Empowering Systemic Design with Causal Loop Diagrams Formalization and Analytics

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Abstract

Systemic Design employs Causal Loop Diagrams (CLDs) to document and visualize the dynamics of complex systems, describing their relevant factors, called variables, and the causal relationships between them. A systemic approach is essential to understanding causal relationships and improving the decision-making process, especially in complex, multidisciplinary contexts where the implementation of reactive and proactive measures is pivotal (e.g., public health, transport, urban development, public involvement). While CLDs provide a consolidated and widely adopted visual representation, they have yet to be formalized in the context of data-driven modeling and analysis.

We characterize CLDs using a metamodel that clarifies the role of each component, including causal loops, i.e., circuits of causal relationships. Relationships within loops are characterized by a positive or negative polarity; by aggregating the polarities along each loop, loops are then characterized as balancing or reinforcing. Within CLD diagrams, we define the new concept of causal route, i.e., a chain of relationships connecting any two pairs of nodes, denoted as source and destination. We can then compare any pair of causal loops having one node in common or any causal routes having the same source and destination, and define for such a pair whether the loops or routes are agreeing or disagreeing. Thanks to these characterizations of causal loops and routes, CLDs enable the identification of interesting patterns that can be extracted over the meta-model, thereby empowering systematic reasoning on complex systems diagrams and improving the related decision-making processes.

Keywords

Systemic Design, Causal Loop Diagrams, Conceptual Modeling, Metamodel, Data Analytics, Graph Databases

1. Introduction

Systemic Design is an emerging field driven by the ambitious objective of understanding, making sense of, and addressing complex problems in terms of "relationship and global dynamics", rather than isolated components. Being addressed mainly by design schools, the systemic design community has created a strong *Systemic Design Association* (https://systemic-design.org/), which produced scholarly publications (journals and conferences) and educational programs and is gaining interest and adoption for approaching complex problems, typically fostering domain expertise exchange [1]. From a foundational point of view, it capitalizes on well-established design approaches to complex challenges, including *design thinking* [2] and *systems thinking* [3]. The core function of systemic design is to grasp and assess the dynamics governing systems' behaviors, with a broad vision, so as to ensure consistency in solutions at the system level. From an aspirational point of view, systemic design seeks to integrate a *human-centered* approach, placing humans in all their dimensions at the center of inquiry, with a social innovation approach, addressing *main societal challenges* (e.g., as summarized in [4, 5]).

An important instrument of systemic design is the description of complex systems' dynamics by means of Causal Loop Diagrams (CLDs, [6]). These diagrams, of which Figure 1 shows an example instance, illustrate systems' behaviors at an abstract level, by means of nodes and edges. Nodes typically represent *variables* describing factors causing or affecting the problem. Only a few variables are

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measurable (e.g., can be quantified precisely using a well-defined metric), and most variables express generic concepts (e.g., *exploitation of natural resources*, or *product quality* vs *product lifespan*). Directed edges between nodes express causal relationships (from a source to a destination node), and – in particular – emphasize the influence of one w.r.t. another, in qualitative terms. Such influence, denoted as *polarity*, is *positive* when the growth of the value of the source variable causes the growth of the value of the destination variable, and *negative* when the growth of the value of the source variable determines the reduction of the value of the destination variable.

Based on these simple descriptions, diagrams are inspected for finding *causal loops*, i.e., cyclic paths looping from one variable back to the same variable. Each loop is associated with a given characterization, namely *balancing (B)* or *reinforcing (R)*, based on a simple inspection of the edges involved in the loop (edges with negative polarity along a loop are counted, and a loop is balancing when the count is odd, reinforcing when the count is even).

In addition to causal loops, we define the new concept of *causal routes*, consisting of paths of edges connecting two nodes, denoted as source and destination. Similar to causal loops, causal routes can also be associated with positive and negative polarity (edges with negative polarity along a route are counted, and a route is denoted as *increasing* when the count is even, *decreasing* when the count is odd).

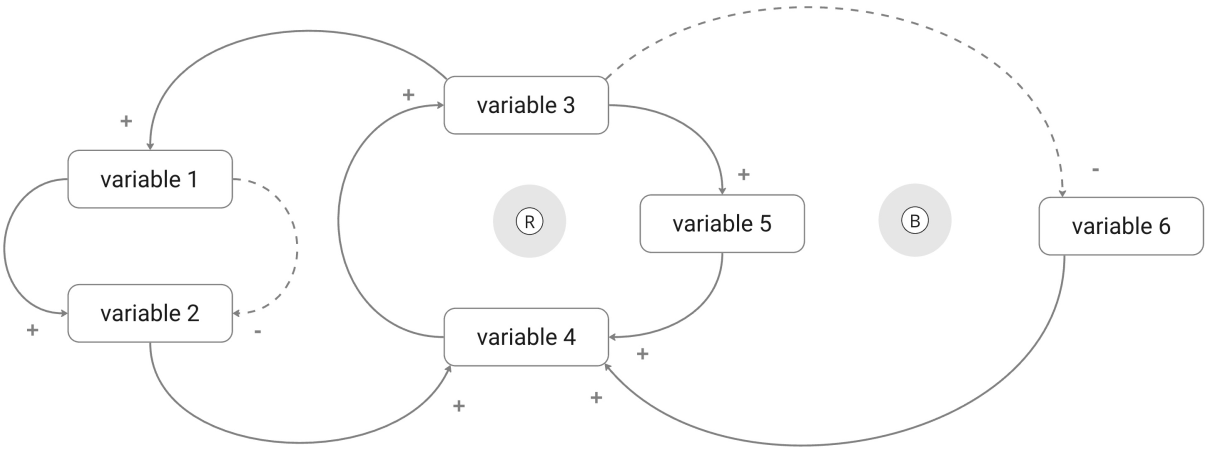

Figure 1: Example of a simple Causal Loop Diagram, with six variables, positive and negative edges, two loops (circuit of variables 3, 5, 4, 3 [reinforcing (R)] and circuit of variables 3, 6, 4, 3 [balancing (B)]), and causal routes (e.g., between variables 1 and 2 or betwen variables 3 and 4).

Diagrams provide a clear picture of mutual influences; their analysis facilitates the generation of novel insights that can be leveraged to assess areas or intervention points, even those not immediately apparent, and their potential impact. The simple Causal Loop Diagram in Figure 1 includes causal loops and causal routes.

