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RESEARCH ARTICLE

Employing a Mental Model Framework to Explore Systems Thinking

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ABSTRACT

This article conceptualizes systems thinking from the perspective of mental models. It portrays systems thinking as a combination of perception, prior knowledge and reasoning processes for guiding decision-making in complex, dynamic situations. Systems thinking is mostly considered as a skill, and assessment instruments are based on the observable products of thinking. However, there is a lack of research on the cognitive processes involved in generating mental representations of complex dynamic systems, deriving possible behaviours and decisions. Thus, we propose a conceptual framework that combines *mental models of dynamic systems* and the cognitive theory of reasoning with *mental models of possibilities*. This theory identifies an intuitive and a deliberative reasoning process describing how the deliberative process influences the mental model of the perceived situation. While remaining compatible with the existing literature on systems thinking, this framework addresses this gap. Through examples, the study illustrates how the distinct levels of systems thinking knowledge of three stylized agents lead to different models, even when the reasoning process is identical. Boundary mismatch errors in the represented structure lead to errors in judging-system behaviours as necessary, possible or impossible, leading to different decisions. Based on this finding, several new research questions are proposed concerning the dynamics of the cognitive processes and mental models over the iterations of dynamic decision-making in laboratory experiments. We close with a call for more research to move beyond the current limitations.

1 | Introduction

This article contributes to research on systems thinking (ST) from the perspective of mental models and focusing on the ways people attempt to regulate their decisions when interacting with a complex dynamic *situation*. This complexity stems from many interacting elements, and they are dynamic because their behaviour and partially opaque structure can change. People experience complex *problems* (Dorner and Funke 2017) when they must interact with the *system* underlying such a situation and therefore need to discover or recognize (a) the system's structure, (b) the range of possible behaviours and (c) how to best proceed given their needs or wants. At the surface, the *situation* is a set of salient behaviours of variables (e.g., global temperatures and CO_2 emissions). Then, the gap between how global temperature evolves and how they want it to be is a complex *problem* in the sense of the three above-mentioned elements. Once a course of action has been decided and implemented, the ensuing actions can have the intended effects on the system or trigger unplanned consequences. This then leads to another iteration of complex problem solving. In the remainder of this article, *situation* is shorthand for complex dynamic situations. Thinking

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Summary

- Mental models combine prior knowledge and perceptions of complex problems.
- Deliberate reasoning assesses more possible system behaviours than intuitive reasoning.
- Reasoning with mental models links structural knowledge to decision policies.

systemically promises to be helpful, and it is important for the population at large because everybody is currently interacting with such situations. Unsurprisingly, it has been the theme of over 260 articles published in *Systems Research and Behavioral Science* between 2002 and 2023 (80 of them since 2020, according to Web of Science).

Thinking is a set of mental processes that work with and transform knowledge and mental representations 'to characterize actual or possible states of the world' (Holyoak and Morrison 2005, 2) and to plan and execute behaviours (Minda 2015, 4). Interestingly, most of the over 20 definitions and assessment instruments for systems thinking identified by Dugan et al. (2022) concentrate on the products of such thinking. However, only few authors discuss the aspects of cognition, identifying common general features. The products are undoubtedly an important aspect, and methodologies for thinking systemically, such as the soft systems methodology (Checkland and Poulter 2020), have guided practitioners for decades. Also, the various instruments developed to assess people's systems thinking skill level are relevant.

Yet, we contend that an exclusive focus on skill overlooks important elements of the internal mental or cognitive processes. A clearer understanding of the thinking process itself (e.g., learning more about how reasoning processes and personal knowledge interact and how this allows attaining certain skill levels) would help advance the field.

To make a first step in this direction and start a scholarly debate, we lay out a conceptual framework for reasoning that is compatible with the skill-set view of systems thinking and combines two well-established domains of mental model research. First, in various areas where people and managers decide on courses of action, researchers have conceptualized the inner representations decision-makers hold of the situations they face as mental models (Johnson-Laird 2004; Schaffernicht and Groesser 2024). The concept of *mental models of dynamic systems* has been operationalized specifically for decision-making in complex dynamic situations (Groesser and Schaffernicht 2012; Schaffernicht 2019; Schaffernicht and Groesser 2024). This kind of mental model denotes how someone considers a situation to be structured, and we use the term *structure model*.

The second domain is the cognitive theory of reasoning with mental models of possibilities (Johnson-Laird and Ragni 2019; Khemlani, Byrne, and Johnson-Laird 2018). It proposes that people think about situations and their decisions in terms of *mental models of possibilities*. The theory also describes two different reasoning processes: one for quick processing of the most salient possibility, and the other for deploying and processing all reasonable possibilities (Stanovich 2012). Our focus is on possible behaviours of variables, hence the term *behaviour models* in this study. The second reasoning process can also alter the structure model based on personal knowledge (Khemlani and Johnson-Laird 2022), which makes this theory particularly interesting for iterated decisions where each iteration can provide new knowledge.

We combine mental models of dynamic systems that describe causal structure with mental models of possibilities representing this structure's possible behaviours. Through an example based on previous studies, we show how three individuals with distinct knowledge bases—without prior knowledge, with context-specific knowledge, and with knowledge of systems principles—construct their respective structure model combining situational information and knowledge (where available) and then derive behaviour models, leading to decisions of distinct degrees of adequacy. This also reveals two types of mental model errors, the first of which are boundary mismatches: The structure model lacks elements needed to account for the system behaviour. The second type of errors happens at the behaviour models level: People can (a) obviate relevant possibilities but also (b) mistakenly process presumable possibilities that are impossible in the particular situation. The latter is a consequence of structure model boundary mismatches. This underlines the importance of prior knowledge to avoid structure model errors. We observe that adequate context-specific knowledge and knowledge of more generic systems principles both lead to equivalent behaviour models and decisions.

The article is organized as follows. Section 2 reviews the extant literature, examining the conceptualizations of systems thinking and relevant links to other themes in cognition and arguing that treating systems thinking as a skill-set leaves the cognition aspects out of focus. Next, Section 3 introduces mental models at large, with both types of mental models used here and later combined. Section 4 discusses the proposed framework, together with some of its implications and research questions arising. The conclusion section summarizes our results, outlines some limitations and calls for empirical studies.

2 | Systems Thinking

2.1 | Conceptual Definitions

Systems thinking is 'a broad church' (Burnell 2016, 472), described by some very aggregated and general conceptual definitions. For instance, Cabrera, Cabrera, and Powers (2015) proposed four universal components. This kind of thinking occurs from a particular *perspective*, which allows people to *distinguish* certain features in the situation taken as a whole, and the *relationships* perceived between the distinguished fragments bring everything back together to form the perceived *system*. Others define it as a cognitive paradigm for perceiving oneself and the world as interdependent entities that continuously generate emergent patterns (Randle and Stroink 2018, 646).

These conceptual definitions delimit the general meaning without the specifics needed to tell whether or to which degree a particular act of thinking is systemic. However, at a more disaggregated level of description, definitions are diverse. Buckle Henning and Chen (2012) synthesized 14 definitions into five knowledge domains: People should know particular laws, basic system types, system dynamics and archetypal patterns and multiple methodologies developed by systems scholars; they should also know how to draw visual models of a system (475). This study also identified the following six cognitive characteristics: mental orientation towards causality, logic, data sources, explicit and implicit structures, subjectivity and self-reflection (478).

