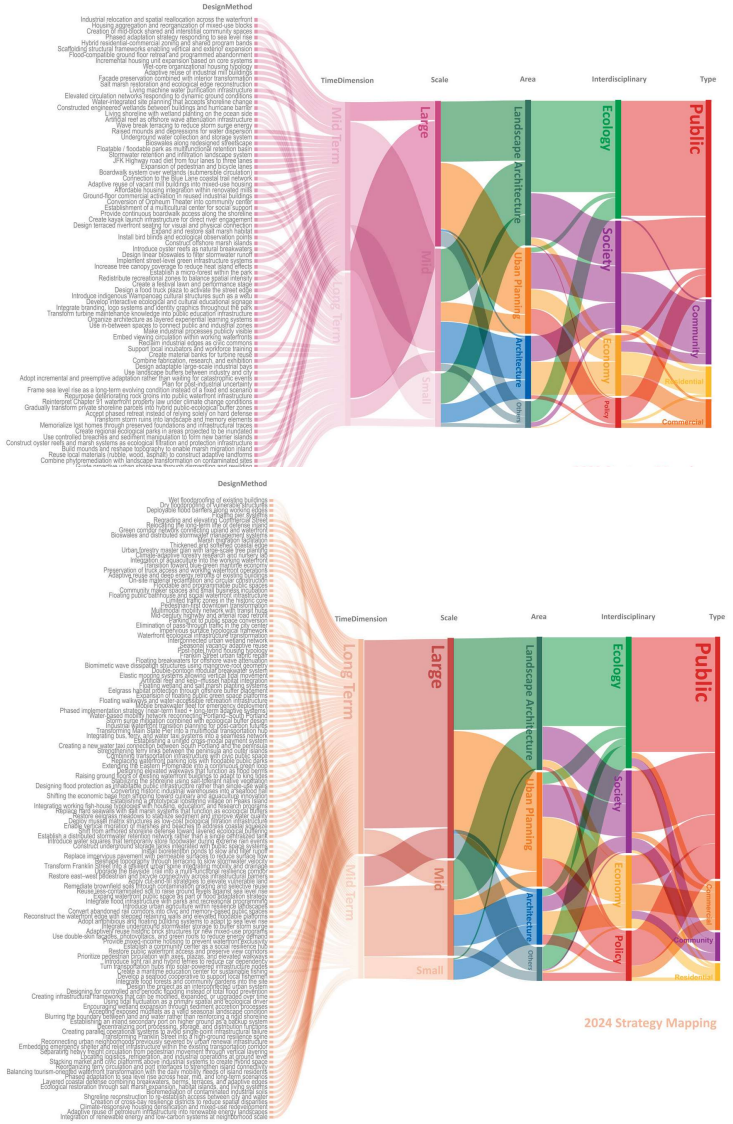
file:///Users/chenxinhe/26winter/capstone/validation_visual.html 6/7



STRATEGY ANALYSIS







INTERNAL SURVEY

Timestamp	Email Address	What is your name?	What was your role in this challenge?	Please select which phase(s) you were most active in:
11/4/2025 10:43:49	cxinhe@umich.edu			
11/4/2025 12:19:36	yunjiazo@umich.edu			
11/14/2025 16:11:00	cvanvoorhis@envisionresilience.org	Charlotte Van Voorhis	ERC program organizer	Pre-challenge (planning and set-up), Post-challenge (follow-up, implementation, or outreach)
11/17/2025 11:15:31	cjensen@remain.org	Cecil	staff/strategic advisor	Pre-challenge (planning and set-up), Challenge (design and engagement period), Post-challenge (follow-up, implementation, or outreach), Exhibitions, communications, administration
11/17/2025 11:24:16	kdeans@envisionresilience.org	Kate Deans	ERC program organizer	Pre-challenge (planning and set-up), Challenge (design and engagement period)
11/23/2025 17:26:01	ccox.advisor@envisionresilience.org	Carolyn Cox	ERC program organizer	Pre-challenge (planning and set-up), Challenge (design and engagement period), Post-challenge (follow-up, implementation, or outreach)
11/25/2025 13:55:34	cmartin@envisionresilience.org	Claire Martin	ERC program organizer	Pre-challenge (planning and set-up), Challenge (design and engagement period), Post-challenge (follow-up, implementation, or outreach)
11/25/2025 16:03:53	sakufo@envisionresilience.org	Sandra Akufo	Student Participant in the 2023 New Bedford Challenge; ERC program organizer in the 2024 + 2025 challenges	Pre-challenge (planning and set-up), Challenge (design and engagement period), Post-challenge (follow-up, implementation, or outreach)
11/26/2025 11:14:54	wjoseph@envisionresilience.org	Wendell T. Joseph	ERC program organizer	Challenge (design and engagement period)
12/3/2025 11:22:08	rjmiklos@gmail.com	Robert Miklos FAIA	Academic Advisor for the ERC program	Pre-challenge (planning and set-up), Challenge (design and engagement period), Post-challenge (follow-up, implementation, or outreach)