We then consider cases when causal loops share a common variable and classify them as *agreeing* (i.e., all balancing or reinforcing) or *disagreeing* (i.e., when both options are present). Similarly, we consider causal routes between the same pair of variables and classify them as *agreeing* (i.e., all routes share the same polarity) or *disagreeing* (i.e., some routes have different polarity). These analyses can help with reasoning about possible balancing or counterbalancing effects within the same diagram.

While systemic design is gaining increasing interest in the design community, so far it has not influenced technical, engineering-oriented communities much; in particular, it is not well-known to conceptual modeling scholars. In our article, we aim to build a first bridge by describing a CLD metamodel (i.e., a model of diagrams' components) and then reasoning upon the insights that such formalization can bring. We first present a chronology and brief description of some major references on CLDs – without any claim of being exhaustive (Section 2). Then, we present our metamodel of CLDs (Section 3), allowing us to formally define a series of new concepts, which we deem interesting for deepening a causality analysis. For describing the power of the CLD model, we present two large use cases (Sections 4–5). The first one is used to explain our concepts in action, applied to the COVID-

19 pandemic; the second one targets the fashion industry, allowing us to apply systemic design at large, generating insights that can be leveraged to assess areas or intervention points, even those not immediately apparent, and their potential impact. Finally, we discuss the importance of assisting systemic design with our data-driven approach (Section 6).

2. Related work on Causal Loop Diagrams

Causal Loop Diagrams were introduced in a work written in 1986 by Richardson [7], and then formalized by Haraldsson in 2004 [6]; the latter introduces variables and their connections, explains positive and negative polarities, and the essence of balancing and reinforcing loops based upon edge polarities. It also introduces observed behavior patterns and uses them to illustrate several loop dynamics.

The concept of Stock/Flow Diagrams (SFD) was introduced by Binder et al. [8] in diagrams explaining causal relationships; all variables are quantifiable and represent either *stocks* (accumulations) or *flows* (activity rates); SFDs are compared/contrasted with CLDs because, while the latter are informal descriptions of reality, the former are quantifiable descriptions, e.g., of physical processes. The article includes a method for progressively transforming CLDs into SFDs. SFDs are also extensively described, in a plain style, by Meadows [3].

A mathematical perspective on CLDs is offered by Hayward [9]. In this work, several mathematical rules describe the variation of stock levels when connected within one or more loops, further describing each flow as a mathematical function, with first and second derivatives. The author explains several biological models, including epidemic growth and the predator-prey model. Among more speculative works, CLDs are explained in terms of Algebraic Quantum Field Theory in modern mathematics [10].

Methods for advancing the development and use of CLDs are constantly being researched (e.g., in the Ph.D. thesis of Kenzie [11] and the recent generation through LLMs [12, 13, 14]). In terms of applications, several efforts employed CLDs for bridging domain expertise gaps [1] or explaining complex/critical domains. Specific examples concern the obesity causes and possible interventions [15, 16], fashion retail supply chain [17], tourism management [18], or sustainable conflict/peace balance [19].

A formalization of the design process for complex CLD, with multiple stakeholders, is described in [18] in the context of renewable energy technology (RET) adoption for hotels in Queensland (Australia). It shows several versions of CLDs, each one undergoing phases of proposition and approvals. In the final CLD version, most variables are provided with some reference that explains/justifies them, and some variables introduced in the early phases of the process are removed based on deeper analysis. The process is very laborious and time-consuming, but in the end, the system designers succeed in their mission, i.e., to show the pros and cons of RET adoption at a high conceptual level; they acknowledge that achieving convergence (e.g., about which variables and relationships should be selected or retained) through several rounds of discussions involving different stakeholders requires a lot of time and energy.

While CLDs are effective as an instrument for describing complex systems at a high level of abstraction, bridging them to design activities concerning the development of information systems is not trivial; to our knowledge, the only method for bridging CLDs to information system design is provided by Tulinayo et al. in [20] and further discussed in [21].

Conceptually, CLDs can be compared to the i^* framework [22], used in software engineering, to support goal-oriented modeling of socio-technical systems and organizations [23]. CLDs are rooted in systems thinking and emphasize feedback loops, capturing the dynamic interdependencies and cause-effect relationships among system variables. They are particularly effective for visualizing how changes propagate through a system over time, making them well-suited for understanding system behavior and identifying leverage points for intervention. In contrast, the i^* framework centers on intentionality and strategic relationships among actors within a system. It models goals, dependencies, and rationales behind actors' behaviors, offering a more agent-oriented perspective, especially useful in early-stage requirements engineering and socio-technical system analysis.

