Busara Groundwork

RESEARCH AGENDA

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Behavioral systems: Combining behavioral science and systems analysis

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Abbreviations and acronyms

ABM	Agent Based Model
GBV	Gender Based Violence
NA	Network Analysis
PESTLE	Political, Economic, Social, Technological, Legal, and Environmental
SD	System Dynamics
SPACE	Standards; Process mechanics and policies; Accountability; Culture within institutions; and Evaluative and iterative feedback
SNA	Social Network Analysis
WHO	World Health Organization

Introduction

Many challenges the world faces arise from broken behavioral systems: systems with multiple levels of interacting actors in which people make the best choices they can given their limitations. However, by doing so, they generate outcomes that no one actually wants.

In these systems, people are embedded in a context that shapes their behavior. Their actions then shape both how the system behaves and the very set of choices that the individuals within it face, often in non-obvious ways. Once we start looking, it is not hard to find these broken behavioral systems: they arise in everything from fisheries management to racial wealth inequality to corrosive norms of behavior on social media.

Busara, and the field of behavioral science overall, could play an influential role in understanding and reimagining these broken behavioral systems: with our focus on how cognitive limitations and localized context shape decision making and action. We do not play that role.

Instead, behavioral science is trapped in a box of its own making. We have developed cost-effective interventions grounded in empirical evidence. However, our field has rightfully been critiqued for addressing small questions and delivering small effects. Our academic knowledge base and our practice have evolved remarkably little in the past five years, as we have struggled to take on bigger picture, structural and systemic problems.

Outside of behavioral science, however, rich traditions of systems analysis have worked on such systemic problems for decades. Computational and quantitative approaches such as system dynamics, social network analyses, and complex adaptive systems study these systems; so do qualitative approaches from systems thinking to systems mapping in the design community.

Behavioral science has much to learn from these time-tested traditions, while also contributing its unique perspective. Too often, existing systemic approaches lose sight of individual agency and decision-making. While they are excellent at understanding how a system behaves, and even what needs to change, they often falter when it comes to providing practical solutions that individuals are genuinely inclined to adopt. Behavioral science has the tools and empirical evidence to help close that gap.

In this Groundwork piece, Busara shares our journey to understand and grapple with broken behavioral systems. We will look at how such systems function, the many tools and techniques of systems analysis, and how behavioral scientists have sought to contribute to the discussion. We will then outline a potential path forward: a unified toolkit for bringing these disciplines together to address broken behavioral systems.

At Busara, we have experience with each of the pieces of this toolkit individually, but we are only now starting to run large, end-to-end projects that include all of it. We are learning as we go along. We share what we have so far in the spirit of openness: because we welcome and need the research community's help. We hope to draw from the experiences of others, refine this approach, and move our field forward collaboratively. We are trying to put these pieces together, but we cannot do it alone. Towards that end, we conclude this report with a call for collaboration: open, thoughtful exchange and partnering across the diverse fields needed to tackle these societal challenges.

Our method, in brief

For a subset of our readers, we recognize that a fifty-page discussion of the properties and tools of systems analysis, including a review of budding efforts of other behavioral scientists to grapple with these issues, will be a long detour from what is most interesting: how to actually do it. To honor those readers, here is a summary of the approach we are testing in the field.

The purpose

As applied behavioral scientists, we have an overarching goal: to design, deploy, and test interventions that measurably improve people's lives. Here, we will use systems analysis to improve behavioral science. Lessons from behavioral science can and should also be used to improve systems analyses: by offering a more realistic representation of human decision-making and behavior.[1] Both approaches are vital and interesting; here, we are squarely focused on how to make behavioral science more effective at driving behavior change to tackle systemic problems.

The toolkit for behavioral systems

Busara's work-in-progress approach to behavioral systems is a six-step process:

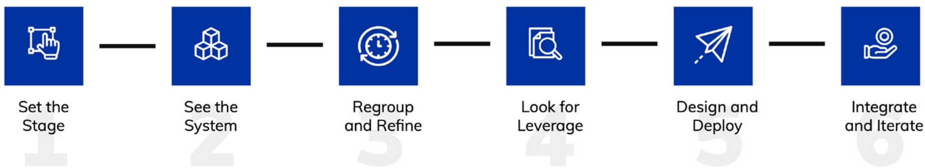

Figure 1: The six stages of Busara's approach to behavioral systems

1 Indeed, the systems analysis community is far ahead of behavioral science in doing just that: integrating behavioral insights into realistic models. See, for example, Marco Janssen's considerable body of work in this area.

The process starts when we **set the stage,** identifying the system at hand, what is known about it, and what we want to accomplish. Sometimes, we have a behavioral system that produces adverse outcomes and we are looking for behaviorally viable options to improve it. In other cases, we have a particular behavioral intervention and want to understand both the structural influences that may influence its effectiveness and anticipate ripple effects throughout the system. In the full report, we outline eight use cases we are exploring at Busara.

We then seek to **see the system:** by working with the existing literature and stakeholders to develop a qualitative understanding of the system. This entails mapping out the interacting people and groups, filling in blind spots with PESTLE, and mapping bi-directional causality and feedback loops. The result is a person-centered causal loop diagram with multiple overlays for relevant policies, existing data, etc.

Next, we **regroup and refine:** we narrow our focus within complex systems to promising opportunity areas and actors. Where possible, develop a computational model of the system with the (behaviorally informed) decision-making rules explicitly captured. We then validate the model against observed facts and known system behavior with either the initial qualitative or the computational model.

With the validated model in hand, we **look for leverage:** rigorously analyzing the system for leverage points to affect change. These may lie in specific components or relationships, the rules of the system, or its underlying goals.

With these potential opportunities for change identified, we further articulate the causal pathways around them with power mapping and behavior change hypotheses and vet and prioritize our list of options.

For our top-priority leverage points, we employ a traditional behavioral science process to **design and deploy** targeted interventions. We align with stakeholders on the localized behavioral problem: the specific target actor and behavior identified previously. We conduct mixed-methods research to understand the local context, design interventions, and assess their impact. We augment this process with futures thinking to assess the brittleness of our interventions to uncertain future conditions.

Finally, we return to the broader system, to **integrate and iterate.** We use qualitative or computational tools to trace the ripples from the local intervention to broader systemic effects, update our list of opportunities for change, and share the results with stakeholders before embarking on a new iteration of the process.

Within each step, we outline the specific stages and options available to the researcher, depending on the systemic challenges and available resources. Image 2 depicts the process in more detail.

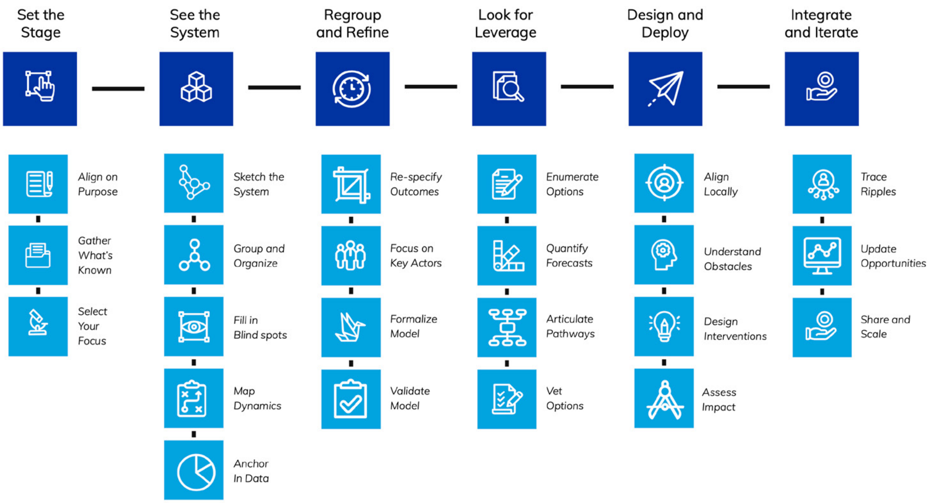

Figure 2: A detailed look at the sub-steps within Busara's approach to behavioral systems

This process draws on techniques from systems analysis to expand and improve behavioral science: our goal is to develop a broader, systemic understanding of the contexts in which we work. We then use that understanding to develop better interventions: interventions carefully targeted at specific and impactful changes to the system, which we then evaluate locally and systemically.

With that overview of the process, let us return to the beginning and go step-by-step through how we got there.

Understanding systems

As system dynamics researcher and founder of systems thinking, Donella Meadows, described:

> *"A system is a set of things-people, cells, molecules, or whatever-interconnected in such a way that they produce their own pattern of behavior over time. The system may be buffeted, constricted, triggered, or driven by outside forces. But the system's response to these forces is characteristic of itself, and that response is seldom simple in the real world."* **- Meadows (2008)**

In other words, a system is more than the sum of its parts: the relationships and interactions between its components shape both how the components behave and the outcomes of that system, often in non-obvious and counter-intuitive ways. Structure shapes behavior.

Four critical parts of any system are its components, relationships, governing rules, and outcomes.

- **Components:** the individual elements, actors, or "forces" within a system. For example, individual humans, companies, or economies.

- **Relationships:** the connections between components. For example, friendships, client-vendor agreements, or international shipping routes.
- **Rules:** how interactions are governed along the relationships (between the components) and within components over time. For example, reciprocity, mutual agreement on price, or colonial dependency.
- **Outcomes:** the behaviors that come from the system. For example, how friends treat each other, whether companies go out of business, or whether countries go to war.

Take a market, for example, where buyers and sellers trade. The components here are the buyers, sellers, and goods. The relationships govern who can (currently) buy and sell from whom. The rules could be as simple as "buy low, sell high" or as detailed as specific auction procedures or payment terms. The outcomes of this market are pre-planned outcomes like completed trades, but they could also include emergent phenomena like collusion or a secondary market for used products.

In another example, consider what is known as the racial wealth gap: the vast difference in average wealth between racial and ethnic groups in many parts of the world, especially the United States. The components of this system include the individual members of each racial or ethnic group as savers, the employers who hire them (or don't), the banks that serve them (or don't), the school educators who differentially teach their kids, etc. These components form strong geographical connections, influenced by kinship, ethnicity, and race, creating multiple subsystems within the broader system.The rules for individuals include when to save, spend, change jobs, and move locations. In contrast, the rules for others might include the determination of the level of service or education provided. Outcomes of interest would include each group's aggregate and average wealth, social mobility, education attainment, and employment rates.

In behavioral science, we often find ourselves navigating a myriad of systems. However, our analytical tools are not designed for them. We usually analyze simple causal chains: Situation A causes behavior B, leading to outcome C. We intervene in this chain to drive a change in behavior and beneficial outcomes. This chain may have many pieces, and there may be multiple causes for a single effect in a complex map of causal interactions. Nevertheless, across most of the models and theories of change used in behavioral science, causality flows in the same direction: from initial conditions, through interventions, to our outcome of interest.

In a more complex system, causality is two-way and time-dependent: B influences C, triggering changes in A, which, in turn, affects B and so forth. In system dynamics terms, these bi-directional relationships arise from feedback loops, and they greatly complicate our ability to forecast the effect of an intervention on the system. In addition, the relationships between elements may be so complicated and adaptive that it is nearly impossible to guess intuitively how the system will behave: we can only observe in order to understand.

Researchers and practitioners have developed multiple tools to understand such systems: from system dynamics to complex adaptive systems. Each helps us understand different types of systems and the opportunities for change. Let us turn to the major approaches next.

The tools of systems analysis

To apply behavioral science at a systemic level, we need to understand the system we are working with. There is no single "systems approach", however; there are multiple traditions and tools used to model and understand complex human systems.[2] These go back at least to the 1950s with Forrester's work on system dynamics models, the systems thinking approach popularized by Donella Meadows starting in the 1970s, and later work on Complex Adaptive Systems by the Sante Fe Institute, Argonne National Labs and others in the 1990s.

Each of these approaches to modeling systems serves as a lens that allows us to explore and engage with a different aspect of a system. Practically speaking, the approach we use to model a system guides which components are considered relevant, where the boundaries of the system are, and how we structure and analyze the relationships and rules over time.[3] We cannot understand a system without a tool to model it, formal or informal. The

2 The term systems analysis is used widely across many disciplines, each defining the particular tools they use to analyze systems relevant to their domain. For example, computer science has their own systems analysis, as does logistics management. Here, we're focusing specifically on systems that express the set of external factors that shape and are shaped by human decisions and behavior.
3 Underneath the hood, we can intentionally create systems models using different approaches that are mathematically identical and produce the exact same outcomes: however, the language and tools of each approach create tendencies that lead to divergence in approach and focus.

modeling approach effectively co-defines the system. Each approach has its strengths and weaknesses.