Please select your year(s) of involvement (check all that apply):	Were you involved in the 2021 Envision Resilience Challenge (ERC) in Nantucket, Massachusetts?	Approximately how many community participants or partners did you involve in planning this challenge?	Which methods did you use to engage with the local stakeholders?
	No		
2023 (New Bedford & Fairhaven, Massachusetts), 2024 (Portland & South Portland, Maine), 2025 (Midcoast Maine)	No		
2021 (Nantucket, Massachusetts), 2022 (Narragansett Bay, Rhode Island), 2023 (New Bedford & Fairhaven, Massachusetts), 2024 (Portland & South Portland, Maine)	Yes	25-30 people	Regular meetings, Shared digital tools (like Miro), Workshops, Informal discussions
2025 (Midcoast Maine)	No		
2021 (Nantucket, Massachusetts), 2022 (Narragansett Bay, Rhode Island), 2023 (New Bedford & Fairhaven, Massachusetts), 2024 (Portland & South Portland, Maine), 2025 (Midcoast Maine)	Yes	50	Informal discussions
2021 (Nantucket, Massachusetts), 2022 (Narragansett Bay, Rhode Island), 2023 (New Bedford & Fairhaven, Massachusetts), 2024 (Portland & South Portland, Maine), 2025 (Midcoast Maine)	Yes	~15-25, with ~10 core partners	Regular meetings, Shared digital tools (like Miro), Informal discussions
2023 (New Bedford & Fairhaven, Massachusetts), 2025 (Midcoast Maine)	No		
2025 (Midcoast Maine)	No		
2021 (Nantucket, Massachusetts), 2022 (Narragansett Bay, Rhode Island), 2023 (New Bedford & Fairhaven, Massachusetts), 2024 (Portland & South Portland, Maine), 2025 (Midcoast Maine)	Yes	50 or more	Workshops, Informal discussions

For your top three most influential collaborators overall, please list their name and three adjectives that best describe their contribution or role:	Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?	Which types of key advisors were most influential in shaping this challenge? Select up to three.	Is there anyone not listed who you believe played a significant but less visible role in building or maintaining engagement networks in this challenge?
Robert Miklos, Marty Hilton, Harrison Fraker	Both connectors and bridges	Nonprofit organizations, Municipal or government staff, Technical or scientific experts, Local residents, Private sector/business partners	Anne Dougherty
Cecil Barron Jenson, funder, nonprofit, connector Bob Miklos, cofounder, architect, networks Marty Hylton, historic preservation, connector,	Marty Hylton, Bob Miklos	Nonprofit organizations, Technical or scientific experts, Students/faculty from other universities	Carolyn Cox and Claire Martin did the most
Mary Bergman - historian, community-centric, innovative leader Jen Karberg - ecologist, data-driven, mentor Sarah Bois - community-centric, researcher, mentor	Mary Bergman, Marty Hylton, Cecil Barron Jensen, Bob Miklos, Chuck Larson, Harrison Fraker, MJ Levy Dickson, Jen Karberg, Sarah Bois, Chris Reed	Nonprofit organizations, Technical or scientific experts, Artists, cultural or heritage groups, Local residents	Vince Murphy, Tobias Glidden, Niles Parker, Harvey Young
Chuck Larson, Jennifer Karberg, Emily Molden	Cecil Baron Jensen, Marty Hylton	Nonprofit organizations, Municipal or government staff, Technical or scientific experts, Conservation Fnd Partners	Claire Martin