The question arises how the research object 'systems thinking' intersects with other cognition constructs. Davis and Stroink (2016) used an assessment scale developed for the definition described by Randle and Stroink (2018) and investigated the relationships between several personality measures and decision tasks developed in psychological research (Randle and Stroink 2018; Thibodeau, Frantz, and Stroink 2016). They found that intelligence and cognitive complexity overlap with systems thinking, but they do not fully explain the diversity of systems thinking performances (Randle and Stroink 2018). From the standpoint of psychology and cognition, systems thinking merits to be investigated in its own right.

Turning to other cognition aspects, prior (content-related, system-specific) knowledge and general conceptions influence people's reasoning about a particular system (Mambrey, Schreiber, and Schmiemann 2020). Here, knowledge refers to conceptually knowing what the entities in the system are, how they are interrelated and how they usually behave. Novices without such knowledge focus on readily available, salient information and static surface features, whereas domain experts integrate the aspects of the system's inner structure and behaviour. However, although flawed mental representations are attributable to a lack of 'systems-specific content knowledge' (Sweeney and Sterman 2007, 305), content-related knowledge is not systems knowledge: The former may contain systemic features but is specific, as opposed to the latter, which is general an abstract.

In contrast to system-specific knowledge, general conceptions are intuitive notions and beliefs people have about things. Humans approach decision-making situations by employing 'reasonable and viable conceptions based on their experiences in different contexts or in their daily life activities' (Fujii 2014, 453). Treating the new through what is already known allows to steer decisions and behaviours in a fluid and economical manner, but it also leads to systematic errors when being at odds with scientific principles. This has led to terms such as 'naïve beliefs' or 'misconceptions', albeit without a pejorative intent (Resbiantoro, Setiani, and Dwikoranto 2022). In addition, individuals without special training, who employ such naïve beliefs, are referred to as laypeople (Buckle Henning and Chen 2012) without value judgements.

Some conceptions can make people focus on linear causal chains and overlook interdependencies, a phenomenon studied under the term 'misperception of feedback' (Gary and Wood 2016; Moxnes 2000, 2004; Moxnes and Saysel 2009; Sterman 1989). Another conception is that in a cause–effect relationship, the effect is analogous to the cause; however, this fails when one factor is a flow rate and the other a stock (state variable) accumulating the flow (Sterman 2010; Sweeney and Sterman 2000; Sweeny and Sterman 2005). Both problems have been reported for individuals without domain-specific knowledge or systems knowledge. General education does not appear to overcome these shortcomings (Cronin, Gonzalez, and Sterman 2009), and mathematical training has a limited effect (Qi and Gonzalez 2015; Sterman 2010). There is evidence suggesting that thinking styles and metacognition may be partially responsible (Aşık and Doğança Küçük 2021; Baghaei Lakeh and Ghaffarzadegan 2015; Brauch and Größler 2022), but they do not fully explain the phenomenon. Contrary to individuals without specific preparation, trained subjects tend not to fall victim to these flaws related to systems thinking (Plate 2010). In such cases, flawed 'understanding of basic systems concepts' is a hindrance (Sweeney and Sterman 2000, 251). Buckle Henning and Chen (2012) also observed the absence of a unified set of principles and conceptions.

2.2 | Systems Thinking as a Skill

System-specific conceptual knowledge, general conceptions and basic systems concepts are types of knowledge. Hosted in long-term or in working memory, they are apparently used in the reasoning processes, but are not the processes themselves. Yet, they influence people's systemsthinking performance. Performance has to be connected with a skill. Indeed, most publications have discussed systems thinking as a skill-set. Whereas the above manifestations of knowledge are mental in the sense of private to the individual, skill is a relational phenomenon, involving an individual's actions in a task, classified by some schema containing certain dimensions. A skill combines knowledge and performance in a specific class of situations (Sadler 2013; Shavelson 2010): A skill shows in the performed ability to distinguish what is going on, to decide what is to be done and then do it. Skills are not innate but can be learned and developed through stages or levels from novice to expert (Dall'Alba and Sandberg 2006; Eraut 2000). The performative aspect differentiates skills from knowledge and basic conceptions, leading to the following two consequences: (1) A concrete situational context is required to learn a skill and to assess the current skill development stage of an individual, and (2) skill assessment depends on the possibility to observe performance.

Considering the first consequence, systems thinking as a skill is usually taught in the context of a specific knowledge area containing systems. Most authors justify this by the usefulness of systems thinking to better understand the respective knowledge field. Importantly, improved domain knowledge has been found to improve systems thinking performance (Mambrey, Schreiber, and Schmiemann 2020), suggesting a fruitful interaction between domain knowledge and systems thinking. Teaching starts in early childhood (Feriver et al. 2020), where applications have concentrated on Earth systems and geography education (Assaraf and Orion 2005, 2010; Batzri et al. 2015; Lee, Gail Jones, and Chesnutt 2017; Mambrey, Schreiber, and Schmiemann 2020; Mehren et al. 2018; Sweeney and Sterman 2007), sustainability (Mahaffy et al. 2019) and STEM education (York et al. 2019) as well as Next Generation Science

(Eidin et al. 2023). In high school and at the undergraduate level, systems thinking is taught in biology (Raved and Yarden 2014; Tripto, Assaraf, and Amit 2018), chemistry (Paschalidou, Salta, and Koulougliotis 2022; Pazicni and Flynn 2019; York and Orgill 2020), engineering (Dugan et al. 2022) and physiology (Wellmanns and Schmiemann 2022).

The fact that systems thinking is being taught does not mean that it cannot be learned independently. The question of the extent to which people without specific training think systemically motivated Burnell (2016) to develop an assessment tool based on the six aspects proposed by Buckle Henning and Chen (2012). Burnell reported that individuals with systems thinking training have a higher tendency towards causality, logic and self-reflection than people without such training. In addition, a study of systems knowledge levels and the attitude towards systems thinking as a tool among individuals without specific training found that respondents 'tend to either overestimate or underestimate their knowledge of systems, social systems, and use of systems thinking' (Dawidowicz 2012, 9).

Several operational definitions come from educational contexts and provide a clearer understanding of the concept. They establish sets of skills that, taken together, constitute the systems thinking competence. Moreover, by specifying more detailed 'abilities', these definitions enable us to infer specific items of knowledge required or useful for systems thinking. In a systematic literature review, Dugan et al. (2022) identified 27 assessment tools developed in a range of thematic fields (mostly engineering, chemistry, biology, environment and STEM) for diverse educational levels from pre–high school to professional. The definitions of systems thinking underpinning the assessment tools varied widely (see 852–856); some high-level conceptual definitions, such as 'seeing the whole', and many contain the ability to identify a system's elements and the relationships between them and to understand its dynamic behaviour, reminiscent of the above mentioned universal components. Only 18 assessments used a sufficiently operational definition to be evaluated, and 13 of them revealed operational details of systems thinking, explicitly accounting for a system's elements, relationships and behaviour.