Existing approaches range from the statistical to the mathematical, to the computational, to the qualitative. Some of these techniques appear natural fits for integration with behavioral science; others have been less explored or are less appropriate. In short, the most likely candidates appear to be:

- **Agent-based models.** In an agent-based model, the modeler identifies the types of people ("agents") who interact in the system, their decision-making rules, and the environment in which they interact.[4] This environment can include any range of factors: from organizational structures and regulations to the climate, depending on what is deemed relevant. The modeler then activates the model, allows the agents to interact with each other over time, and observes the resulting outcomes. This is a bottoms-up approach to modeling, and its unique benefit is that it allows the modeler to discover the emergent properties of a system and the complex adaptation of that system over time. See, for example, Miller and Page (2007).
- **System dynamics.** A system dynamics model is expressed as the stock and flow of key variables of interest over time. For example, a stock may

4 For the purposes of behavioral systems, we are intentionally focusing on ABMs that model people and their decision making. ABMs are used for any type of "agent" including animals, viruses, businesses, etc., though human-level ABMs are perhaps most common.

be the level of trash in an urban park; two flows might be the cleanup of trash by maintenance workers and interested citizens and the addition of new trash by disinterested visitors. In these models, human decision rules are embedded as mathematical functions within the flows. System dynamics models can uniquely capture and clarify feedback loops in the system and the pattern of outcomes over time in key variables of interest. See, for example, Forrester (1961).

- **Systems thinking.** Formal systems thinking is a qualitative generalization of system dynamics. In this approach, the modeler outlines the major components involved and their positive or negative relationships with each other in a non-mathematical, usually graphical, form. The components and relationships are not necessarily stocks and flows of a resource (as in system dynamics). However, systems thinking retains the same focus on feedback loops and the pattern of outcomes over time. See, for example, Meadows (2008).
- **Social network analyses and models.** SNA models are focused on the network of relationships between people of interest. They are especially useful for understanding concepts of centrality or the influence of specific roles or individuals in the social network in spreading ideas or innovations. They do not (generally) incorporate other potential system components, such as organizational structures or markets. See, for example, Wasserman and Faust (1994).
- **Network analysis.** NA is a generalized version of an SNA that looks at the interrelationship between entities of interest – such as the co-occurrence of different types of intimate partner violence in a society. The relationships are not human one-to-one relationships (as studied

in SNA) but statistical relationships. Like SNA, these are analyzed with statistical tools that focus on network structure but not usually on the dynamic interactions over time or decision-making or adaptation.

Less relevant tools

There are many other modeling techniques available, but they may be difficult to integrate into behavioral science. In theoretical physics, for example, researchers use **dynamical systems** and **stochastic processes** to model the complex time-dependent interactions between entities and the evolution of the state of a system. **Markov chains** are used to model probabilistic transitions between states, depending solely on the current state of that system. These are powerful, well-known approaches.

On the surface, at least, these approaches leave little room for integrating behavioral insights about human decision-making and cognitive limitations. For example, Markov chains can be used to model all possible variables and states of those variables of a complex system of interacting people and organizations; it is simply non-obvious and challenging. They also require a level of mathematical sophistication that is rarely taught in behavioral science programs.[5]

5 For systems modelers, our goal to design, deploy, and test more effective behavioral interventions means that we do not necessarily seek the same level of mathematical precision in our models as experts in these fields; rather we need roughly-right insights that we can empirically test in the field. These purposes also align with SD, ABM, and systems thinking approaches.

Game theory provides compelling tools to understand the unintended consequences of individually rational human decisions and how they affect both individual and communal outcomes. Dynamic games and differential games also allow for an analysis over time. However, they work best for small, simple systems, focusing on specific interactions. They become unwieldy when the system has a significant number of interacting parts or people, as many behavioral systems of interest do.[6] Nevertheless, game theory lessons are invaluable to understanding human interactions involving common pool resources, for example.

Comparing relevant methods

Within this space, agent-based models are the most wide-open, “anything is possible” approach: any type of interaction and actor you can imagine can be included in an ABM. That is also their most significant weakness because they require explicit assumptions and modeling choices across a dizzying array of possibilities. They are also a popular bottoms-up tool that aligns with research on human decision-making: the modeler specifies the people involved and their decision rules, and then sees what happens, including what structures emerge out of the individual components.

6 Similarly, chaos theory is often applied to small numbers of interacting components (and their variables) to study how outcomes of that system devolve into unpredictably divergent outcomes (chaos). Complex systems with a significant number of interacting components and relationships may similarly create those outcomes but the focus of complex systems (and the agent based models often used to study them), is the structure and relationships.

System dynamics is a top-down approach in which the modeler decides at the onset which components and relationships are relevant to the system. The modeler defines the structure and then observes the non-obvious *systemic consequences of that structure.* This approach requires translating human decision-making rules and behavior into specific mathematical flow functions: for example, determining the rate at which maintenance workers pick up trash in the urban park.

Systems thinking is perhaps the best-known and most popular of these approaches, but it also appears to be widely misunderstood. The founder of systems thinking, Donella Meadows, was deeply grounded in the lessons and tools of system dynamics and brought those insights to a broader audience. For example, she helped popularize the causal loop diagram, which shows the structure of a system and its feedback loops. A unique strength of systems thinking is that it facilitates participation from a broad array of stakeholders: it makes the modeling process accessible and meaningful outside of the modeling community. However, the term “systems thinking” also has come to be used for various design and graphical approaches that depict the interconnection of various components, regardless of feedback loops or dynamic interactions over time. The practical value of these approaches for analytical purposes is often unclear. Here, we will focus on the version of systems thinking inspired by system dynamics.

How we select an approach for a specific problem

As mentioned above, each approach shapes the thinking of the modeler and the definition of the system. While it is possible to express a wide range of systems in each approach, agent-based models tend to focus attention on the *choices and behaviors* of the components (usually people). Social network and network analysis models focus on the (usually static) *structure of the relationships* between people or components. System dynamics models focus on aggregate quantities of interest and the flows between them over time. Systems thinking is perhaps the least constraining, conceptually.

At the same time, the requirements of each tool differ. ABMs do not require any empirical data, but quickly become disconnected from reality and hard to interpret without it. SNA and NA models require extensive data on the specific people and relationships involved to be effective. System dynamics models use precise flow functions, ideally based on empirical data about those quantities of interest. Systems thinking requires greater self-restraint and empirical validation to ensure that the elements included are practically important and not simply anecdotally interesting.

The right tool to understand a particular system depends on the data and resources available and where the focus of that analysis needs to be. Here is a summary of the key questions to ask:

1. **What is our unit of analysis?** If the unit of analysis is people, then SNA or ABMs are most natural. If it is "entities" then SD, ABMs (sometimes), systems thinking, NA, dynamical systems, or stochastic processes are appropriate.

2. **Do we need to study change in the system (dynamics) over time?** If yes, SNA and NA are less appropriate; they are usually a static model of relationships. Instead, we need ABM, SD, systems thinking, dynamical systems, or stochastic processes. Dynamic versions of SNA and NA are possible but require advanced stats and data (network and spatial autocorrelation models with time-series cross-sectional data).

3. **Do we want to forecast or describe the relationships?** Alternatively, do we want to explore hypotheticals or fit existing data? For hypotheticals over time, ABM and SD are best for simple models, and dynamical systems and stochastic processes are appropriate for quantitatively detailed systems. The dynamic versions of SNA and NA describe dynamic data; they do not (normally) forecast future outcomes.[7]

7 With a limited exception in the form of link prediction (Zareie and Sakellario 2020)

4. **How quantitative do we need to be, and what level of data do we have access to?** A full SD model requires detailed quantitative data to create the equations and parameters. An ABM can range from a toy conceptual model (no quant inputs) to a carefully calibrated empirical one, which needs more quantitative data than an SD model. Dynamical systems and stochastic processes similarly require heavy quantitative modeling and data to calibrate (except for things like cellular automata, which are conceptual models like ABMs).

5. **What skills are available on the team?** A detailed SD model takes mathematical rigor and expertise to build; an ABM takes little rigor to construct but usually requires a programmer. SNA and NA require specific statistical expertise. Dynamical systems and stochastic processes require specialized mathematical expertise. Systems thinking requires no formal background, though experience with formal modeling can significantly help to ground the process and aid in analysis.

As we will describe in more detail below, at Busara we have found that a mix of system dynamics, agent-based models, and formal systems thinking are most useful for our goals: understanding and shaping the broken behavioral systems we encounter in international development. Specifically, we seek to forecast system behavior, especially over extended periods (dynamics). Our natural unit of analysis is a person. We also recognize that the majority of our staff members do not have an extensive mathematical background; they do, however, have some statistical expertise and programming knowledge:

enough to work with basic ABMs and SD models and to thoughtfully partner with external experts who have more expertise in these areas. A significant portion of our staff also have design experience and experience with collaboratively generating causal diagrams, which aligns with systems thinking.

For another organization, with different goals and use cases, other approaches could certainly be used, and each approach has its strengths and weaknesses.

How behavioral science has approached systems analysis to date

Historically, behavioral science has focused on individual behavior with the common goal of understanding and shaping the factors influencing individual decisions and actions. While wider groups are considered, they usually serve to illuminate potential influences on individual behavior. For instance, we might investigate how social norms impact health-seeking behavior, but we will mainly focus on how the norms might influence an individual's inclination to get vaccinated. In other words, causal links all flow in one direction, towards the individual.

Similarly, our approach to understanding individual behavior has been predominantly mechanistic: we aim to uncover the underlying drivers of behavior, the cause-and-effect relationships, with the understanding that modifying parts of this mechanism changes the behavior or outcome. We might determine, for instance, that an individual's behavior is shaped by their belief in a social norm. We then theorize that altering the norm (or the individual's perception) will change their behavior. This method forms the backbone of much of microeconomics (i.e., individual utility maximization), where behavioral economics started. It is thus unsurprising that behavioral science is rooted in the same mechanistic thinking.

As behavioral scientists have sought to consider larger scales, from individuals to systems, we have often simplified systems as mechanistic factors affecting individuals. After all, if human behavior is mechanistic, it seems logical to extrapolate those individual components and rules into a systems-level analysis. In other words, the starting position of behavioral science has been to dissect systems into constituent parts to understand the elements that affect a target population. For instance, in a hospital, we might scrutinize the roles of patients, doctors, nurses, administrators, and the rules governing each to understand the influence on a specific group's decisions and behavior. By adjusting specific rules for each component (e.g., providing doctors with checklists and reminding nurses to wash their hands), we can alter the system's properties (e.g., reduce hospital-acquired illnesses and improve patient outcomes). This analysis tends to create linear causal chains: we look at the web of forces that flow together in one direction to affect individual behavior and our outcome of interest.

In contrast, many systems are better understood through a holistic approach, focusing on the fundamental rules, interactions, and emergent properties that arise from the system as a whole. For instance, if we are trying to bolster the effectiveness of a social movement, we will want to concentrate on the key rules that shape behavior, model how individuals interact, and comprehend the emergent properties (e.g., marches, viral social media posts, violence, advocacy, misinformation). By shaping these rules, we will stand a better chance of improving the movement's outcomes. We are starting to do that as a field, but the work is still nascent.

We see the need, but we do not have the tools

Within behavioral science, the most prominent articles about behavioral systems are likely the "I-frame / S-frame" article by Chater and Loewenstein (2022) and its rebuttal by Michael Hallsworth (2023a). Chater and Loewenstein passionately argue against an approach to social problems that is individually sourced and solved (an "i-frame"), and instead look at them structurally and as part of broader systems ("s-frame"). Their article is a call to action, not a guidebook on how to take action.

In response, Hallsworth rightfully argues that practitioners of behavioral public policy have integrated individual and structural considerations for many years. Hallsworth's integration of behavioral insights is nevertheless deeply embedded in the necessary messiness of policy making. His examples are powerful and thoughtful but are not a clear and usable process. He points to a set of tools practitioners could use to analyze problems at various levels, such as Jilke et al.'s (2019) micro-, meso- and macro- approach. Exactly how practitioners can bring together these puzzle pieces to address systemic issues, especially as one looks beyond public policy, is unclear.

Indeed, as we look beyond the recent back and forth between Chater, Loewenstein, and Hallsworth, other voices are similarly struggling with the practical "how" of systemic behavioral science. These include Thaler's article on the future of nudging and choice architecture, in which he too, questions the value of individually-focused nudges and calls for a broader aperture in our work: “My basic point here is that behavioral science researchers are almost always trying to nudge in the context of complex systems in which they can at best tweak behavior at the margin (Thaler 2020)”. Hallsworth’s “A Manifesto for Applying Behavioral Science” (2023b) similarly calls for our field to advance by harnessing existing tools and developing new approaches that better grapple with complex systems.

