THE DYNAMICS OF SUSTAINABILITY TRANSITIONS: AN ARCHETYPE FOR TRANSFORMATION

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ABSTRACT

Significant global sustainability challenges include among others, energy, climate, and sanitation. Previous Sustainability Transition research has attempted to understand transformation complexity and interdependence, primarily through single-case methodological studies or large-scale analytical frameworks such as the Multi-Level Perspective. This leaves a knowledge gap on common dynamics underlying transition processes and emergent behaviors. To fill this gap, we conducted a cross-sectoral analysis of five system dynamics sustainability transition models with the objective of finding a common system archetype. An archetype emerged from a multi-step, mixed method structural analysis of these models. The extracted archetype captures generalizable sustainable transition dynamics across a diversity of research domains and temporal scales. The structural drivers of sustainability transitions within this archetype are used to discuss future research and practice that seeks to provide insight on common transition dynamics, deeper clarity on leverage points capable of managing transitions, and a framework for subsequent transition modeling archetype analyses.

Keywords:
Sustainability Transitions
System Dynamics Modeling
Model Structure/Behavior/Pattern Analysis
Systems Archetype
Archetype Analysis
Multi-Level Perspective

1. INTRODUCTION

Humanity must overcome a number of grand challenges such as climate change (IPCC, 2018), decarbonizing energy consumption (Sovacool, 2016), and inadequate access to sanitation or clean water (Walters and Javernick-Will 2015; Prouty et al. 2020). While these examples represent different problems, they share a common need for a societal-level transition to cleaner and more sustainable technologies. However, technologies do not exist in isolation; they are fixed within, and have coevolved with society (Ropohl, 1999), creating a deeply intertwined set of consumer behaviors, cultural values, business firms, economics and politics. There are a number of such *socio-technical systems* (STS) providing society with needed services. Examples include energy, water, sanitation or transportation (Holtz, 2011; Holtz, et al. 2015; Li et al. 2015). Each STS is composed of a highly interdependent hierarchy of actors, firms or organizations, operational practices or standards, accumulated knowledge, cultural norms and regulatory agencies interactively providing the sector's service to society (Markard, et al. 2012; Geels, 2004). Solving grand challenges facing humanity transcends simple technology replacement; a widespread technological shift also fundamentally transforms the STS, redefining the actors, firms or organizations involved, with subsequent impacts on practices, knowledge, cultural norms and regulations. Such a change may be defined as a sustainability transition (ST), where a large-scale restructuring of technologies, market dynamics, user preferences and social perceptions (Edmondson et al. 2019) result in new types of STS (Elzen et al. 2004; Grin et al. 2010).

The field of transition research has expanded in the last decade to encompass studies in a variety of sectors, geographies, and methodological approaches. A common theme found in these studies is the need for multidimensional perspectives capable of incorporating the feedback-rich, complex nature of transitions (Geels, 2004; Geels, 2002; Köhler et al. 2019). A number of qualitative analytical frameworks derived from large scale historical studies (Markard, et al. 2012; Köhler et al. 2019) are used in transition studies, including the Multi-Level Perspective (Geels, 2002), Strategic Niche Management (Kemp et al. 1998) and Transition Management (Loorbach, 2010; Rotmans et al. 2016). However, research at a '*systems level'*, has been conducted primarily through meta-analyses (Wiseman, et al. 2013) transition pathway typologies (Geels and Schotz, 2007), or innovation systems studies (Hekkert and Negro, 2009). Additionally, the focus of ST research has predominantly been on in-depth, single-case studies conducted at regional to supra-national scales (Köhler, et al. 2019). The emphasis on single-case, single-scale research has created a need to understand underlying processes and emergent behavior of transition dynamics by balancing complexity with a greater degree of abstraction (Köhler, et al. 2019). One promising approach capable of bridging case-specific descriptive studies with generalized insights is quantitative and/or qualitative modeling (Köhler, et al. 2019; Li et al. 2015). Modeling can simplify system complexity, provide clarity on attributes and the dynamics between them, as well as allowing for systematic testing of interventions (Holtz et al. 2015). Policy makers have traditionally relied on quantitative linear or nonlinear programming, general equilibrium (Gottschamer and Zhang 2016,) or Integrative Assessment Models (IAM's) methods to better understand interlinked sectors such as energy, water, climate, and agriculture (Trutnevyte et al. 2019; Bolwig et al. 2019). These types of quantitative models are capable of simulating scenarios to better understand future behavior of non-linear socio-technical systems (Hirt et al. 2020; Moallemi et al. 2017). However, these methods cannot fully capture dynamic feedbacks found in sustainable, socio-technical transitions (Gottschamer and Zhang, 2020; Li et al. 2015).

A promising approach to better understand studies is to extract insights from a diversity of cases (Poteete, et al. 2010, Beach and Pedersen, 2016). Research suggests studying patterns found in STs may provide deeper insights on how such transitions unfold (Please refer to Eisenack et al. 2021; Oberlack et al. 2019; Sietz et al. 2019, and Ecology & Society, 2021 for an excellent introduction to sustainability archetypes). The concept of patterns found in STs is grounded in a systems thinking perspective. In this perspective, a basic tenet is that a system's behavior (desirable or undesirable outcomes) is driven by its structure; which are the attributes, interactions, feedbacks and time delays between them (Meadows, 2009). Archetypes are then defined as "*system structures that produce common patterns of problematic behavior*" (Meadows, 2009). Systems containing similar structures produce remarkably similar behavior, even across completely different systems. A well-known archetype is the tragedy of the commons, where overconsumption of a common resource diminishes its utility for all users (Braun, 2002). Specific examples are the degradation of a common pasture used for grazing herd animals, or the rising atmospheric CO_2 level due to fossil fuel combustion. Archetypes depict generalized structure or behavioral patterns (Senge, 1990; Wolstenholme, 2003;Wolstenholme, 2004) and are useful tools for examining current undesirable behaviors (Braun, 2002). Archetypes provide clarity on the fundamental nature of a problem through a deeper understanding of why a behavior manifests (Kim, 1994). They serve as a guide for system interventions, by identifying high-leverage intervention points where the most beneficial change can be implemented for the least amount of effort (Kim, 1992). They also allow policies or protocols to be evaluated against the drivers of current behavior (Braun, 2002). Archetypes can also be a guide for developing more refined models (Braun, 2002).

System Dynamics (SD) has been suggested as a suitable methodology for studying non-linearities and emergent properties found in transitions (Köhler et al. 2018; Köhler et al. 2019; Papachristos, 2019). SD modeling is therefore uniquely suited for the creation of archetypes (Kim, 1994; Meadows, 2009), and could be used to find an archetype that examines the generalized dynamics of STs. However, to our knowledge, no such archetype exists. To fill this gap, this paper presents a novel study applying a cross-sectoral archetype analysis of SD model structures (or interactions between model components). Examining SD model structures across transportation, energy, biofuel, sanitation, and agricultural sectors balances complexity with a greater degree of abstraction, and could provide a deeper understanding of structural patterns (archetypes) found in STs. Identifying a 'ST' archetype would lead to greater clarity on why problem behavior manifests, guide the development of future models, and identify system leverage points. To allow this archetype to emerge, we performed a structural analysis of key components contained in past SD modeling case studies across a diversity of ST domains. Structural analysis entailed a combined analysis of centrality and feedback between key model components modeled within each case study. Comparing, and contrasting systems leverage points helped reveal synergies and tradeoffs for different policies and practices to target multiple transition domains. This analysis had two main objectives; the first was to identify a framework for moving from case-specific SD modeling to higher order processes and behaviors driving transition dynamics. The second was to identify a common ST archetype capable of informing future modeling and transition research.

The remainder of this paper is structured as follows. Section 2 briefly reviews systems thinking, modeling and archetype analysis. Section 3 presents the methods and lays out the framework for studying the selected models. Section 4 discusses the results and Section 5 is a brief conclusion.