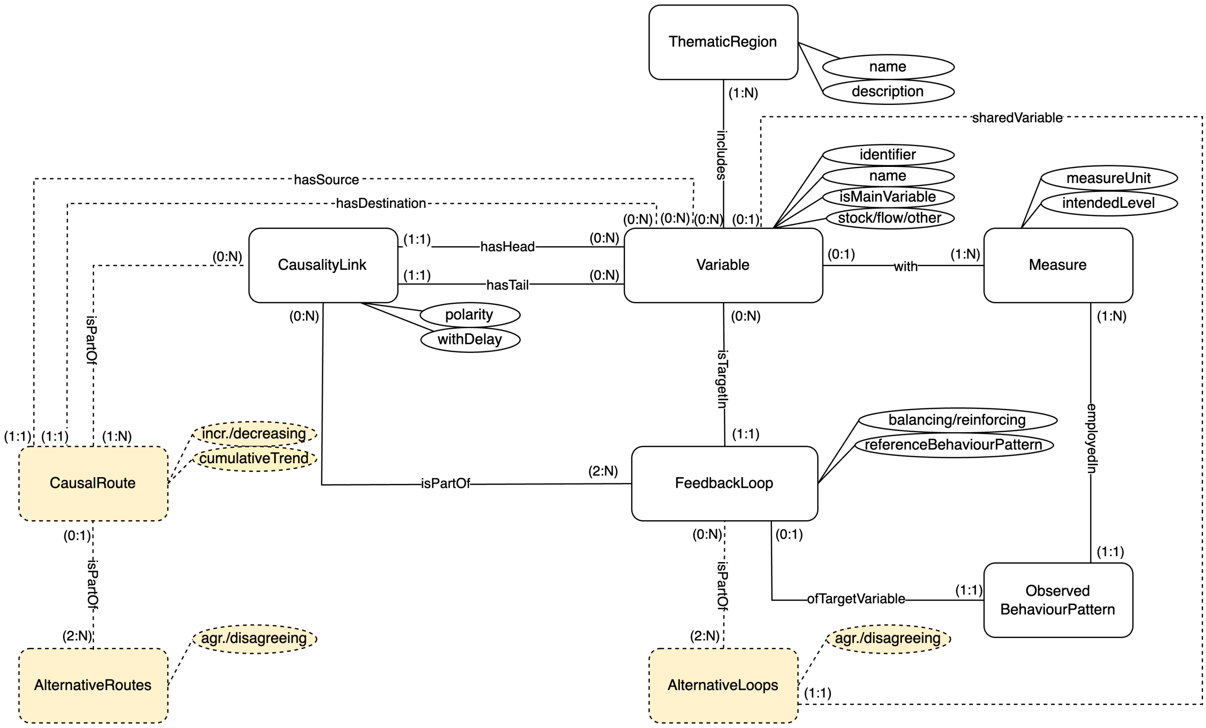

Figure 2: Metamodel for Causal Loop Diagrams. Note that we represent entities as rounded rectangles - together with their attributes described by their name - and relationships as edges; the name of the relationship is provided along the edge, while min-max cardinalities of relationships are shown at the start and end of the edge, along the notation used in [25]. The new entities and attributes introduced by us (in addition to standard CLD elements) are enclosed by dotted lines and highlighted by shaded (yellow) filling.

3. A metamodel for Causal Loop Diagrams

Causal Loop Diagrams (CLDs) represent networks of variables connected by directed edges; next, we describe the metamodel of CLDs, in the form of an ER diagram, to make their semantics accessible to the Conceptual Modeling community. The graphical language of CLDs is represented in Figure 2, a metamodel (in the sense of [24]) showing the available graphic modeling primitives and their abstract syntax (to provide a unique interpretation of CLDs introduced next); here we avoid specifying context-conditions, which are made clear in the text. The metamodel describes all possible CLD models, which in turn provide a description of reality. In addition to modeling the standard graphic elements, we also model new elements introduced by us, enclosed by dotted lines and highlighted by shaded (yellow) filling.

Nodes, edges, and their properties. In CLDs, Variables are visualized as nodes; they are characterized by an *identifier* and a *name*; the identifier is sometimes omitted from the representation. Variables may be quantified by means of a Measure, in turn characterized by a *measureUnit* and, sometimes, an *intendedLevel*. In particular, some nodes may be regarded as *stocks*, to represent *accumulations of material or information that have built up over time* [3], or *flows*, to represent rates at which activities take place or situations evolve [8]; else, we mark them as *other*. This terminology is borrowed from Stock-Flow Diagrams (see Section 2). One variable is considered the most important one (*isMainVariable*), as the whole diagram is designed around it, with the purpose of studying its dynamics and interactions. Variables are included in (possibly many) ThematicRegions – equipped with their *name* and *description* – that represent an area of interest for a given system/context.

Variables are connected through CausalityLinks (i.e., connections), which are directed arrows indicating how the change in one variable (*tail* of the link) influences another variable (*head* of the link). Each connection has a *polarity* that can be positive or negative; positive connections are represented in

CLDs by continuous-line arrows, and negative connections by dashed-line arrows. Positive polarity of an edge from X to Y occurs when *a growth of X causes a growth of Y*, or, equivalently, *a reduction of X causes a reduction of Y*[1]; conversely, negative polarity of an edge from X to Y occurs when *a growth of X causes a reduction of Y*, or, symmetrically, *a reduction of X causes a growth of Y*. Positive and negative polarities can be defined even when they connect variables that are not measurable. Finally, the effects of a causality link can be delayed; when this aspect deserves attention, the symbol // is used on the arrow, and the attribute *withDelay* is true.

FeedbackLoops, CausalRoutes and their properties. Variables and CausalityLinks enable representing arbitrary graphs over thematic regions; the relevant patterns associated with a graph can be derived from them, and represent FeedbackLoops, CausalRoutes (introduced in this paper, not included in the original definitions [6]), and their properties.

A FeedbackLoop is created for each cyclic path of two or more edges going from one variable, called "target variable", back to the same variable. Each loop is either *balancing (B)* or *reinforcing (R)*. This notation is typically placed on a round sticker along the loop; usually, only loops that have been identified as interesting by designers are marked on the visual diagram. The association of loops with stickers may be ambiguous when several loops interfere with each other; for this reason, we denote loops by a list of node identifiers along the cyclic path.

The loop dynamic is dictated by a simple rule: *loops are balancing when they contain an odd number of negative connections, they are reinforcing when they contain an even number of negative connections*. This rule is motivated as follows: if the number of negative connections is odd (1, 3, 5, ...), we can compose the edges' interpretations and say that the growth of the target variable along the outgoing edge will eventually be compensated by a decrease of the same target variable produced by the last (incoming) edge of the loop, regardless of the number of intermediate steps. Thus, growths will be balanced by decreases, whereas decreases will be balanced by growths. Instead, if the number of negative connections is even (0, 2, 4,...), then a growth along the outgoing edge eventually causes a growth of the target variable along the incoming edge, generating a positive reinforcement along the loop – and likewise for a negative reinforcement. Feedback loops have a *referenceBehaviourPattern* referred to their target variable; these are (purely conceptual) functions, drawn on a temporal scale, providing an indication of how the variables will behave as a consequence of changes occurring in the loop. Patterns reflect typical stereotypes: *linear, superlinear, and sublinear*; once associated with either growth or decrease, this yields six possible behavior patterns for each loop. In particular, linear and superlinear stereotypes denote reinforcing loops, while sublinear stereotypes denote balancing loops, as they show a trend toward stabilization.

In addition to feedback loops, we introduce the new concept of CausalRoute, consisting of a sequence of connections from a source node to a destination node. Causal routes are characterized as *increasing/decreasing*, based on the even vs. odd count of negative polarities along their connections, as discussed for balancing and reinforcing loops. In addition, their *cumulativeTrend* provides a (purely conceptual) indication of how the destination variable grows or decreases as a function of the growth or decrease of the source variable; trends reflect typical stereotypes: *linear, superlinear, and sublinear*; once associated with either growth or decrease, this yields to six possible behavior patterns for each causal route.

