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What drives long-term social assistance use among young adults and where are the potential points for intervention?

LESSONS FROM A PARTICIPATORY SYSTEMS MAPPING EXERCISE IN THE FINNISH CONTEXT

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Abstract

In 2021, approximately one-sixth of young adults in Finland relied on means-tested and last-resort social assistance (SA), making it a pressing social policy concern. However, the factors contributing to long-term SA use among young adults are intricate and challenging to disentangle, and existing literature lacks comprehensive understanding. In this study, we employ Participatory Systems Mapping (PSM) as a methodological framework to systematically explore this complexity. Through a series of participatory modelling workshops with experts, we identify 95 interconnected factors linked by 429 causal relationships (both direct and indirect) to long-term SA use. Our approach enables us to capture the complexity of LT-SA while shedding light on drivers often overlooked in previous studies. By subjecting the consolidated map of factors and causal relationships to systems, structural, network, controllability, and tradeoff analyses, we identify potential intervention points for reducing SA use among young adults. Our analyses reveal that both "hard" policy areas such as education and employment, and "soft" factors typically omitted in discussions of SA, including self-awareness, bullying, past-time activities, experiences of success, and discrimination, are significant immediate drivers of SA. Our analysis suggests that intervention strategies should encompass not only hard policy areas like service improvement and education but also soft policy areas such as enhancing service accessibility, addressing loneliness, and tackling structural discrimination. Our findings underscore the importance of connecting different sectors and domains, as interventions that bridge these domains have the greatest potential to effectively and sustainably reduce long-term SA use. More broadly, the consolidated causal map can serve as a valuable resource for future studies, aiding in the formulation of research questions, development of analytical strategies, and contextualization of results pertaining to long-term SA use and other social policy issues. We urge researchers and policymakers to embrace this participatory mapping approach in social policy research for more nuanced insights that account for the intricacies and complexity of the problem at hand. To the best of our knowledge, this study represents the first application of PSM in the field of social policy research. Special thanks go to Lauri Mäkinen, Mari Hirvonen and Eeli Sissonen for their invaluable contributions of this study.

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What drives long-term social assistance use among young adults and where are the potential points for intervention? Lessons from a participatory systems mapping exercise in the Finnish context

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1 Introduction

In this paper, we analyse long-term social assistance use among young adults in Finland within a participatory systems mapping framework. The paper has three complementary aims and contributions: (1) to introduce and demonstrate the use of participatory systems mapping in social policy research (contribution to practice), (2) to complement existing literature by highlighting drivers of social assistance use identified through the elicitation of causal maps during participatory modelling workshops and subsequent network analysis (contribution to knowledge) and, finally, (3) to identify potential policy levers to reduce social assistance use among young adults (contribution to policy). Based on these three contributions, we make a number of policy recommendations in the Finnish context and generalise our findings to establish broader implications for social policy research, practice and implementation in other countries.

In Finland, social assistance (SA) is the last resort form of economic assistance, provided to individuals and households with no spare income or assets to cover their essential consumption needs (Perusturvan riittävyyden III arviointiryhmä, 2019; Gough et al., 1997). Technically, SA consists of direct cash transfers to low-income individuals or households, with the objective of securing an acceptable living standard, as is guaranteed by Finland's Constitution (Kangas and Simanainen, 2021). SA is a means-tested form of economic relief, that is, people's income and assets are evaluated for eligibility by case workers. Other income-related social benefits to insure against income loss due to typical social risks such as unemployment, old age, sickness or parenthood exist, and these social benefits are typically more generous than SA. SA is a subjective right and the eligibility to SA is not to be rejected due to inactivity or any other reasons while its level can be reduced under certain circumstances. While all Finnish residents with insufficient means are eligible, SA also comes with downsides, such as social stigma, benefit dependence and incentive traps (Perusturvan riittävyyden III arviointiryhmä, 2019). In 2023, the basic SA was on average 550 euros per person per month while the level of support differs by the household composition of the applicant. A widespread and long-term reliance on SA is a substantial economic burden to society, as SA is an objective marker of the economic difficulties of individuals.

Long-term social assistance use (LT-SA) among young adults is an ongoing policy issue in Finland. While SA is intended as short-term economic relief to overcome transitory economic difficulties, a non-negligible proportion of young adults are long-term social assistance recipients. Some 16 percent of adults aged 18-24 received SA at least once in 2021 (THL, 2022), a figure that is much higher than in older adults in Finland. The figure is also higher than is reported previously in aged-matched peers in Sweden and Denmark (Lorentzen et al., 2014). The rate of SA use among young Finnish adults has increased in recent years, up from 13 percent in 2006, the earliest year with comparable data available. This is because young adults are typically in more precarious jobs, they are yet to accumulate savings to offset potential income shocks and they are less often eligible for earnings-related social benefits (Raittila et al., 2018). There is no concrete or widely accepted definition of LT-SA use but some 15000 adults aged 18-24 (some 3% of the age group) received SA for more than 9 months in 2021. For young adults, LT-SA indicates not only severe economic difficulties but often also underlying disruptions in school-to-school and school-to-work transitions. For these reasons, LT-SA is an important social wellbeing indicator and the main focus of this study.