2. SYSTEM DYNAMICS MODELLING AND ARCHETYPE ANALYSIS

A systems thinking perspective approaches problem solving by developing not only a deep understanding of the parts of a system, but how relationships between the parts drive undesirable outcomes or behavior (Meadows, 2009). A complex system is composed of many interdependent, but interactive attributes. The way in which attributes are structured; the relationships and feedbacks between them, how strongly one influences another, or the time delay it takes for an influence to propagate, all drive system behavior (Sterman, 2000). SD is a modeling approach grounded in systems thinking. Here, relationships between attributes are defined (where possible), and then circular causality or "feedback loops" involving two or more factors are identified and characterized (Sterman, 2000). Feedback loops are critical transport mechanisms of information and material flows within a system. All feedback loops together create a causal loop diagram (CLD), a qualitative SD model of attributes and interactions hypothesized to drive system behavior. CLDs are then converted mathematically into a stock-flow diagram (SFD), a quantitative SD model, that can be used to test the behavior hypothesized by the CLD structure. SFDs visually display a system of ordinary differential equations representing stocks, and the rate variables controlling flows into and out of them. SD models can include information and decision feedback loops, delays, and technological change (Forrester, 1994). This allows a model to more accurately reproduce behavior by updating itself when information and decisions change the system under study (Ford, 1997). SD is a methodology capable of including information and decision feedback loops, delays, and technological change. A system that changes in reaction to feedbacks presents a more realistic representation of socio-technical transition complexities (Gottschamer and Zhang, 2020; Li et al. 2015) than traditional quantitative linear or nonlinear programming, general equilibrium (Gottschamer and Zhang, 2016) or Integrative Assessment Models methods (Trutnevyte et al. 2019; Bolwig et al. 2019).

Many complex systems have structural patterns and feedbacks that create similar behavior, even across completely different contexts (Meadows, 2009). The field of system thinking has identified a set of these common structures called *archetypes* (Please see Senge, 1990; Kim, 1992; Kim, 1994; Braun, 2002, and Meadows, 2009, for an in-depth discussion). Archetypes depict generalized structure and behavioral patterns (Senge, 1990; Wolstenholme 2003; Wolstenholme, 2004) and are useful tools for examining current undesirable behaviors (Braun, 2002). They are particularly useful in providing a deeper understanding of why a behavior manifests (Kim, 1994), and they can serve as a guide for system interventions, where policies or protocols can be evaluated against the drivers of current behavior (Braun, 2002). Archetypes can also be used to identify high-leverage intervention points, where the most beneficial change can be implemented for the least amount of effort (Kim, 1992). Archetypes are generally depicted using a qualitative conceptual map (CLD) grounded in the system dynamics methodology.

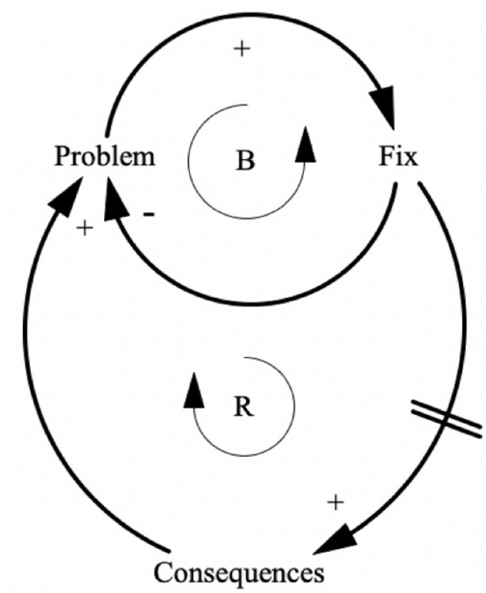

Figure 1: A CLD visually represents system structure, and is a map of elements, interconnections, time delays and the feedbacks influencing undesirable (or desirable) behavior. A 'plus' symbol indicates a positive interaction, where an increase or decrease in the element value at the tail of the arrow drives a same-direction change in the value of the element at the head. A 'minus' symbol indicates a negative interaction; a change in the element at the tail of the arrow moves the head in a similar direction. Fig. 1, illustrates the archetype 'fixes that fail' where a growing problem requires a fix that then reduces the problem. This is a balancing loop, a manifestation of slowing behavior and is labeled with the B1 symbol. However, fixes often take time, and there is a delay between fixes and consequences (denoted by the double lines crossing the arrow between them). Fixes may also have unintended consequences, making a problem worse, this is shown as a reinforcing loop with a R2 (Braun, 2002).

A 'plus'(+) symbol indicates a positive interaction, where an increase or decrease in the attribute value at the tail of the arrow drives a same-direction change in the value of the attribute at the head. A 'minus' (-) symbol indicates a negative interaction; a change in the attribute at the tail of the arrow moves the head in an opposite direction. The example of Figure 1 illustrates the archetype 'fixes that fail' where a growing problem requires a fix that then reduces the problem. This is a balancing loop, a manifestation of slowing behavior and is labeled with the B1 symbol. However, fixes often take time, and there is a delay between fixes and consequences (denoted by the double lines crossing the arrow between them). Fixes may also have unintended consequences, making a problem worse and this is shown as a reinforcing loop with a R2. Reinforcing and balancing loops are classified by summing the number of negative polarities in the loop, where an even (or zero) sum implies a reinforcing loop, and an odd sum implies a balancing loop.

Interest in archetypes as a methodological analysis has expanded out of systems thinking and system dynamics into sustainability research, where recognition that recurring structures and patterns are shaping the sustainability of socio-ecological systems (Oberlack, et al. 2019; Piemontese, et al. 2022). Archetype analyses have also been recently applied to business and diversity (Mathis-Pertilla, 2021), managerial performance (Bureš and Rachs, 2016), crisis management (Armenia et al. 2022) and information technology (Schilling et al. 2017). Archetype analysis examines a set of heterogeneous cases for recurring patterns (Oberlack et al. 2019; Eisenack, et al. 2021). This implies individual cases are the unit of study (Eisenack, et al. 2021) While it has been used to identify "*patterns of interrelated causal factors and outcomes"* (Moser et al. 2019), archetype analysis is not intended to distill universal laws applicable across all cases involved in a study, but to acquire generalized knowledge. Pattern analysis can be conducted using a variety of quantitative, qualitative or mixed-methods (Sietz, et al. 2019), and a small number of cases may provide rich detail (Eisenack, et al. 2021). However, the difficulty with such an analysis is reducing complexity while increasing the level of abstraction across a heterogeneity of cases, without losing the critical features under study.

To address this concern, we followed the best practices disseminated in the recent review and synthesis of the field found in the June 2021 '*Archetype Analysis in Sustainability Research'* special issue published in the Journal Ecology and Society. The special issue first provides a detailed synthesis of the field, laying out archetype analysis core features and best practices (Eisenak, et al. 2021; Oberlak, et al. 2019), design criteria and quality (Eisenak, et al. 2019), as well as the strengths and weaknesses of archetype identification methods (Seitz et al. 2019). Eisenak, et al. (2021), provided a synthesis of the archetype analysis field, defining eight core propositions found in a comprehensive, high standard analysis, shown in Table 1 below.

Table 1. Propositions of Archetype Analysis (Eisenak, et al. 2021)

Number	Proposition
1	Archetype analysis is a comparative approach.
2	Archetype analysis produces a suite of archetypes, not a broadly applicable law.
3	Archetypes characterize critical components such as actors, processes, subsystems or impacts found in some, but not all cases.
4	Archetypes are building blocks capable of different combinations that explain individual cases.
5	An archetype analysis characterizes each archetype in three ways: a configuration of attributes it holds; a theory or hypothesis explaining the relation between the attributes; and a set of applicable cases.

Number	Proposition
6	A suite of archetypes employs a common vocabulary of attributes. These are factors such as: *characteristics, variables, or qualities, etc.* intended to facilitate abstraction.
7	Attributes and archetypes are formulated on an intermediate level of abstraction between analytical frameworks and individual case studies.
8	Archetypes are analytical or mental constructs, and not necessarily material or functional mechanisms or systems.

An important caveat to note is that the field of archetype analysis is still defining its processes and standards, and thus no systemic criteria exists on what constitutes an 'appropriate size, complexity or number of archetypes (Eisenack, et al. 2019). As such, we follow the systems thinking literature (Senge, 1990; Kim, 1992; Kim, 1994; Braun, 2002, and Meadows, 2009), in order to arrive at a simplified archetype that captures generalized dynamics of diverse ST contexts.

