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ARTICLE

Navigating complexity: a pattern language approach for behavioral science in public policy

Katelyn Stenger[1,2] and Ruth Schmidt[2]

[1]National Renewable Energy Laboratory, Buildings Center, Golden, CO, USA and [2]Illinois Institute of Technology - Institute of Design, Chicago, IL, USA
Corresponding author: Katelyn Stenger; Email: kstenger@id.iit.edu

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Abstract
When aiming to change behavior, policymakers confront the challenge of implementing behavioral interventions across contexts. However, the effectiveness of behavioral solutions often hinges on context, posing a significant hurdle to scaling interventions. This study explores the application of a behavioral pattern language approach as a means to enhance intervention efficacy and support policymakers and practitioners who seek to solve problems at scales that cross diverse contexts. The study demonstrates how a pattern language can inform contextually aware solutions, fostering collaboration and knowledge sharing among stakeholders. Additionally, the research finds practitioners deploy multiple solutions within complex systems to achieve more difficult behavioral change goals. Despite challenges related to replicability and evolving methodologies, the findings suggest that pattern languages offer a promising avenue for systematically generating and disseminating behavioral insights. This research contributes to advancing applied behavioral science by providing a structured approach for collaborative policymaking and research endeavors that are contextually relevant and effective.

Keywords: applied behavioral science; policy; sustainability; systems; complexity

Introduction

To address complex issues such as climate change, policymakers often cannot rely on single interventions to do the trick; rather, they look to multiple behavioral interventions operating at a combination of global, regional/institutional and individual scales (Heller *et al.*, 2021; IPCC, 2022). At global and national levels, for example, climate change policies enacted through international agreements like the Paris Agreement and national investments such as the Inflation Reduction Act supply broad leverage. Regional policies (such as the Regional Greenhouse Gas Initiative) and institutional procedures aim to govern regions, organizations and communities toward climate action by targeting geographic or institutional groups. Finally, behavioral solutions at the individual level address the aspects of people's lives, such as their purchasing, transportation (Whillians *et al.*, 2021) and energy use choices (Klotz *et al.*, 2019; Peters *et al.*, 2021).

Policymakers and researchers already commonly consider various contexts when developing behavioral solutions (McCann, 1983; Cash *et al.*, 2017). However, behavioral change is complex, and when contexts and scales vary from those of the original interventions, behavioral solutions that are effective or robust in one setting may fail in others (Bates and Glennerster, 2017; Supplee and Kane, 2020). Context, or the surrounding circumstances that given meaning to something, varies across cultures (Nisbett *et al.*, 2001; Gelfand *et al.*, 2006), population heterogeneity (Soman and Hossain, 2020), the manner in which solutions are delivered (Marques *et al.*, 2021) and evolution of system conditions (Schmidt and Stenger, 2021a), all of which influence the success and efficacy of behavioral solutions (Diener *et al.*, 2022). When contexts change, scaling behavioral solutions becomes a significant challenge (Bothwell *et al.*, 2016; DellaVigna and Linos, 2020). This creates a quandary: while generalizing solutions often entails omitting context, treating individual situations as unique cases with bespoke solutions inhibits knowledge sharing and scalability. It also suggests that synthesizing and organizing contextual components of solutions more systematically might better capture learnings *across* behavioral approaches used for similar challenges in different contexts, which in turn may facilitate more effective scaling of solutions.

In this paper, we articulate the challenges of scaling behavioral solutions to different settings, suggesting that one major difficulty in scaling is due to differences in context. We then introduce the notion of behavioral 'patterns' as a mechanism to systematically capture and compare specifics of the originating problem, solution approach, contextual factors and rationale to yield greater insight into why certain interventions or mechanisms work while also providing building blocks to develop a behavioral 'pattern language' that can be used to solve more complex challenges. We then present an approach for generating behavioral pattern languages in the context of sustainability and conclude with thoughts about further extensions and applications.

Addressing the cross-disciplinary nature of applied behavioral science

In applied behavioral practice, as in many fields, relevant knowledge is dispersed among many people (Hayek, 1945) and yet the ability to share and gather that knowledge is essential to effectively apply behavioral science to policy contexts. Behavioral science researchers and policymakers have generated frameworks, diagrams, taxonomies and other tools that structure knowledge and support navigating complexity when applying behavioral science to real-life contexts. These serve different purposes, providing reminders of common solution components to help individual-facing problems become more accessible with mnemonics like MINDSPACE (Dolan *et al.*, 2012) and EAST (The Behavioural Insights Team, 2014) or through readiness scales that help inform practitioners recognize when the time is right to apply behavioral science in broader policy contexts (IJzerman *et al.*, 2020).