The current policy discourse to reduce LT-SA hovers around social benefits and, in separate discussions, social services while policy makers often acknowledge that a substantial intergenerational aspect of LT-SA exists. Another argument that typically arises in LT-SA discussion is also that the level of basic social security is inadequate, causing individuals to rely on this last-resort assistance (Kuivalainen, 2010; Raittila et al., 2018). Previous quantitative studies have documented that important factors contributing to LT-SA among young people include, for example, mental health problems (Haula and Vaalavuo, 2021), parental debt problems (Lehtonen, 2016), low education (Ristikari et al., 2016), parental education (Ilmakunnas and Moisio, 2019), family income (Vauhkonen et al., 2017) and housing costs (Raittila et al., 2018). These previous studies, using regression-based quantitative methods, have provided important clues about the potential drivers of LT-SA. These studies, however, have been mainly focused on a single predictor of LT-SA while not taking into consideration the complexity in their links and potential mediating factors. Ignoring these complex pathways, as we argue here, may lead to oversimplified conclusions and thereby policy implications that are ineffective or counter-effective, in worst cases.

Our central tenet in this paper is that LT-SA is an unintended outcome emerging from a complex social system. *What is a complex social system?* Actions and decisions, carried out by individuals interacting in a multitude of ways and through physical or digital means, where highly heterogeneous actors are interconnected by kinship, friendship, ethnicity, social class, education, and/or geographical location is a paradigmatic example of a complex social system. SA, as a type of economic benefit or allowance aimed at enhancing human wellbeing (across its various dimensions including physical, emotional, occupational, social, spiritual, intellectual, environmental, and financial) is an archetypical example of a policy that aims to steer a complex social system towards socially-desirable outcomes. The *complexity* of the LT-SA problem—the one we would like to acknowledge and explore in this paper—lies in the nature of the interactions between individual decisions and social policies. These interactions occur within a complex web of causal relationships, thus leading to outcomes that can be very different to those intended by policy makers e.g., a policy or intervention that leads to no change or an increase in LT-SA. An example of this type of policy change was assigning the Social Insurance Institution of Finland KELA, instead of municipalities, the responsibility of granting social assistance, which led to some minor unintended consequences to service delivery (Halmetoja and Rintala, 2020).

We acknowledge that social safety nets are complex policy systems not just socially, but also politically and administratively. In this paper we only deal with social dimensions, yet our methods could be applied and our analyses expanded to incorporate political and administrative dimensions in the future. The complexity of LT-SA is compounded by the interaction of different levels of government (central government vs. municipalities), different actors (NGOs, for-profit sector, public) and multiple upstream influences, some of which are not controllable, that is, beyond the control of any feasible interventions. Examples of upstream determinants of LT-SA include parental economic difficulties, lack of early support in the service sector and regional differences in opportunities of further education. Concretely, SA is mostly paid by the national Social Insurance Institution but supplementary and preventative social assistance can be offered by social workers in the regional wellbeing areas, that is, geographical areas in charge of providing health and welfare services to the residents. LT-SA is also linked to the work of NGO's, in that they guide individuals to apply for SA. These multiple levels of support, and the potential lack of coordination between them, can often compound against efforts to reduce LT-SA (see e.g. (Kivipelto et al., 2021). There is evidence that previous measures to reduce SA use among young adults have proved ineffective in retrospective evaluations. For example, the effect of a digitised notification program aiming to prompt exit from LT-SA was found to be insignificant (Mesiäislehto et al., 2022). The fact that traditional measures have proved inefficient motivates us to explore new approaches to identify alternative pathways through which LT-SA can be reduced.

This paper is motivated by two interrelated research questions: (1) *What are the drivers of LT-SA among young adults in Finland?* and (2) *What would be the most efficient pathways or interventions by which it could be mitigated and/or reduced?* We tackle these questions and embrace the complexity of the LT-SA issue by using participatory complex systems methodologies. We approach these two research questions from a systemic perspective, aiming to provide a better understanding of the chains of causality that lead to LT-SA and point to interventions within its upstream factors (immediate and root cause) factors, rather than changes to the level and eligibility of SA itself.