3. METHODS

Archetype analysis examines a set of heterogeneous cases for recurring patterns (Oberlack et al. 2019; Eisenack, et al. 2021). Eisenack et al. (2019) recommends the following components be included in the analytical process:

> '*collecting data and studying cases, classifying components of cases, identifying an appropriate level of abstraction, construction of a common vocabulary of attributes, identifying patterns and their domains of validity, developing a naming convention for each identified archetype and explanation of the archetype through new or existing theories'* (Eisenack, et al. 2019).

Specifics on how these components were incorporated into our multi-step archetype analysis are detailed in the following sections, and displayed in Figure 2.

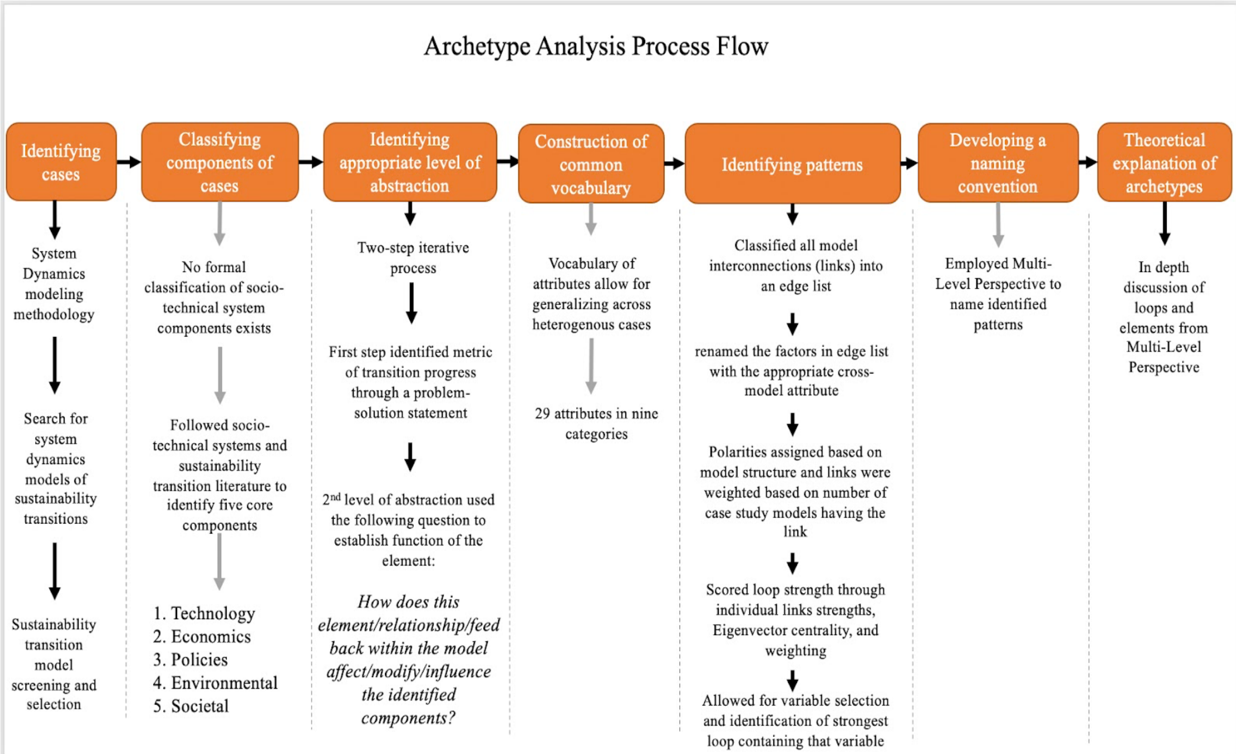

Figure 2: The archetype analysis process used in this study

3.1 IDENTIFYING CASES - MODEL IDENTIFICATION AND SELECTION

SD modeling was selected as the primary methodological focus of this research for its ability to incorporate socio-technical system feedbacks, delays and non-linearities. It has also been extensively applied across a diverse range of transitions. This breadth of modeling topics allowed us to study the core structures from multiple sustainable transition (ST) domains. Searches for suitable manuscripts that applied SD modeling to STs were conducted in Web of Science, ScienceDirect and Scopus. Searches were limited to the English language and the years 1960-2021. The following search terms were used: (System dynamics AND model AND (transition OR sustain* OR socio-technical)). Each database returned thousands of hits, for example Web of Science returned 4,716. These were initially evaluated for the evidence of socio-technical, model, sustainability or transition in either the keywords or abstract. This secondary evaluation narrowed the number of manuscripts to 440. These were then systematically evaluated for a comprehensive CLD, to include both a graphical form and a full textual description of the attributes and feedback loops. This reduced the number of manuscripts to 27. Of these, five models representing different socio-technical ST domains were selected based on the completeness of their CLDs. Included in this analysis are transportation (Rees et al. 2016), aviation biofuel (Kim, et al. 2019), wastewater (Prouty, et al. 2020), solar photovoltaic recycling (Salim, et al. 2021), and a socio-cultural exploration of a coupled human-environmental irrigation system (Turner, et al. 2016). Table 2 provides a summary of characteristics across the five ST models.

Table 2: Summary of ST model characteristics

Model	**Transition Domain (*and notes)***	**Metric of Sustainability Transition Progress**	**Dynamics studied (scenarios)**	**Findings**
Rees et al. 2016	Transportation	Investment in Electric Vehicles.	Business-as-usual, Factors creating barriers to more sustainable transport systems, Drivers of change.	Model reveals strong reinforcing loops acting to minimize impact of change drivers, System is highly dependent on the continued existence of reinforcing policies such as fossil fuel subsidies.
Kim et al. 2019	Aviation biofuel industry	Biofuel utilization percent.	Techno economic and socio-political intervention, Industry techno-economic forces without socio-political governmental interferences, Techno-economic forces and balancing interferences of socio-political forces.	A need for a standardized certification process establishing level of CO_2 savings of a particular biofuel, Transparency on how feedstock is grown and biofuels are produced, Unified public demand pressure that, with assistance of policies, can accelerate diffusion Establishing an open, public form of R&D for aviation biofuels.
Prouty et al. 2020	Wastewater infrastructure transition	Installation rate of improved	new socio-economic decision-making approach,	Socio-technical strategy made the

Model	Transition Domain (**and notes)*	Metric of Sustainability Transition Progress	Dynamics studied (scenarios)	Findings
		wastewater systems.	technology and economic policies, socio-technical behavior change	greatest improvement to nutrient loading, Technology and economic policy was best approach to improve reliability performance measure
Salim et al. 2021	Solar PV cell Recycling	Total Recovered PV.	Market-driven growth, conservative development, shared responsibility, disruptive change.	Shared responsibility balances stakeholder techno-economic motivations (across supply chain) to participate in recovery scheme, Gradual regulatory change allows a period of industry and market development.
Turner et al. 2016	Relationship between community structure and resource management. * *(Acequias are community managed farm-scale irrigation systems.)*	Participation in traditional acequia activities.	No scenarios studies	Physical, social, and economic indicators were strongly linked to both acequia mutualism community participation variables. Absentee decisions, land use preference, community demographic effect, impact of employment on participation, and farm size drive system behavior.

3.2 CLASSIFYING COMPONENTS OF CASES

Each of these five modeling case-studies examined a ST of a complex socio-technical system. Such systems are characterized by a highly interdependent hierarchy of actors, firms or organizations, operational practices or standards, accumulated knowledge, cultural norms and regulatory agencies interactively providing the sector's service to society (Markard, et al. 2012; Geels, 2004). A system-wide technological shift fundamentally transforms the socio-technical system (STS), driving a large-scale restructuring of technologies, market dynamics, user preferences and social perceptions (Edmondson et al. 2019) that ultimately results in a new type of STS (Elzen, et al. 2004; Grin, et al. 2010). However, specific configurations or components of a STS differ between systems (Sovacool et al. 2020). In their 2019 review of the ST field, Köhler et al. 2019 identified a number of components contained within a STS such as technologies, markets, policies, industry and user practices (Köhler, et al. 2019). Geels, 2019, also identified basic attributes characterizing a STS. These include technologies, capital (money), human resources, regulations and markets **(**Geels, 2019**).** In order to combine across cases, apply the appropriate level of abstraction and classify components of these systems, we followed the socio-technical systems and ST literature to identify five core components applicable to this study. These are presented in Table 3 below:

Table 3. Components of cases.