Outside of behavioral science, we can find a diversity of people who have thought about systemic problems. Indeed, most other academic fields of social science have long and deep traditions of analyzing the impact of broad structural factors on both societal outcomes and individual behavior., with clear tools and methods. Examples range from the sociology of racial inequality (Oliver and Shapiro 2019) to grand theory in political science (Mearsheimer 2001), to much of political economy and macroeconomics (e.g., Robinson and Acemoglu 2012). If anything, the bulk of behavioral science (beyond behavioral public policy) is an outlier in its myopic focus on the individual determinants of human behavior.

As described above, we can find a wealth of tools for systemic analyses. The design community has long grappled with how to redesign or design around systemic problems; the systems design toolkit is one such example (Jones and Van Ael 2022). From policymakers to development professionals to “systems thinkers”, it’s not uncommon to find practitioners to discuss the interplay of policy, market forces, and demographic factors (e.g. race, gender) on individual behavior, and provide practical tools to do so, including system dynamics and social network analysis. Again applied behavioral science is an outlier in its lack of discussion of structural forces, despite the thoughtful policy work that Hallworth cites.

Thus, for behavioral science to think about systems and structure doesn't mean we need to create something entirely new: hopefully, and humbly, it will mean we learn from the numerous other traditions around us who have been doing so for generations. Rather, the task we face is to combine lessons from other fields, while retaining the core of what applied behavioral science offers: a focus on rigorously measured change in actual behavior, based on a rich understanding of the quirks of the mind and how our decision-making process interacts with the world around us.

A few have sought to make this combination: using other approaches alongside behavioral science without losing the heart of our field. Ruth Schmidt is one of the most prolific: combining design tools with behavioral insights in her work on behavioral brittleness (Schmidt and Stenger 2021b) and choice infrastructure (Schmidt 2022). Moore et al. (2013) use existing socio-ecological and policy analysis tools alongside behavioral insights to enrich health policy, as does a UN women report on behavioral science to address violence against women and children (ONU Mujeres and The Behavioural Insights Team 2022). At Busara, we previously sought to address systemic issues in a variety of ways. For example, by conducting landscape studies that explicitly map the players involved in addressing a particular behavioral challenge, or identifying structural barriers alongside psychological ones.

At the same time, other researchers and practitioners have sought to pull behavioral science into systems analysis: to better understand systems using empirical insights on the mind and decision making. These efforts, such as thoughtful modeling of behavioral theories within socio-ecological systems (e.g., Schill et al. 2019) are exciting but conceptually distinct. They focus on how to improve the model, to make it more realistic and insightful, which is related but different from that of applied behavioral science: how to design, deploy, and test behavioral interventions that change system outcomes.

The tools we have so far

Across the limited practice in the field, and the hints of ideas bubbling up in the community, we have a few broad approaches to integrate systems analysis into behavioral science:

a. Acknowledging structural forces by tweaking the standard behavioral problem-solving approach
b. Designing more robust interventions, which are *resilient* to structural forces
c. Injecting behavioral insights into public policy
d. Developing a unified toolkit of behavioral and structural methods

This list starts with the most modest changes to existing practice in applied behavioral science and then moves into a more fundamental reimagining of the work we do.

Acknowledging structural forces

Most practitioners in the field apply behavioral science in a problem-solving framework: there's problematic behavior, and we seek to "fix it" (see Wendel, Kahn, and Artavia-Mora 2023 for a more complete discussion). At Busara, we call this process of behavioral AUDAS: Align around the target behavior and population, Understand the context of that behavior, Design interventions to change the behavior, Assess the impact of the interventions, and then Share them broadly.

Within Busara, we've started to acknowledge structural forces in three ways:

1. **Align phase:** Asking whether a particular problem is "behavioral" (rooted in the choices of an individual that don't align with their preferences) versus structural.

2. **Understand phase:** Identifying barriers and levers for behavioral change that are both psychological and structural.

3. **Design phase:** When we recognize that a particular group is disproportionately affected by broader structural forces - such as women who are kept out of technical employment due to early career tracking, social norms, and parental leave policies - we can design our interventions to provide targeted support for those groups.

In each case, we take note of but don't tackle structural issues. We focus on what we can change: behavioral problems and behavioral barriers, with a structural awareness of our limitations. It's a start, but a rather ineffectual one.

Schmidt and colleagues (Schmidt et al. 2021; Hatch and Schmidt 2021) developed the SPACE tool to help the user systematically acknowledge structural forces: it reminds us to think about Standards, Process mechanics and policies, Accountability, Culture within institutions, and Evaluative and iterative feedback.

Similarly, as behavioral scientists, we can use frameworks such as the socio-ecological model in public health (McLeroy et al. 1988). Figure 3 shows one such example used in the development: UNICEF's socio-ecological model (McKee et al. 2008) later adapted and taught by USAID. Another approach is to consider the individual, social, and material (ISM) factors that influence a person's behavior (Darnton and Horne 2013).

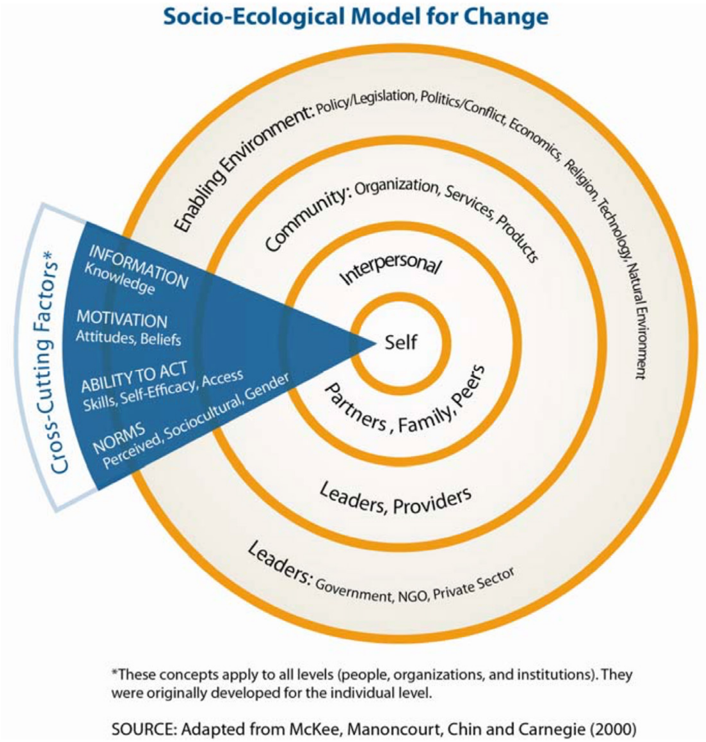

Figure 3: UNICEF's socio-ecological model

These tools can also be combined with applied behavioral science in other ways, which we'll come back to later – here, we note that they are often used to help us recognize non-behavioral forces at work on an individual's choices, and not the individual's effects on social forces. Concretely, the "result" of these analyses are structurally informed behavioral maps: a more thoughtful and detailed analysis of what's at work in a given situation.

Designing robust interventions

Structural factors may be barriers to the effectiveness of our interventions: what appears to work in one context or time may not work in other places and times because of structural forces outside of the intervention itself. We can attempt to make context- (and structure-) robust interventions to overcome this.

The more straightforward way to ensure robustness across contexts is replication and testing: measuring whether a particular intervention does work across time and space. Schmidt and her colleagues (e.g., Schmidt and Stenger 2021a) encourage us to push further: proactively thinking through future scenarios to stress test interventions in other potential environments. They argue that current methods in applied behavioral science (context-specific intervention design and field testing with RCTs), foster three forms of brittleness.

1. Contextual brittleness (C), in which interventions may not sufficiently account for variable perception and uptake in different populations

2. Systemic brittleness (S): Insufficient insight into broader system conditions and forces may underestimate their effect on interventions' effectiveness

3. Anticipatory brittleness (A): Optimizing for stable, present-tense conditions can result in solutions with limited or short-term relevance when conditions evolve

In each case, a thoughtful analysis of potential future scenarios can help us create interventions that are good approximations now, and keep their value in the future. A "futures thinking" or "strategic foresight" approach has a long tradition in strategic studies (the study of war) and in policy analysis more generally.

This process may feel too open-ended and qualitative for most applied behavioral scientists, who are used to a (potentially misleading) sense of quantitative precision in their impact analyses. A quantitative approach to addressing brittleness comes from Strategic Multiple Assignment Randomized Control Trials (SMART) - which explicitly seek to adapt the intervention to changing parameters (Collins et al. 2007).

The RE-AIM framework (Glasgow 2006) can also help us design robust interventions regarding their 'real world' impact. This framework asks us to evaluate policies (in our case, interventions) by their:

a. Reach: the proportion of the target group that the intervention reached.
b. Efficacy: the success rate (biological, behavioral, and quality-of-life outcomes).
c. Adoption: the settings that adopt a policy or program.
d. Implementation: the extent to which the intervention is implemented as intended.
e. Maintenance: the extent to which a program is sustained over time.

Concretely, the result of this approach is better behavioral interventions: the tools can help us design more thoughtful inventions in light of structural forces; the approach, however, is still one of individual behavioral change brought about by targeted interventions.

Injecting behavioral insights into policy development

Chater and Lowenstein (2022) offer ideas on how to bring behavioral insights into policy development: specifically into policies that seek to tackle structural problems. They recommend, for example:

1. **Improving the policy-making process,** by applying behavioral science to the decision-making processes of policymakers themselves. They recommend looking at both the influences of diverse parties from lobbyists to other branches of government, and analyzing and addressing the biases of decision-makers.

2. **Understanding and reversing industry exploitation of human psychology,** by regulating the negative applications of behavioral science that exist, especially by private companies.

3. **S-frame changes that improve i-frame decision-making,** by fundamentally changing the rules of the game, rather than using nudges to work around them. For example, instead of nudging people to consider self-interested advice by financial advisors, remove the financial incentive for advisors to give that advice.

4. **Avoiding psychologically naïve policy prescriptions,** by adding a deeper layer of understanding in addition to incentives: how a desire for autonomy and fairness, for example, can change how people respond to new policies.

Hallworth (2023a) argues that behavioral practitioners (like himself) are already doing this, but the prescriptions and concepts are similar. The behavioral public policy community appears the most advanced in thinking about these issues, and how to practically go about tackling systemic problems with behavioral science. Concretely, the result of this approach is better policy: policy informed by behavioral insights. There are two key challenges, though: there does not appear to be a publicly available guide on how, practically, to address s-frame problems with behavioral science, nor does this approach inform how to use non-public policy tools (like technological innovation or cultural change).

Changing the system

Our goal here is to move beyond seeing the system, and making our interventions robust in the face of systemic forces. We want to use behavioral interventions to change systemic outcomes, using all available tools, policy-making or otherwise. At Busara, we have collaborated with the IRC's Airbel Impact Lab, and they will soon publish their approach to do this: we have each seen the same need, and developed approaches in parallel. Beyond the IRC's efforts, there does not appear to be any publicly accessible materials on how to do so.[8] In this absence, we are sharing our ideas and approach thus far, hoping to both learn from others to improve our approach and catalyze a broader discussion in the field.

8 While this section has focused on attempts within the behavioral science community to incorporate systemic analyses in our work, let us not forget that various systems analysis traditions have studied systemic problems for decades, and have experimented with how to incorporate behavioral insights within their tools and methodologies. For example, the MoHuB framework (Modeling Human Behavior; Schlüter et al. 2017), provides a live simulation tool for switching decision making theories. The paucity of work lies within applied behavioral science: leveraging systems analysis to design, deploy, and test systematically effective behavioral interventions.

Busara's toolkit for behavioral systems

Here, we seek a new approach to behavioral science, a tool that allows us and others to design, deploy, and test interventions that tackle broad systemic problems. We refer to this approach as "Behavioral Systems":

> **Behavioral Systems employs behavioral insights and methods to address systemic or societal problems. This entails analyzing a dynamic system of interacting actors, identifying pressure points within the system, and then deploying behavioral interventions to measurably improve the functioning and outcomes of that system.**

Many of the pieces are already in place; they just need to be woven into a unified whole. Creating a unified toolkit for behavioral science means welcoming the contributions of other fields that have long thought about analyzing and changing systems. By learning from their traditions, we can better contribute to broader social issues without losing the heart of our discipline: a pragmatic and empirically grounded focus on behavior change for social good.

Busara has developed a rough draft of such an approach as a starting point, which we are trying out in the field now. The approach entails six steps:

1. **Set the stage** by aligning with stakeholders, identifying the problem, and what is known about it.