One definition is operational—the 'systems thinking hierarchy' (STH), originally developed for Earth systems education (specifically the water cycle) by Assaraf and Orion (2005). It comprises eight skills organized into three levels. Level 1, *analysis*, is the ability to (1) identify the components of a system and processes within the system. *Synthesis* is the second level, and it comprises the ability to (2) identify the relationships among the system's components, to (3) organize the systems' components and processes within a framework of relationships, to (4) make generalizations and to (5) identify dynamic relationships within the system. The third and the highest level is to (6) understand the hidden dimensions of the system (recognizing patterns of change and interrelationships not visible on the surface), to (7) understand the cyclic nature of systems and to (8) think temporally (i.e., *retrospection and prediction*; 523).

Mehren et al. (2018) further expanded the STH, proposing an empirically corroborated skills model with three stages of systems thinking skill development. Individuals at the first stage identify a system's organization: (1) its boundary and (2) the internal organization. Someone who understands (3) a system's past behaviour, (4) its emergent characteristics, (5) the interactions between components and (6) the system's dynamics, has reached the second stage. At the third stage, a person is able to (7) predict the system's future behaviour and (8) conceive of regulatory measures.

These definitions come from specific knowledge areas, but they arguably describe more general and area-independent skills. Being able to identify a boundary, the elements inside it and the relations among them implies either prior area-specific knowledge or the general knowledge that systems have a boundary with interrelated elements inside, paired with the practical knowledge to use the conceptual knowledge. Similarly, being able to explain observed behaviours referring to the structural components is the consequence of either retrieving the respective explanations from long-term memory or knowing the principles of how behaviour is driven by structure and the practical knowledge of applying them. The same holds true for the ability to think up regulatory interventions and their likely consequences, even though deriving possible behaviours from structure may be more difficult than explaining observed behaviours by structure.

Next, we consider the second consequence of the performative aspect of skill, which is that performance implies observability. For instance, the cockpit behaviour of pilots reveals their skill level and is directly observable (for a classical application, see Dreyfus and Dreyfus 1980). Contrary to this example, how an individual *thinks* is usually not observed directly but must be inferred from the outcomes of the thinking process (answers to closed or open questions and/or decisions in simulation experiments). Yet, thinking as the mental process is performed by the mind before becoming externally observable.

The above definitions establish the desired *products* of systems thinking. These products articulate the mental content of the thinking process when it concludes and is articulated. In the earlier stages of the mental processes, basic conceptions and prior knowledge have been found to interact with the situational perception, and the mental or cognitive process then interacts with this content until the individual articulates something observable (Mambrey, Schreiber, and Schmiemann 2020). The interplay between cognitive structures and processes comes before what skill assessments mostly capture. Although some systems thinking authors mention the difference between the *process* of reasoning on one hand and the *structure* of the mental representations referred to as knowledge (Buckle Henning and Chen 2012) or as mental models (Cabrera, Cabrera, and Powers 2015) on the other, they do not address details.

2.3 | The Need to Include Reasoning Processes

Differences in the observed levels of systems thinking skill may stem from the reasoning process as much as from prior knowledge (content-related knowledge or conceptions). Reasoning has interested philosophers and scientists who have proposed cognitive theories based on mental logic (O'Brien 2011; O'Brien 2014), probabilistic reasoning (Holyoak and Morrison 2005; Oaksford and Chater 2009; Sloman and Lagnado 2015) and mental models (Johnson-Laird 2010; Johnson-Laird and Ragni 2019; Khemlani, Byrne, and Johnson-Laird 2018).

Here, a theory of reasoning must describe how people perform the mental tasks implied by skillful systems thinking. Looking at a partially opaque situation, people only have a mixture of perception prior to domain-related knowledge and conceptions (Johnson-Laird 2010), and they must first construct their mental equivalent of the situation through induction or abduction—a process yielding putative explanations (Johnson-Laird, Girotto, and Legrenzi 2004).

The first dimension in the definition developed by Mehren et al. (2018) contains an inductive/abductive task, which is making up one's mind about the structure of the situation. A system's conceptual boundary thus emerges according to the individual's goal and perspective. The result may but does not have to be a feedback-rich causal structure with interdependent elements that drive the system's relevant behaviour traits from the inside (endogenously), making it resilient regarding external influences (Buckle Henning and Chen 2012, 474). Scholars from diverse areas have discussed this aspect (Amissah, Gannon, and Monat 2020; Arnold and Wade 2015, 2017; Assaraf and Orion 2010; Cabrera and Cabrera 2019; Evagorou et al. 2009; Kunc 2008; Plate and Monroe 2014; Raved and Yarden 2014; Shastri and Ajjanagadde 1990; Stave and Hopper 2007; Sweeney and Sterman 2000, 2007).

The remaining dimensions call for deduction—explaining past dynamics in terms of that structure and elaborating a hypothetical course of action. Past behaviours are part of the individual's knowledge, allowing people to compare deduced to known behaviours. However, predicting the likely consequences of different interventions and devising a promising course of action cannot draw on knowledge of the particular situation as a benchmark to identify flawed expectations; nonetheless, it can benefit from the individual knowing this type of situation or becoming knowledgeable about systems principles.

A cognitive theory of reasoning for systems thinking must therefore comprise inductive (abductive) as deductive reasoning. To the best of our knowledge, the cognitive theory of mental models is the only one providing a detailed description of how the mind brings prior knowledge to induce the representation of a situation (Johnson-Laird and Ragni 2019; Khemlani, Byrne, and Johnson-Laird 2018; Khemlani and Johnson-Laird 2019).

3 | Mental Models

3.1 | Mental Models in General

A general tenet of mental model researchers is that people make internal iconic representations of situations so that they can know what the case is and plan their moves. Iconic here means that such models are analogous to the situation. Johnson-Laird, Girotto, and Legrenzi (2004) mentioned Peirce (1931–1958) as a precursor of this idea; albeit the term *mental model* was first used by Craik (1943) and has since been adopted by several disciplines (for an overview of mental models as knowledge representation, see Jones et al. 2011). In an early overview of the term and its use across different fields, Rouse and Morris (1986) discussed mental models as knowledge representation. Although they underlined the usefulness of prior knowledge, they also emphasized that the diversity of what researchers consider mental models to be risks to make the term uninformative.

Many believe that mental models contain people's personal knowledge of a situation's structure (concordant with the importance of prior knowledge signalled by Mambrey, Schreiber, and Schmiemann 2020). Experts in policymaking postulate mental models to contain variables connected by causal links and attribute flawed decision policies to overlooked elements and interdependencies or insufficient ability to deduce behaviour from this causal structure (Forrester 1961, 1971, 1992). Dynamic decision-making conceptualizes mental models as combinations of cues, actions and outcomes (Gonzalez, Fakhari, and Busemeyer 2017) driven and used by cognitive processes. Researchers of human–computer interaction are interested in how users of interactive systems build mental models that help them prevent or mitigate user errors (Gentner and Stevens 1983). Management researchers investigate shared and team mental models that contain personal knowledge of a team's tasks or its structure to explain differences in team performance (DeChurch and Mesmer-Magnus 2010; Langan-Fox, Anglim, and Wilson 2004; Mathieu et al. 2005; Mohammed, Ferzandi, and Hamilton 2010; Mohammed, Rico, and Alipour 2021). The concept of *mental model* is as broad as systems thinking, but there are two particular types of mental models that prove to be useful: (a) to construct a representation of the situation's causal structure and (b) derive possible behaviours from that structure.