COMPONENT	DEFINITION
Technology	The technology component includes not only a novel replacement technology but the dominant technology in use as well.
Economics	Economics of transitioning from a dominant technology to that of a novel replacement. This includes the cost differential between the two related to economies of scale, capital costs, as well as other factors such as: production, distribution, installation, and maintenance. Also includes cost adjustments to both categories of technologies due to policy mechanisms.
Policies	Transition policies may support an innovative technology through price subsidies, tax breaks or production/installation credits. Policies may also favor dominant technologies through path-dependent environments, such as continued subsidies.
Environmental	Environmental concerns are represented by pollutant emissions, climate change in general, or specific impacts caused by climate change.
Societal	This broad category includes social acceptance of novel technologies, activism for or against innovations as well as user preferences, norms, values and perceptions.

3.3 IDENTIFYING AN APPROPRIATE LEVEL OF ABSTRACTION

Analyzing unique, heterogenous cases for common patterns requires careful consideration of the level of abstraction employed. In this study, we employed a two-step iterative process that first abstracted each model into a problem-solution statement. For example, Prouty, et al. (2020), examined the vulnerability of wastewater treatment systems to extreme climate events, and the challenges of transitioning such systems to improved treatment trains. Their problem solution was the installation of improved wastewater treatment systems. This level of abstraction allowed us to identify an attribute capable of measuring progress towards each model's solution. In Prouty, et al. (2020), it was the change in value for the attribute '*installation rate of improved wastewater systems*'. However, every model in this analysis had its solution variable (an attribute the model builders' intended as a metric of ST progress) influenced by either all, or a combination of the previously identified components representing social, technological, economic, policy and environmental attributes. We then followed Eisenack, et al. (2019) requirement of being able to combine across the cases by iteratively abstracting the attributes within these components. We found the most appropriate level of abstraction capable of bridging case-based specifics with a generalization transferable across cases, was by characterizing how an attribute's *function* was represented within the models based on the following question: *How does this [attribute/relationship/feedback] within the model [affect/modify/influence] the identified components?* For example, the attribute 'cost of improved wastewater system' in Prouty, et al. (2020) was abstracted to the level of '*Perception of Current Regime Benefits over Innovation'*. This abstraction still captured the original meaning, but allowed for application across other models.

3.4 CONSTRUCTION OF A COMMON VOCABULARY OF ATTRIBUTES

The level of abstraction discussed in Section 3.3 allowed the social, technological, economic, policy and environmental domains to be classified into a common vocabulary of *attributes* across the selected ST models. Constructing a common vocabulary of attributes enabled us to recreate a causal loop structure that merged links from each of the five selected models. Here we follow Eisenack, et al. (2019) definition of attributes:

> '*characteristics, variables, qualities, factors, or other properties chosen at an intermediate level of abstraction to achieve a balance between case-based validity and generalization* (Eisenack, et al. 2019).

This analysis followed systems thinking and system dynamics modeling concepts to construct a vocabulary of 29 attributes. These attributes followed SD modeling best practices (Sterman 2000), and are intended to be neutral. This ensures consistency in model meaning when progressing to identifying pairwise connections across the five ST models. The attributes in the nine categories are summarized in Table 4 below.

Table 4. Sustainability transition attributes, their definitions, and associated category

ATTRIBUTE CATEGORY	ATTRIBUTE	DEFINITION
Current System State	Current System State Economics	Parameter values at model initialization; capital costs, operating costs etc.
	Current System State Environmental	Parameter values at model initialization; baseline environmental state without climate change impacts
	Current System State Knowledge	Parameter values at model initialization; societal awareness of innovation
	Current System State Policy	Policies in place at model initialization; either pro, or anti-innovation

ATTRIBUTE CATEGORY	ATTRIBUTE	DEFINITION
	Current System State Resources	Available resources at model initialization
	Current System State Societal	Broad descriptive attribute describing regime at model initialization; includes perceptions, infrastructure, willingness to engage in innovation, etc.
	Current System State Technology	Regime-level dominant technology at model initialization
	Impacts of Current System State Environmental	Environmental impacts at model initialization
Desired System State	Desired System State	Problem or symptom alleviation (solution)
Transition Drivers	Societal Awareness of Gap Between Problem and Desired Solution	Societal-scale recognition of a problem requiring engagement in transition actions.
	Transition Resistance	Economic, policy, or narrative pushback against innovation
Economic	Perception of Current Regime Benefits over Innovation	Increasing the competitiveness of an innovation requires 'leveling the playing field' by artificially lowering the higher costs typically associated with a new market entrant.
	Economic Driver of Sustainability Transition	Any economic factor capable of driving sustainability transition such as fossil fuel resource limitation
	Economic Impact of Climate Change	Cost of climate change environmental impacts
	Economic Mitigation Strategy	Incentivization strategy to offset cost differential
	Economic Resistance to Sustainability Transition	Vested interest groups deploying economic resources to counter innovation
	Pressure to Invest in Innovation	Capability to commit economic resources to innovation
	Economies of Scale	Cost savings associated with increased production or implementation
Environment	Environmental Driver of Sustainability Transition	Environmental impact resulting in increased pressure to adopt innovation
	Impact of Environmental Anomaly	Specific impact of abnormal environmental event
Gap between current and desired condition	Economic Driver of Gap Between Current and Desired System States	Landscape driver reinforcing status-quo; GDP growth, etc.
	Gap Between Current and Desired System States	Difference between problem symptoms and perceived solution
	Reducing Gap Between Desired and Current System States	Action to reduce gap
	Societal Driver of Gap Between Current and Desired System States	Path dependent societal factors reinforcing a gap; consumption patterns, behavior, willingness to invest, etc.

ATTRIBUTE CATEGORY	ATTRIBUTE	DEFINITION
Policy	Policy Intervention	Any number of policies intended to either increase the diffusion of an innovation, or actively resist diffusion through support for the dominant technology.
Solution variable	Sustainability Transition Progress	The metric used to quantify the progress towards sustainability goals. Generally represented by the installed number of innovative technology units or systems. This represented the 'outcome variable' of interest in the combined CLD.
Technology	Technological Advantage	Technological benefits associated with innovation.
	Technological Driver of Sustainability Transition	Innovation's benefits compared to dominant technology.
	Technological Mitigation Strategy	Technology intended to address problem driving a need for a sustainability transition

3.5 IDENTIFYING PATTERNS - A DOMINANT ARCHETYPAL STRUCTURE

With a common list of 29 ST attributes, it was possible to create a cross-model CLD with weighted attribute connections across all five ST models, and to then structurally analyze this CLD to extract the archetype driving STs. The process used to accomplish this objective is shown in Figure 3.

Creation of the cross-model CLD entailed first developing an edgelist: a table organizing all the *unique* directional, pairwise connections between the attributes. The edgelist was created by systematically considering all of the pairwise connections from the five selected models and renaming the factors in these connections with the appropriate cross-model attribute. In instances where two of the same pairwise connections were present within a model, only one instance of this connection was considered. Each unique pairwise connection was then given a polarity based on the most likely dynamics (either + or -), existing between the two attributes, as indicated by the CLD in the model study. Considering only unique pairwise connections within each model enabled inference on the connection 'strength' based on the number of models across which the connections were present. For example, if a unique pairwise connection was present in two models, the connection was given a weight of 2. The resulting edgelist, in csv form, was then analyzed to identify, score, and rank feedback loops containing the main attribute of interest: Sustainability Transition Progress. The loop detection algorithm developed by Gupta and Suzumura (2021) was used to identify all unique feedback loops containing the attribute '*Sustainability Transition Progress*', based on the number and order of attributes within a loop. Loops were then scored based on the averaged product of connection strength and eigenvector centrality values (Wasserman and Galaskiewicz, 1994) for the factors found in each loop. For example, if the three factor loop Factor A → Factor B→ Factor C had link strengths of (2, between A and B), (1 between B and C) and (1, between C and A), and eigenvector centrality scores of (0.75, Factor A), (0.65, Factor B), and (0.67, Factor C), the loop score would be $(2 \times 0.65 + 1 \times 0.67 + 1 \times 0.75)/3 = 0.91$. Eigenvector centrality was the network centrality metric chosen to score loops because of its ability to evaluate attribute connectivity within the entire ST model (Walters, et al. 2022). In addition, scoring loops based on pairwise connection strength and eigenvector centrality offered the level of granularity necessary to find the top loop out of thousands of unique feedback loops (Nabong, et al. 2022). Feedback loops containing *Sustainability Transition Progress* were then ranked based on their relative loop scores. Figure 3 summarizes each step of this mixed-method model creation and analysis process.