2. **See the system** collaboratively with stakeholders through a refined version of a causal loop diagram.

3. **Regroup and refine** the model: often, the initial model will be overwhelming, with too many potential intervention points. We focus our attention and convert the model into a computational one where possible.

4. **Look for leverage** points in the system: specific opportunities for targeted behavioral interventions (including behavioral interventions with policymakers or companies to effect structural changes).

5. **Design and deploy** interventions at our highest priority leverage points.

6. **Integrate and iterate** on our local understanding from those interventions, tracing their effect across the larger system and iterating on the model and opportunity list as the need arises and budgets allow.

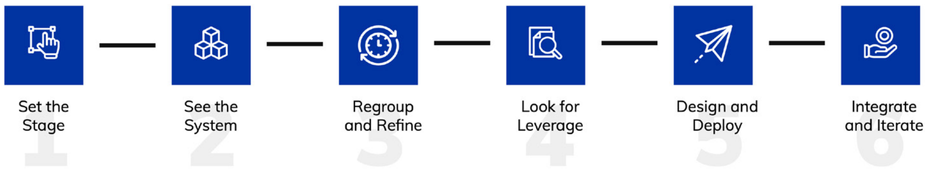

Figure 4: The six stages of Busara's behavioral systems approach

At times, we will want to do all of this, from end to end. At other times, we will want to address a particular stage alone. The pieces of the toolkit and their deliverables should thus be able to stand independently. We will start with the entire process and examine each of its stages. Afterward, we will look at particular use cases that employ a subset of these steps.

For clarity, we will use a running example of deforestation.

Step 1: Set the stage

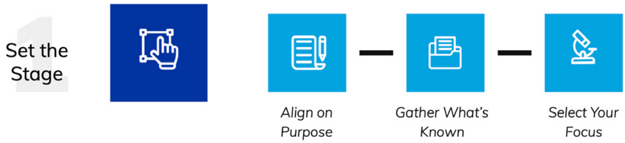

Figure 5: Detail on step 1 of behavioral systems: "Set the stage"

Setting the stage ensures stakeholders are on the same page about the goal and the status quo. We think about it as three sub-steps.

1.1 Align on the purpose

Why do we do applied behavioral science? We frame our work as changing behavior, but in reality, we are often driven by the presumed outcome of that behavioral change. We care about behavioral change because we can positively impact the lives of the people we serve and society overall. Policy makers usually have similar goals, as do applied economists and sociologists, etc. By reframing our work in terms of those outcomes, we build a foundation to collaborate with and learn from our peers.

Thus, this process starts by focusing on outcomes instead of behaviors. What good do we seek to accomplish? What systemic problem do we seek to solve? To seek alignment, we express the effort's vision in a briefing document, encompassing the target outcome, the resources available for affecting change, key constraints (budget, timeline), and roles of the participants working on the endeavor. In applied behavioral science terms, this is an outcome-focused behavioral brief.

Sometimes, we may start with a general phenomenon we want to change. The "system," in this case is the collected set of factors that directly or indirectly lead to the bad outcome. For example, we might view deforestation of the Amazon as inherently bad, and we can analyze the system of factors that drive it. At other times, we know that a particular process or system has various problems, and we want to understand that system better to improve one or more outcomes it generates. For example: we know that enforcing environmental regulations in a particular state in Brazil is problematic in many ways, and we want to untangle the system leading to that localized, negative problem. Thus, our focus is much narrower but still systemic.

At this stage, we want to avoid discussing both causes and potential solutions. We do not want to cast the problem as either 'I-frame' (individual) or an 's-frame' (structural) in Chater and Lowenstein's terminology. We simply do not know enough; we need to gain clarity about the outcome before proceeding.

1.2 Gather what is known

Next, we look at the existing research on that problem or system. For example, do desk research on the stakeholders and the causes of deforestation in the

Amazon. What we're looking for in particular is (a) who experiences the bad outcome(s), (b) what is the sequence of events before and after those bad outcomes(s), (c) what research and theories are available on potential causes and consequences of those bad outcomes (d) what organizations or other stakeholders are involved in their causes, consequences, and mitigation.

As we look for existing literature on the topic across different research communities, intentionally include diverse perspectives - from macroeconomic research, from anthropology, from feminist scholarship, from people with direct experience, etc. Who has a clear sense of the problem we can build upon within the constraints we have identified in the alignment stage? As behavioral scientists, we look for research with the most robust empirical evidence and predictive power.

We are also looking explicitly for existing causal models, especially those that are dynamic, i.e., they help us understand the relationships between interactions of groups of people and how those interactions can affect the system's functioning over time. Where possible, build on existing, empirically grounded models rather than recreate them!

1.3 Select your focus

Next, we go into more detail about the people involved. Unlike a general system dynamics model that deals with abstract quantities and variables, we will ground our model in the specific people involved with specific interactions that generate those variables. In particular, we look for a place to start our analysis, an initial focal point. Our systemic analysis will not end with this focal group; rather this is the specific and observable core we build the structure around. It makes the causal analysis concrete and quantifiable.

If the "bad outcome" affects a particular group of interest, they would be our focal point. For example, in an analysis of systemic unemployment, we would often start our analysis with the unemployed people. In an analysis of gender-based violence, we would start with the victims/survivors. This personified focus helps us remember throughout the process that if we do not improve outcomes for the actual people involved, then any behavioral interventions we develop are hollow.[9]

In other cases, the consequences of the outcome are diffuse (deforestation), and the starting point might be the group of people most directly involved in causing the problem or the group most likely to address the problem. We will include other stakeholders in the next section.

9 A human focus will also help us delineate mitigating strategies: into those that stop the outcome, those that stop the negative experience of the outcome, or those that turn it into an advantage. With abstract concept like unemployment, our natural inclination will be to stop it (increase employment) and lose our on other strategies like financial support (limit the negative experience), and community art and projects.

Step 2: See the system

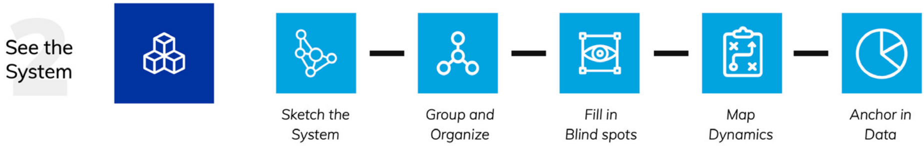

Figure 6: Detail on step 2 of behavioral systems: “See the system”

At this stage, we are ready to start illustrating the system itself. We employ a participatory process that pulls in various stakeholders and their expertise. No one will have the complete picture of many complex systems, and community participation is vital to creating it.

However, community participation significantly restricts the modeling process: we need a method that non-technical people can understand. Here, we use a behaviorally-focused version of a causal-loop diagram based on qualitative systems thinking (Meadows 2008). To generate the diagram, we build upon Hovmand (2013)’s Community System Dynamics approach.[10]

10 A range of other participatory modeling techniques are available; see Abrami et al. (2021) for a summary.

In stage 3, when feasible, we convert the qualitative model into a computational or mathematical one for more detailed analysis.

2.1 Sketch the system

The key to systems analysis is that we analyze how events unfold over time. Our approach combines the systems thinking and system dynamics community's Causal Loop Diagram with journey maps and behavioral maps from the behavioral design community.

Above, we discussed the primary use case for this approach: understanding a bad systemic outcome like deforestation. In that use case, we start our model by tracing the sequence of events for our initial focal group (from step 1.3) that occur leading up to, experiencing, and reacting to the negative systemic outcome. For example, consider the sequence of events that lead up to a farmer slashing and burning a field in the Amazon. In our participatory group, we accomplish this by repeatedly asking "what next", "what comes before that", and "what else influences this" until we have a detailed map.

This core sequence is our "level 1" systems diagram: the micro-level of individual people and behavior. Visually, it may be easiest to place this core sequence at the center of the diagram: we will add successive layers on the sides of it. If, at this stage, other actors are directly involved in the outcome of interest, we can include them as well. Note who the actor is in each component of the diagram.

The diagram should be very familiar to any behavioral scientist at this point:

it is a simple journey map or behavioral map. We know that decision-making and behavior are profoundly shaped by the context a person is in, and that is what we add to the map next.

We add forces and factors that influence our level-1 elements to the diagram. These may be other people (e.g, environmental regulation enforcement agents) or personal traits or feelings (e.g., the famer's trust in the government). Those are our level-2 elements. Repeat the process with the forces and factors that influence our level-2 elements: these are now our level-3 elements (e.g., government budgets affect the ability of agents to enforce the rules; market prices affect the demand for cleared land for beef and soya beans). Make sure to cover all of the "big ideas" from the community and literature. We can have as many levels as we need, radiating out from the level 1 focal group and the "bad outcomes" we seek to understand.

In a community process, we can identify level 2 and 3 elements by asking the participants to focus on what causes or influences each interior level of the diagram. At this stage, the diagram will still look familiar: it is now a (complex) theory of change as used in applied behavioral science. Most or all causal links will flow toward the center, towards the particular people and events at the center of our analysis.

In the case of deforestation in the Amazon, that diagram may show how the act of deforestation is driven by a mix of forces, including the expected price of lumber and crops to be grown on that land, government regulations around land use and deforestation, their ability to enforce those regulations, cultural and religious traditions on the handling of forests, the political sway of farmers, and local climate, and physical access to ports and mills. In other words, there are both a multitude of potential actors and a variety of lenses one could use to analyze the problem. Next, we need to organize them.

2.2. Group and organize subsystems

The diagram starts to get overwhelming by this stage. Ensure levels are still clearly defined and displayed (level 1, level 2, level 3, etc.). Then, within each level, look for similar types of components. In the deforestation example, market forces drive the farmer's act of deforestation, cultural factors, and governmental factors (regulation, enforcement, or lack thereof). Group them and provide space between these group factors and the others.

There is no "correct" way to group the factors into subsystems within the broader system. Instead, the grouping process itself expresses the stakeholders' understanding of the interconnectedness between components. Follow the group's intuition on what belongs together and how they think about the similarity of forces: we will return to these subsystems and test their unity later.

Figure 7 provides an example of grouping components into subsystems from the USAID/Uganda Feed the Future Market System Monitoring Activity (Goentzel et al. 2022).

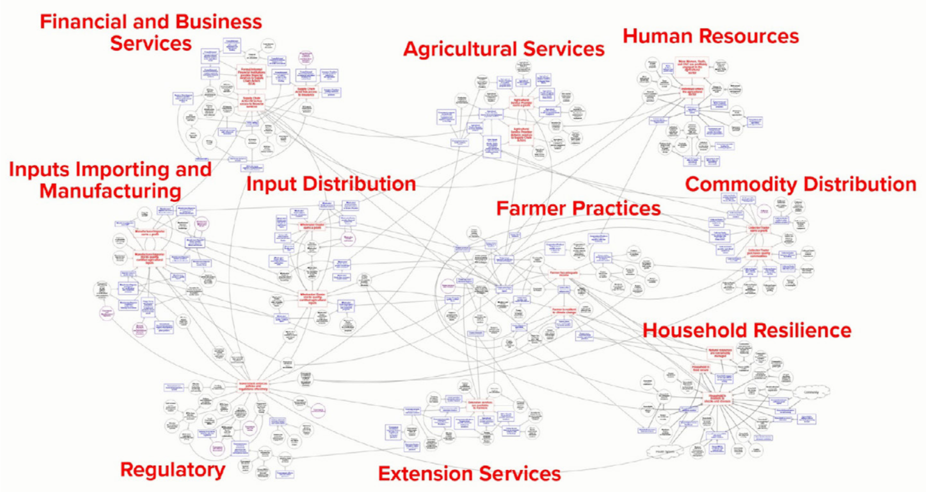

Figure 7: A USAID systems map for Ugandan food markets, grouped into subsystems

2.3 Fill in blindspots

Group discussions can get into a rut of focusing on a particular type or level of analysis (e.g., farmer and their incentives) and forget to look at the role of other factors. We can use checklists like SPACE or PESTLE to overcome this. SPACE stands for Standards, Process mechanics and policies, Accountability, Culture within institutions, and Evaluative and iterative feedback. PESTLE stands for Political, Economic, Social, Technological, Legal, and Environmental. Both of them provide a checklist of factors to ask the group about: for example, how does technology affect deforestation? How is the current political environment? We can also use the socio-ecological model, ORGANIZER (when working with organizations), or the Individual-Social-Material framework to help prompt broad thinking.

For each new factor the group identifies, place it on the map: how, precisely, does it affect existing parts of the map? The group does not simply identify that structural (etc.) forces are at work: it should add the missing factors as specific interactions or inputs in the model. We want to show how they may influence the other stakeholders and outcomes we care about.