Frameworks also offer a more systematic approach to interpreting situations and creating relevant solutions. For example, frameworks like the COM-B model (Michie *et al.*, 2011) or the BASIC toolkit (OECD, 2019) help to classify approaches to behavioral challenges. Taxonomies from rigorous analysis describe solutions when applying behavioral science (Michie *et al.*, 2013), their underlying principles (Cash *et al.*, 2020), the ways solutions are delivered (Marques *et al.*, 2021) and the reasons (i.e., mechanisms) behind these solutions (Ludwig *et al.*, 2011; Carey *et al.*, 2019). Seeking to close the gap between theory and practice, common problems have also been mapped directly onto generalized solutions, (Bohlen *et al.*, 2020; Cash *et al.*, 2020; Khadilkar and Cash, 2020). Collectively, these tools have proven useful for policymakers and researchers to learn common approaches for applying the behavioral sciences in a repeated, replicable way in order to generate and deploy behavioral solutions on other populations or on themselves (Reijula and Hertwig, 2020).

While these tools can help policymakers and researchers navigate a certain amount of complexity, frameworks and taxonomies may still neglect the contextual, relational and evolutionary aspects of applied behavioral science. As a result, even models that understand the critical nature of context, helping practitioners to systematically consider beliefs, barriers and context when developing solutions to influence behavior (Hauser *et al.*, 2018), tend to target singular psychological mechanisms. This can prove a challenge when navigating greater degrees of contextual complexity and uncertainty required when designing for cultural differences (Nisbett *et al.*, 2001; Gelfand *et al.*, 2006) or the evolution of conditions (Schmidt and Stenger, 2021c) and the material environment (Diener *et al.*, 2022). In addition, policymakers often deploy multiple solutions in their programs to guide decision-making, yet typically lack systematic ways of capturing these combinations and relationships of solutions. This suggests that a problem-solving approach that incorporates relational knowledge may prove useful to take on complex challenges, helping practitioners consider what works well together to develop a program and adapt when conditions change.

In addition, scaling behavioral solutions beyond their original choice environments to address variations in organizational, institutional and civic conditions or sociocultural system forces remains a challenge (Schmidt, 2022). Where behavioral frameworks and other choice architecture tools have proven useful when proposing direct adjustments to immediate choice environments, including nudges (Thaler and Sunstein, 2009) or reminders, eco-labels and defaults (Johnson *et al.*, 2012; Tromp and Hekkert, 2018), there has been an increased call for policymakers to expand and scale solutions beyond the individual context for which they were originally designed (Ewert, 2019). Some efforts to address these more varied organizational, institutional and civic conditions and interventions at the level of social, technical and environmental infrastructure, can be seen, for example, in examples like the Belief–Barriers–Context model (Hauser *et al.*, 2018) and the SPACE model (Schmidt, 2022). These proposed approaches include more structural and procedural interventions in the form of company policies, standards and community campaigns, and increased attention to sociocultural system conditions, such as historical tendencies and conventions, to inform regulations and legislative policy at greater scale.

Finally, tools must accommodate the fact that the field of applied behavioral science will continue to evolve as researchers expand upon, reinforce or fail to replicate current bodies or evidence used to inform intervention development and policymakers accumulate and apply new findings in the context of solutions. Rather than attempt

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to 're-taxonomize' current practice to respond to a continually changing landscape, a flexible framework that captures these insights about what works may help contribute to the development of a shared language and knowledge base among researchers and policymakers, establishing a more cohesive community of practice. For these reasons, a tool that accommodates the contexts, relationships and evolution of solutions warrants further investigation.

A pattern language approach

In addition to material processes described above, social processes like collaboration, dialogue and problem-solving are critical to knowledge-sharing. However, these social processes have been somewhat limited in applied behavioral science practice, due to the lack of a common conceptual base to help practitioners share outcomes across varied disciplinary contributors (Feitsma and Whitehead, 2019; Buyalskaya *et al.*, 2021). Without this common language, findings tend to remain both contextualized and fragmented. This suggests that supporting the communicative and social aspects of applied practice that enable researchers and policymakers to share processes and findings more easily may be of equal importance to expanding a shared knowledge base.