Were you involved in the 2022 Envision Resilience Challenge (ERC) in Narragansett Bay, Rhode Island?	Approximately how many community participants or partners did you involve in planning this challenge?	Which methods did you use to engage with the local stakeholders?	For your top three most influential collaborators overall, please list their name and three adjectives that best describe their contribution or role:	Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?	Which types of key advisors were most influential in shaping this challenge? Select up to three.	Is there anyone not listed who you believe played a significant but less visible role in building or maintaining engagement networks in this challenge?	Were you involved in the 2023 Envision Resilience Challenge (ERC) in New Bedford & Fairhaven, Massachusetts?
Yes							Yes
No							Yes
Yes	10-15	Regular meetings, Co-design sessions, Informal discussions	Bob Rulli, Curt Spalding, Tereasa Crean		Nonprofit organizations, Municipal or government staff, Artists, cultural or heritage groups	Barnaby Evans, Water Fire Arts Center	Yes
No							No
Yes	50	Regular meetings, Informal discussions	Bob Rulli, planning, climate Teresa Crean, connector, academic Curt Spalding, science, climate, water	Bob Rulli and Teresa Crean	Municipal or government staff, Technical or scientific experts, Students/faculty from other universities	Claire Martin and Carolyn Cox	Yes
Yes		Shared digital tools (like Miro), Workshops, Informal discussions	Teresa Crean - community planner, SLR specialist, ideator Bob Rulli - connector, visionary, planner Rachel Robinson - historian, archivist, resource	Teresa Crean, Kate Michaud, Bob Rulli, Dave Everett, Nicole LaFontaine	Nonprofit organizations, Municipal or government staff, Technical or scientific experts, Students/faculty from other universities	faculty, students, ER team, Anne Tate, RISD and URI partners, Mary Bergman, Lisa Craig, Shaun O'Rourke, Grover Fugate	Yes
No							Yes
No							No
Yes	15	Regular meetings, Workshops, Informal discussions	Curt Spalding, Bob Rulli, Teresa Crean	Curt Spalding	Nonprofit organizations, Municipal or government staff, Technical or scientific experts, Students/faculty from other universities	Claire Martin	Yes

Approximately how many community participants or partners did you involve in planning this challenge?	Which methods did you use to engage with the local stakeholders?	For your top three most influential collaborators overall, please list their name and three adjectives that best describe their contribution or role:	Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?
100	Regular meetings, Workshops, Informal discussions	Adelsa Mendes - galvanizing, dynamic, inclusive; Mary Rapoza - insightful, comprehensive, welcoming; Ethan de Aguiar - creative, visionary,	Emma York, Adelsa Mendes, Will Gardner, Skylah Reis, Kathryn Duff
5-10	Regular meetings, Informal discussions	John Bullard, Rodney Avila, Gordon Carr	All of them!
50	Regular meetings, Workshops, Informal discussions	Kathryn Duff, connector, planning John Bullard	Kathryn Duff
40-50	Regular meetings, Shared digital tools (like Miro), Co-design sessions, Workshops, Informal discussions	Kathryn - architect, visionary, connector Rodney - fisherman, connector, storyteller Adelsa - organizer, visionary, builder/collaborator	Michelle Paul, Rodney Avila, John Bullard, Adelsa Mendes, Mary Rapoza, Gordon Carr
3 (I was a student in this challenge)	Regular meetings, Informal discussions	Kathryn Duff (insightful, grounded, vision minded), Adelsa Mendes (inclusive, empathetic, community-minded), and Corinn Williams (resourceful, service-oriented, civically engaged)	Kathryn Duff was a speaker for our entire class in the 2023 challenge and has been a juror in subsequent challenge years.
20	Regular meetings, Co-design sessions, Workshops, Informal discussions	Kathryn Duff, Mary Rapoza, John Bullard	Kargryn Duff