Having a technique to identify and rank feedback loops enabled us to create a driving archetypal structure for the weighted CLD composed of links and attributes across the five ST models. The driving archetypal structure was derived from the list of ranked loops by finding the top scored loop containing *Sustainability Transition Progress*, which we call the ‘prime loop’, and then adding links and factors within and outside of this loop based on the top loops - using the previously described technique for loop identification and scoring - for each factor within the prime loop. This level of abstraction out from the prime loop was considered sufficient to add both granularity and meaning to the resulting archetype, while keeping a parsimonious archetypal structure.

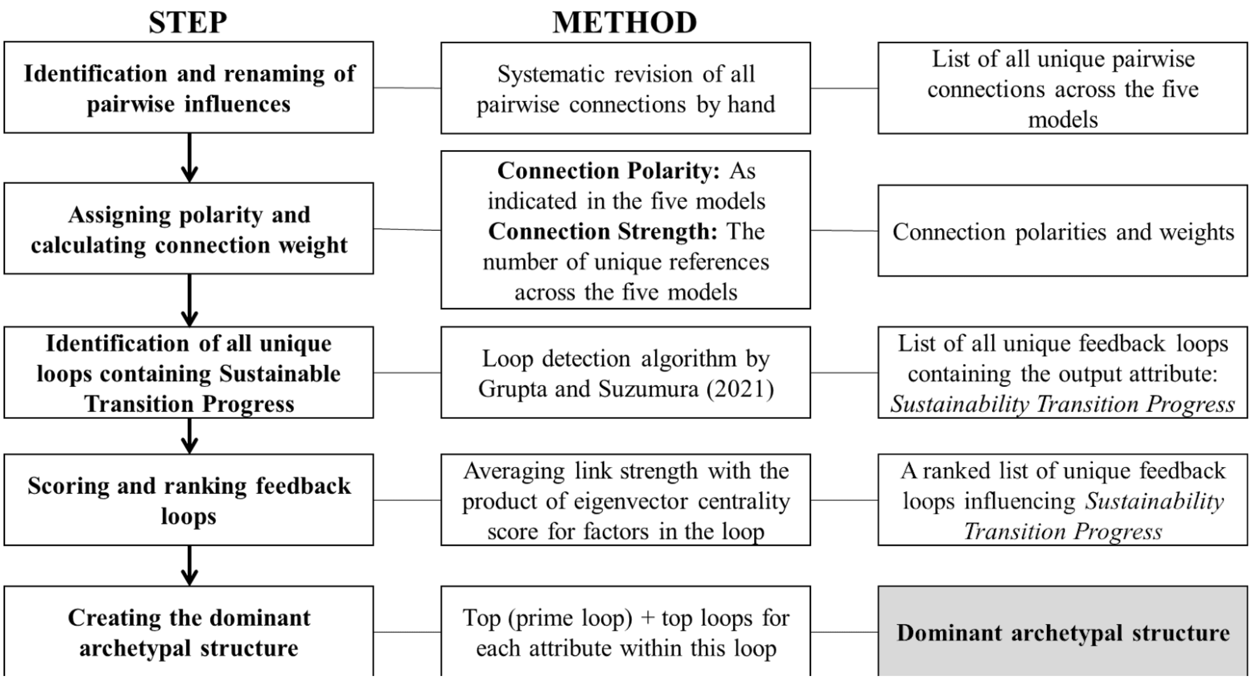

Figure 3: Process for identifying a dominant ST archetype

3.6 DEVELOPING A NAMING CONVENTION

Following Eisenack, et al. (2019) best archetype analysis practices, we developed a ST archetype naming convention of the dominant feedback structure (loops) that emerged using the process described in Section 3.5. To accomplish this, we employed the Multi-Level Perspective (MLP) (Geels, 2002), a widely used analytical framework used to understand societal-scale socio-technical transitions. While there are a number of theoretical frameworks for understanding transitions, the MLP is both widely accepted in the transition studies field (Köhler et al. 2019), and adequately captures the dynamics found in the identified archetype.

The MLP, first advanced by Geels (2002), postulated technological innovation is the result of three interacting levels; niche, regime and landscape. In this framework technological innovations manifest at the smallest, or niche level. Niches are protected spaces where technological innovations can occur in the absence of selection pressures from the next higher level, the regime. Examples are specific markets or application domains (Markard, et al. 2012), but they may also be driven by price and performance improvements, or learning processes (Papachristos, 2018). Above the niche is the regime. This middle level represents a socio-technical state, where a dominant technology has co-evolved with society, creating an interlinked set of technologies, industry practices and knowledge bases, market economics, political actors and policies, social perceptions and behavioral or consumption patterns (Geels, 2002; Geels, 2004; Geels et al. 2017; Papachristos, 2018). However, this state is semi-stable due to internal tensions, for instance shrinking markets, loss of confidence in technology, addition or removal of supportive policies, diminished political capital of the dominant technology or changing societal pressures such as climate change concerns (Geels, et al. 2017). On one hand, the ability of an innovation to move up from a niche, and be competitive at the regime level depends on the benefits and improvements it offers, and the policy/economic/societal support it receives (Geels, et al. 2017). On the other hand, an innovation is in itself disruptive, and its ability to create and/or exploit regime tensions can also drive subsequent diffusion rates (Geels, et al. 2017). Both niche and regime levels are situated within a larger enabling environment, the landscape: a broad tapestry of heterogeneous factors forming the shape of society (Geels, 2002). Factors within the STs landscape include cultural and normative values, political coalitions, wars, economic growth or collapse (Geels, 2002). Such broad exogenous factors influence regime dynamics, driving changes in the intensity, duration and focal point of tensions within it. Landscape factors can dramatically influence the regime, creating shocks that create, or expand tensions, generating opportunities for innovations to diffuse. Landscape shocks can be price volatility of fossil fuels, energy scarcity/security, political upheaval, war, etc. (Sovacool, 2016). Taken together, the three levels make up the various interactions, temporal scales, and dynamics found in a ST.

4. RESULTS & DISCUSSION

The systematic consideration of pairwise connections for each of the five models resulted in 127 unique connections between the 29 transition attributes, presented in the edgelist in Table S1. Of these 127 connections, one connection was shared across three models, 21 links were shared across two models, and 105 connections were considered in only one. The cross-model CLD is shown in Figure 4, drawn in Kumu (2021).