For example, we might notice that we have not included the influence of the politicization of environmental policy in Brazil and add it as an influence both on the attitudes of government workers and the funding and morale of the enforcement agents. Alternatively, we may not have thought about the role of technology - and the increasingly sophisticated LIDAR and other remote sensing technology that can rapidly locate forest fires on the edge of farmland.

2.4 Map the dynamic complexity

Thus far, we have a complex map of people's experiences and their influences on it. Now, we look at how the system emerges from these experiences and their consequences.

First, we ask: how do **lower-level** elements affect **higher-level** ones? How does the experience of a farmer burning a field (level 1) and lack of enforcement by government agents (a level 2->level 1 cause) subsequently influence the community of farmer's expectations of punishment (a level 1 -> level 2 cause)? Similarly, how does the cultivation of burned fields (level 1) affect the local price of that commodity (level 1 -> level 2), which then affects the incentive to burn additional fields (level 2 -> level 1)?

Draw each of the connections that the group feels are important to understand the consequences of the system. To make the process manageable, we can look at each component and ask when this happens (or changes), what else is significantly affected?

Second, for each connection (newly added and from the prior version of the diagram), we label them:

1. Does it have a **positive or negative effect?** A simple + or - sign can do.

2. Does it affect the **current group or future groups?** A "c" or "f" will do.

For example, environmental regulation enforcement decreases crop burning among those specific farmers. It does not directly affect other groups of farmers in the future; they are affected only through subsequent word of mouth, news stories about enforcement, etc.—pathways of influence that can be dysfunctional).

Then, we look for loops: anywhere that the consequences (outputs) of that component directly or indirectly affect the causes (inputs) of the component.

In system dynamics and systems thinking, there are two common structures that can arise from these loops: reinforcing feedback loops (loops that cause a variable to grow or decline without constraint), and balancing (loops that maintain a variable within a specific range). Reinforcing loops can be positive (exponential growth) or negative (a rapid crash into oblivion).

For example, consider a contrived example using deforestation. When enforcement is high, an increase in deforestation might lead to an increase in the number of cases in the news, which makes farmers slightly less willing to deforest and break the law. Lower willingness to deforest drives a decrease in the number of cases that can be enforced until there are few news stories and people feel they can get away with deforesting again (balancing feedback).

There could also be a positive, reinforcing feedback loop between the development of detection technology and deforestation. The more effort is put into detection technology, the more accurate it becomes at catching deforestation and driving on-the-ground change. This increased accuracy, in turn, attracts more funding for its developers, leading to further improvements in accuracy, and so on. Like most reinforcing feedback loops, there is a hidden limit that the system would eventually reach when there is no deforestation to detect.

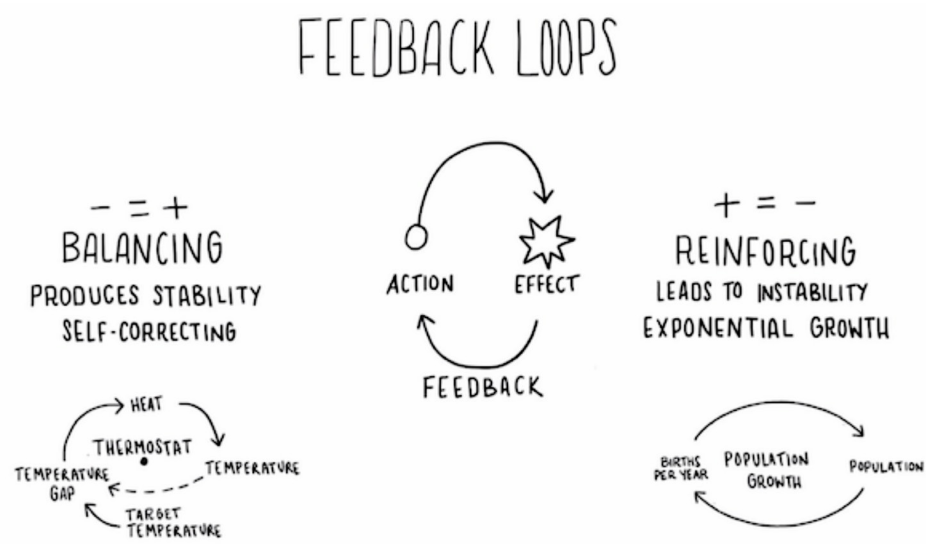

Figure 8: A summary of major types of feedback loops, by Hanu (2019)

We now have what is known as a causal loop diagram in the SD literature: one that is grounded in the specific experience of a focal group and the forces that affect their behavior.

2.5 Ground it in data

Our diagram shows a group of people's negative outcomes, buffeted by forces that drive those outcomes and interconnected by multiple webs of cross-cutting causality.

The more we can ground this diagram in actual data, the better. If qualitative data is available through experts, ask them for two things: the current state of each of the components (nodes) in the diagram and the relative importance of the relationships (causal links). We would want to know roughly how many people are currently involved in each component. In our deforestation example, we want the total number of farmers, the percentage of farmers who deforested in a given year, the number of enforcement officials, and so on. We also want the relative importance of each causal factor (relationship) affecting a specific component: if the threat of enforcement influences the farmer's decision to burn a field, the price of soya, the weather, and her/his cultural background, can the experts roughly rank them? One way of eliciting this ranking is to ask: "If we did X, how would that affect the farmer's decision?" If we doubled the price of soya, how would the farmer behave differently? How would the farmer behave differently if we cut the number of enforcement officers in half?

If quantitative data is available, however, that is ideal. We want the status quo for each component (often the number of people in a particular situation or doing a particular thing) and the importance of each causal factor. If available, we also want to gather data on the components' and relationships' variability over time; Blair et al. (2021) use a similar method in their "data-layered causal loop diagram" for Ugandan farmers.

Step 3: Regroup and refine

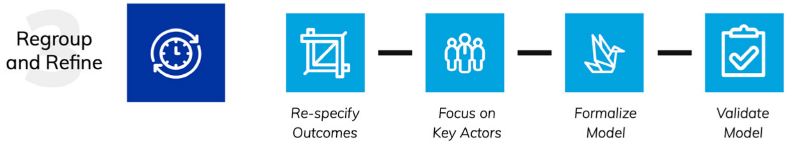

Figure 9: The components of step 3 of behavioral systems: “Regroup and refine”

3.1 Identify more specific outcomes (if needed)

Within a broad system, we may find that there are simply too many potential problems to consider. For example, in a model of racism centered on the experience of the individuals discriminated against, there may be too many varieties and proximal causes of discrimination to handle, from biases in the hiring process to real-estate redlining to the expectations of teachers on “appropriate careers” for students of a given ethnicity. When each problem is caused by its own set of complex factors and dynamics, we need to simplify.

To do so, we can zoom in or zoom out. First, check whether the proximal causes are driven by common underlying factors such as cultural expectations. If so, we can group the proximal causes and affected level-1 steps accordingly. If not, then focus on a specific area of interest. Put aside the original model and repeat the process in brief to create a refined, focused model around the problem we most want to target. This should go quickly: most of the factors we identified previously in the "big picture" model will be aggregated up into a few higher-level elements. For example, within a broad model of deforestation, we might re-focus on government enforcement and the factors that drive and are driven by it.

A Busara project to address Gender-Based Violence (GBV) in Guatemala (explored in detail in the section "Case Study of the Toolkit in Practice: Gender-Based Violence in Guatemala") illustrates this re-focusing approach. Initially, our team sought to map the entire GBV system in Guatemala, a task that quickly became overwhelming due to its complexity. To optimize our Behavioral Systems process, we refined our focus to analyze the interactions within the victim's and survivor's journey through the health system when seeking support. This focused approach aligns with our project's original goals and allows for a more straightforward, more in-depth analysis of the most pivotal aspects of seeking help after GBV in Guatemala. Ultimately, this refined strategy will significantly influence the creation of our final outputs—a set of behaviorally-informed interventions and strategic redesigns, all designed to improve the support journey for GBV victims and survivors.

3.2 Add specific actors

When we can influence a specific set of actors, we can add an actor-specific lens to the system-level model.

For example, if we are working with policy makers, we might add a "policy implementation" lens. In this case, we annotate our diagram with the specific policies relevant to the outcomes and dynamics (interactions over time) of interest. If there are not any policies relevant in a particular part of our diagram, we aggregate that section into fewer, higher-level elements. We still know they are relevant to the system's dynamics, but we will not focus our direct attention on them.

3.3 Formalize the model

Qualitative models are accessible and flexible, and most of the process that remains can be done using them. However, they suffer from significant weaknesses: they are easily biased toward vivid examples and anecdotes. It is difficult to know whether a particular causal link is crucial, or simply top of mind. Similarly, it is more difficult to analyze how a qualitative model will behave over time, including how the system will respond to interventions to change it.

For this reason, it is useful - though not strictly necessary - to develop a parallel, quantitative, or computational model. Our two tools of choice at Busara are ABMs and System Dynamics, but other tools may be used depending on the team's skills, and the data available to power them. A discussion of the strengths, weaknesses, and requirements of the various systems analysis tools is available elsewhere in this report.

One of the primary challenges of ABMs, and to a lesser extent System Dynamics models, is their grounding in the real world. Our data gathering and qualitative modeling up through this point help solve that problem. In the qualitative model, we not only have a community-developed model of the real world, but also, we have a structure we can base the computational model on. In an ABM, the components of the level 1 model become agents. The causal links affecting those level 1 agents become the internal decision functions that drive the agents' behavior. The level 2+ components become other types of agents or contextual elements (such as government regulations and detection technology) with which the agents interact. To the extent that distance matters for the interactions, the agents can be readily distributed across a spatial model using tools such as Repast Simphony.

In a System Dynamics Model, we want to standardize the components of the qualitative model to ensure they are consistent quantities of interest: number of farmers, level of social norm, etc. We then use the relative ranking of causal factors to develop rough flow functions for the key relationships. The data on status quo quantities gathered in step 2.4 becomes the system's initial state.

In our deforestation example, we can readily convert our qualitative model into an agent-based model. The farmers are one type of agent, following the decision rules that our experts told us about during the exercise when we asked, "What if we changed X? How would farmers respond?" Enforcement officials would also be another type of agent with their own decision rules. The farmer would interact with the land and change the level of forest on it. Rainfall, runaway forest fires, and other factors might also affect the level of forestation. And so forth - including each of the factors that the participants identified as important to the question of deforestation.

3.4 Validate the model

Now that we have a detailed qualitative and, hopefully a detailed computational or quantitative model, we return to our data and community to validate it. There is an extensive literature on model validation, but a few points are worth citing here.

a. **Test novel, observable implications.** "If the model is correct, then….." One source of novel implications comes from feedback loops: because few people intuitively understand them. Look at each feedback loop and ask the group about the implications of that loop. For example: "If all of the farmers in Brazil plant soya, would that decrease the pressure to deforest the Amazon and plant more soya?" (No, since the next-best commodity, such as beef, might still apply pressure).
b. **Compare across models.** If we have both a quantitative and qualitative model, they should produce similar results for simple, status quo scenarios. If they do not, investigate. The quantitative/computational model helps fight inclusion-by-anecdote in the qualitative model, and the qualitative model helps provide constraints on the expected behavior of the quantitative model.
c. **Review the components with experts** in each area, step by step. For ABMs, this includes the agents' decision-making functions; for SD, this includes the flow functions. Do they each pass the "sniff test," or are they missing significant factors?
d. **Test against novel stylized facts** and novel real-world data. Look for truths about the world that were not incorporated in the model's

design. Does the model come to a similar conclusion/prediction about its simulated world?

e. **Run it and watch for extreme outcomes.** As we execute both SDs and ABMs models, we can watch their behavior over time. In the real world, outcomes are rarely chaotic or extreme (“trees do not grow to the sky”) - if outcomes are extreme, then a balancing feedback loop is likely missing.

A key lesson here is that having both a qualitative and a computational/ quantitative model improves their testability and strength: the computational model does not supersede the qualitative one; instead, they each play different roles in the process.

Step 4: Look for leverage

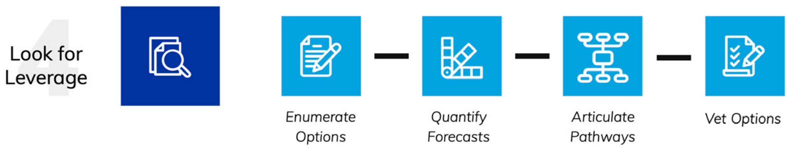

Figure 10: The components of step 4 of behavioral systems: “Look for leverage”

We have completed building our system; now we switch to analyzing it to find opportunities for change. In short, we outline the set of potential changes to the system and then assess the impact of changing each one.