As an addition to the original formalization, we also add the AlternativeLoops concept, representing those loops that have an arbitrary *sharedVariable* (not necessarily the target one); they are *agreeing* when they are all balancing or reinforcing, *disagreeing* when at least one is balancing and at least one is reinforcing. Similarly, we add the concept of AlternativeRoutes, representing two or more causal routes connecting the same source and destination variables; they are *agreeing* when they are all increasing or decreasing; they are *disagreeing* when at least one is increasing and at least one is decreasing.

[1]We provide both readings because, when causality links form loops or routes, one of the readings more naturally explains the link role in relation to the entire route.

Feedback loops in some CLD examples are also described by means of an ObservedBehaviourPattern, listing several ordered observations of measured variables to show their phased evolution (growth or decrease along the cycle). As these patterns are not well formalized and we consider them as not very effective in the description of complex systems, we disregard them in CLDs that are presented next.

We deliberately excluded from the metamodel some CLD aspects, for instance, the discussion of loop dominance [8], as it was hard to systematically deal with it; similarly, we did not make use of observed behavior patterns, i.e., the gathering of quantitative variable observations, as we found this aspect not at the same level of abstraction w.r.t. the systemic design approach.

4. Causal Loop Diagram for the COVID-19 pandemic

The COVID-19 pandemic has moved the scientific community at large in order to study its effects; a number of models have studied in-depth mitigation measures [26, 27] economic aspects [28], and misinformation impact [29]. Several CLDs have been employed during the COVID-19 pandemic to analyze the complexity of the unprecedented business response [30] and socio-economic impacts [31], along with the environmental-health impacts [32]. In Figure 3, we summarize salient systemic aspects that regard: economic growth, government actions, impacts on society, and healthcare management related to the number of confirmed cases; we omit to discuss the effects of vaccinations, therefore, temporally situating our CLD at the beginning of 2021. In this way, we put to work our systematic CLD analysis, supported by metamodeling, in confirming aspects that are rather well-known, as they have been in the public interest of relatively recent years. In particular, we see that the main variable of this CLD is the number of *confirmed cases*; most strategies at government levels, although quite different within different regions/states and at different times of the pandemic, were instrumented to react to increases of this accumulation variable.

Our first analysis is concerned with feedback loops that target this variable. Confirmed cases rise when a new dangerous variant becomes dominant. We recognize a main loop B1 (circuit 12, 9, 6, 12) that sees an *increase of intensive care admissions* (an immediate measure of the disease's spread and severity) causing an *increase of interventions* bringing, with a given delay, to the *reduction of confirmed cases.* Another similar loop B2 (circuit 12, 8, 6, 12) justifies an increase in *interventions* as a result of a (delayed) *government action.* These two alternative loops agree on their balancing effect.

Another interesting loop is B3 (circuit 12, 14, 15, 16, 9, 6, 12), which also agrees with B1 and B2. It is also balancing, along the reasoning that an *increase of confirmed cases* causes an *increase of load on health workers*, hence a *reduced health service capacity* that translates to a *reduced access to health services*, and then to an *increase of intensive care admissions* because patients reach the hospital when their health status is already very severe; then B3 merges with B1's last two edges. Note the reading of this balancing loop, where the odd number of negative loops produces, in the end, a balancing effect over the target variable.

However, the increase in health worker load is at the base of two reinforcing loops, R2 and R3. Loop R2 (circuit 14, 15, 14) indicates a well-known *deadly spiral* in which healthcare has been trapped during the pandemic, where, as a consequence of the high load of health workers, health service capacity has been reduced, leading to even higher health worker load due to COVID-19 and other emergencies. Loop R3 (circuit 14, 15, 16, 18, 14) illustrates that a reduction of health services causes, with some delay, a reduction of prevention practices for many pathologies other than COVID-19, causing -in the long run-heavier health worker loads. Thus, when R2 and R3 are observed by taking the *health worker load* as their shared variable, these two alternative loops are both reinforcing and agreeing.

The (relatively) simple CLD shown in Figure 3 shows another reinforcing loop R1 (circuit 4, 1, 2, 4), at the intersection of the economy-government thematic regions, reflecting another *deadly spiral*, this time relative to the job market, where interventions cause business restrictions, which in turn cause a *reduction of economic growth*, which in turn causes an *increase of unemployment* and therefore a further *increase of business restrictions.*