One such alternative approach to generalized solutions that also solves for the communicative and social aspects of shared problem-solving borrows from Christopher Alexander's notion of a 'pattern language', which consists of an organized network of patterns (i.e., partial solutions) gleaned from real-life implemented solutions that can then inform future problem-solving (Alexander, 1977, 1979). Alexander described a 'pattern' as a solution to a specific thing that can be modified and combined, much like a dressmaking pattern can serve an essential function of serving as a guide for an article of clothing while also remaining modifiable (e.g., it can be adjusted to various lengths or have short or long sleeves and still maintain integrity). Where individual patterns describe individual instances or variants of solutions, a 'pattern language' denotes the way multiple individual elements can be integrated differently depending on the context. Pattern languages have been employed to characterize processes central to public policy like implementation tool patterns (e.g., community design processes) and place governance (e.g., polycentric governance) (Mehaffy *et al.*, 2020). Describing a problem and the core solutions, a pattern language facilitates scaling across contexts and characterizes relationships between patterns to support policymakers and designers, suggesting that the use of a pattern language approach as a model for organizing and transferring insights may be equally relevant and useful to applied behavioral science.

Common pattern components may include the core problem, solution, context for applying the problem–solution pair and rationale behind employing the solution (Salingaros, 2000); in the case of applied behavioral science, a behavioral pattern can be constituted by several components or aspects of contextualized behavioral problem-solving. When developing behavioral interventions, for example, policymakers and researchers first identify and frame a problem to envision an ideal state of behavior. They also discuss what solutions are most likely to work, ideally considering possible alternative or complementary approaches. Finally, practitioners weigh these options to determine which options may be most appropriate and the specifics of when or where to implement them. In short, therefore, the different aspects of context can be described

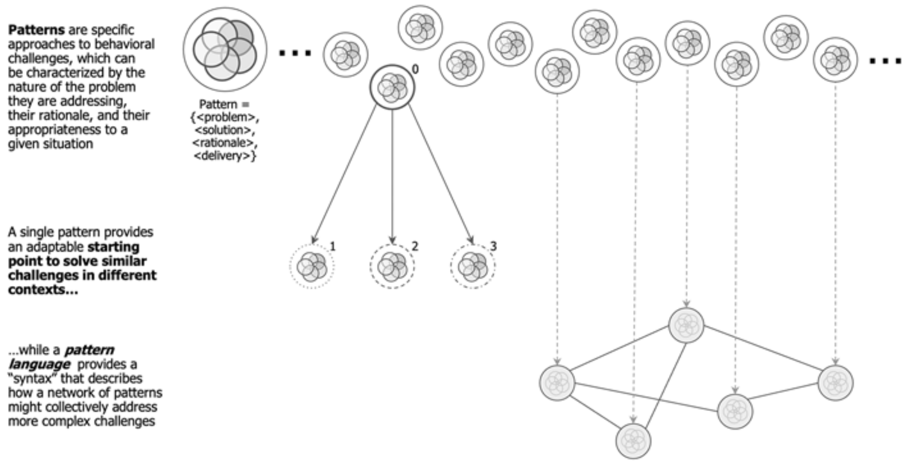

Figure 1. Pattern languages approach.
Patterns are specific approaches to behavioral challenges, which can be characterized by the nature of the problem they are addressing, their rationale, and their appropriateness to a given situation a single pattern providesan adaptable starting point to solve similar challenges in different contexts while a pattern language provides a "syntax" that describes how a network of patterns might collectively address more complex challenges.

succinctly as the problem, the solution, when to employ the solution and the rationale for choosing it (Alexander, 1977).

Where a singular 'pattern' might describe this cluster composed by the problem, solution, reasonings, scale and specifics of context, a 'pattern language' organizes these patterns by scales and their relationships to one another in a flexible structure. By breaking down and positioning solutions in relationally, a pattern language approach can provide greater contextual awareness and nuance than the wholesale mapping of a generalized solution to a new context (Figure 1). As such, pattern languages hold promise for synthesizing and structuring behavioral solutions across varied scales (Schmidt and Stenger, 2021b), increasing practitioners' ability to transfer behavioral solutions between similar conditions. In addition, pattern languages have the potential to expand on current methodological approaches through their ability to overcome contextual, relational and evolutional limitations that result from distributed sources of knowledge.

Below, we explore the viability of a pattern language approach for building a better understanding of public policy and behavioral solutions. We present a novel methodology for developing a pattern language and primary findings, followed by implications for the applied behavioral sciences in supporting policymakers and researchers tasked with the complex task of influencing behavior to combat climate change.