4.1 Enumerate options

Systems can change in many ways: from changing a variable that affects the model (for example, changing the price of soya) to changing the rules that actors follow (training the police to use community-based enforcement techniques), to changing the structure of the system itself (introducing eco-tourism as an alternative revenue source; adding a farmer's union). Key characteristics are those that, when changed, would have the most significant impact on our outcome of interest: these are the "leverage points" of the system (Meadows 1999).

If we could, we would analyze every possible change to determine which ones are most impactful to improving the system. With qualitative models, we are limited to perhaps twenty changes that we can analyze at most. Computational models make it possible to explore large numbers of scenarios, but not an infinite number. Therefore, the process of enumerating the potential changes is also one of purposeful selection. Based on our research thus far, which changes have people proposed? Which links or variables are considered most important? We do not need to decide yet how they would change – that comes later – at this point, we want to identify the options. For example, "the number of officers," "the number of children per farmer," and "political party of the governor." Meadows (1999) warns us that modelers naturally think to change specific nodes or variables, but often more powerful changes occur when we change the feedback loops that underlie the rules and goals of the system.

This process results in a long list of potentially impactful changes to the system: parameters, connections to add/remove, actors to add/remove, etc.

4.2 Quantify forecasts

We can analyze the impact of changes to key system characteristics using the qualitative and computational models. We use informal tools like "what if" and scenario analyses for the qualitative model. For computational models, we have automated, rigorous tools like computational laboratories (e.g., Dibble 2006). For example, in both cases, we can analyze the following: What would happen to local deforestation if the price of lumber dropped? What if people moved to the cities instead of staying on the land after deforestation?

The computational laboratory also allows us to look for the underlying sensitivity of the model to its parameters: it may turn out, for example, that the price of lumber is largely irrelevant to deforestation because of continued demand for deforested land from soya and beef. Similarly, we can find non-linear responses and breakpoints in the model, where certain parameters are especially relevant to the outcomes of the system.

These scenarios are about local changes to the system, not interventions themselves. In other words, we do not want to evaluate yet how we might change the price of lumber; instead: what would happen if it did change? This process creates a set of impact forecasts: one per relevant characteristic of the system. We can then process and visualize these simulation results to understand the behavior of the system in a holistic way. Figure 11 provides one such example, from an analysis of retirement savings adequacy among American households (Wendel 2020).

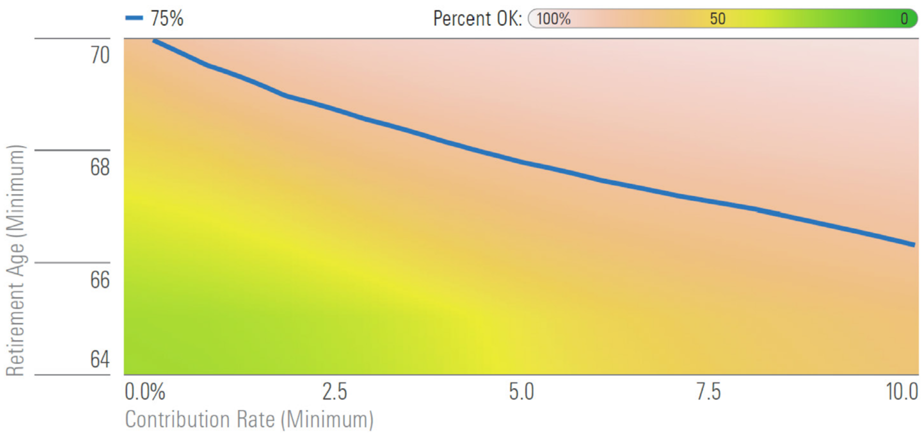

Figure 11: Heatmap visualizing output from a computational laboratory used across 400 million simulations in Wendel (2018)

4.3 Articulate pathways

With these critical characteristics in hand, we then look at the how: interventions. If we are looking to change the price of lumber, how might that happen? This is where behavioral science has a trump card: most policy problems, economic problems, and organizational dynamics are, at their root, shaped by human behavior. It is just a question of identifying which person and which behavior is impactful and changeable. For example, a set of key decision-makers at lumber companies and investment firms could decide to invest money in alternative paper products, thereby decreasing the demand (and price) of lumber. It is a particular set of politicians and police officers who decide whether or not to enforce regulations. What we need are potential targets for behavior change.

For each key characteristic, we ask: who could change this characteristic? We can conduct a power mapping—an analysis of who can effectively make change in that system. As applied behavioral scientists, the "capacity" question is usually tightly constrained: we work with a specific group of people who could change their own behavior. Here, the question is broader and in three stages: first, who could change that characteristic; second, what specific action would they take; and third, how feasible is it for us to affect that change?

4.4 Vet options

In behavioral science, we have a set of tools already to analyze the value of potential interventions, as do many other fields: - including cost-effectiveness, degree of uncertainty, ethical foundation, and impact on marginalized or underserved groups. RE-AIM and futures thinking, discussed above, would also help stress test the ideas.

The final result is a prioritized list of potential targets for behavior change, i.e., opportunities for change. We have broken a broad systemic problem into specific high-impact moments and behaviors that we can address using behavioral science tools to affect large-scale change.

Step 5: Design and deploy

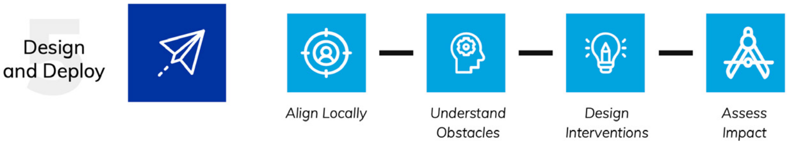

Figure 12: The components of step 5 in behavioral systems: “Design and deploy”

Next, we develop the intervention themselves, using the standard toolkit of behavioral science: understanding the situation and obstacles, designing and prototyping solutions, and then assessing the impact. For this purpose, we can use the normal Busara process (AUDAS: Align, Understand, Design, Assess, Share) or any similar toolkit (Wendel et al. 2023). This standard process covers steps 5.1 to 5.4.

We can also draw upon more recent concepts in systemic behavioral science. With policy interventions, for example, we might use Chater & Lowenstein’s framework to help improve the decision-making process among policymakers, or avoid psychologically naive policy prescriptions.

When we think about interventions, we want to look more broadly than “change x, make y happen.” Instead, we have a range of tools available to us: we can seek to change the prior choice itself, enable the behavior, or change the infrastructure that makes good decision-making possible (choice infrastructure).

Then, with a potential intervention(s) in hand, we would want to assess its robustness with approaches from Schmidt and her colleagues for evaluating brittleness and context-dependence. Our goal is to be roughly right across a range of scenarios, not perfectly right in only one scenario (Schmidt and Stenger 2021a; Schmidt and Stenger 2021b).

A crucial part of the design process is openness and humility: someone else has probably already thought about this far more than we have. Systems are often overwhelming and understudied, but the specific target group of people and behavior we have identified likely has a literature and body of experts who already know a great deal about it. Thus, we should ask and learn from them. As behavioral scientists, our contribution does not have to be in coming up with a new idea; instead, we can thoughtfully evaluate the existing interventions in the field with an eye toward rigorous empirical evidence, likely backfire effects, and the plausibility of the underlying cognitive mechanisms at work.

Step 6: Integrate and iterate

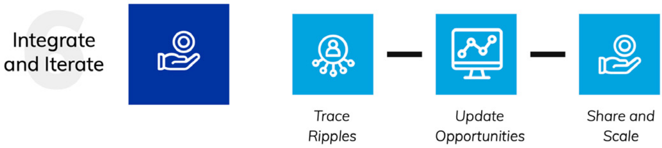

Figure 13: The components of step 6 in behavioral systems: “Integrate and iterate”

As behavioral scientists, we know both the value of rigorous empirical evidence and unintended effects that might arise from any intervention. Thus, to assess the impact of our interventions, we use our toolkit at two levels. First, we look at the characteristic-specific impact: did we change the specific behavior we intended. As with other fieldwork, this should usually involve a mix of quantitative (RCT) and qualitative (observation, interviews) techniques. Second, we look for the systems-level impact. This is often harder to measure quantitatively – especially with clear causal attribution. However, tools are available to help - again, from outside of behavioral science. Suppose we have specified our system model quantitatively. In that case, we can use structural equation estimation to understand better the likelihood that any system-level outcome we see is attributable to our intervention. Similarly, simulation models allow for a rigorous analysis of whether our interventions would affect the overall system in a computational laboratory.

With the local and systemic lessons from the intervention, we update the model and quickly re-execute steps 4.1 to 4.4, updating our list of opportunities. As budgets and time allow, we can then iterate on the model (Steps 1-3) or move straight to prioritized interventions (Step 5).

Use cases for subsets of the process

We have now completed the entire end-to-end process: from identifying a system outcome to interest creating a behaviorally-informed model of the system and designing and deploying targeted interventions within it. We do not always need all of these steps, however.

At Busara, we have identified a set of narrower use cases that we are exploring with smaller initiatives. We group them into use cases before a standard behavioral intervention focused on a target behavior and those that occur after.

Behavioral systems use cases before a “normal” behavior change project

- **Seeing the system:** Understanding the systemic context of a problem can be interesting and useful to inspire further research or to direct subsequent energies. The approach used here is especially useful to identify how people’s behavior and choices fit into the broader picture. In this case, we Set the Stage to align on the scope (Stage 1), then See the System qualitatively (Stage 2).
- **Discovering “system behavior”:** The structure of a system can shape

outcomes in non-obvious ways by constraining and guiding the choices of people and organizations. In understanding this system behavior, we can execute steps 1.1 to 2.4 (focusing on "mapping the dynamics") and/or jump to a formal model with a computational laboratory to analyze it (3.3, 4.2).

- **Identifying leverage points:** Assessing what changes could have the greatest systemic effect within a given system. These can include changing norms, changing pathways of influence and relationship, or more individual consumer choices. The goal is to find the "right people and the right behavior" to target with behavioral interventions to drive systemic change. Assuming we already have a model from prior work, this entails running through Stage 4 ("Look for Leverage").
- **Observing emergent properties:** Watch how individual choices "add up" to systemic outcomes like segregation and discrimination and thus inform the potential for change. If we want to analyze hypothetical people and situations, this entails Steps 2.1-2.2 and 3.4; if we want to ground it in a real-life situation, then 1.1-3.4 are needed.

During and after a "normal" behavior change project

- **Placing behavior in context:** Showing how political, economic, social, technological, legal, and environmental factors enable and constrain the potential for contextual behavior change. In this use-case, we would start with the target behavior at the center of 1.3, then use 2.1 to map out the assumed theory of change. 2.3 would help us understand the PESTLE or other factors that complicate or undermine that theory of change.

- **Collective interventions:** Reimagining the intervention process to go beyond individual-level nudges (and even individual nudges applied to broad populations, like SBCC), and incorporate the interplay between people, organizations, and the interventions. This would entail an analysis of hypothetical mass interventions in 4.2 (instead of an enumerated list of individual changes) using an ABM or SD model.
- **Vetting for brittleness:** Applying futures thinking to analyze a range of possible scenarios and find "roughly right" interventions that can endure a changing future. Given a list of potential interventions, we would jump straight to 4.4 with a qualitative or simple computational model (2.1-2.4, 3.3-3.4).
- **Systemic robustness:** Given an existing model, we can use the computational laboratory from 4.2 to analyze the range of possible parameters instead of the range of possible interventions. This creates a probability distribution of behavioral and system outcomes from our interventions that helps us understand the system's stability, thresholds for change, and potential extreme outcomes.

A brief review

Systemic behavioral science is still in its infancy. Research on the influence of structural forces on human behavior and societal outcomes is not. For behavioral science to move beyond our small but effective nudges to address systemic problems, first and foremost, we should open ourselves to the lessons from other research communities. We strongly believe that we will find valuable tools we can use to build a new form of applied behavioral science: one that retains the heart of our field but enables us to contribute to systemic challenges effectively.

Here, we have presented an initial model of what systemic behavioral science might look like, one that weaves together existing behavioral tools with less familiar ones from systems thinking and other disciplines. In particular, this process would mean we:

1. **Set the stage by aligning with stakeholders**
2. **See the system collaboratively with the community**
3. **Regroup and refine the model, building a computational version where possible.**
4. **Look for Leverage points in the system: opportunities for behavioral interventions**
5. **Design and deploy prioritized interventions**
6. **Integrate lessons and iterate on the model**

Throughout this process, we leverage the special contributions of our field: including a deep understanding of decision-making and context, the surprising potential for behavioral change, and a healthy skepticism of the impact of any intervention without rigorous local evidence.