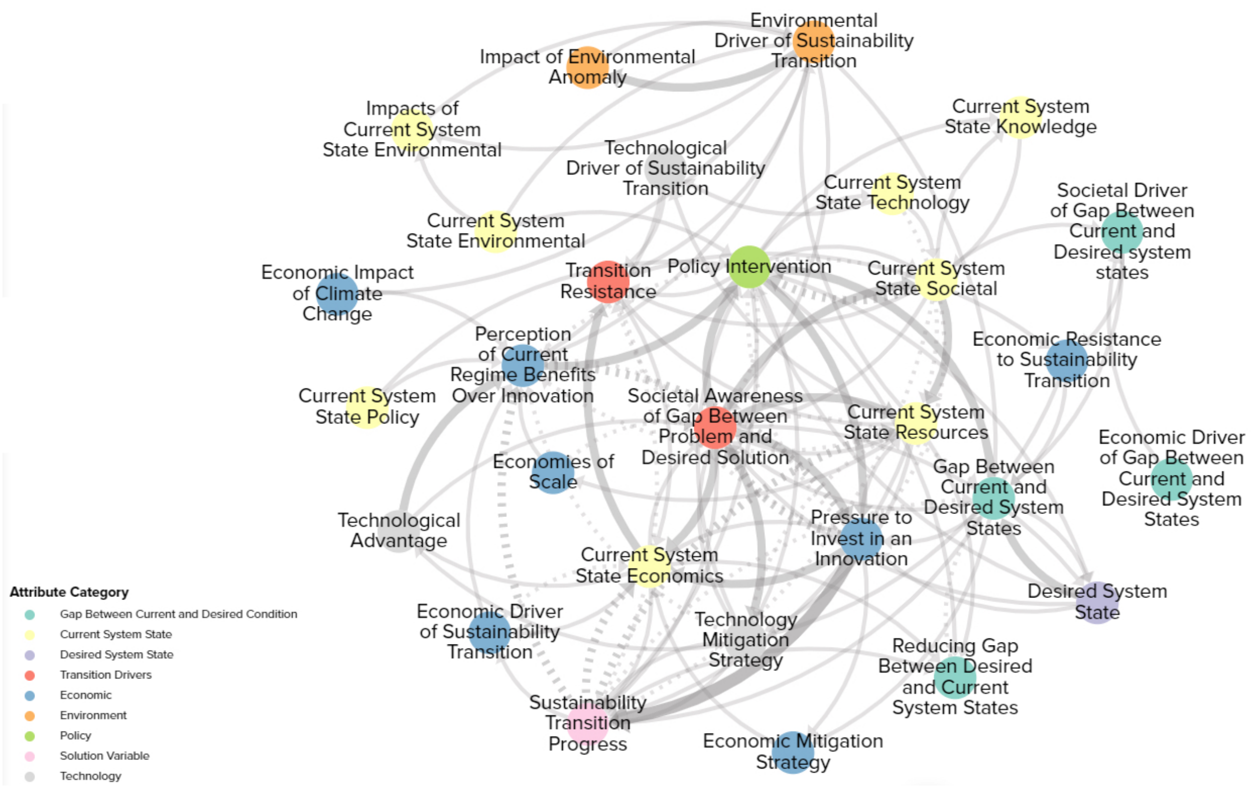

Figure 4: The cross-model CLD colored by attribute category. Line width indicates connection strength, based on the number of models that include that connection. Dashed lines indicate negative polarity.

Through the archetype identification process outlined in Section 3.5, a core feedback structure emerged from the prime loop and loops for each attribute within the prime loop, shown in Figure 5. The archetype that emerged from this process contained five sustainability transition attributes (Table 3): *Sustainability Transition Progress* (the solution variable), *Perceived Advantage of Innovation Resulting from Intervention, Pressure to Invest in Innovation, Societal Awareness of Gap Between Problem and Desired Solution, and Policy Intervention*, connected through a series of feedback loops. From this point forward, we will refer to this entire archetype as the 'Sustainability Transition Archetype'. The Archetype is composed of four balancing feedback loops representing different transition dynamics. These can be categorized as building blocks, or a 'suite of archetypes' (Eisenak, et al. 2021) that can be combined in any number of ways to characterize cases. The four feedback loops composing the Sustainability Transition Archetype are identified as:

- Loop 1: *Perception of Problem Severity Driving Investments*,
- Loop 2: *Niche Level Diffusion*,
- Loop 3: *Transitioning into the Regime*, and
- Loop 4: *Regime Level Competition*.

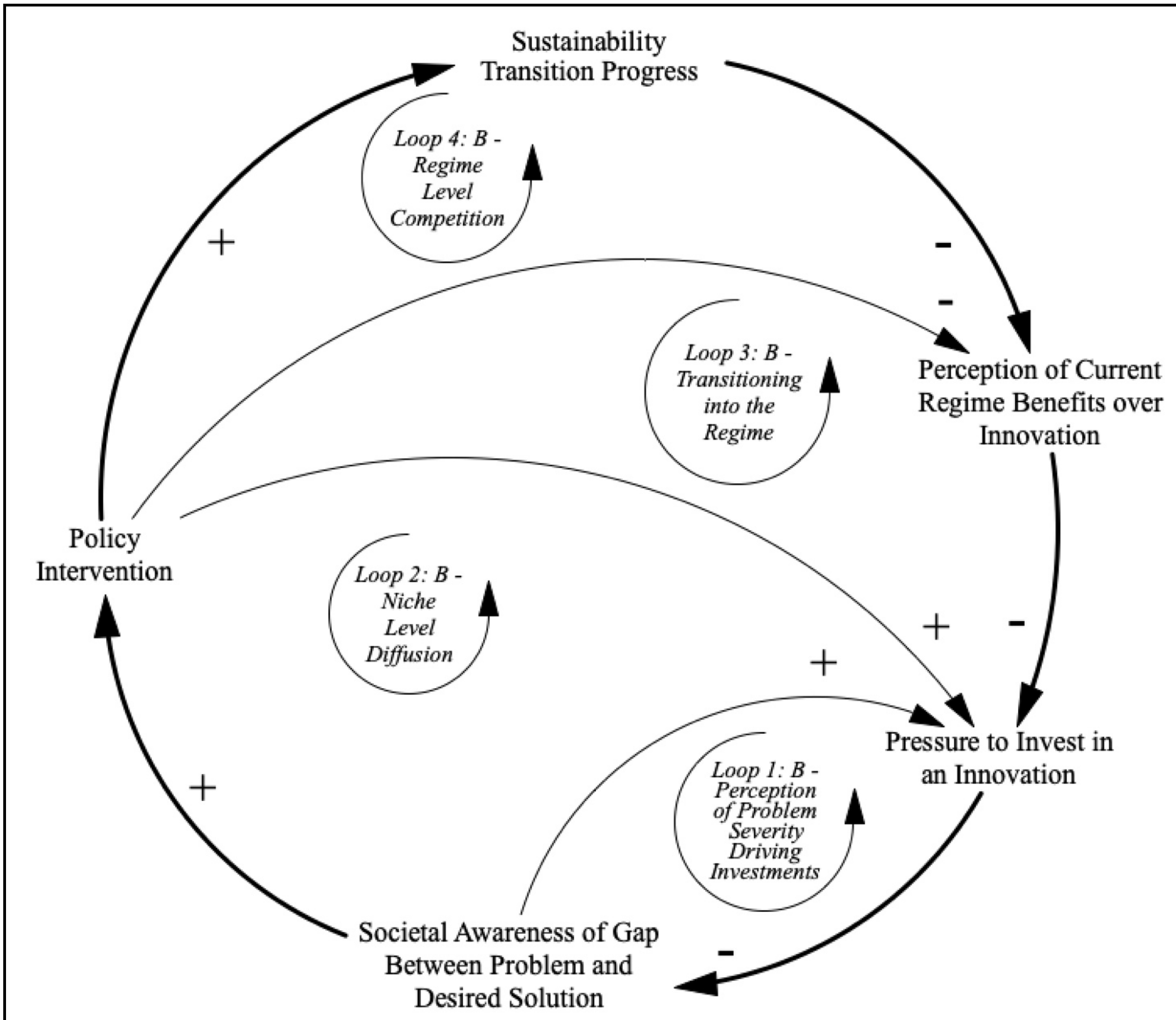

Figure 5. Transition Archetype. Bold lines indicate the connections present in the prime loop, while thin links indicate connections added through the process of finding the max loop for each attribute in the prime loop, per the process outlined in Section 3.5. Loop 1 represents the dynamics between societal perception of a problem and committing economic resources to its solution. Loop 2 is the societal recognition of a problem driving policy interventions increasing an innovation's economic competitiveness. Loop 3 captures rising contestation as an innovation moves out of the niche and into the regime. Loop 4 represents open competition between the innovation and dominant technology.