Research methods

This study uses a pattern language approach to characterize common problems, solutions and contexts for applying behavioral science. An overview of the research methodology and respective data for each step are shown in Figure 2.

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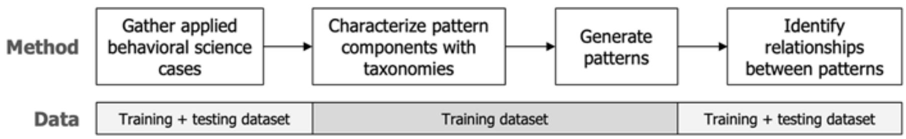

Figure 2. Research methodology.

Table 1. Summary of baseline inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
• Cases must address sustainability issues by applying behavioral science	• Cases that do not meet ethical standards
• Cases must be applied and focus on real-world applications	• Cases that do not have complete information
• Cases must be available on internet	• Cases using lab studies that do not address real-world applications
• Cases must be identifiable within a 20-minute search of firm's website	• Cases on agriculture, eating habits, investing and fundraising

Cases from applied behavioral science teams were collected to create a pattern language (Alexander, 1977, 1979; Salingaros, 2000), making use of a valuable but neglected source of policy information (Green, 2008; Smith-Merry, 2020). Case studies covered countries, cultures and contexts, allowing for diverse solutions. The cases were split into testing and training datasets, a practice used for pattern recognition; the training dataset allowed for pattern generation whereas the testing dataset evaluates the reliability of the patterns generated (Salingaros, 2000; Bishop, 2006). Relationships in how patterns were applied were identified and synthesized as a network resulting in a prototype behavioral pattern language. The data that support the findings of this study are openly available in Open Science Framework at http://doi.org/10.17605/OSF.IO/MJE3F (Stenger, 2023).

Gather applied behavioral science cases

Cases were collected through multistage, purposive sampling that were published by applied behavioral science teams and used to characterize common solutions and problems when applying behavioral science in nonexperimental environments, which provide evidence for how behavioral science is applied 'in the wild' and aligns with best methodological practices (Cash *et al.*, 2022). Cases were tested against baseline inclusion and exclusion criteria (Table 1).

Cases were identified by searching 551 applied behavioral science team's websites, which were collated by Applied Behavioral Science Association (www.behavioralscience.org) and represented 52 countries across government, non-profit, academic and for-profit entities. A total of 201 cases met inclusion and exclusion criteria.

Quality of cases was assessed with criteria in Table 2, using best practices from other applied behavioral science work (Carey *et al.*, 2019) and aims to increase research integrity by considering a wide variety of contexts and decreasing selection bias.

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Table 2. Summary of quality criteria

Case quality score	Characteristics
Not passing quality (0)	• Summary of past designs or synthesis
	• Is missing a core case component: the solution (or opportunity), problem, context, does not mention design process or failure.
Passing quality case (1)	• Describes core components: solution, problem (or opportunity) and context
	• Does not describe design process or design failures
High-quality case (2)	• Describes core components: solution, problem (or opportunity) and context
	• Describes design process and/or design failures

Publication year, target behavior, source or language didn't exclude cases; Google translate was used for non-English cases.

Cases were included if they described a problem (or opportunity), solution, context and rationale (Table 2). Of the 201 potential cases collected, 86 cases had passed quality cases, of which 33 cases were high-quality. Aligning with mixed-methodology purposive sampling recommendations, 20 high-quality cases were selected for the training set (Onwuegbuzie and Collins, 2007). Cases were split into specific problem-solution pairs (i.e., designs) as many cases used multiple solutions to result in behavioral change. For example, a case described multiple problem–solution pairs when providing feedback to energy customers to shift energy consumption, including calling on the phone to ask customers to shift energy usage, texting customers that peak energy usage will occur in the next hour and employing both solutions (Metcalfe, 2018; Brandon *et al.*, 2019).

Characterize pattern components with taxonomies

By applying previously developed taxonomies, pattern components were characterized. As previously mentioned, pattern components include the problem features, solution, how to deliver the problem–solution pair and the rationale behind the solution. Taxonomies were selected if they were developed from applied behavioral science cases and reliably demonstrated. A single rater assessed cases. Table 3 summarizes the taxonomies used to characterize pattern components.