3.2 | Mental Models of Dynamic Systems as Structure Models

We assume people to make their decisions according to implicit or explicit policies that are at least subjectively consistent with their respective *mental model of the dynamic system* (Forrester 1971, 1987), which is analogous to the decision situation (Doyle and Ford 1998, 1999). When articulated, such mental models are represented as sets of 'reinforcing and balancing feedback loops emerging from stock, flow, and intermediary variables that interact in linear and mostly nonlinear, delayed ways' (Groesser and Schaffernicht 2012, 61). Two questions may arise here. The first one is whether the elements of a mental model are always variables. The second one is whether all variables are stocks, flow rates or intermediate. As far as complex dynamic decision problems are concerned and decision-makers repeatedly attempt to influence the behaviour of the problem's elements, the elements of concern are variables (quantities of something that change over time). Sometimes, only compound statements about such elements are articulated, like with personal constructs in SODA (Eden 2004), which combine a variable and its desired and feared behaviours. Turning now to the second question, the behavioural consequences of causal links between a flow rate and a stock (state) variable are unlike those of links from a stock to a flow rate. As discussed in the literature on the 'stock and flow failure', people's ability to infer behaviours from causal structure is impaired when overlooking this difference (Cronin, Gonzalez, and Sterman 2009). Some individuals may not distinguish stocks from flows or may overlook feedback loops: People often use only some of the definition's features (Lane and Rouwette 2023). However, the data structure derived from this definition has enough expressive power to capture all relevant aspects in case people distinguish stocks from flows and address feedback loops, as well as to compare elicited mental models regarding differences and similarities.[1]

A mental model of a dynamic system then contains an externalized representation of how someone mentally represents the structure of a situation (ElSawah et al. 2015; ElSawah, McLucas, and Mazanov 2013; Schaffernicht 2017, 2019; Schaffernicht and Groesser 2014). Therefore, we use the term *structure model* as shorthand for mental model of a dynamic system.

3.3 | Mental Models of Possibilities as Behaviour Models

Structure models are important *for* reasoning, but the reasoning process itself is a distinct entity, using the structure model to generate models of a second type that refer to possible behaviours of that structure. This cognitive theory represents humans processing conditional assertions such as 'if CO_2 emissions drop, then global temperatures will decrease' (similar to the situation used by Sweeny and Sterman 2005), deploying mental models of what may be possible to assess the assertion's validity as either necessary, possible or impossible. This kind of mental models is called *mental models of possibilities*. Depending on the level of cognitive effort engaged, individuals can deploy either the most obvious possibility or an entire set. In the second case, they also draw on prior knowledge to complement their first impression of the situation. Laboratory experiments using spatial, relational, temporal, causal and other reasoning tasks have provided evidence that the theory correctly predicts people's assessments of such assertions (see table 2 in Khemlani and Johnson-Laird 2013, 7). Moreover, some shortcomings of competing theories are avoided by the theory of reasoning with mental models (for a discussion, see Ragni and Johnson-Laird 2020; Ragni, Kola, and Johnson-Laird 2018).

The theory takes possibility as any event or fact that may happen. Because we focus on thinking about a complex dynamic situation, we narrow this notion to possible behaviours and therefore use the term *behaviour model* as shorthand for *mental models of possibilities*.

Here, three basic principles of this reasoning theory are require: (a) *representation*, (b) *dual process* and (c) *modulation*. The appendix offers a more detailed presentation (for a complete list of principles, see Khemlani, Byrne, and Johnson-Laird 2018).

3.3.1 | Representation

Mental models are 'iconic': Their content is analogical to the situation to which they refer (Khemlani and Johnson-Laird 2022, 292). Conditionals such as the assertion regarding CO_2 comprise an antecedent p (CO_2 emissions drop), a consequent q (global temperatures decrease) and a causal link as 'if p then q'. Several implications follow from this. First, if p is possible, its contrary *not-p* is possible by default, too: For example, emissions do not drop. Therefore, there is a second possible scenario where p does not happen (Khemlani and Johnson-Laird 2022, 291). People represent each possibility as one behaviour model (Johnson-Laird 2012) following a general pattern:

1. p and q, which is the salient possibility that first comes to mind when reading the assertion.
2. *not-p* and *not-q*: *CO_2 emissions do not drop* and *temperatures do not decrease*.
3. *not-p* and q: *CO_2 emissions do not drop*, but *temperatures decrease*. Realizing that there may be other causes of a surface temperature decrease requires more cognitive effort (as discussed in the part about the principle modulation in the following).

A fourth combination (p and *not-q*) contradicts the initial statement and is impossible by default.

A conclusion drawn from the assertion 'if p then q' is necessarily valid if it holds in every possible scenario. If it holds in at least one scenario, it is possibly valid, and invalid otherwise (Khemlani and Johnson-Laird 2022, 292).

When thinking systemically about a complex dynamic problem, possibilities refer to the possible behaviour of variables representing the underlying system. 'Behaviour' can refer to the state of the system at a point in time or to the state changes over time (Schaffernicht 2010). Descriptions of change can be static (is greater than before) or dynamic (drops, decreases). In the latter case, they can mention slope (e.g., constant, increasing, decreasing, quicker than and slower than) and curvature (e.g., accelerates and decelerates). Some individuals may also recognize combined shapes, according to their prior knowledge (e.g., the phases of a business cycle, types of oscillations or modes such as logistic growth, overshoot and collapse and others). However, people need not know a particular behaviour mode taxonomy. For instance, in the assertion about CO_2 emissions, 'drops' and 'decreases' only mention a slope. However, acceleration and deceleration are important behaviour features, and researchers wishing to assess the level of systems thinking will define a set of reference shapes or modes to classify the elicited material. We will use 'behaviour model' as shorthand for mental models of possibilities. The terms p and q are decomposed into a structure and a behaviour component. For instance, 'CO_2 decreases' becomes 'CO_2' (*p-variable*) and 'decreases' (<u>p-behaviour</u>). This facilitates connecting the structure model with behaviour models using the *p-variable* parts. Printing p-variables in italics and p-behaviours underlined is a typographic convention to make this connection salient in this text.

3.3.2 | Two Distinct Cognitive Processes

The 'dual process' theory (Stanovich 2012) postulates that humans have two distinct cognitive systems for reasoning. A widespread convention is to speak of 'System 1' for intuitive reasoning, heuristics and judgement (e.g., Randle and Stroink 2018). In contrast, 'System 2' is deliberate and detailed (Kahneman 2011). The former is fast, approximative and inexpensive in terms of the brain's energy consumption, whereas the latter is slow and more accurate but more effortful and energy intensive. Heuristics as mental shortcuts are driven by the intuitive System 1, but the existence of deliberative System 2 implies that people do not always follow heuristics. When an individual perceives a familiar situation (no uncertainty) or is under time pressure, System 1 is more convenient. Yet, under uncertainty and when enough time is available, System 2 is more accurate (Khemlani, Byrne, and Johnson-Laird 2018, 1896). For instance, deliberate reasoning can help individuals avoid a pattern-matching heuristic ('the curve of the dependent variable will look similar to the curve of the dependent variable') in tasks where the former variable is a flow variable whose values are accumulated in a stock variable (Hendijani 2021). System 2 activates gradually, ensuring that the benefits of using it outweigh the additional effort. Here, we assume all-or-nothing activation for the clarity of discussion.