This paper proceeds as follows. Section 2 outlines our theoretical stance and methodological approach. Section 3 provides an overview of our case study using the 4P framework (Purpose, Process, Partnerships, and Products). Section 4 describes the participatory systems mapping process and analytical tools used in the case study. Section 5 presents the results of the PSM exercise, which includes a suite of network centrality, controllability, and structural analyses undertaken on a causal map elicited over the course of three stakeholder workshops. In Section 6 we interpret and discuss our findings, leading to policy recommendations in the Finnish context and broader implications for social policy research, practice and implementation in other countries.

2 Methodology

A core challenge in embracing and studying the complexity of LT-SA is that we cannot expect all individuals to respond in the same way to the implementation of a new SA benefit, service, or intervention. The outcomes of SA use are not just the sum of individual reactions to these policies—those reactions evolve and adapt as mediated by day-to-day social interactions in neighbourhoods, schools, families, and digital platforms. The success (or failure) of any SA policy is therefore a result of many individual decisions, the way those decisions interact, and the policies that are put in place to steer individual and collective decisions in a given direction.

Our intent to examine LT-SA using complex systems methodologies (also known as complexity science or complexity) is not new. The application of complexity to public policies related to healthcare, urban systems, infrastructure planning, land-use and macroeconomics—see (Gatti et al., 2010; Gomes and Gubareva, 2021; Parker et al., 2003; Rus et al., 2018; Thompson et al., 2016) for comprehensive reviews of complexity science in these domains—has grown tremendously in the past two decades. At the time of writing, however, we have not found any scientific literature using complex systems methodologies to examine SA or LT-SA issues. The closest application we have found (Kim and Maroulis, 2018) examines the issue of social welfare fraud from a complex systems perspective, arguing for deeper insights that could be derived from an agent-based model, yet without actually developing one.

Our methodological approach is inspired by Mago et al (2013), who used a Fuzzy Cognitive Mapping (Kosko, 1986) to analyse the impact of social factors on homelessness in Canada. Tools such as Fuzzy Cognitive Mapping (FCM) are particularly suited to the modelling of complex social problems, such as homelessness, due to their inherent ability to model intricate, interactive systems. Mago et al (2013) used this approach to map and analyse the chains of causality surrounding the issue of homelessness. The first step was to develop a "common-sense" map based on the researchers' personal and historical knowledge of the factors and causal relationships which they perceived to affect homelessness. The "common-sense" map was subsequently refined by the authors—via discussion and deliberation—based on a corpus of peer-reviewed empirical literature, which the authors used to verify, add and remove concepts and to establish the strength of influence (weight) of causal relationships within the map. Through a dynamic network analysis of their FCM, the authors concluded that Education is the dominant force and has the greatest impact on the dynamics and complexity of homelessness as a social problem.

Here, we adopt a similar, yet more generic and nuanced methodological approach known as Participatory Systems Mapping (Barbrook-Johnson and Penn, 2022). To the best of our knowledge, this is the first time that Participatory Systems Mapping (PSM) is applied to social policy research. PSM is a cooperative modelling methodology—in this approach, a team of stakeholders collectively creates a straightforward causal map of a particular issue in a workshop setting. This collaborative process results in a map composed of various elements, referred to as factors. These factors stand for variables, meaning entities that can fluctuate or vary in some way (can in some way go up or down). The connections between these factors signify causal relationships, establishing the network within the map. The ultimate goal of this map is to depict what stakeholders perceive to be the causal architecture of the system that's being examined. This visual representation aims to clarify their understanding of how different components of the system influence one another. The map can be built using a whiteboard or simple pen and paper materials on a large table or a digital platform. The process of building a map can be hugely valuable to participants. The digitised version of the map can be a useful resource that can be shared and updated over time. Also, a number of qualitative and quantitative analyses can be conducted on the map created.

There are three key differences between the FCM approach adopted by Mago et al (2013) and the PSM approach presented here. Unlike Mago et al., our approach emphasises stakeholder engagement, with a participatory and iterative process spanning three workshops over six months. While Mago et al. quantified relationship weights using a 5-level likert scale, we focused on accurate factor identification and causal relationships, with participants categorising strengths as low, medium, or high. Additionally, we employed novel analysis methods from graph theory, network centrality, network controllability, and structural analysis (Section 4), which have not been previously applied in this domain.

The participatory systems map created and analysed in this study provides a graphical description of LT-SA that facilitates the understanding of this complex social problem. Through network centrality, controllability, structural, tradeoff analyses (described in Section 4) and their results (presented in Section 5), the we demonstrate the usefulness of the approach and discuss implications for its use in policy decision making (Section 6). The aim of the following sections is to demonstrate that the application of PSM to complex social problems, allow for refinement of knowledge through graphical understanding, various network, controllability and structural analyses that may be useful in improving SA policies with the goal of reducing LT-SA. Figure 1 summarises our methodological approach.