This process is undoubtedly incomplete, and quite possibly it is outright wrong in some places – but it is a starting place for Busara and, potentially, for others in the field.

Case study of the toolkit in practice: Gender-based violence in Guatemala

Here, we share how Busara uses the complete toolkit in an ongoing project in Guatemala, in partnership with Palladium and USAID.

The GBV context in Guatemala

Gender-based violence (GBV) is a deeply entrenched and pervasive issue in Guatemala, with broad-reaching implications for the overall well-being of the population. The nation grapples with alarmingly high rates of GBV: national data reveals that 21% of girls and women aged 15-49 have experienced physical and/or sexual intimate partner violence, with 19.2% having encountered some form of physical violence (WHO 2018).

Guatemala's broader societal context is marked by organized crime and corruption, which cast a long shadow over the effective functioning of the government, including the implementation of Guatemala's existing policies to address GBV. Access to justice remains a challenge, particularly for Indigenous communities. Conviction rates for reported crimes are dismally low, often influenced by harassment and threats directed at judges and prosecutors (WOLA 2019).

Additionally, although rates have decreased in recent years, Guatemala grapples with femicide, with a rate of 1.5 in 2021 (Aceña 2022). Since the establishment of femicide as a distinct legal offense in 2008, 2,168 cases have been reported, with 71% remaining unresolved (ibid). Alarmingly, many girls experience physical abuse and sexual harassment within educational institutions, resulting in approximately nine out of every ten girls who become pregnant discontinuing their education (Landa Ugarte 2018).

Patriarchal norms weave into the complex tapestry of Guatemalan society, manifesting in institutional discrimination and profoundly ingrained gender biases. Machismo, a traditional belief asserting male dominance over women, perpetuates an unequal power dynamic, evident in households, streets, and society at large. These deeply rooted attitudes, coupled with stark power differentials, fuel objectification, abuse, and violence against women.

Cultural norms further exacerbate GBV, as women struggle with limited access to and control over critical assets and resources, such as land ownership, while grappling with poverty and wage disparities. A striking 81.6% of men in a 2009 INE survey believed women required permission to leave their homes, underscoring the magnitude of entrenched gender disparities (INE). This intricate backdrop underscores the urgency of addressing GBV through innovative approaches, and it is within this context that our project seeks to make a meaningful contribution by implementing this innovative systemic behavioral approach.

Groundwork for systems mapping

In response to the pressing challenge of Gender-Based Violence (GBV) in Guatemala, Busara and the Palladium Group have embarked on a collaborative initiative under the multi-year Promoting Results and Outcomes through Policy and Economic Levers (PROPEL) Health project. The partnership is committed to developing a deep understanding of the multifaceted factors contributing to GBV, which include behavioral, social, and structural elements. It aims to assess its impact on Guatemala's Health System, and how policy can be effectively used to mitigate and respond to GBV in Guatemala.

Due to the complex interactions between government policy, social norms, the health and legal systems, and the individual perpetrators and victims/survivors themselves, we decided to take a systems approach, as described in this report. Thus far, we have completed Steps 1.1 through 3.2 of the process and are currently formalizing the model as an Agent-Based Model (Step 3.3).

We initially met with the Palladium team to understand the central outcome USAID wanted to address: the poor implementation of health policy, particularly GBV policy, in Guatemala (Step 1.1). Busara and Palladium conducted detailed background research to understand the current state of GBV across Guatemala's diverse districts, the stakeholders, and the range of policies related to GBV (Step 1.2). While policy implementation itself is crucial, we focused our attention on the experience of victims/survivors in the country to ground the process in the real lives of those affected (Step 1.3).

Based on the background research, we drafted initial journeys showing the step-by-step experience of victims/survivors in Guatemala (Step 2.1, first draft), which we organized into home and school interactions and interactions with the health and legal systems (2.2, first draft). The process fails women at so many points along the way that the initial journey maps became too complicated for general use and created high-level, aggregated versions in preparation for field research.

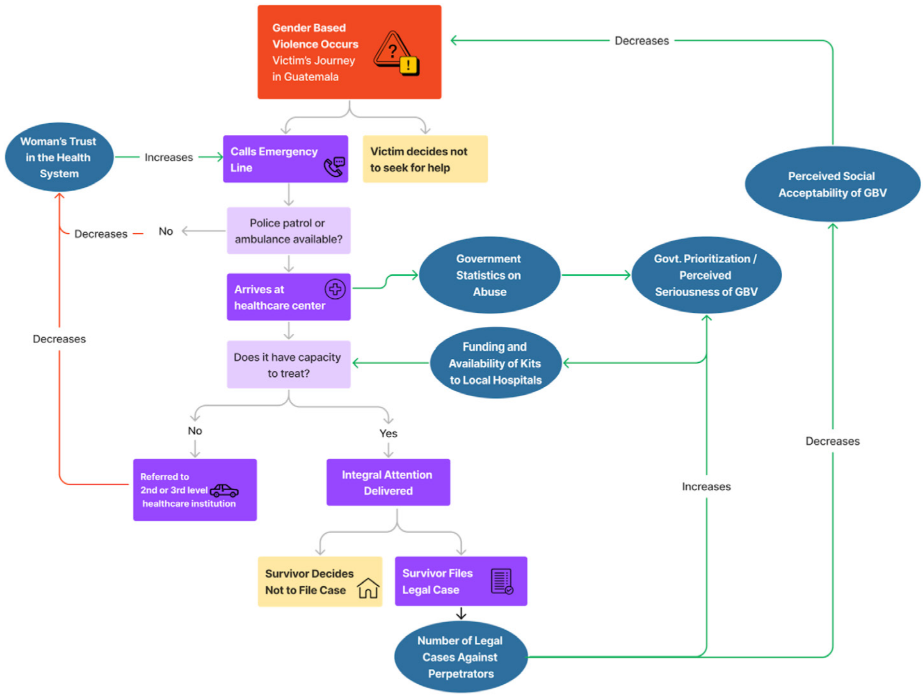

Figure 14: A simplified causal loop diagram of GBV, the experience of victims/survivors with the health system

Figure 14 shows one of our high-level maps, showing how the paucity of reported cases in the country drives a culture of impunity and a sad state of normalcy around GBV; both making further incidences of GBV more likely.

Qualitative field work

Our (native Spanish-speaking) team then partnered with Palladium's Guatemala team to organize qualitative and community-based meetings. We used a variation on Hovmand's (2013) participatory research process to better understand the V/S's experience more. Then we added layers to the map to show the specific interactions with legal, bureaucratic, and cultural factors. The process included government leaders, staff members, NGO leaders, civil society representatives in solidarity, and first-line GBV responders.

From these detailed qualitative sessions, we further refined the organization and structure of the system maps (Step 2.2, revised draft). For instance, with insights from the workshops, we could understand the decision-making processes survivors embark on when choosing whether to seek support from the Guatemala Health System, as well as their subsequent actual journey through the system.

Additionally, these sessions allow us to identify missing pieces (Step 2.3) by addressing various PESTLE factors in the sessions with community-based actors, providing a broader understanding of the issue's context.

Most importantly, these sessions were crucial to trace the dynamic complexity of GBV over time (Step 2.4). We identified and charted essential connections to comprehend the system's flow and consequences, and we recognized relevant positive and negative feedback loops. This comprehensive approach was vital in grasping the multifaceted nature of the GBV issue in Guatemala. This work culminated in key insights encompassing essential actors across governmental, community, and individual levels, vital for understanding prevalent issues and obstacles surrounding the experience of a GBV victim/survivor. It identified gaps in protocol adherence and policy execution, as well as common underlying causes of those gaps, such as economic limitations or budget restrictions, awareness deficits, entrenched social norms, and stigma related to sexual health.

Earlier in our systems mapping process, we hit the immense complexity of GBV dynamics in Guatemala and started focusing on specific areas of interest to USAID. After the first round of qualitative field work, we continue to refine and focus on the systems map (Steps 3.1, 3.2).

Computational modeling

We are now developing the computational model, following directly from the qualitative map (Step 3.3). We chose an Agent-Based Model structure using the freely available Repast Simphony package. The agents include the victims/survivors, hospital and legal system workers, and neighbors who shape the decision to seek help. The model differentiates between rural and urban contexts and between Spanish-heritage and indigenous peoples, following the insights from the qualitative interviews. The baseline data (distribution of people, rates of violence, rates of reporting etc.) are drawn from the existing literature and qualitative interviews. The decision rules (whether the V/S decides to seek help, whether the hospital decides to treat the V/S, etc.) come from our team's GBV expert, verified and expanded upon during the qualitative interviews.

Once the model is complete, we will validate it (3.4), and conduct a series of simulated changes to the model to quantify and articulate potential opportunities for change (Steps 4.1-4.3). The project's next phases include more traditional behavioral intervention design and testing at the critical leverage points (5.1-5.4) and integrating these local results back into the systemic model and policy recommendations (6.1-6.3).

Contextualizing GBV policy implementation

Overall, Busara's collaborative initiative with the Palladium Group represents a new approach to addressing the complex issue of GBV policy implementation in Guatemala. By infusing the project with systems analysis and behavioral sciences insights, we aspire to bring about significant and sustainable enhancements in this critical area. As we move forward, we aim to improve the lives of those affected by GBV and support more effective policy in the country.

A new tool for international development

Stepping back from the details of the methodology and the case study we just reviewed, we would like to take a moment to consider the potential role of this approach in international development.

In international development, we sometimes grapple with systems that are difficult to address with conventional development approaches. Traditional tools, such as point-in-time interventions and linear theories of change, might not be equipped to capture the intricate dynamics and multifaceted outcomes within these systems. A more nuanced approach is needed.

To illustrate, imagine planning an educational intervention in a low-income country. A traditional theory of change might map out a linear progression: training teachers leads to improved instruction and then better student performance. As development practitioners, we can often anticipate the influence of diverse contextual factors on our intervention: low resource availability may undermine the ability to train teachers.

What we may miss in our analysis is how our interventions and broader social dynamics interact to shape the context: we miss bidirectional causality that plays out over time and space. The results are interactions that produce unpredictable outcomes. Additional training, without other improvements to the teachers' working environment, may spur the most promising teachers to find jobs outside the country, leaving the students worse off. At the same time, increased student performance may disrupt cultural expectations about underprivileged ethnic groups, which has a longer-lasting but more indirect impact than the training program itself.

Two types of development problems

The solution to these types of development challenges is not to throw out our tools and seek new ones; rather, we need to broaden our tools and know when to select the right tool for the job. The teacher training example is one where bidirectional causality makes forecasting and linear analysis difficult. Not all problems in development are like that, however. The type of problem (bidirectional and complex versus mechanistic and linear) influences the type and depth of evidence required to support interventions. Imagine a water sanitation program where each step, from water source protection to safe water storage, depends on specific rules and components. When working with highly mechanistic or linear systems, we can identify and document the causal flow and how each component, rule, and process fits together. If we want to add fluoride to the water system, we can reasonably analyze the concentration and effect of fluoride throughout it.

Bidirectional causality and complex interactions work differently. It is difficult to forecast how such systems might behave intuitively. We instead focus on what decisions are made, by whom, and why. These individual-level decision rules drive system behavior, and altering them can lead to substantial, though unpredictable, system-wide changes. For instance, in a program aimed at reducing gender inequality, understanding the few key cultural, economic, and political rules that perpetuate inequality could be more crucial than attempting to address every individual discriminatory practice.

This also affects the way that we should monitor, evaluate, and learn within programs. If the program is linear and unidirectional, we can trace back from the outcome of interest to see the lines of causality and the components, relationships, and rules that drive them. We can create a detailed theory of change, generate evidence on the linkages in that theory, and evaluate the program by investigating the final outcomes. When things go wrong, we can work backward through the cause-and-effect relationships to find what is missing, where we can intervene, or what specific interactions we need to change.

If the program has bidirectional causality and complex interactions, we should examine the components, fundamental rules, and unexpected outcomes. We should appreciate that the outcomes can arise organically and that small changes in how people make decisions and take action can lead to unexpected outcomes. We focus our evidence gathering on the rules that the system follows rather than an overriding theory of change. When things go wrong, we start at the bottom, trying to understand how the rules give rise to the outcomes and try to experiment, or model, how changing the rules may lead to the desired outcome.

Of course, in practice, programs have both linear and bidirectional elements to them. Consider the example of the educational system, which has linear causal relationships (e.g., the government sets standards, teachers and students follow) and more complex dynamics (e.g., teacher interaction and motivation and social dynamics shaping student performance). Programs like these require a combination of tools—mapping the system as a whole and creating the proper framework for learning, evaluation, and iteration when things go wrong.