3.3.3 | Modulation

Systems 1 and 2 process the implied possibilities differently. System 1 only deploys the salient possibility: *p* and *q* (*CO_2 emissions drop* and *global temperatures decrease*). If this is possible, the assertion is accepted. This is quick but overlooks other, less salient possibilities. The second behaviour model mentioned above can be deployed without additional information: If '*p* and *q*' can be, it can also not be (*CO_2 emissions do not drop* and *global temperatures do not decrease*).

Next, the assertion does not state that *q* can only happen if *p* happens, so other factors may be related to *q*, and it can occur without *p* (*CO_2 emissions do not drop to zero* and *global temperatures decrease*). Personal understanding of the world, not referenced in the statement, can influence the situation through modulation: a meteor striking Earth, super-volcano eruptions or a nuclear conflict—these would cause falling temperatures without humanity reducing CO_2 emissions.

Modulation can also block behaviour models that contradict known facts (Johnson-Laird and Yang 2011). A slightly changed version of the above assertion shows this: 'if CO_2 emissions drop to zero, global temperatures will decrease'. Even without rich prior knowledge, common sense suggests that zero CO_2 emissions are impossible, so the behaviour model *p* and *q* is blocked.

People's knowledge is updated by new information, and this makes modulation relevant for iterated decisions because unexpected consequences of previous decisions may trigger people to adjust their structure model (Metcalfe 2017).

3.4 | Thinking About a Complex Dynamic Situation With Structure and Behaviour Models

The cognitive theory articulates how people deploy and process one or several *behaviour models* drawing on prior knowledge. However, it leaves open how an individual represents the situation, which is only implied through the conditional assertion. Nonetheless, with complex dynamic situations, individuals face a rich set of external information (reports, briefings and discussions). Their pool of applicable prior knowledge can contain knowledge at distinct hierarchical levels, that is, the conceptions and context-related elements described by Mambrey, Schreiber, and Schmiemann (2020). When someone thinks deliberately, their structural model contains a combination of externally provided elements and prior knowledge, combined into a single representation of the situation through modulation. We use CO_2 emissions to exemplify how the theoretical process constructs the structure model and then deduce behaviour models of the possible effects to derive a decision.

In the example, participants in an experiment were provided with introductory information (Sweeny and Sterman 2005, 216). The briefing stated that anthropogenic CO_2 emissions have been rising since the industrial revolution, together with a graph displaying emissions behaviour and trend. It also contained a graph of the stock of CO_2 in the atmosphere, however, without mentioning a relationship between both variables. In addition, it stated that these emissions are contributing to global warming, and a graph showed the behaviour of global temperatures. The task was to decide how global temperature may continue if CO_2 emissions drop.

A thought experiment with three fictitious individuals—Alf, Betty and Cesar—with distinct prior knowledge exemplifies how the cognitive process operates. Alf has no detailed knowledge of either the carbon cycle and its interactions with temperatures or systems thinking per se, and despite activating System 2 because of his unfamiliarity with the situation, his structure model only contains information drawn from the briefing.[2] The structural model comprises p-variables, causal links and loops:

A1: Changes in *CO_2 emissions* cause changes in the same direction in *global temperatures*.

A2: There is a stock of *CO_2 in the atmosphere*.

Betty is acquainted with the context area and can combine it with the briefing information. Her System 2 activates when she considers the briefing information, where the apparent implications of a change in emissions contradict her prior knowledge. Initially, B1 and B2 are identical to A1 and A2, but there are some additional components:

B1: Changes in *CO_2 emissions* cause changes in the same direction in *global temperatures*.

B2: There is a stock of *CO_2 in the atmosphere*.

B3: *CO_2 emissions* increase the stock of *CO_2 in the atmosphere*.

B4: Oceans and forests *absorb CO_2* from the *CO_2 in the atmosphere*.

B5: The stock of *CO_2 in the atmosphere* increases *net radiative forcing* from the Sun.

B6: Changes in *net radiative forcing* lead to changes in global temperatures that have the same sign.

Betty also knows about the effects of global temperature (especially in the oceans) on CO_2 absorption and can add:

B7: Changes in *global temperatures* cause changes with the opposite sign in *CO_2 absorption*.

It follows that B1 must be blocked because if emissions remain greater than absorption despite reduction, the increase in temperature will be lower than before, but the temperature will not decrease. In the new statement, 'sign of change' replaces 'direction':

B1: Changes in *CO_2 emissions* cause changes with the same sign in *global temperatures*.

Even without specialized training in systems modelling, she may realize there is a feedback loop between *CO_2 in the atmosphere → net radiative forcing → global temperatures → CO_2 → absorption → CO_2 in the atmosphere* and that this loop will reinforce (accelerate) the changes in CO_2 in the atmosphere.

Cesar has no prior knowledge of the subject, but he knows systems' principles and the correct definition of polarity. Modulation therefore blocks A1 and deploys C1 instead.

C1: Changes in *CO_2 emissions* cause changes with the same sign in *global temperatures*.

His modulation process constructs a structure model similar to Betty's. Recognizing the stock of CO_2 in the atmosphere as a stock variable, he concludes that CO_2 emissions are an inflow to this stock:

C3: *CO_2 emissions* add to *CO_2 in the atmosphere*.

Although there are no indications of CO_2 absorption in the briefing, his modelling knowledge suggests that nothing grows forever and that a stock cannot decrease is hardly possible: The stock must also have outflows:

C4: Some *outflow* decreases the stock of *CO_2 in the atmosphere*.

Next, global temperatures are a state, so this is a stock variable and will only change through a net flow rate, which depends on other stocks. Therefore, changes to global temperatures must depend on the stock of CO_2 rather than CO_2 emissions. This reasoning leads to blocking the original statement C1 and replacing it by:

C1: Changes in *CO_2 in the atmosphere* cause *global temperature* changes with the same sign.

Then it is unlikely that CO_2 absorption (statement C4) should be constant when all other factors are changing, search for information about CO_2 absorption and realize that:

C5: Changes in *global temperatures* cause changes with the opposite sign in *CO_2 absorption*.

Cesar knows about feedback loops and recognizes a reinforcing loop between *CO_2 in the atmosphere → net radiative forcing → global temperatures → CO_2 absorption → CO_2 in the atmosphere*.