Broadly speaking, the archetype captures the progress rate of a sociotechnical sustainability transition (as measured by the attribute *'Sustainability Transition Progress'*) and economic, societal, and policy dynamics. In Loop 1, the attributes *'Societal Awareness of Gap Between Problem and Desired Solution'* and *'Pressure to Invest in Innovation'* are linked together in a balancing feedback loop named '*Perception of Problem Severity Driving Investments*'. The driver is the level of awareness, and perception of severity of an exogenous, landscape level pressure for a ST. In the case of Prouty, et al. (2019), the example is population growth driving increasing demand for a problematic wastewater treatment service. In Rees et al. (2016) transportation study, it is social perceptions of dwindling fossil fuel resources manifested as *'concern for energy* *security'*. As recognition of the need for a ST grows, societal will or pressure to address the problem with economic solutions also grows (Loorbach, et al. 2017). Social consensus about the severity of the problem drives where investments take place, positively impacting the attribute *'Pressure to Invest in Innovation'* and ultimately reducing the perception of severity, closing the *'Societal Awareness of Gap Between Problem and Desired Solution'*.

The second Loop, '*Niche Level Diffusion*', represents action intended to foster innovation diffusion and includes the '*Societal Awareness of Gap Between Problem and Desired Solution', 'Policy Intervention' and 'Pressure to Invest in Innovation'* attributes. Although barriers to innovation diffusion are socio-technical in nature, representing among others, economics, knowledge, trust, and individual socio-demographics, the higher capital costs associated with an innovation is arguably one of the most critical factors driving innovation diffusion (Geels, 2002; Balcombe, et al. 2013). This requires risk comfortable investors, or financial incentives from the government. There are many approaches directly targeting market inequalities that innovations must overcome. Two examples are greater investment in Research & Development (Jacobsson and Lauber, 2006), or economic incentives designed to address the market inequalities (Hekkert and Negro, 2009). Both are present in the included case studies, with R & D found in Kim, et al. (2019), and incentives found in Rees, et al. (2016), Kim, et al. (2019), and Salim, et al. (2021). Each of these impacts the *'Pressure to Invest in Innovation*' attribute, by artificially reducing the cost or investment risk. However, we recognize niche or innovation diffusion is more finely nuanced, containing (among others) characteristics of both the adopters and the innovation itself (Rogers, 1962; Metcalf, 1981), how the number of previous adopters influences subsequent adoption (Bass, 1969) as well as communication channels, information flows and the communities to which consumers belong to (Noll et al. 2014). The five models included in our combined ST model focused primarily on economic drivers of diffusion and as such these other, critical factors are not fully addressed in this study.

The third Loop, '*Transitioning into the Regime*', is also balancing and represents transition dynamics as innovation diffusion accelerates, moving from the niche into the regime. STs require policy support to guide both their trajectory and pace. However, expanding out of specialty markets or limited geographies brings an innovation into contact with a much broader set of socio–technical system actors, firms, and vested interests, each with their own subjective definitions on what is the best innovation, trajectory, or pace (Köhler, et al. 2019). Differing perceptions and values result in disagreements, creating contextualized geographical, political, social and economic contestation over a transition's normative directionality (Köhler, et al. 2019**)**. Whereas the '*Niche Level Diffusion'* directly incentivizes specific innovations in order to begin diffusion into specialty markets, '*Transitioning into the Regime*' represents a greater diversity of socio-technical system actors, firms, and vested interests as well as their contestation for policy, with policies either facilitating an innovation's continued expansion of market share, or manifesting as resistance to transitions (Gottschamer and Zhang, 2020). This loop contains the attributes; *'Societal Awareness of Gap Between Problem and Desired Solution', 'Policy Intervention', 'Pressure to Invest in Innovation*. The dynamics discussed above are represented in the Rees et al. (2016) model with push-pull tensions manifesting on one hand as oil company subsidies, and on the other with fuel taxes and policies supporting alternative fuels.

The fourth loop, '*Regime Level Competition',* extends '*Transitioning into the Regime'* dynamics as the innovation exits the niche, entering into the regime as a competitive alternative to the dominant status quo. This loop captures the dynamics of increasing competition. As the quantity of the solution variable, *'Sustainability Transition Progress'* increases, cost reductions driven by learning-by-doing and learning curves occur. As the cost drops, there is a corresponding decrease in the *'Perceived Advantage of Innovation Resulting from Intervention'* attribute and a subsequent rise in *'Pressure to Invest in Innovation'*. However, the innovation still has a number of significant diffusion challenges related to the nature of socio-technical systems. Such systems are characterized by the co-evolution of technologies, consumption behaviors, supply chains, and a number of other reinforcing factors (Geels, et al. 2017a).

This co-evolution and alignment results in deeply entrenched, mutually reinforcing feedback loops stabilizing the dominant regime, and reorganization is generally incremental and path dependent (Klitkou, et al. 2015; Hughes, 1987). Path dependency or 'lock-in' can be economic, where sunk investments or economies of scale favor the continued use of the dominant technology (Geels, 2019). Lock-in can also be enforced through social norms, behaviors and lifestyles (Nelson, 2008). Additionally, lock-in can be institutional, where existing regulations and policies disproportionately favor dominant technologies (Walker, 2000), or political, where vested economic interests employ policy-influencing networks to protect the status quo (Gottschamer and Zhang, 2020; Normann, 2017). At this stage, general disagreements over the normative direction of the transition still exist. However competition is intensifying as greater quantities of firms, actors, consumers etc., unite around an innovative technology (Geels & Schot, 2007). Competition occurs in the economic domain, manifesting as market inequalities favoring the dominant technology or between new and vested business entities. Competition is also political; with attempts made to influence policy-making favoring vested special interests. Vested interests can also influence public discourse, with competing narratives attempting to shape how problems and associated solutions are framed.

As more resources are allocated to *'Investments in Innovation'*, '*Policy Intervention'* becomes highly politicized with intense competition for pro- or anti-innovation policy. Unstable and inconsistent policy environments then impact the *'Sustainability Transition Progress'* rate, with subsequent influences across *'Perception of Current Regime Benefits over Innovation','Pressure to Invest in Innovation', 'Societal Awareness of Gap Between Problem and Desired Solution'* attributes. The models included in our study captured these competition dynamics; Rees, et al. (2016) by including policy support for both fossil-based and alternative fuels. Kim, et al. (2019) examined environmental impacts driving societal awareness, which then influenced subsequent policy support and investment into biofuel R&D. Salim, et al. (2021) included government R&D backing for recycling end-of-life PV panels, and enforcement actions intended to increase industry support for recycling. Turner et al. (2016) modeled feedback between a community and its willingness to engage in resource management practices. This, in turn, influenced land-use with subsequent changes in both economics and environmental impacts.

The transition archetype presented in this study closely captures generalized socio-technical ST dynamics pertinent to a diversity of cases. At the landscape level, the archetype describes dynamics between a problem requiring a sociotechnical-scale transition, and a willingness to take economic or policy action. These dynamics then influence the quantity of niche-level opportunities for creating and diffusing innovations. However, niche level dynamics do not favor innovations, and expanding beyond niche users or early adopters requires policy interventions to address significant market inequalities. As innovation diffusion increases, the dynamics of transitioning into the regime manifest; where a greater diversity of socio-technical system actors, firms, and vested interests drive contestation for policy. Policy support for innovations is still critical to diffusion at this stage. However, contestation dynamics drive policy instability, where policies either facilitate or hinder innovation diffusion. As an innovation gains regime-level market share, structural realignment of the socio-technical system comes into play as new actors, firms, and vested interests coalesce around the innovation. This intensifies contestation, creating ongoing competition across political, economic, social and technological domains. Regime-level dynamics of contestation, path-dependency, and active transition resistance shape the pace, and success of such transitions.

4.1. IMPLICATIONS AND FUTURE WORK

Archetypes are useful tools for examining current undesirable behaviors (Braun, 2002). They provide clarity on the fundamental nature of a problem through a deeper understanding of why a behavior manifests (Kim, 1994), identify high-leverage intervention points where the most beneficial change can be implemented for the least amount of effort (Kim, 1992), allow policies or protocols to be evaluated against the drivers of current behavior (Braun, 2002) and serve as guide for developing more refined models (Braun, 2002). The archetype extracted in this study through a comparative analysis of SD ST models provides novel insights on generalizable leverage points and behavior, as well as illuminating the types of attributes and feedback loops SD modelers are including in socio-technical STs.