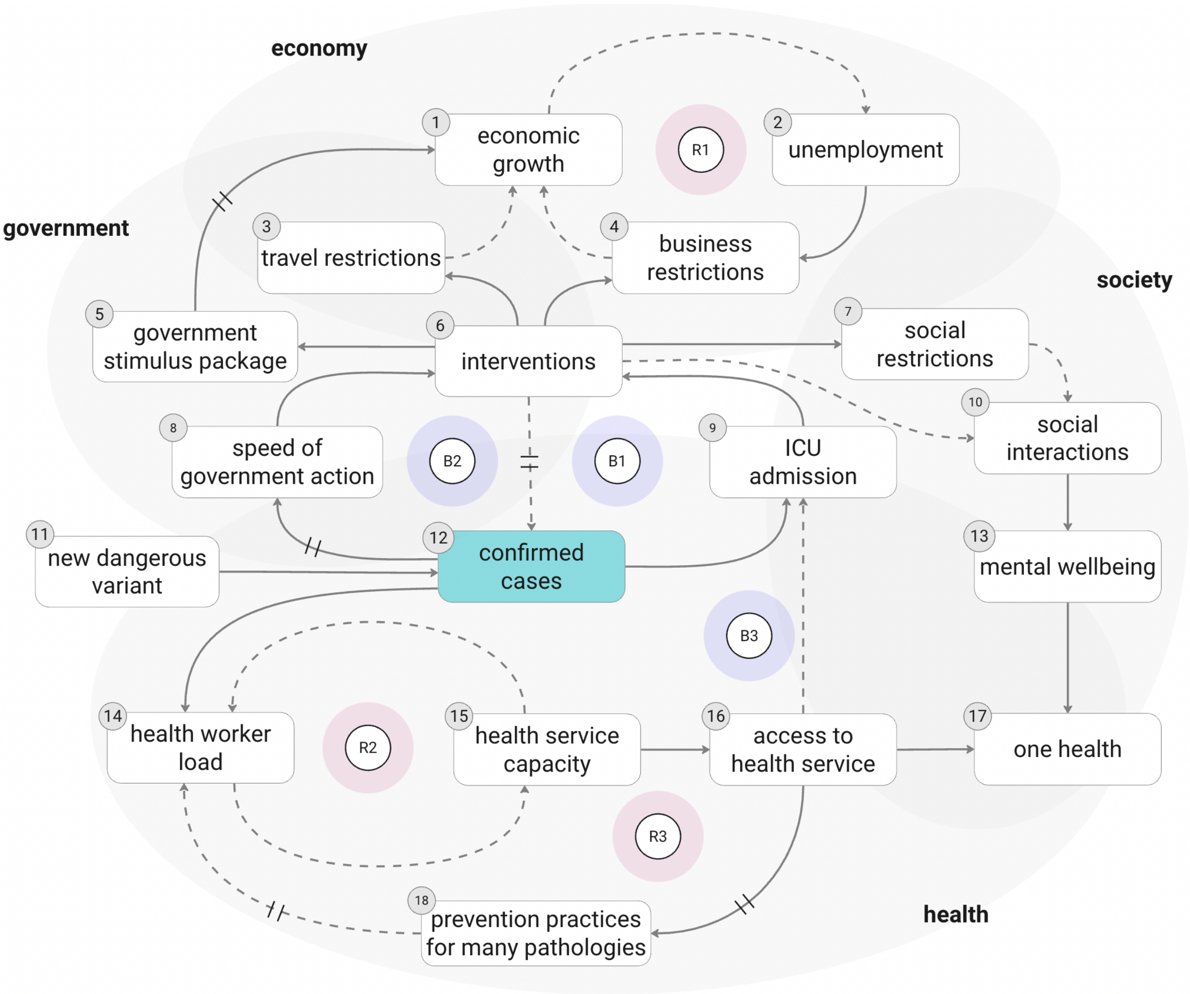

Figure 3: Causal Loop Diagram for COVID-19.

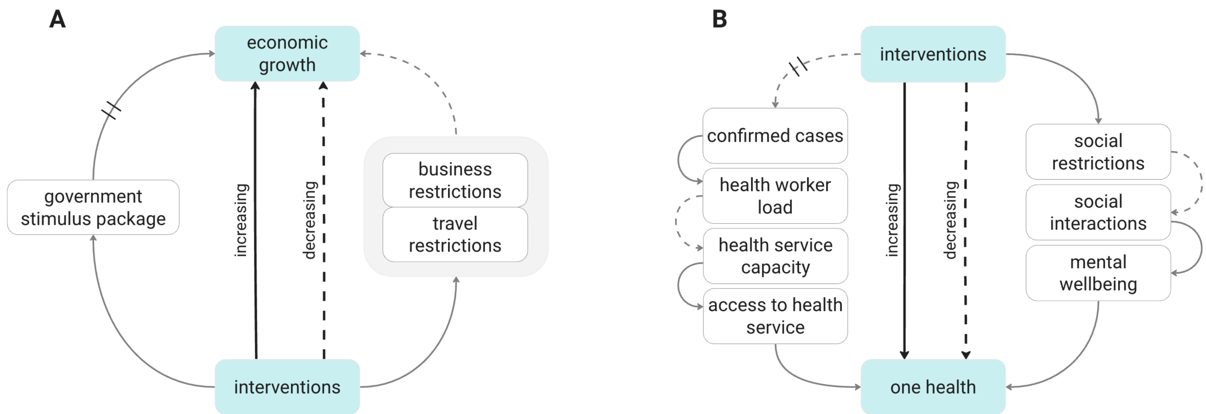

Figure 4: Alternative routes in the COVID19 Causal Loop Diagram.

The just discussed R1 reinforcement loop introduces an interesting alternative route from *interventions* to *economic growth* (see Figure 4A), where stimulus packages introduced by the government lead to increasing economic growth and compensate, although with delay, for the restrictions on travel and businesses, which instead cause a reduction of economic growth (as discussed above). Summary edges represented at the center of figures describing alternative routes clarify each route's polarity: the route on the left side is increasing (it has no negative edges, hence an even number of negative connections), whereas the route on the right side is decreasing (one negative connection). This simple set of disagreeing causal routes hints at the huge, complex decision processes leading to the deliberation, by the world's governments, of effective stimulus packages for combating the negative effects of COVID-19 on economic growth.

Another intriguing decision process is discussed in Figure 4B and concerns the connection of *interventions* to the *one health* concept [33], i.e., the inclusion within health factors of a number of dimensions and not just disease treatment. In particular, along the increasing route on the left, we see that interventions *reduce confirmed cases*, which *reduce the health worker loads*, which then *increase the health service capacity*, hence *the (general) access to health services*, thus *improving one health*. Along the decreasing route on the right, we see that interventions cause an *increase of social restrictions*, leading to a *reduction of social interactions*, hence a *reduction of mental wellbeing*, thus *worsening one health*. In general, the one health concept is developed with the ambition of finding many other determinants, not necessarily related to our health (for instance, including animal health), so as to holistically consider them; an encompassing study of the one health concept using CLDs could lead to many significant insights.

5. Causal Loop Diagram for the fashion industry footprint and sustainability

Our second use case is dedicated to analyzing the fashion industry; in particular, it is focused on a critical assessment of the industry's footprint and sustainability, looking for hidden/interesting aspects. The CLD, with *fashion industry footprint* as its target variable, is illustrated in Figure 5; it spans over the Market, Consumption, Production, and Policies thematic regions, and is weakly inspired by the CLD presented in [34].