Which methods did you use to engage with the local stakeholders?	For your top three most influential collaborators overall, please list their name and three adjectives that best describe their contribution or role:	Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?
Regular meetings, Informal discussions	Curtis Bohlen - enthusiastic, knowledgeable, engaging; Eli Rubin - responsive, open, excited; Jesse Thompson - insightful, constructive, guiding	Addy Smith-Reiman, Municipal Climate Action Program Team at the Gulf of Maine Research Institute, Curtis Bohlen, Jesse Thompson, Eli
Regular meetings, Co-design sessions, Informal discussions	Curt Bohlen, Bill Needleman, Jesse Thompson	All of them
Regular meetings, Informal discussions	Climate action at GMRI, science, connector Curtis Bohlen, science, academic Jesse Thompson, architect, connector	Addy Smith-Reiman
Regular meetings, Shared digital tools (like Miro), Co-design sessions, Workshops, Informal discussions	GMRI - community pillar, connector, research, organizer Curtis Bohlen - scientific, research, field work Eli Rubin - planner, local knowledge, site specific Bill Needleman - local historian, waterfront coordinator, fisheries liason	GMRI, Curtis Bohlen, Addy Remain-Smith, Ethan Hipple, Jesse Thompson,
Regular meetings, Workshops, Informal discussions	Curtis Bohlen, Jesse Thompson, Bill Needleman	Curtis Bohlen, GMRI

Which types of key advisors were most influential in shaping this challenge? Select up to three.	Is there anyone not listed who you believe played a significant but less visible role in building or maintaining engagement networks in this challenge?	Were you involved in the 2025 Envision Resilience Challenge (ERC) in Midcoast Maine?	Approximately how many community participants or partners did you involve in planning this challenge?
		Yes	
Municipal or government staff, Technical or scientific experts, Local residents	Ryan Kanteres, Cara Bionde, Troy Moon, Julia Tate, David Reidmiller, Amy Magida, Alex Zipparo, Jon Kachmar, Chris Cary	Yes	75
Nonprofit organizations, Municipal or government staff, Private sector/business partners	Brian Smith, curator	No	
		Yes	My role does not directly interface with the community
Nonprofit organizations, Technical or scientific experts, Students/faculty from other universities	ER staff and advisors	Yes	30
Nonprofit organizations, Municipal or government staff, Technical or scientific experts, Artists, cultural or heritage groups, Local residents, Students/faculty from other universities, Private sector/business partners	Ryan Kanteres, Local Artists and Libraries,	Yes	20-30
		Yes	I mainly write challenge briefs before the studio begins and create a report after the studio ends; I personally do not interact with partners that much
		Yes	n/a
Nonprofit organizations, Municipal or government staff, Technical or scientific experts, Local residents, Students/faculty from other universities, Design Professionals	Ryan Kanteres	Yes	25

Which methods did you use to engage with the local stakeholders?	For your top three most influential collaborators overall, please list their name and three adjectives that best describe their contribution or role:	Based on your experience, which advisors acted as connectors or bridges—either between groups within this challenge or across different challenge years?	Which types of key advisors were most influential in shaping this challenge? Select up to three.
Regular meetings, Workshops, Informal discussions	Rod Melanson - supportive, conscientious, welcoming; Jamie Hark - open, warm, inviting; Gayle Bowness - reliable, connective, supportive	Gayle Bowness, Rod Melanson, Debora Keller, Jamie Hark, Holly Parker	Nonprofit organizations, Municipal or government staff, Local residents
Regular meetings, Informal discussions	Rod Melanson, sustainability, connector Holly Parker, academic, community	Rod Melanson	Municipal or government staff, Technical or scientific experts, Students/faculty from other universities
Regular meetings, Shared digital tools (like Miro), Co-design sessions, Workshops, Informal discussions	Rod Melanson - innovator, connector, forward-thinking/progressive, open Jamie Hark - new Mainer (young/local), ideator, designer Holly Parker - passionate, involved, student-connected		Municipal or government staff, Technical or scientific experts, Local residents, Students/faculty from other universities
Informal discussions	Curtis Bohlen (Only collaborator that I met); Adjectives Ecologically-informed, place-based, observational	Curtis Bohlen has been an advisor in the 2024 and 2025 challenge years	Nonprofit organizations, Municipal or government staff, Local residents
Regular meetings	n/a	n/a	
Regular meetings, Co-design sessions, Workshops, Informal discussions	Rod Melanson, Jamie Hark, Jenn Curtis	Rod Melanson, Curtis Bohlen, Jamie Hark	Nonprofit organizations, Municipal or government staff, Technical or scientific experts, Local residents, Private sector/business partners