The archetype provides novel insights on a number of ST leverage points. The first is related to landscape pressures shaping *Societal Awareness of Gap Between Problem and Desired Solution'*. The landscape is a broad tapestry of factors such as cultural and normative values, climate change, wars, economic growth or collapse factors (Geels, 2002). These reside above the regime level, influencing regime path-dependency dynamics through status-quo reinforcement, or destabilization and creation of innovation diffusion opportunities. Substantial research examining landscape influence on regime dynamics is lacking (Kanger, et al. 2020) and what research exists suggests interventions designed to shape trajectories require addressing globally diffused factors. Kanger, et al. (2020) indicate international, or global-scale binding agreements such as the Kyoto Protocol can be effective. Fuenfschilling and Binz, (2018), describe how socio-technical system cultures reside not only in specific geographies, but also across distributed networks of service providers. The act of same-service provision across a broad suite of actors and geographies creates a shared culture of structurally similar accepted practices, resulting in mutually reinforcing, landscape-level challenges to innovation diffusion. Only two of the included models had exogenous attributes describing openings in the regime for innovation. Prouty, et al. (2020) modeled increased population growth driving wastewater treatment demand, and Kim, et al. (2019) included economic growth driving aviation emissions from fossil fuels. Transition research would benefit from including such topics in future modeling efforts. An additional leverage point with *'Societal Awareness of Gap Between Problem and Desired Solution'* is societal perceptions of the problem. This entails not only an awareness of what the problem is, but the acceptance of the problem's validity and severity. There is a broad swath of research examining societal perceptions of transitions (Devine-Wright, 2005; Devine-Wright, 2011; Henkel et al. 2013). However, only one model, Kim, et al. (2019) included feedback between resource consumption, environmental impact and public awareness driving policy making. This is also a research area ripe for further modeling efforts.

Another critical leverage point is how the attribute *'Policy Intervention'* is modeled. SD has an extensive history of policy analysis applications and while modeling policy levers is not a novel application, the specifics of how modelers are approaching transition dynamics is revealing. Four of the five models incorporate supportive government strategies for innovations by influencing diffusion economics, most commonly by addressing an innovation's higher cost. Kim, et al. (2019) included biofuel subsidies and investments in R&D, Salim, et al. (2021) included R&D, Rees, et al. (2016) included policies subsidizing alternative fuels and fossil fuel taxes. While not explicitly present in their CLD, Prouty, et al. (2020), discussed how policy levers can facilitate investments in novel technologies. However, policy contestation was underrepresented, present in only Rees, et al. (2016) by dynamics between oil company subsidies, and both fuel taxes and policies supporting alternative fuels. The modeling focus on policy impacts while excluding contestation or competition dynamics, highlights a promising arena for future transitions research.

Another point to highlight is the way in which the ST archetype appears to bias towards balancing loops. Balancing loops slow the behavior of a system (Sterman, 2000), and we believe the lack of reinforcing loops in the ST archetype stems from an abstraction level focusing on slowing landscape-level behaviors driving transitions. There were numerous examples within the included case studies of critical reinforcing loops driving dynamics. For example, Rees, et al. (2016) included a *'reinforcing the status quo'* loop. Kim, et al. (2019) included reinforcing *'demand-production-price'* feedback driving cost reductions in aviation biofuel.

Conducting a comparative analysis of system dynamics models across multiple socio-technical STs domains revealed both challenges, and insights pertinent to the STs field. While we followed established best practices in archetype analysis to extract generalizable meaning from individual transition models, two significant challenges in the process were identified. The first was classifying common attributes to use across the different model contexts. A significant body of research highlights various socio-economic-political-technological attributes found in socio-technical system transitions. However, these differ across specific systems (Please refer to Markard, et al., 2012; Geels, 2004; and Köhler, et al. 2019). While Köhler et al. (2019) recommended a formalized set of indicators to measure transitions, these were intended as metrics to capture progress across multiple economic, technological, social or environmental domains (Köholer et al. 2019) not as mid-level abstracted components intended for use in an archetype analysis. To the best of our knowledge, no such typology of transition components exists. Given this, we followed the socio-technical systems and ST literature to arrive at five core components. Future archetype analyses based on SD, or other modeling approaches would benefit from a harmonized set of transition attributes.

The second challenge related to an archetype analysis of SD transition models is identifying an appropriate level of abstraction. While this study followed established protocols, we acknowledge it is highly subjective. The first of our two-step process allowed us to identify the attributes the model builders' intended as a metric of ST progress. Abstracting other attributes was iterative, grounded in the question, *'How does this attribute/relationship/feedback within the model affect/modify/influence the five identified components?* Using this as a guide, we arrived at an abstraction level based on an attribute's functional impact within the identified components (Section 3.3). This captured both the attribute's original meaning, while allowing for the construction of a common vocabulary of attributes applicable across cases.

We acknowledge further work is needed to better integrate best archetype analysis practices from socio-ecological studies with both system dynamics, and other ST modeling methodologies. One critical knowledge gap is identifying core components found in such transitions. The components, and their definitions used in this study represent a first attempt to delineate categories of attributes within transitions. Another fruitful area of future research is formalizing the level of abstraction required to create cross-model attributes. Although we followed standard system dynamics protocols for abstracting neutral cross-model attributes, we acknowledge that this first attempt opens the door for further refinement in this area. Furthermore, future transition studies would benefit from this research topic across modeling methodologies. One other critical research area is the modeling focus on economic-policy-technology drivers of STs. These attributes are highly influenced by other critical factors such as ideas of normative directionality and contestation. Further transition studies would benefit from research on what is driving the economic-policy-technology drivers. Abstracting core dynamics from attributes that are influencing these drivers would likely provide greater insights on economic-policy-technology leverage points.

4.2 LIMITATIONS

We recognize this novel archetype analysis of system dynamics sustainability transition models has a number of critical limitations. The first is the low number of ST models used in the study. The archetype analysis required comparing system structure across diverse transition modeling domains, necessitating a comprehensive CLD. While many published SD transition models exist, few contain CLDs that were sufficiently detailed for this type of analysis. The SD transition modeling field would benefit from standardized inclusion of CLDs and SFDs. A second limitation related to case study models is the focus on technological aspects of STs. Four of the five case-study models examined technological innovations, emphasizing economic-policy feedback influence on diffusion rates, over other equally critical transition factors (or attributes) such as social perceptions, norms, behaviors and acceptance. Future archetype analyses using SD or agent-based modeling that include such factors would likely illuminate other generalizable transition dynamics. Another limitation is the lack of a formal socio-technical system definition of included ST attributes. This study followed both ST, and socio-technical systems literature to arrive at the five components of cases used in this analysis. These components were instrumental in defining attributes, and future studies applying archetype analysis to transition models would benefit from a formal definition of both components and attributes. A fourth limitation to this research is the level of abstraction employed to extract generalizable meanings from the case studies. Although we followed archetype analysis best practices, the abstraction level, as well as the common vocabulary of attributes employed entailed a degree of subjectivity. We believe that the process of deriving both is a starting point that can be extended into future ST archetype studies. Such studies would benefit from a formalized conceptualization of how best to abstract model structure.

5. CONCLUSION

ST research has typically focused on single case studies to understand dynamics and provide actionable insights policy makers can use for shaping both transition trajectories and pacing. While broad analytical frameworks are used to understand transitions, a knowledge gap lies between case-specific transition studies and such frameworks. Specifically, this gap entails an understanding regarding common structures and the interactions of factors and patterns across STs. This study bridges that gap through a novel archetype analysis of System Dynamics ST models. Comparing structural patterns found in transition models across a diversity of research domains allowed an 'archetype' to emerge that captures not only generalizable dynamics, but also illuminated leverage points as well. The archetype found in this study captures transition dynamics as an innovation moves from early adoption to open competition with the regime-level status quo. In so doing, this study presents a novel synthesis of ST dynamics capable of bridging the gap between large-scale analytical frameworks such as the MLP, and case-study specific studies of individual transitions. Future research grounded in a systems perspective can provide actionable understanding capable of providing insights on how to address transition complexities. Understanding, and managing such complexity rests not only on the macro-scale analytical frameworks currently shaping ST discourse, but must include both the specific factors related to a highly contextualized ST, as well as broader insights derived from a systems level recognition of common patterns and dynamics.

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