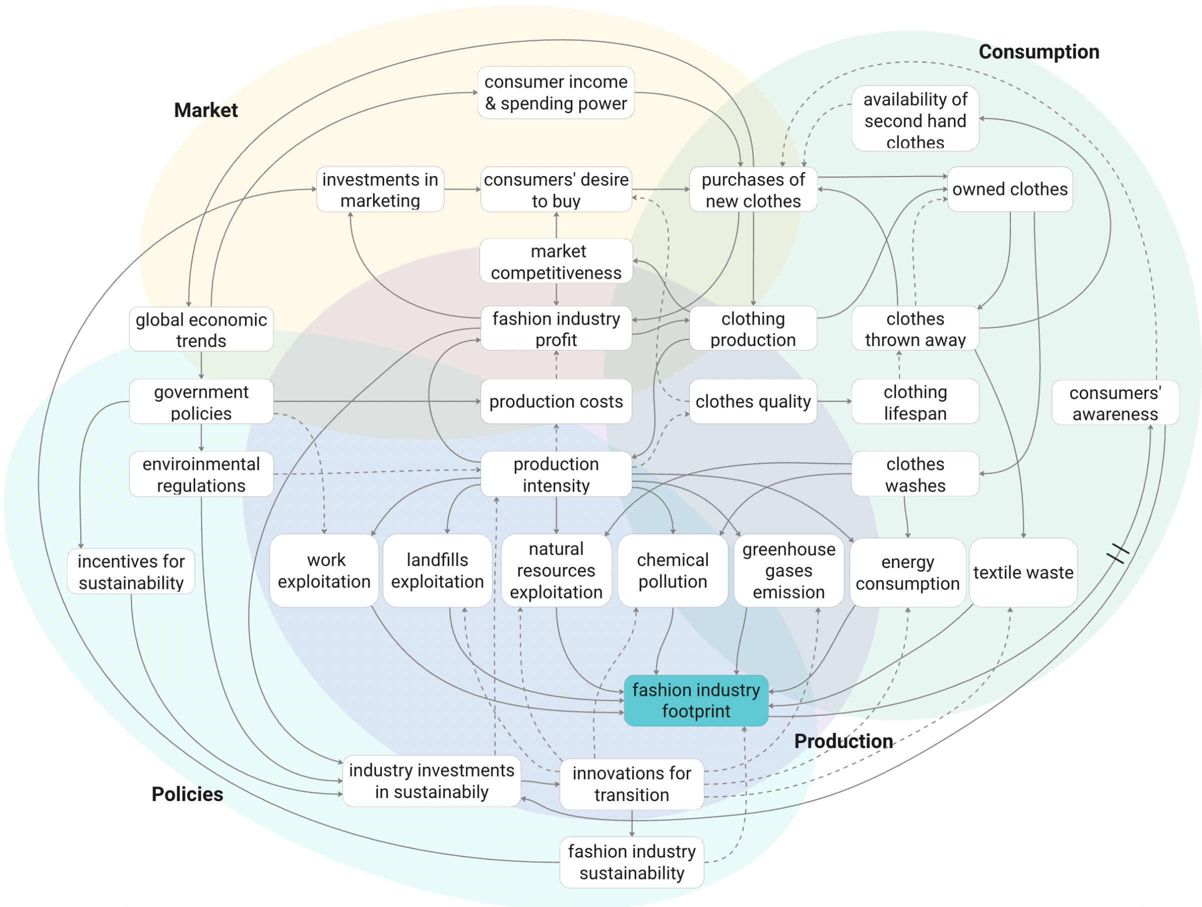

Figure 5: Causal Loop Diagram for the footprint analysis of the fashion industry.

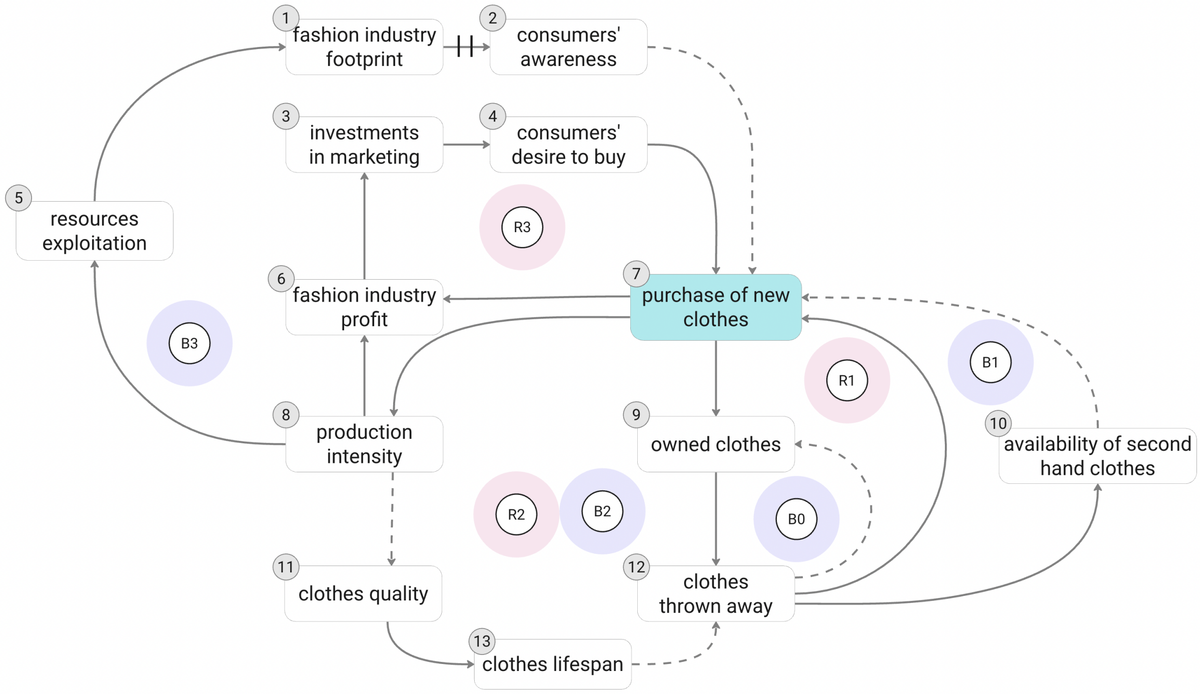

Figure 6: Analysis of six alternative loops sharing the *purchase of new clothes* variable.

As in our first use case, we start with a focus on feedback loops, shown in Figure 6, which highlights several alternative loops sharing the *purchase of new clothes* variable. Reinforcement loop R1 describes a simple consumerist behavior (circuit 7, 9, 12, 7): with purchases of new clothes, owned clothes increase, then thrown-away clothes increase, and finally, new clothes are purchased. Along this reasoning, loop B0 (circuit 9, 12, 9) simply indicates that an increase in thrown-away clothes causes a decrease in owned clothes.

More interestingly, the balancing loop B1 (circuit 12, 10, 7, 9, 12) signals that when clothes are thrown away, there is a higher availability of second-hand clothes, and this can *reduce the purchase of new clothes*; thus, R1 and B2 are alternative and disagreeing. An increasing causal route, common to loops R2 and B2, goes from *purchases of new clothes* to *clothes thrown away* (sequence 7, 8, 11, 13, 12) occurs because, with increased purchases of new clothes, production intensity increases, but then the quality of clothes decreases; this reduces the lifespan of clothes, and eventually, more clothes are thrown away. This route can be completed both as a reinforcing loop R2 (by considering the direct connection to purchases of new clothes) and a balancing loop B2 (through second-hand clothes availability, node 10).