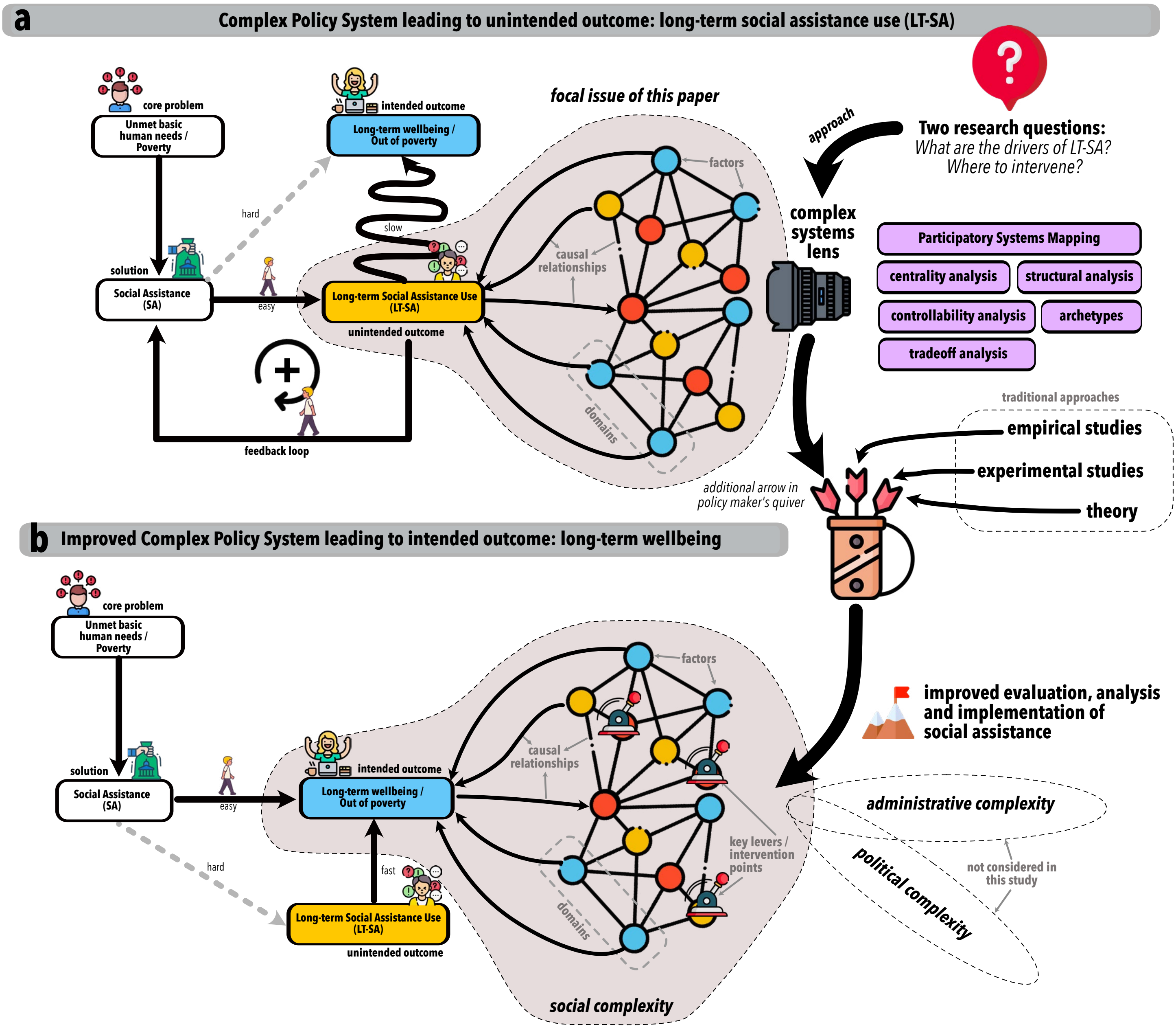


FIGURE 1. Graphical summary of the methodological approach adopted in this paper. Methods and tools (in purple) are described in detail in Section 4.

3 Case study

3.1 PURPOSE FOR SELECTING A PM APPROACH (THE WHY)

The purpose of this study was to identify key drivers of LT-SA use among young adults in Finland and further recognize potential points of interventions to reduce LT-SA while addressing its underlying upstream factors. We selected LT-SA use among young adults as our focal factor for this participatory modelling. While there have been multiple reports and studies on the social exclusion of young people in general and social assistance use in particular, these have mainly focused on few variables and neglected the interlinks between the drivers of social assistance use. We selected participatory fuzzy cognitive mapping (FCM) as a tool to make the mental models of stakeholders explicit and extract knowledge from them, explained below (Kosko, 1986). The reasons for this choice are the flexibility of FCM to consider a range of sources of knowledge and interdependencies, its ease to understand among stakeholders and its applications in subsequent network analysis.