Similarly, attempts to intervene in complex systems with top-down rules and structures may not yield the anticipated results and could even backfire. For example, introducing a rigid rule in a fluid social system, such as a law mandating a quota for women in leadership positions in a society with deeply ingrained gender biases, may not lead to the desired effect of gender equality. It could even lead to backlash or superficial compliance without meaningful change. The rules we introduce are unlikely to displace the core system rules, and since such systems can exhibit emergent behaviors, directly managing these emergent behaviors is not as straightforward as controlling deterministic behaviors in a linear system.

Overall, understanding whether the systems we engage with in international development are complex or mechanistic is pivotal in designing effective interventions. It not only influences the way we approach problem-solving but also determines the kind of evidence we need, the interventions we design, and the outcomes we can expect.

A different approach

Members of the development community have increasingly embraced systems thinking to understand the contexts in which we work (e.g., Goentzel et al. 2022). Systems thinking is a powerful tool, but we need more to move from an understanding of the system to practical techniques to shape it. As we have seen here, the implications of complex systems go beyond tracing causality: they influence the types of evidence we need to gather beforehand, the types of interventions we use, and how we monitor their impact over time. When facing complex systems, we should not look at a point in time and intervene to "fix things"; that approach is appropriate for linear systems. Instead, examine the underlying rules that steer the interactions and how they play out over time.

The approach presented here – one that combines systems analysis with a behaviorally informed leverage point analysis and behavioral science interventions – allows us to grapple with the complexity of international development problems and our interventions to improve them from start to finish. The approach is still new, and we have much to learn, however; thus, we seek collaboration with our peers in the field.

A call for collaboration

Behavioral science faces problems we do not yet have the tools to handle—broken behavioral systems. These systems, with their unique components, rules, and properties, influence the behavior of individuals and collectives alike, shaping the patterns we observe in societies, economies, and cultures. The interplay of these systems and our adept navigation of them will form the foundation for effective behavioral change.

Similarly, in international development, complex systems underscore the importance of adapting our strategies to align with the inherent characteristics of the situations we work in. From acknowledging the unpredictability of emergent properties to the significance of the underlying rules that govern these systems, this nuanced understanding can guide us toward more effective and sustainable interventions.

Furthermore, exploring tools appropriate for each type of system underscores the importance of tailoring our approach based on the nature of the system at hand. Through the judicious selection and application of these tools, we can dissect the intricacies of these systems and design effective interventions.

There is no simple set of tools to handle these systems, nor the humans at their heart. Within the behavioral science and design communities, we see pioneering work by Ruth Schmidt at Illinois Tech's Institute of Design, Airbel Impact Lab at the International Rescue Committee, BehaviourWorks at Monash University, and Michie's Systems Mapping at University College London provide early examples of what is possible. Similarly, outside of behavioral science, we can draw upon the long history of work at Sante Fe and Argonne on complex systems and ABMs, the efforts at the Massachusetts Institute of Technology and many others on System Dynamics and Systems Thinking, and the development of other techniques such as Social Network Analysis. There are early attempts within those communities to integrate behavioral science lessons, but the onus is on us to improve behavioral science by welcoming and learning from their approaches.

At Busara, we continue to engage with these systems and grapple with ways to combine the lessons and tools of behavioral science with systems analysis. Through understanding, exploration, and intervention, we believe that we and the broader community can learn to navigate the complexities of these systems, bringing about meaningful, sustainable change. We have shared our work so far in this report and the tools within it. We welcome feedback on them, but most importantly, we look forward to collaborating with our peers in the field and learning from your efforts as well.

References

1. Abrami, G., Daré, W., Ducrot, R., Salliou, N., & Bommel, P. (2021). Participatory modelling. In The Routledge Handbook of Research Methods for Social-Ecological Systems (pp. 189–204). Routledge.
2. Aceña, M. del C. (2022). Estudio de femicidios en Guatemala – CIEN – Centro de Investigaciones Económicas Nacionales. CENTRO DE INVESTIGACIONES ECONOMICAS NACIONALES. https://cien.org.gt/index.php/estudio-de-femicidios-en-guatemala/
3. Blair, C., Gralla, E., Wetmore, F., Goentzel, J., & Peters, M. (2021). A Systems Framework for International Development: The Data-Layered Causal Loop Diagram. Production and Operations Management, 30(12), 4374–4395. https://doi.org/10.1111/poms.13492
4. Chater, N., & Loewenstein, G. (2022). The i-Frame and the s-Frame: How Focusing on Individual-Level Solutions Has Led Behavioral Public Policy Astray (SSRN Scholarly Paper 4046264). https://doi.org/10.2139/ssrn.4046264
5. Collins, L. M., Murphy, S. A., & Strecher, V. (2007). The Multiphase Optimization Strategy (MOST) and the Sequential Multiple Assignment Randomized Trial (SMART): New Methods for More Potent eHealth Interventions. American Journal of Preventive Medicine, 32(5 Suppl), S112–S118. https://doi.org/10.1016/j.amepre.2007.01.022
6. Darnton, A., & Horne, J. (2013). Influencing Behaviours: Moving Beyond the Individual. A User Guide to the ISM Tool. https://www.gov.scot/publications/influencing-behaviours-moving-beyond-individual-user-guide-ism-tool/
7. Dibble, C. (2006). Computational Laboratories for Spatial Agent-Based Models. In Handbook of Computational Economics: Vol. Volume 2 (pp. 1511–1548). Elsevier, North-Holland. http://www.sciencedirect.com/science/article/B7P5C-4JR414P-P/2/88067a30a2c48cf8e1d3c882dce6f459

8. Forrester, J. W. (1961). Industrial Dynamics. M.I.T. Press.
9. Glasgow, R. E. (2006). RE-AIMing research for application: Ways to improve evidence for family medicine. J Am Board Fam Med, 19(1), 11–19. https://doi.org/10.3122/jabfm.19.1.11
10. Goentzel, J., Blair, C., Gralla, E., Russell, T., Wetmore, F., Wiseman, M., Peters, M., & Downing, T. (2022). System Pathways Mapping Toolkit [USAID Whitepaper]. USAID/Uganda Feed the Future Market System Monitoring Activity.
11. Hallsworth, M. (2023a). A manifesto for applying behavioural science. Nature Human Behaviour, 7(3), Article 3. https://doi.org/10.1038/s41562-023-01555-3
12. Hallsworth, M. (2023b). Misconceptions about the Practice of Behavioral Public Policy (SSRN Scholarly Paper 4328659). https://doi.org/10.2139/ssrn.4328659
13. Hanu. (2019, January 4). Thinking in systems—Book notes. Medium. https://medium.com/@hanu/thinking-in-systems-book-notes-c42b70843928
14. Hatch, A., & Schmidt, R. (2021). SPACE to evolve academic assessment: A rubric for analyzing institutional conditions and progress indicators. https://doi.org/10.5281/zenodo.4927605
15. Hovmand, P. S. (2013). Community Based System Dynamics. Springer Science & Business Media.
16. Jilke, S., Olsen, A. L., Resh, W. G., & Siddiki, S. (2019). Microbrook, Mesobrook, Macrobrook (SSRN Scholarly Paper 3442606). https://papers.ssrn.com/abstract=3442606
17. Jones, P., & Van Ael, K. (2022). Design Journeys through Complex Systems. https://www.systemicdesigntoolkit.org/
18. Landa Ugarte, A., Salazar, E., Quintana, M., & Herrera, M. (2018). USAID/Guatemala gender analysis report. United States Agency for International Development: Washington, DC, USA, 147.
19. McKee, N., Manoncourt, E., Yoon, C. S., & Carnegie, R. (2008). Involving People, Evolving Behaviour: The UNICEF Experience1. Communication for Development and Social Change, 254.

20. McLeroy, K. R., Bibeau, D., Steckler, A., & Glanz, K. (1988). An ecological perspective on health promotion programs. Health Education Quarterly, 15(4), 351–377. https://doi.org/10.1177/109019818801500401
21. Meadows, D. H. (1999). Leverage Points: Places to Intervene in a System. Whole Earth. https://donellameadows.org/wp-content/userfiles/Leverage_Points.pdf
22. Meadows, D. H. (2008). Thinking in Systems: A Primer (First Printing). Chelsea Green Publishing.
23. Mearsheimer, J. J. (2001). The tragedy of great power politics. WW Norton & Company.
24. Miller, J. H., & Page, S. E. (2007). Complex adaptive systems: An introduction to computational models of social life / John H. Miller and Scott E. Page. Princeton University Press.
25. Moore, L., de Silva-Sanigorski, A., & Moore, S. N. (2013). A socio-ecological perspective on behavioural interventions to influence food choice in schools: Alternative, complementary or synergistic? Public Health Nutrition, 16(6), 1000–1005. https://doi.org/10.1017/S1368980012005605
26. Oliver, M. L., & Shapiro, T. M. (2019). Disrupting the Racial Wealth Gap. Contexts, 18(1), 16–21. https://doi.org/10.1177/1536504219830672
27. ONU Mujeres, & Behavioural Insights Team'. (2022). Estrategias basadas en el comportamiento para involucrar a los hombres en la prevención de la violencia ejercida contra las mujeres y las niñas. https://lac.unwomen.org/es/digital-library/publications/2022/05/estrategias-basadas-en-el-comportamiento-para-involucrar-a-los-hombres-en-la-prevencion-de-la-violencia-ejercida-contra-las-mujeres-y-las-ninas
28. Robinson, J. A., & Acemoglu, D. (2012). Why nations fail: The origins of power, prosperity and poverty. Profile London.
29. Schill, C., Anderies, J. M., Lindahl, T., Folke, C., Polasky, S., Cárdenas, J. C., Crépin, A.-S., Janssen, M. A., Norberg, J., & Schlüter, M. (2019). A more dynamic understanding of human behaviour for the Anthropocene. Nature Sustainability, 2(12), Article 12.

https://doi.org/10.1038/s41893-019-0419-7

30. Schmidt, R. (2022). A model for choice infrastructure: Looking beyond choice architecture in Behavioral Public Policy. Behavioural Public Policy, 1–26.
31. Schmidt, R., Curry, S., & Hatch, A. (2021). Creating SPACE to evolve academic assessment. eLife, 10, e70929. https://doi.org/10.7554/eLife.70929
32. Schmidt, R., & Stenger, K. (2021a). Behavioral planning: Improving behavioral design with "roughly right" foresight. Strategic Design Research Journal, 14(1), Article 1. https://doi.org/10.4013/sdrj.2021.141.12
33. Schmidt, R., & Stenger, K. (2021b). Behavioral brittleness: The case for strategic behavioral public policy. Behavioural Public Policy, 1–26. https://doi.org/10.1017/bpp.2021.16
34. Thaler, R. (2020). What's next for nudging and choice architecture? Organizational Behavior and Human Decision Processes. https://doi.org/10.1016/j.obhdp.2020.04.003
35. Washington Office on Latin America (WOLA), & Myrna Mack Foundation. (2019). Guatemala's Justice Capacity Building and Judicial Independence—Guatemala | ReliefWeb. https://reliefweb.int/report/guatemala/guatemalas-justice-system-evaluating-capacity-building-and-judicial-independence
36. Wasserman, S., & Faust, K. (1994). Social Network Analysis: Methods and Applications. Cambridge University Press.
37. Wendel, S. (2018). Easing the Retirement Crisis [Morningstar Investor Success Whitepaper]. Morningstar. https://www.morningstar.com/articles/878431/easing-the-retirement-crisis
38. Wendel, S., Artavia-Mora, L., & Khan, Z. (2023). The Applied Behavioral Scientist's Toolkit. In Behavioral Science in Development. Bescy Press.
39. WHO. (2021). Violence Against Women Prevalence Estimates, 2018. World Health Organization. https://www.who.int/publications-detail-redirect/9789240022256
40. Zareie, A., & Sakellariou, R. (2020). Similarity-based link prediction in social networks using latent relationships between the users. Scientific Reports, 10(1), Article 1. https://doi.org/10.1038/s41598-020-76799-4

Busara Groundwork
RESEARCH AGENDA

About Busara

Busara is a research and advisory organization, working with researchers and organizations to advance and apply behavioral science in pursuit of poverty alleviation. Busara pursues a future where global human development activities respond to people's lived experience; value knowledge generated in the context it is applied; and promote culturally appropriate and inclusive practices. To accomplish this, we practice and promote behavioral science in ways that center and value the perspectives of respondents; expand the practice of research where it is applied; and build networks, processes, and tools that increase the competence of practitioners and researchers.

About Busara Groundwork

Busara Groundwork lays the groundwork for future research and program design. As think pieces, they examine the current state of knowledge and what is needed to advance it, frame important issues with a behavioral perspective, or put forward background information on a specific context.

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