Other feedback loops share the *purchase of new clothes*; in particular, reinforcing loop R3 (circuit 7, 6, 3, 4, 7), along classic mechanisms of expanding markets, indicates that an increase in purchases of new clothes increases the fashion industry's profit, which in turn increases investments in the market, which in turn increases customer's desire to buy, yielding to increasing of purchases of new clothes; this loop only includes positive connections. A more subtle balancing loop B3, however, involves consumers' awareness of the fashion industry's footprint (circuit 7, 8, 5, 1, 2, 7). Along with an increase in purchases of new clothes, production intensity rises, which then causes greater resource exploitation and therefore an increase in the fashion industry's footprint. This may, in the long run, affect consumer awareness and cause a reduction in new clothes purchases.

At this point, six loops insist on the shared variable *purchase of new clothes*, out of which three are balancing (B1, B2, B3) and three are reinforcing (R1, R2, R3); understanding their interdependencies and determining the strengths of each of them requires deeper analyses, but their underlying mechanisms are well identified.

The analysis of some alternative and disagreeing causal routes of the original CLD in Figure 5 provides more insights. We first consider, in Figure 7A, the polarity of *environmental regulations* upon the *fashion*

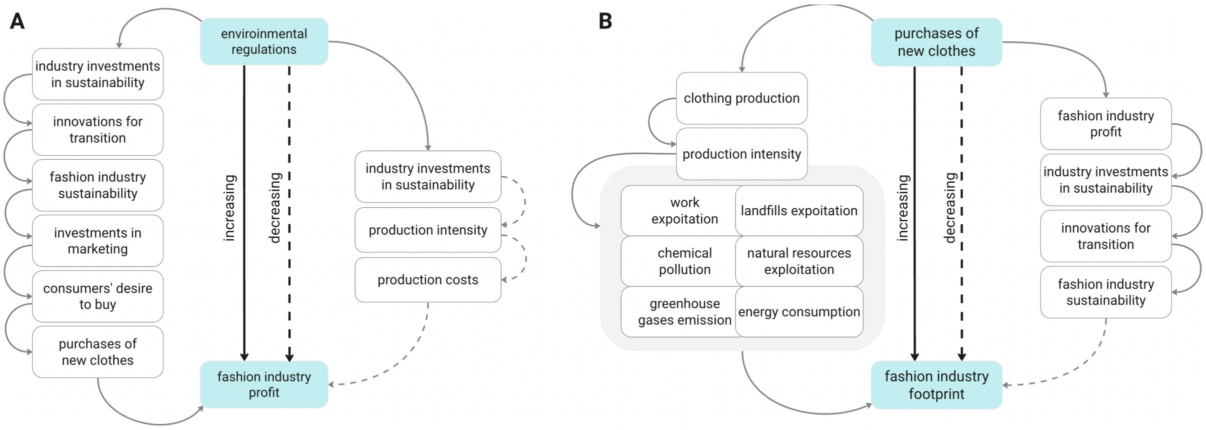

Figure 7: Analysis of alternative disagreeing causal routes in fashion industry CLD.

industry profit. The standard causal route, with a negative polarity, indicates that environmental regulations require higher industry investment in sustainability, causing a reduction of production intensity and, therefore, an increase in production costs, and then a decrease in profits. However, a less obvious causal route, with a positive polarity (contributed by a sequence of connections with positive polarities) indicates that greater investments in sustainability can generate greater innovation for supporting the sustainability transition, followed by higher investments in marketing that highlight these achievements, and these in turn may rise the customer's attention and desire, leading to higher purchases of new clothes and eventually to an increase of profits.

We next consider, in Figure 7B, the influence of *purchases of new clothes* upon the *fashion industry footprint.* As before, the standard causal route, with a positive polarity, indicates that an increase in purchases causes a more massive production, a higher production intensity, hence higher exploitation in all six considered categories, and eventually a rise in the industry footprint. However, an alternative route considers the rise of profits, which descends from higher purchases of new clothes, which are used for investing in sustainability, thereby facilitating the industry's transition and eventually obtaining higher sustainability, leading to a reduced industry footprint.

6. Discussion and conclusion

CLDs are a formalism providing high-level descriptions of complex systems; as such, they allow focusing on areas of intervention that can be deepened/assessed by means of further analysis. An example is provided, in our fashion design use case, by the insight that improving the fashion footprint not only causes an increase in the cost of production but also can be a factor for pushing innovation and a means for stimulating the consumer's awareness and creating a new strategy for market penetration, thus balancing the "negative" impact of increased costs with possible "positive" outcomes – process innovation and marketing positioning. A complementary analysis could be performed on *fast-fashion* influence on countries from the Global South, such as Bangladesh, with a garment industry worth 55B US dollars a year, now facing an unsettled future after protests, due to low pay and poor working conditions, particularly for women [35].

In parallel work [36], we describe a demo application that implements all our concepts; the prototype includes as predefined cases the COVID and Fashion Design use case; it also includes the use case about renewable energy technology (RET) adoption for hotels in Queensland (Australia) described in [18], the largest and most documented CLD that we found in the literature, with 42 variables, 74 relationships, 143 causal loops and 62171 causal routes. Our prototype incoporates LOOPY [37], a open-source visual tool, for entering a new CLD; it supports the systematic analysis of causal loops and causal routes, the selection of specific loops and routes for direct comparison, and the production of a PDF report where the result of an explorative interaction can be extracted, together with selected loops or routes.

The prototype demonstrates the potential of computational tools to support systemic modeling and reasoning; practitioners can use it to identify leverage points and explore the systemic consequences of interventions, while researchers gain a framework for formalizing and querying alternative models within the same domain.

The current prototype is a basis for building a more robust infrastructure, capable of documenting the design process for a given use case (using different progressive CLD versions) and organizing several use cases within a CLD repository. The combination of metamodeling, structured representation, and a queryable CLD repository will provide the foundations for more deliberate and evidence-informed systemic design.

Looking ahead, future work could include the integration of dynamic simulation capabilities, the use of external data sources for real-time or evidence-based modeling, and the implementation of collaborative features. Additional potential lies in the application of machine learning to detect recurring causal archetypes and in the development of natural language interfaces to support accessibility. An additional interesting research concerns the exploitation of suitably trained Large Language Models to automatically recognize causal relationships and their polarities from texts.