Robust applied behavioral science taxonomies were used to identify problem features, solution, mode of delivery and rationale by reading each design described by the cases written by applied behavioral science teams. After classifying pattern components, designs were grouped by problem features because a pattern often addresses a common problem. Problem features include high or low change demand as well as high or low behavioral constraint (Cash *et al.*, 2020). Change demand describes the difficulty a person may have with an intended behavior and comprises sub features – novelty, scope and frequency – to indicate the difficulty of the intended behavior. When an intended behavior is new, requires many different steps, and occurs frequently (i.e., daily), it would be a high change demand.

Table 3. Characterize pattern components with taxonomies

Component	Taxonomy and description
Problem feature	Problem features taxonomy (Cash *et al.*, 2020): The problem features taxonomy categorizes elements essential for behavioral design, like change demand and behavioral constraint, providing practitioners with a structured framework to address challenges in behavior change interventions. It aims to enhance practitioners' ability to develop tailored solutions by systematically defining and operationalizing key features of behavior change.
Solution	Solution principles taxonomy (Cash *et al.*, 2020): The solution principles taxonomy offers a structured framework for designing behavior change interventions, focusing on guiding principles rather than specific behaviors or interventions. Developed through a systematic process of identifying, filtering and clustering candidate principles from various sources, it provides practitioners with a comprehensive set of principles applicable across domains.
Mode of delivery	Mode of delivery ontology (Marques *et al.*, 2021): The mode of delivery ontology categorizes modes of delivering behavior change interventions, aiding precise reporting and facilitating evidence synthesis. It comprises 65 unique modes organized into 15 upper-level classes, with inter-rater reliability of 0.80 for those familiar with it and 0.58 for those unfamiliar. This ontology facilitates consistent and coherent specification of intervention delivery in evaluation reports, enhancing evidence comparison, synthesis, replication and implementation of effective interventions.
Rationale	Mechanism of action ontology (Carey *et al.*, 2019): The mechanisms of actions ontology characterizes how behavioral solutions bring about change. The taxonomy was developed through analysis of a large corpus of published literature and characterizes the reasoning behind why behavioral solutions might work.
See Also	Pattern relationships (Salingaros, 2000): The pattern relationships examine how patterns, inspired by Christopher Alexander's work, can be interconnected, combined or interchangeable. It highlights examples of coupling between patterns and discusses challenges in integrating Alexandrine patterns into practice.

Behavioral constraint describes the difficulty of changing the contexts of a planned intervention, which include social, technological and physical features. The more difficult it is to change these contexts, the more behaviorally constrained the problem context.

Generate patterns

By grouping designs by problem features, similarities in solutions were examined as well as the way solution components were integrated differently depending on context, informing pattern generation. Problem–solution pairs were tagged for further analysis if they occurred more than two times within a specific problem feature quadrant and shared the same rationales and mode of delivery. The pattern components – problem, solution, mode of delivery and rationale – were structured to cohesively form a pattern (Alexander, 1977; Salingaros, 2000). A pattern needs to be conceptually distinct from other patterns, meet the Alexandrian format for patterns, and occur two or more times within the training set. Through a process of systematically studying and abductively evaluating pattern components in relation to one another, a common qualitative and design methodology used for generative inquiry, 3 potential patterns were removed because they lacked conceptual distinctiveness, resulting in 22 patterns (Timmermans and Tavory, 2022).

Identify relationships between patterns

Patterns were tested on the remaining set of cases as well as the training set of cases for occurrence, scale and relationships. Scale was specified by whether the pattern addressed the immediate choice environment; organizational, institutional and civic conditions; or sociocultural system conditions (Schmidt, 2022). Just as combining solutions across scales can offer strategic resilience to policy programs (Nair and Howlett, 2016), policymakers can similarly benefit from insight into relationships between patterns. Pattern relationships were identified by reviewing how the patterns were used in each case. Complementary relationships were identified when two patterns were used within the same design, completing one another to work better together than alone. Interchangeable relationships were characterized by grouping the designs across problem features and identifying when two patterns solved for the same problem in different ways, offering the potential for alternatives (Salingaros, 2000). Both can productively inform behavioral problem-solving. Tableau and RStudio were used to plot occurrences.

Results

A pattern language composed of 22 patterns resulted from the analysis. An example pattern is shown below, and a full set is available in the Supplementary materials.