We conceptualised this study as an explorative project with few prior hypotheses. Nevertheless, we expected varying views on the importance of different drivers of LT-SA use. We also anticipated major power asymmetries around the issue, an expectation which led us to select a participatory modelling approach and public as the modelling team strategy. Taking the views and knowledge of stakeholders and different scientific fields were deemed essential in building a robust and shared understanding of key drivers of LT-SA. Our modelling project had "a substantial function"(Jones et al., 2009), that is, we aimed to recognize the most promising points of interventions to reduce the use of long-term social assistance among young adults.

3.2 PROCESS BY WHICH THE PUBLIC WAS INVOLVED IN MODEL BUILDING OR EVALUATION (THE HOW)

While we did not pre-register this study given its iterative and evolving nature, we followed commonly accepted standards of the participatory modelling processes. Our participatory modelling project consisted of an initial planning phase, a series of participatory modelling workshops and an analysis phase.

In the initial planning phase, the members of the research team familiarised themselves with the literature and recognized the key issue of interest. While our initial idea was to improve the understanding of the intergenerational nature of socio-economic disadvantage in the Finnish context, we recognized the need to select a more specific focal factor to keep the focus of the project concise. The research team collectively selected LT-SA use as the key factor for four reasons. First, LT-SA, as such, is a major policy issue due to its massive burden on individual life-trajectories and public budget as explained in the first section of this paper. Second, the previous research has identified LT-SA use as a key transmission phase through which socioeconomic disadvantages transmit from a parent to the life trajectories of their children. The expectation was, then, that addressing LT-SA use would project a double dividend by also reducing the intergenerational nature of social disadvantage. Third, LT-SA use is an important metric because it often reflects issues in other sectors of society, such as primary social benefits and access to school and employment opportunities. Fourth, data on LT-SA use is easily available, implying that we had the possibility to supplement our analysis in subsequent investigations with quantitative data from population registers.

After the planning phase, we held three workshops over 6 months with some 30 stakeholders participating in total. Each workshop lasted some 2 hours. We started with an online workshop with a multidisciplinary group of researchers. The researchers participating in the workshop were not randomly selected. Instead, they were selected using prior knowledge of the research team. The eligibility criteria for selecting were that the researchers were familiar with the Finnish context and had previously studied issues around social assistance use, education or employment among young adults. The academic backgrounds of the researchers were in sociology, social policy, social work, psychology, and economics. The participants were asked to fill out a survey before the workshop to comment on the relevance of the selected focal factor (LT-SA use) and to mention some key factors linked to the focal point. The workshop then consisted of an introduction, and mapping exercise in three break-out rooms. Causal maps were built using MIRO boards. Participants were asked to discuss influencing LT-SA. The workshop facilitator led the discussion and aimed to achieve consensus about the added factors and their relationships. Given that the workshop was too short to cover all potential relationships between the factors, the facilitators added links between the identified factors to top up the existing ones after the workshop.

The second workshop consisted of a group of experts from NGOs. The invitees were selected based on existing contacts of the research team. The participants were from organisations working with young people in different services, such as child welfare services, mental health services and student organisations. The workshop consisted of an introduction phase and then a mapping exercise. Participants were divided into two break-out rooms, each of which had a slightly starting point of the discussion. Participants were asked to improve the map that was formed in the previous researcher workshop.

The third and final workshop consisted of experts by experience recruited from NGO organisations. Five experts by experience participated in this face-to-face workshop in addition to the research team. The workshop aimed to validate and expand the map. Participants were shown the factors, which were identified in the first and second workshops, but the key links from the map were hidden. Participants were asked to contribute to the map first individually, second in two groups from different starting points and finally collectively while identifying the strategic points of interventions. In all workshops, the Itla research team was actively involved in the process of drawing and discussing the causal maps.

No personal data was collected at any stages of this process. There was no discussion about personal experiences. The deliberative discussions were at a general level. The participation in the workshops was voluntary. All workshop participants were adults. For these reasons no research ethics review was sought from ethical review boards.