As a further opportunity for investigation, we noted possible synergies with the i^* framework. Currently, the systemic design community and the i^* community both offer valuable perspectives for modeling complex systems, but they differ significantly in focus and methodology. While CLDs provide a macro-level view of system dynamics, the i^* framework offers a micro-level view of stakeholder motivations and interactions. Taken together, these approaches could complement each other, with CLDs shedding light on system-level feedback and i^* revealing the underlying intentions that drive individual and organizational actions.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] L. Crielaard, et al., Refining the causal loop diagram: A tutorial for maximizing the contribution of domain expertise in computational system dynamics modeling, Psychological Methods (2022).

[2] H. Plattner, et al., Design thinking research, Springer, 2012.

[3] D. H. Meadows, Thinking in systems: A primer, Chelsea Green Publishing, 2008.

[4] The World Bank, Annual report 2023, https://www.worldbank.org/en/about/annual-report#anchor-annual, 2023. Last access: August 8th, 2025.

[5] United Nations; Dept. Economic and Social Affairs Sustainable Development, The 17 goals, https://sdgs.un.org/goals, 2015. Last access: August 8th, 2025.

[6] H. V. Haraldsson, Introduction to system thinking and causal loop diagrams, Department of chemical engineering, Lund University Lund, Sweden, 2004.

[7] G. P. Richardson, Problems with causal-loop diagrams, System dynamics review 2 (1986) 158–170.

[8] T. Binder, et al., Developing system dynamics models from causal loop diagrams, in: Proc. of the 22nd International Conference of the System Dynamic Society, 2004, pp. 1–21.

[9] J. Hayward, Model behavior and the strengths of causal loops: Mathematical insights and a practical method, in: International System Dynamics Conference, 2012.

[10] F. Ciolli, et al., QED representation for the net of causal loops, Reviews in Mathematical Physics 27 (2015) 1550012.

[11] E. S. Kenzie, Get your model out there: Advancing methods for developing and using causal-loop diagrams, Ph.D. thesis, Portland State University, 2021.

[12] N. Hosseinichimeh, et al., From text to map: a system dynamics bot for constructing causal loop diagrams, System Dynamics Review 40 (2024) e1782.

[13] T. J. Gandee, P. J. Giabbanelli, Combining natural language generation and graph algorithms to explain causal maps through meaningful paragraphs, in: International Conference on Conceptual Modeling, Springer, 2024, pp. 359–376.
[14] N.-Y. G. Liu, D. R. Keith, Leveraging large language models for automated causal loop diagram generation: Enhancing system dynamics modeling through curated prompting techniques, arXiv preprint arXiv:2503.21798 (2025).
[15] J. McGlashan, et al., Quantifying a systems map: network analysis of a childhood obesity causal loop diagram, PloS one 11 (2016) e0165459.
[16] S. Allender, et al., A community based systems diagram of obesity causes, PloS one 10 (2015) e0129683.
[17] R. Iannone, et al., Modeling fashion retail supply chain through causal loop diagram, IFAC-PapersOnLine 48 (2015) 1290–1295.
[18] N. Dhirasasna, O. Sahin, A multi-methodology approach to creating a causal loop diagram, Systems 7 (2019) 42.
[19] L. S. Liebovitch, et al., Approaches to understanding sustainable peace: qualitative causal loop diagrams and quantitative mathematical models, American Behavioral Scientist 64 (2020) 123–144.
[20] F. Tulinayo, et al., From a system dynamics causal loop diagram to an object-role model: a stepwise approach, Journal of Digital Information Management 10 (2012) 174–186.
[21] F. Tulinayo, et al., Enhancing the system dynamics modeling process with a domain modeling method, Int. J. of Cooperative Information Systems 22 (2013) 1350011.
[22] E. S. Yu, J. Mylopoulos, Enterprise modelling for business redesign: The i* framework, ACM SIGGROUP Bulletin 18 (1997) 59–63.
[23] X. Franch, et al., The i* framework for goal-oriented modeling, Domain-Specific Conceptual Modeling: Concepts, Methods and Tools (2016) 485–506.
[24] G. Guizzardi, On Ontology, ontologies, Conceptualizations, Modeling Languages, and (Meta)Models, in: O. Vasilecas, J. Eder, A. Caplinskas (Eds.), Databases and Information Systems IV, volume 155, IOS Press, 2006, pp. 18–39.
[25] C. Batini, et al., Conceptual database design: an entity-relationship approach, Benjamin-Cummings Publishing Co., Inc., 1991.
[26] R. M. Anderson, et al., How will country-based mitigation measures influence the course of the COVID-19 epidemic?, The Lancet 395 (2020) 931–934.
[27] A. Bernasconi, et al., Data-driven analysis of amino acid change dynamics timely reveals SARS-CoV-2 variant emergence, Scientific Reports 11 (2021) 21068.
[28] G. Bonaccorsi, et al., Economic and social consequences of human mobility restrictions under COVID-19, Proc. of the National Academy of Sciences 117 (2020) 15530–15535.
[29] F. Pierri, et al., Online misinformation is linked to early COVID-19 vaccination hesitancy and refusal, Scientific Reports 12 (2022) 5966.
[30] K. Zięba, How can systems thinking help us in the COVID-19 crisis?, Knowledge and Process Management 29 (2022) 221–230.
[31] N. Strelkovskii, E. Rovenskaya, Causal loop diagramming of socioeconomic impacts of COVID-19: state-of-the-art, gaps and good practices, Systems 9 (2021) 65.
[32] O. Sahin, et al., Developing a preliminary causal loop diagram for understanding the wicked complexity of the COVID-19 pandemic, Systems 8 (2020) 20.
[33] World Health Organization, One health, https://www.who.int/news-room/questions-and-answers/item/one-health, 2023. Last access: August 8th, 2025.
[34] System Mapping Academy, System Mapping Toolkit, https://miro.com/app/board/uXjVP0ou690=/?fromEmbed=1, 2025. Last access: August 8th, 2025.
[35] N. Inamdar, Fast fashion drove bangladesh - now its troubled economy needs more (2024).
[36] A. Bernasconi, et al., CLD-Explorer: Toward a Tool for Causal Loop Diagrams Analytics, 2025. Companion Proc. 44th Int. Conf. on Conceptual Modeling: Posters and Demos.
[37] LOOPY, https://ncase.me/loopy/, 2025. Last access: August 8th, 2025.