> **Title**: Community Agreements
> **Problem**: Institutions seek to sustainably manage a shared resource within a community. However, ensuring consistent and desirable behaviors among community members can be challenging.
> **Context**: This pattern arises when institutions or community organizers recognize the need for collective action to maintain and manage a shared resource effectively.
> **Solution**: Institutions establish community agreements by:
>
> 1. Inviting key members of the community to participate in developing the agreements.
> 2. Defining desired behaviors, goals and expectations for resource management.
> 3. Providing guidance and resources to support community members in achieving these behaviors.
> 4. Implementing mechanisms for evaluating and monitoring behaviors over time.
>
> **Examples**:
> - A fishing community establishes agreements committing to work toward sustainable management practices and fishing schedules.
> **Related Patterns**:

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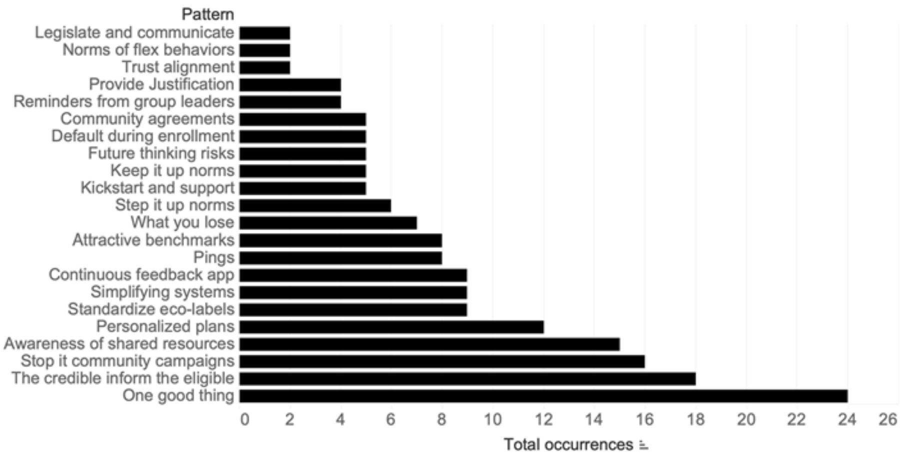

Figure 3. Pattern occurrences.

Table 4. Change demand and average number of patterns applied in design

	Change demand			
	None	Low	Medium	High
Average number of patterns applied	2.8	3.6	4.2	8.0
Designs represented	18	23	16	3
Cases represented	7	8	6	1

- "Awareness of shared resources": Addresses broader strategies for recognizing shared resources.
- "Legislate and communicate": Strategy where institutions align laws across different levels of governance and foster meaningful relationships among stakeholders.

All patterns were evaluated for occurrences across the full set of cases ($N = 86$), as shown in Figure 3.

Patterns varied in their occurrence, with '*One good thing*' occurring 24 times, and '*Trust alignment*' occurring 2 times. All patterns are described in the data repository. The presence of the patterns across training and testing cases suggests the methodology is viable in synthesizing practice and generating patterns using cases published by applied behavioral science teams.

Many behavioral science teams use multiple solutions to address challenges. Using the training dataset, Table 4 shows the number of patterns used in a single case relative to the case's difficulty (i.e., change demand) as well as the designs and cases represented.

As the change demand of the case increased, the total number of patterns practitioners applied increased (Table 4). When change demand was none, the average number of patterns applied was 2.8; whereas when the change demand was high, the

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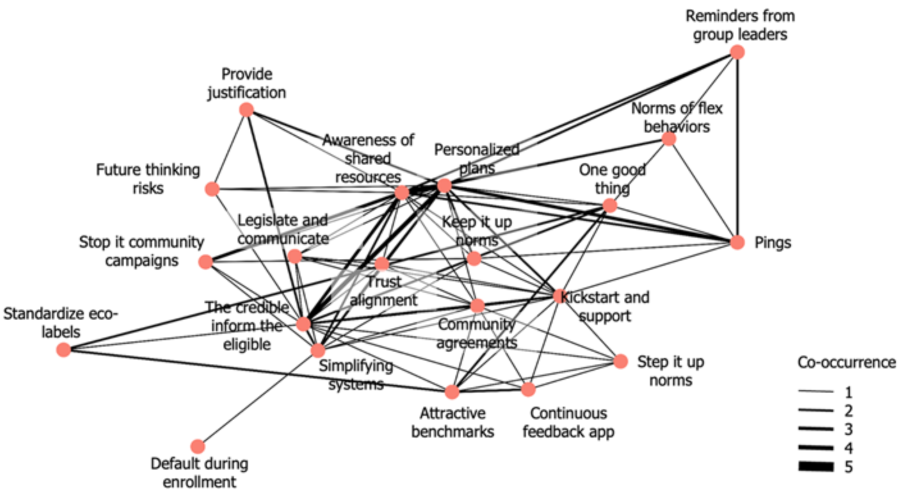

Figure 4. Complementary relationships between patterns.

average number of patterns applied was 8. The evidence presented in Table 4 suggests an interesting relationship in deploying solutions, where applying more patterns might be more useful when behavioral change demand increases.