3.3 PARTNERSHIPS FORMED (THE WHO)

The project was a partnership project with Canberra University and Itla Children's foundation. Itla is an independent research foundation, under the Finnish parliament, focusing to improve the wellbeing of children and their families in Finland. The partnerships were initiated in the context of Itla's multi year program on child poverty aiming to identify key risk groups of child poverty, how to reduce it and how to translate this knowledge into policies. Other key partners in this project were the workshop participants, that is, researchers, NGO workers and experts by experience. The project was advertised on the Itla's web page. More information about Itla is available online (Itla.fi/en).

The stakeholders were motivated to participate in the workshop for a number of reasons. While we did not conduct post-workshop surveys, the research team's impression was that the participants gained shared understanding, new contacts and some ideas about the methodology of participatory modelling. The research and NGO were not compensated for their participation because the participation was part of their job. The experts by experience were paid according to a standard rate if the participation was not part of their current job.

3.4 PRODUCTS THAT RESULTED FROM THESE EFFORTS (THE WHAT)

The main product of this project was a consolidated causal map and the network and the structural, centrality, controllability, archetype and tradeoff analyses involved, which are explained in detail in Section 4. Other products include the following items: a participatory modelling training lecture, a podcast on the project, short video and research report. These additional items were necessary in order to maximise the impact and public engagement in this project. A motivation for multiple outputs was also the goal of this project to expand participation modelling thinking in public policy preparations and social policy and social work research fields.

The analysis of the consolidated causal map has led to deeper insights on the drivers of LT-SA (see Section 5) which motivate a series of recommendations for policy interventions and future research (see Section 6). The participatory process and methodological approaches applied in this study can serve as a blueprint to examine other issues and interventions related to the wellbeing, equality and position of children (in Finland and beyond). The proposed process and approaches support Itla's focus on the anticipation and prevention of problems, early intervention, community engagement, and systemic change.

4 Methods

The social sciences have a long tradition of using network representations to encode the relationships between the components or variables that describe the dynamics of complex social systems. The structure of a network is represented by a graph, so we will speak of nodes and links in the following. In the causal map (network) that we have elicited during the PSM process, nodes represent factors and links represent the causal relationships that connect them. The map, as a whole, is a systemic representation or model of the social complexity of the LT-SA issue.

Networks can be used to represent the complexity of LT-SA by capturing the relationships between various factors that contribute to this issue. The nodes in the network can represent different variables such as individual attributes, social programs, policies, social services, and other factors that can impact LT-SA. The connections or edges between nodes represent relationships between the variables such as causal links, dependencies, feedback loops, or other types of interactions. For example, the connection between an individual and a social program node can represent the enrollment of that individual in a particular social program. By analysing the network structure, we can identify the key factors or nodes that contribute to LT-SA, as well as the relationships between these factors. This can help policymakers and social service providers to identify the most effective strategies to address this issue, such as improving access to education or job training programs, increasing the availability of affordable housing, or improving the effectiveness of social assistance programs. Furthermore, network analysis can help identify patterns of social assistance use that may be related to particular demographic or socioeconomic characteristics, allowing for more targeted interventions to address the needs of specific populations. Overall, using networks to represent the problem of LT-SA can help to provide a more comprehensive understanding of the issue and inform more effective solutions. In this context, a common application is to gauge the prominence of nodes or links to identify key elements and drivers of the system.

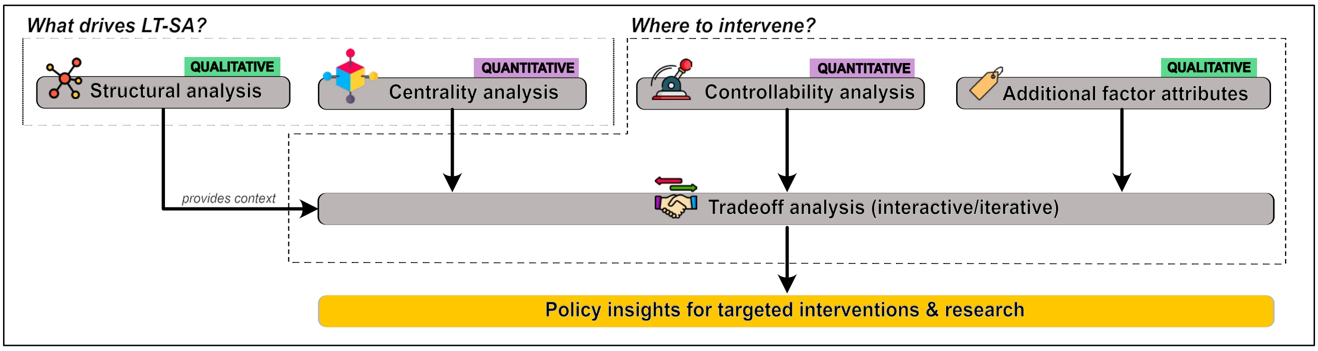


FIGURE 2. Graphical representation of the qualitative and quantitative approaches used to answer our two research questions: "What drives LT-SA?" and "Where to intervene?". The process is intended to embrace the causal complexity of this issue and in doing so, develop more effective and targeted policy interventions to mitigate LT-SA.