Figure 1 displays the three structural models as causal loop diagrams, where arrows represent an attributed causal link with either positive or negative polarity and feedback loops are

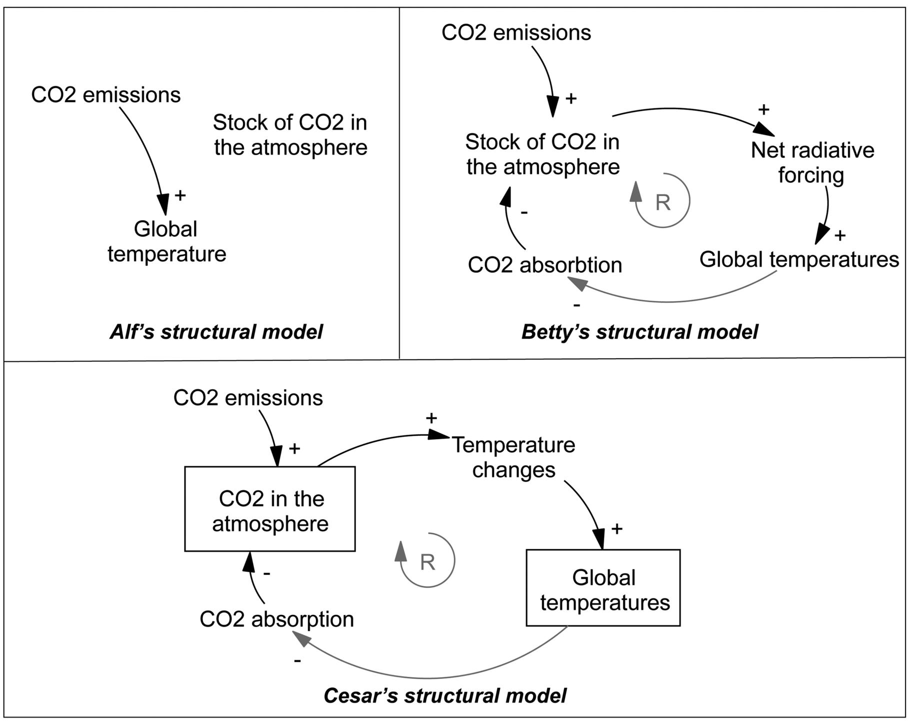

FIGURE 1 | Three structural models deployed when reflecting on the assertion that 'if CO_2 emissions drop to zero, global temperatures will decrease', depending on prior knowledge of the context domain or systems modeling.

cyclic sequences of links, in this case of the reinforcing type (marked R).

Alf's structural model contains one isolated factor. CO_2 emissions are the only influence on global temperatures. The other models only differ in making the stock nature of CO_2 in the atmosphere and of global temperatures explicit.

Consider now how these individuals deploy behaviour models and assess them. Assume that each of them activates System 2; Alf does so because his lack of prior knowledge prompts deliberate reasoning. For Betty, the assertion is counterintuitive given her domain knowledge. Cesar draws on his systems knowledge to deliberate.

At the outset, they all deploy the salient and the two other possibilities. The behaviour models combine p-variables and p-behaviours:

P1: *p* and *q*: *CO_2 emissions* <u>drop</u>, and *global temperatures* <u>decrease</u>.

P2: *not-p* and *not-q*: *CO_2 emissions* <u>do not drop</u>, and *global temperatures* <u>do not decrease</u>.

P3: *not-p* and *q*: *CO_2 emissions* <u>do not drop</u>, and *global temperatures* <u>decrease</u>.

By default, *p* and *not-q* are not considered because they contradict the assertion itself.

According to Alf's structural model, P1 is consistent with the causal link connecting CO_2 emissions and temperature; the positive causal link means dropping CO_2 makes global temperature decrease. There is no other link to influence temperature, meaning that without a drop, there is no decrease; this is what P2 states. And without such a second influence, P3 is impossible and, therefore, rejected.

Betty analyses P1 through her structural model and concludes that this can happen, but it can also not happen because the stock of CO_2 in the atmosphere changes according to the net flow between emissions and absorption. This means that P1 is possible, but not unavoidable, and it also follows that P3 is possible. This also implies that emissions can drop, but temperatures do not decrease because the CO_2 net flow was still not negative. By consequence, modulation deploys P4, which now is possible. In contrast, P2 is unavoidable according to the structural model. The reinforcing feedback loop would imply that, as CO_2 in the atmosphere grows, P1 will become less possible, contrary to P3. However, without quantitative information, accounting for the loop will not change the assessment of the behaviour models.

Cesar ignores the concept of net radiative forcing. He accepts the more abstract notion of temperature changes between the two stocks in his structure model. His System 1 then deploys and classifies all four possibilities in the same way Betty does.

None of them rejects the idea that surface temperature could decrease owing to decreasing CO_2 emissions. But while Alf finds this is necessarily the case, Betty and Cesar only find it is possible because emissions are only one component of the CO_2 net flow affecting the atmospheric stock. Their deliberation also considered P4, which was not considered by Alf.

Table 1 summarizes these classifications. Only Alf accepts the assertion as necessarily valid. Betty and Cesar detect that its validity depends on specific conditions, so it can but need not happen. Modulation leads to a different assessment of P1, to the conclusion that *q* can but does not necessarily follow from *p*, that P3 is possible and that even P4, which is by default impossible, is possible.

Consider the conceptualizations developed by the Intergovernmental Panel on Climate Change (IPCC) as a reference for judging these conclusions and the underlying mental models (for an overview, see Sweeny and Sterman 2005, 213). When using these models for comparison, we identified errors in both kinds of mental models. Each individual's structural model must comprise the elements needed to think through the behavioural models that lead to an adequate conclusion. The assertion is not incompatible with the IPCC's findings, so Betty and Cesar would be right. They may even realize that the loop will increasingly decrease the chances that reducing emissions makes temperatures decrease.

Alf does not the original P1 and to deploy P4. He also rejects P3. We consider this a behavioural model error. A distinct variant of this type of error occurs when System 1 processes the assertion, since in that case, modulation would not occur, and wrong conclusions would follow. But because Alf used System 2, not blocking a behavioural model like P1 and not deploying P4 are consequences of the structure model lacking relevant elements.

Alf's structural model misses several relevant features as an approximative representation of the carbon cycle. Our planet has several CO_2 containers, such as oceans, biomass and fossils, and there are diverse flows between them. CO_2 can be emitted into the atmosphere and absorbed out of it, but it is always somewhere. Without these elements in the structure model, there is no absorption flow to complement the emissions, and one will

TABLE 1 | Assessment of the situation according to different pools of prior knowledge.

Behaviour models	**Alf**	**Betty**	**Cesar**
P1: *p* and *q* (salient)	Necessary	Possible	Possible
P2: *not-p* and *not-q*	Necessary	Necessary	Necessary
P3: *not-p* and *q*	*Rejected*	Possible	Possible
P4: *p* and *not-q* (impossible by default)	*Not deployed*	*Possible*	*Possible*
Conclusion about the assertion	*Necessary*	*Possible*	*Possible*

mistakenly accept the original P1.[3] So, Bettys and Cesar's respective structure models correspond to the IPCC findings. The differences in the aggregation level of global temperatures they contain do not lead to behaviour model errors and present no problem for the decision to take. However, Alf's structure model shows a boundary error, missing a factor to drain CO_2 out of the atmosphere. The missing links with the stock of CO_2 in the atmosphere are also boundary mismatches in principle, but they have no consequences here (like Betty not classifying the two stock variables as such).

Some boundary mismatches in structure models entail behaviour model errors. This is relevant because both types of errors are consequential for an individual's ability to assess the validity of assertions about a problematic situation. Someone committing a boundary mismatch shows a low systems thinking level for not adequately representing the system's structure (applying a rubric, for instance, the one developed by Mehren et al. 2018). Furthermore, behaviour model errors, like the ones in our example, reveal problems at the systems thinking levels where one explains observed or projected behaviours by structure. Arguably, flawed assessments of possibilities will compromise the quality of decision policies crafted for regulatory interventions.