Complementary and interchangeable relationships between patterns were identified using the training set. Complementary relationships occurring two or more times were identified between patterns shown in Figure 4.

The complementary relationships between the patterns form a highly connected network. The relationships show what patterns have worked well with other patterns. For example, informing individuals of a shared resource (i.e., '*Awareness of shared resources*') and supporting individuals with a '*Personalized plan*' in a simplified system (i.e., '*Simplifying systems*') may prove more effective together than on their own. Patterns with interchangeable relationships are shown in Figure 5.

Some patterns show clusters of interchangeable relationships. For example, '*Attractive benchmarks*' were interchangeable with '*Standardize eco-labels*'. Both complementary and interchangeable relationships can guide policymakers during solution development and deployment to consider what solutions might be useful to deploy together and what solutions might offer an interchangeable approach.

During development, practitioners may use the existing pattern network design for the multiple scales (i.e., individual, institutional, sociocultural systems) that inform behavioral conditions. Even more, when solutions miss the mark during implementation, a pattern language may offer alternative paths so that practitioners may quickly adapt to achieve their strategic goals. The pattern language aims to be an evolution of practice and is by no means prescriptive towards current practice. The interchangeable and complementary relationships expand on previous taxonomies that form exclusively hierarchical (i.e., parent–child) relationships. The pattern language indicates

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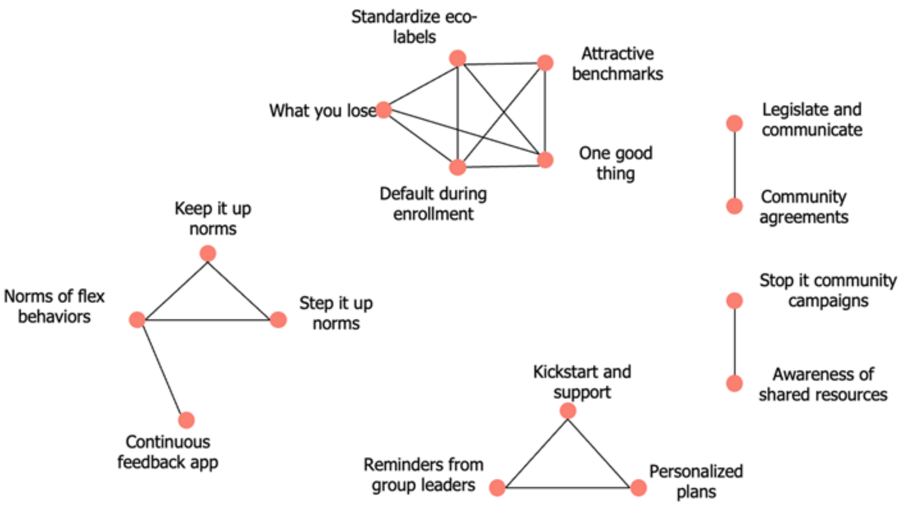

Figure 5. Interchangeable relationships between patterns.

opportunities to combine and apply solutions creatively and assist practitioners who navigate complexity and uncertainty.

Discussion

Pattern language supports understanding behavioral solutions

The study demonstrated how a behavioral pattern language approach can build a better understanding of the wider context of public policy interventions and address the cross-disciplinary nature of applied behavioral science by synthesizing behavioral solutions in relation to one another. Our approach shows how a behavioral pattern language can demonstrate how patterns can be integrated and modified across contexts and further how these contextual clues, while not comprehensive, can also help policymakers and researchers consider other contexts where the pattern may apply. The combinations between patterns provide useful, relational knowledge about applying behavioral science to real-world instances, and the need to consider and apply patterns in complementary and interchangeable fashions. As a result, using a behavioral pattern language allows practitioners to suggest more contextually aware solutions with greater confidence that they will work.

In addition, the use of patterns and pattern languages provides a shared format for systematically capturing and describing behavioral interventions that is currently lacking in applied practice. Patterns were shown to be used across cases and contexts, signaling their effectiveness in capturing knowledge about successful solutions to recurring problems, solutions, ways to deliver solutions and the rationale behind this solution. These pattern occurrences also indicate how patterns may support knowledge sharing and inform a *lingua franca* for discussing design problems and solutions, facilitating better communication among scientists, designers, public policymakers and stakeholders. While the patterns themselves likely won't surprise an expert, the ways they form a language to capture and share knowledge about successful solutions to recurring problems provides novel information for beginners and experts alike.