To examine our two research questions we used a mix of qualitative and quantitative methods, following the process shown in Figure 2. Each question was explored using qualitative and quantitative methods: "*What drives LT-SA?*" using structural analysis (qualitative) and centrality analysis (quantitative), and "*Where to intervene?*" using controllability analysis (quantitative) and additional factor attributes (qualitative). These two lines of inquiry were subsequently integrated into a collaborative tradeoff analysis (with the aid of interactive parallel coordinate plots). Tradeoff analysis provides a visual means to encourage deliberation (among the research team and/or with stakeholders) and facilitate creative thinking about the complexity around the LT-SA issue. Details of these methods and the process used to combine them are explained below.

WHAT DRIVES LT-SA?

Structural analysis

The process of analysing a map involves the creation of submaps, which are smaller sections of the overall map that are designed to help focus on particular questions or issues. The submaps are intended to provide a manageable way of navigating the otherwise large and complex diagram that is the full map.

To create a submap, one must first decide on a starting point. This can be based on either "stakeholder suggested" or "system suggested" factors. Stakeholder suggested factors are those that have been identified as important by the stakeholders themselves. They may represent current interventions or areas that stakeholders believe are vulnerable to change. On the other hand, system suggested factors are identified through network analysis and may have interesting properties in the network, such as having many connections or bridging different parts of the map. Once a starting point has been selected, the next step is to generate the submap using a set of rules. These rules are based on one of three different methods: following the arrow directions upstream or downstream from the starting factor, examining the ego networks of the starting factor, or tracing paths between multiple factors of interest. The number of steps to take upstream or downstream can vary, and the choice may depend on the specific research question or issue being explored. Furthermore, the rules can also be combined using unions or intersections to show multiple submaps together or where ego networks overlap. For example, if researchers want to look both upstream and downstream from a particular node of interest, they might create two submaps and show them together. Alternatively, they might identify multiple factors of interest and generate a submap that shows the paths between them.

Structural analysis is often conducted in a sequential manner where one submap leads to the creation of another by generating relevant questions. The process of creating submaps is iterative and exploratory and should ideally involve stakeholders to ensure their inputs and perspectives are included. The approach can be modified and combined in multiple ways to address the questions that are most pertinent to the participants. In this study, however, due to time and resource constraints it was not possible to undertake the structural analysis with stakeholder participation, so this step was achieved via deliberation within the research team. The results of this analysis are presented in Section 5.2.1.

Centrality analysis

Centrality measures are an important quantitative tool in network analysis —they are used to analyse the relative importance or influence of nodes in a network. Here, we define the importance of a node by how much its modification influences the operation of the network. The goal in practical applications is to change the behaviour associated with the network in some desired way. By identifying the most central or influential nodes in a network, these metrics can provide valuable information to prioritise resources or interventions, and to understand the underlying structure and dynamics of the system as a whole. There are several different types of network centrality measures, below we explicitly outline the rationale behind metric selection, what they aim to measure and describe, and how the maths translates to the target concepts and rules of interpretation (Morrison et al., 2022):

Out-Degree centrality (ODC): ODC measures the number of outward connections that a node has in a network. In other words, it measures how well-connected a node is in terms of *sending* information, resources, or influence to other nodes in the system. To understand the drivers of a system using ODC, we focus on the nodes with the highest scores. These nodes—often called "hubs"—are considered to be influential in the network, as they have a significant impact on other nodes that they are connected to. In the LT-SA map, for example, we might find that high ODC nodes are situational or contextual variables of an individual such as access to services, mental health, education, etc. We can then scrutinise in more detail their function, importance, or location in the network, to understand why they have a high out-degree centrality and how their influence could be leveraged. When thinking about potential policy interventions, we can look more closely at the controllability (more details on this below) of these variables to better understand the extent to which the state of the system could be improved—e.g., *is this variable amenable to intervention or change? Is this variable (economically, socially or politically) costly to intervene? How long does it take for this variable to affect the focal factor?* Nodes with a high ODC score are considered *sources* of influence, resources or information within the network, and therefore should be primary targets for intervention.