4 | Discussion

4.1 | The Conceptual Framework

Our example reveals some noteworthy features. First, the basic reasoning processes (Systems 1 and 2) are the same for everyone. People can differ in their personal conceptions and context-relevant knowledge. They can also switch between these systems for various reasons. However, the dual-process theory (Stanovich 2012) implies we all use the same cognitive systems. The intuitive System 1 deploys only the salient possibility to derive a decision. In contrast, System 2 allows to complement the structure model thanks to personal knowledge. People use System 1 by default, unless circumstances require deliberate reasoning. Prior knowledge can be part of such circumstances, when available information contradicts such knowledge, like for Betty and Cesar. Thus, distinct pools of knowledge lead to interindividual differences in the activated reasoning process and in the structure model. As an individual's structure model of a situation is constructed using this person's knowledge, it will only contain elements the individual can also interpret to derive behaviour models consistent with that structure. Second, once the structure model is constructed and one reasoning system is in control, the behaviour models and the decision follow. This implies that two individuals with equivalent structure models and the same reasoning process activated (like Betty and Cesar) deploy the same behaviour models and reach the same decision.

Third, this also means that boundary mismatches an individual commits at the level of the structure model (structure model errors) are predictable, given the individual's relevant knowledge. Fourth, in System 2 mode, the behaviour model errors are a consequence of structure model errors.

When a conclusion is reached, the decision can lead to an action on the system that is presumably beneath the situation, but it can also be a rule. For example, people make choices between taking personal action to help reducing CO_2 emissions and not taking personal action; an individual's personal rule for selecting one option or the other depends on if they concluded that CO_2 emissions can be reduced enough to halt the rise in global temperatures.

Last but not least, context-specific knowledge is bound to the situations inside a particular context, but systems principles apply across contexts. This introduces a hierarchical difference between two sets of knowledge: 'domain as system' and 'systems per se'.

Based on these points, we propose a conceptual framework of systemic thinking about complex dynamic situations. This framework conceptualizes two interdependent domains: the individual and the complex dynamic situation (as illustrated in Figure 2, where the individual appears as a rectangle).

The individual is subdivided in two spheres. First, actions performed (revealed choices) are observable from the outside. To represent this sphere, we propose three stages of the systems thinking skill (following Mehren et al. 2018). The second sphere of the individual (separated by a light grey line in Figure 2) is mental, and there we locate personal knowledge, the reasoning systems 1 and 2, the structure model (mental model of a dynamic system) and the behaviour models.

System 1 is in control unless circumstances require System 2. When situational information is perceived, the momentary structure model combined with the individual's knowledge can lead to activation of System 2 and to modulation of the structure model. The structure model can be articulated and is the basis for assessing whether the individual is at least at Stage 1 of the systems thinking skill. Depending on which cognitive system is operating, one or several behaviour models are deployed, and when articulated, they serve as data to evaluate whether this person is at Skill Level 2 (past behaviours) or 3 (possible future behaviours). If the processing of the behaviour model(s) leads to generate a rule, the person may be classified at Stage 3. Then, the decision is implemented, and a new iteration begins.

The cognitive theory of mental models does not specify what kind of knowledge is contained by an individual's knowledge base. Indeed, long-term memory contains distinct kinds of elements, ranging from concrete concepts allowing to recognize objects, to conceptions, principles and methods. Adhering to the distinction between conceptions and context-specific knowledge (Mambrey, Schreiber, and Schmiemann 2020), we propose that knowledge of systems principles belongs to the pool of conceptions an individual can have. Without trying to be exhaustive, the ideas of interdependence and feedback loops, multiple causal influences (inward and outward), non-linear reactions or emergence are conceptions. Knowing classes of particular systems, such as the carbon cycle or the water cycle, is then context-specific knowledge. This is more concrete than conceptions, but still more abstract than knowledge of one specific system. These types of knowledge interact: Subject matters like Earth systems science teach about a context by teaching, say, the carbon cycle, and this indirectly develops conceptions, too.

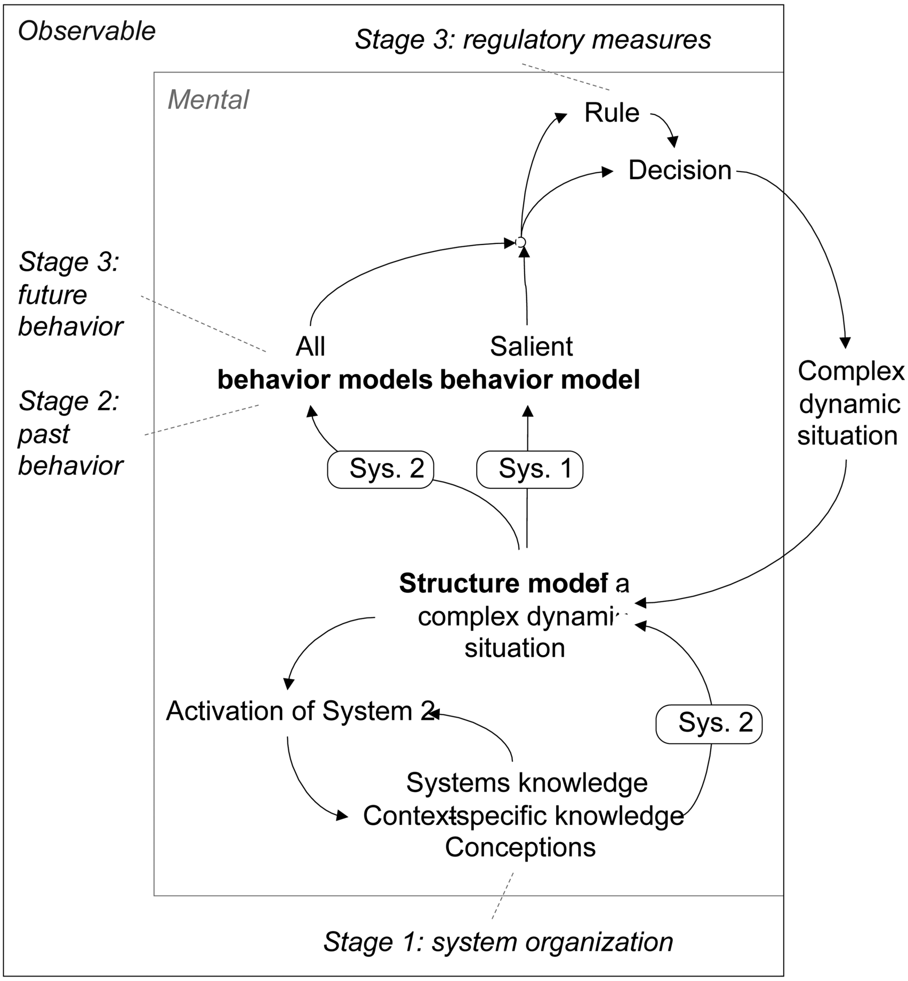

FIGURE 2 | A conceptual framework of systems thinking about complex dynamic situations distinguishes the domain of externally observable actions from the domain of mental structures and processes.

Such knowledge enables individuals to identify a system's boundary and its internal organization, equivalent to systems thinking Skill Level 1 (Mehren et al. 2018). For Level 2 (understanding how past behaviour emerged from the interactions between parts of the system), one person may remember how the components of a particular system interact and react to one another, whereas another person can know some system principles and derive an equivalent understanding. As it is easier to connect the structure model to behaviours already observed than to project likely behaviours, people will explain past behaviours (Skill Level 2) before they predict future consequences of interventions and devise regulations (Level 3). One can suspect that the level of abstraction of these elements makes them transferable across diverse context domains; yet a discussion of differences and similarities between 'applied' and 'pure' systems knowledge is beyond the scope of this article.