In which of the following areas do you think ERC has had the strongest community influence? (Select up to two)	How do you personally define "impact" in the context of the Envision Resilience Challenge? (This helps us understand how participants conceptualize success and influence.)	Are there examples of lasting effects from any challenge you've participated in (such as continued partnerships, implemented projects, curriculum changes, or new community initiatives?) If so, please describe them.	Any additional comments or reflections about engagement or networking during your ERC experience?
Design innovation, Policy influence	Community members who feel hopeful after working with our program.	We continue to have partnerships in New Bedford with Love the Ave and Parks + Rec, who are working on implementing a piece of a 2023	
Community empowerment, Public awareness	Permanently changing people's – seeing the future with optimism, agency, and hope	Yes! Community education impact in Nantucket and New Bedford. Resilience projects on Nantucket and New Bedford.	The interconnection between study areas is powerful and lasting. The network that ER has built will continue to expand. While it also bridging communities and identifies communication opportunities – it also allows for shared opportunities for successful resilience planning, construction, and long-term policy changes.
Education, Community empowerment	To me, it is about an ability to comprehend and imagine a future that is different and improved.		
Design innovation	Helps community see future potential	too numerous	NA
Education, Public awareness	In the context of ERC, impact is about our ability to advance innovative planning and design in the face of climate change. This can look like educating, inspiring, conversating, showcasing, building, etc. with community members and leaders through the lens of design, providing context, research and examples of resilient neighborhoods and futures. Impact means inspiring communities to think differently, optimistically even, about a future with more water, hotter temperatures, etc. Impact means training the next generation to work more holistically, equitably and intersectionally about design.	1. New Bedford, Massachusett's Riverside Park playground in the North End neighborhood marks the first design build inspired by Envision Resilience. Plans to replace a 20-year old playground by New Bedford Parks and Rec and the City of New Bedford were informed by the mapping analysis of the 2023 Northeastern team. Students' research led them to determine that the playground and splash pad needed to be moved inland to ensure longterm access by residents. The design work was used to secure a grant, which was awarded fall 2025. Project design will take place in 2026 and construction in 2027. 2. Public art partnerships have inspired existing community initiatives in New Bedford where the Envision Resilience mural (more information on the website) - a collaboration between UMass CVPA, NB Creative, Love the Ave, Envision Resilience - has inspired additional murals to be installed throughout the city. 3. Curtis Bohlen, Jamie Hark, Jesse Thompson, GMRI partners, have now been involved in all three iterations of the Envision Resilience Challenge in Maine (from early 2023 outreach and planning to outreach and planning for 2026). This exemplifies the network we've convened and build off of to inform the work. 4. There is a lot of continuity in faculty, jurors, speakers over the years. Speakers Katie Swenson and Alan Ricks of MASS Design have led to a partnership with that design firm. 5. Washington Street Resilience Framework - a private, public partnership on Nantucket, Mass. between the Nantucket Land Bank, the Town of Nantucket and Remain, along with SCAPE, Woods Hole Group and Parc, often references inspiration from the student design work of the 2021 Envision Resilience Challenge.	We are a very self-reflective organization. Each year, we incorporate feedback of students, faculty, community partners and jurors to improve our programming and our impact. We do our best to show up as curious listeners, with humility, believing in the notion that the experts as those who live in the communities we are working in.
Education, Community empowerment	Impact in ERC - The implementation of student projects into grants/city planning; recorded sentiments of community members post-challenge/exhibition; growing interest of design studios who want to participate in future years and tackle place-based, climate-related issues	New Bedford Challenge – student mural for ERC was painted in the city by local artists;	N/A
Education, Community empowerment, Public awareness	I would define "impact" as 'the extent to which ERC supports, inspires, and catalyzes actionable next steps in the communities we've worked with, whether than be more in-depth, focused conversations, projects/policies, new partnerships, etc. Our mission is to advance innovation in student and community partnerships and we do this, in part, by working with community partners already doing amazing, incredible work. So, should our adding capacity through ERS resources + networks + university partners directly/indirectly lead to tangible outcomes, that is impactful.	n/a	I never get tired of seeing how people we're connecting with for the first time respond to our mission and our work. I've seen/heard people express numerous times how much this work is needed and the impact they feel it can/will have in their community. Some have been very generous with their time, others have been generous with their networks + making connections, and there are those who just want to be kept in the loop. It's affirming.
Education, Design innovation, Public awareness	broadening awareness of climate risks but also innovative adaptive design strategies	Several -Town Warren, New Bedford Parks, Portland Community + Planning	Need to reach larger community participation- possible with online community workshops

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