Finally, the use of patterns also contributes materially to applied practice by converting the results of individual interventions into a new source of data that can inform broader applications. Too often, an intervention's success is measured in isolation and with little insight into how it may directly inform other similar challenges, with findings languishing in papers if they are published at all. The research sampled cases that were published by applied behavioral science teams, leveraging an often-neglected source of evidence that is critical to understanding how behavioral science is used 'in the wild,' and are often omitted from high-quality systematic reviews (Green, 2008; Center for Community Child Health, 2011; Smith-Merry, 2020). Greater inclusion of practice-based cases in syntheses and reviews provides policymakers and researchers with complementary insights.

Implications for applied behavioral science

Many policymakers know that achieving strategic goals means engaging with complex systems, which are characterized by nonlinearity and unpredictability. Rather than betting big on one robust study, we suggest a need for redundancy by applying multiple solutions. Influencing behavior in complex systems frequently benefits from two simple strategies: design for many scales and deploy multiple solutions (Sheard and Mostashari, 2009; Mueller, 2020).

Redundancy in a system is a central feature of resilient solutions (Nair and Howlett, 2016). When one solution fails because conditions change (or were misinterpreted), another solution can support the desired behavior. For instance, policymakers wanting to sustainably manage fisheries have communicated desired behaviors to individual fishers, aligned community trust and legislated rules for harvesting fish (Rare, 2022). The prevalence of using multiple solutions for more difficult problems may reflect a conflict between behavioral science's preferred methodology, which consists mainly of hypothesis-driven experiments, and an openness to apply this science to more complex contexts and systems.

Applying many solutions at once has been criticized by those with preferences for experiments as a 'kitchen sink' approach that sullies scientific rigor (Hauser *et al.*, 2018). Yet for many practitioners wanting to effect change, the findings also suggest that deploying a combination of solutions may be a beneficial strategy for more challenging problems given that causality, a key benefit of experiments as performed by behavioral science, can be limited in complex systems (Diener *et al.*, 2022). Designing programs and interventions for complexity is central to public policy; as problems get harder, more solutions are used, and combining solutions can help policymakers build strategic programs. Indeed, in related public policy fields, expanding methodologies to consider complementary combinations of behavioral solutions and how they might be interchanged and applied over time has been an advantageous perspective for researchers and policymakers (Howlett, 2019). The pattern language method aims to capture evolving behavioral solutions in complex settings by offering a complementary perspective on applied behavioral science, which in turn aims to help policymakers and researchers create more strategic programs to achieve goals like climate action through the identification of patterns that depict complementary and interchangeable linkages.

Lastly, the pattern language approach explicitly accounts for the diversified nature of applied behavioral science and the fact that it will continue to evolve. As the field codifies certain results, fails to replicate others and grows in knowledge, a pattern language aims to facilitate who can systematically generate and share behavioral solutions. More powerfully still, the evidence- and domain-agnostic nature of pattern languages can also aid in synthesizing and structuring often neglected practice-based evidence to supplement the familiar norms of evidence-based practice.

The project described here used a pattern language approach to find patterns, to infuse context into patterns and facilitate apply solutions across contexts. The 22 patterns generated are far from exhaustive, and are not meant to be complete; rather, they should be seen as a catalyst for future (and omitted) patterns. While on the one hand they have recognized limitations – with cases constrained to environmental issues and primarily developed by teams in the Global North, and conducted by a single rater – they should also be viewed as a proof of concept that can inform patterns in other sectors, such as finance and health, which may both overlap in pattern combination and present new challenges needing further investigation.

The struggle to transfer learning between different practitioners or from one setting to another will continue to be a challenge for researchers and policymakers. Pattern languages can help address this by increasing the ability to gather and synthesize insights from across solutions and share them more broadly to distributed teams, and subsequently enabling policymakers to build programs, collaborate with interdisciplinary partners, and adjust to changing situations. In doing so, the behavioral pattern language lowers the bar to applying behavioral science across contexts and affords a greater opportunity for collaboration, which may include support for self-nudging and exploration of more personalized solutions (Mills, 2020; Ruggeri *et al.*, 2020). Imagining these solutions in a synergetic fashion will likely reveal exciting opportunities for policymakers and researchers.

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