Next, the three initial behaviour models only deployed by System 2 connect with systems thinking conceptions:

P2: *not-p* and *not-q*. The polarity of causal links has two facets because the causing variable can change with either a positive or a negative sign. The facet associated to a positive change sign (the variable has higher values than what would otherwise have been the case) is salient: If there is a positive link from CO_2 in the atmosphere to global temperatures, and the briefing information describes a scenario of decreasing CO_2, the salient possibility is that decreasing CO_2 leads to lower temperatures. But the link also implies that an increasing stock of CO_2 causes temperatures to be higher than what would otherwise have been the case. While not salient for individuals unfamiliar with the conception of polarity, this is true and can be inferred through deliberate reasoning.

P3: *not-p* and *q*. Are there other factors influencing the variable? This remits to a basic conception of the world. Individuals believing that things happening are the consequences of a single cause and that one event or action will affect one thing have no reason to accept this as possible. However, those assuming that there is more than one cause are likely to accept P3. Their modulation process may even deploy the possibility of *p* and *not-q*, as other factors, such as a decrease in CO_2 absorption because of hotter oceans and diminished forests, may outweigh the effect of a decrease in CO_2 emissions.

The framework also comprises rules (also referred to as decision policies). Someone who is about to take a decision can instantiate a set of conditional assertions like the emission example and mentally go through the possible effects. The result of comparing these can be expressed as production rules, structured like conditional statements 'if <conditions> then do <actions>'. In the realm of the cognitive theory of mental models, such rules are *deontic* conditionals prescribing what to do in response to certain conditions (Khemlani, Byrne, and Johnson-Laird 2018, 1888). Others have proposed a framework linking the perceived causal structures to decision rules via strategies (Gary and Wood 2016, 104; Figure 1); however, they focused on econometric estimation of decision rules to replicate the decisions taken. The framework proposed here emphasizes the process leading from a structure model to decision rules through the deployment and processing of behaviour models. This feature provides a connection between research on how people represent the structure of complex dynamic problems and on deliberate decision-making in such situations. Several research questions arise.

4.2 | New Research Questions

First, it is now becomes an empirical question to which point both types of mental model can be elicited sufficiently to corroborate the respective kinds of mental model error discussed.

Second, if we recall that the decision-maker interacts with the underlying dynamic system over several iterations, a question concerning the dynamics of the two cognitive processes arises. Because System 1 consumes less energy than System 2 (Stanovich 2012), the individual will only appeal to System 2 when there is a need for it. However, System 1 implies incomplete processing, misjudgements and flawed decisions that lead to surprise effects. Gaps between the expected results of decisions in one iteration and the actual results observed after the fact can hint at that need. Error feedback (Metcalfe 2017) may then trigger System 2 and open the possibility of modulation, leading to changes in the model, which in turn will update the set of deployed behaviour models. Elicitation during the iterations is therefore expected to provide data to detect such changes (Schaffernicht 2019; Schaffernicht and Groesser 2011; Schaffernicht and Groesser 2024).

Third, an additional question is whether the mind only operates with one of these cognitive processes at a time or whether partial activation of both reasoning systems is possible. As an example, highly trained individuals, such as aircraft pilots, easily interact with emergent dynamically complex flight situations that leave almost no time for reflection, instantly classifying the problem without deliberate reflection. We assume that training can enable people to have instant modulation of their structure model, especially so in what regards conceptions.

Fourth, most citizens, voters, consumers and producers are not trained in all the context domains they interact with. In the discussion contributed by Lane and Rouwette (2023), their thinking would therefore be rather 'naïve' than 'sophisticated'; but nevertheless, they take decisions and affect dynamic political, economical, social and natural systems. However, even without context-specific knowledge, people reasoning deliberately commit fewer errors, which leads to asking which kind of situational cues trigger System 2. Interestingly, the meaning of words in the assertions can trigger modulation (Johnson-Laird and Byrne 2002), calling for an examination of potential framing and priming effects.

A fifth question refers to the generalization and transferability of knowledge. Systems knowledge is abstract and can take advantage of common features in the deep structure of superficially different situations. Analogical reasoning may allow the transfer of knowledge gained from one situation to another, superficially distinct situation (Gonzalez and Wong 2012), leading to the question of which factors influence the number of instances someone needs to abstract patterns out of the situations, generalize and build a stock of systems knowledge.

5 | Conclusions

We introduced a conceptual framework that describes the reasoning process leading from mental models of the causal structure of a complex dynamic system (structure models) to the assessment of possible system behaviours. The framework combines these structure models with the cognitive theory of mental models and its mental models of possibilities, here referred to as behaviour models because each represents a possible behaviour. Considering a complex dynamic situation, the most salient behaviour model comes to mind intuitively, but less obvious possibilities require deliberate mental effort. The framework represents systems thinking as a cognitive process using either the intuitive reasoning System 1 or the deliberate System 2, and where the deliberate one has access to prior knowledge of context-specific aspects and of general conceptions (systems principles).

We showed how context-specific knowledge and systems principles influence structure models and how behaviour models are deployed and processed based on the structure model. Two types of mental model errors appeared, both leading to flawed conclusions. First, structure model errors occur when relevant elements of the situation are missed or misconstrued. This can happen because the person uses the intuitive reasoning system and makes no use of relevant knowledge or because there is a lack of relevant knowledge (context-specific or conceptions). Behaviour model errors have several forms: deploying erroneous possibilities, not deploying relevant possibilities and misjudging whether a possibility can realistically materialize in the analysed situation. The intuitive reasoning system generates all of them because it only accounts for the most salient possibility. In contrast, the deliberative reasoning system produces these errors when someone lacks relevant pieces of knowledge. We conclude that there may be several reasons for a low level of skill observed in systems thinking.

The framework is compatible with the skill-set view of systems thinking. The reasoning systems and their interaction with prior knowledge provide a link from perceived causal structure to decision rules. This leads to new questions for systems thinking research. We have proposed five research questions.

Currently, the proposed framework is entirely conceptual and only draws on prior publications from two distinct fields of mental model research, together with systems thinking literature. This is an important limitation calling for empirical data.

Moving in this direction, we are designing lab experiments to encounter individuals from diverse perspectives with complex dynamic systems. We also observed a need for advancement in elicitation methods. Another limitation stems from the dynamic character of cognitive research on reasoning, where future advancements may become important for systems thinking research. Despite these limitations, we hope other researchers will find this mental model framework useful, advancing it conceptually as well as empirically.

Endnotes

[1] Elicited variables are therefore recorded with a 'type' attribute initially set to 'undefined', but this can be changed to 'stock', 'flow' or 'intermediate'. Links and loops have a 'polarity' attribute with default value 'undefined' (similar with a 'delay' attribute).

[2] Interpreting the words 'global warming' as a description of the behaviour of global temperatures.

[3] In addition, global temperatures should be decomposed into at least two parts: atmosphere plus upper ocean, and deep ocean separately, again with flows from net radiative forcing and heat transfers between both containers. As this is not required for our point, we have left it out of the discussion.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.