In-Degree centrality (IDC): IDC measures the number of inward connections that a node has in a network. In other words, it measures how well-connected a node is to other nodes in terms of receiving information, resources, or influence. In the context of understanding the drivers of a system, IDC can be used to identify nodes in a network that are more likely to be influenced by other nodes. Specifically, nodes with high IDC are those that have more incoming connections—

they can be considered as *sinks*—which means they are more likely to receive information, resources, or influence from other nodes in the network. Sinks are also indicative of core issues that emerge and gravitate around the focal factor. Therefore, sinks can be used to identify areas in the map that could be expanded or explored more deeply in subsequent PSM workshops. In general, nodes with high IDC *and* low ODC are *not* good candidates for intervention (i.e., these highly influenced factors that have little influence on the rest of the system).

Betweenness centrality (BTC): BTC measures the number of times a node lies on the shortest path between other nodes in the network. Nodes with high BTC act as intermediaries or "bridges" in the network. To understand the drivers of a system using BTC, we focus on the nodes with the highest scores. These nodes are considered to be critical in maintaining the flow of information, resources, or influence between different parts of the network. By analysing the characteristics of the nodes with high BTC, we can gain insights into what drives the system. For example, if the high scoring nodes are situational or contextual variables of an individual, we can look at their position or role within the network and what could be done to improve the outcomes in the system. Nodes with high BTC are strategically important in terms of designing interventions—they concentrate the shortest and most direct paths for transmission of influence, resources and information. Securing control over these nodes has the potential to minimise the time and cost of interventions by increasing coordination between the chains of causality in the system. These nodes' ability to broker influence and resources throughout the system needs to be leveraged and secured *before* targeting, for example, nodes with high out-degree, closeness or PageRank centrality (see below)—i.e., they should be intervened first. These insights can inform decisions about interventions, investments, or strategies aimed at improving the efficiency or resilience of the system.

Closeness centrality (CLC): CLC measures the average distance between a node and all other nodes in the network. Nodes with high closeness centrality are located in central positions within the network. In the context of a system, CLC can provide insights into the drivers of the system by identifying nodes that are more influential or important due to their proximity to other nodes. Nodes with high CLC are more likely to have a greater impact on the overall functioning of the system because they are more central and can transmit information, resources, or influence more efficiently and effectively to other nodes in the network. In the case of LT-SA, a node with high CLC might be a specific psychosocial factor, a social program, policy or service. For example, in a social service delivery system, a node with high CLC could be a service provider that is located in a central location and has many connections to other service providers or clients. By targeting this service provider with additional resources or training, policymakers could improve the overall effectiveness of the service delivery system. In addition, closeness centrality can be used to identify potential bottlenecks or areas where the intervention may be less effective. Nodes with low closeness centrality may be less connected to other nodes in the network, indicating that they may be less influential or may have less impact on the overall success of the intervention. By identifying these nodes, policymakers can develop targeted strategies to increase their participation or engagement with the intervention.

PageRank centrality (PRC): PRC measures the importance of a node based on the importance of the nodes that link to it. Nodes with high PRC have wide-reaching influence because they are connected to other important nodes in the network. PRC works by assigning a score to each node in the network based on the number and quality of links pointing to that node. Nodes that have more links from other influential nodes are assigned a higher score, indicating that they are more important or influential within the network. Nodes with high PageRank centrality scores are more likely to have a greater impact on the overall functioning of the system because they are more central and can transmit information, resources, or influence more efficiently and effectively to other nodes in the network. These nodes may be specific benefits, services or contextual factors that have a significant impact on the psychosocial factors leading to LT-SA. Furthermore, analysing the distribution of PRC scores can provide insights into the overall structure and dynamics of the system. A network with a few highly influential nodes and many low-scoring nodes may be more vulnerable to cascading failures or disruptions, while a network with a more even distribution of PRC scores may be more resilient and adaptable.

In the context of social policy interventions, PRC can be used to identify influential services, benefits, training and/or education programs that should be part of the intervention. These nodes can then be targeted for resources, training, engagement, collaboration, or outreach to increase the likelihood of success for the intervention. In addition, PRC can be used to identify potential barriers or obstacles to the success of the intervention. Nodes with low scores may be less influential or less well-connected within the network, indicating that they may be less effective targets for an intervention. By identifying these nodes, policymakers can ensure that interventions are targeted and effective, ultimately leading to better outcomes for individuals and communities. This may involve engaging with key decision-makers to advocate for policy changes or reforms on high PRC nodes.

Justifying how many metrics one should use in network analysis is challenging—the answer depends on the problem domain, time, resources and knowledge of the end user. Based on a structured review of literature to provide clarity on the raison d'etre behind metric selection, Morrison et al. (2022) found that the average number of metrics observed in this review is three; while the majority of studies adopt fewer than three. Centrality metrics are typically used to capture specific characteristics of a network, such as evaluating how a single node is connected to the rest (degree centrality), which provides a static overview of network structure. From a more dynamic perspective, BTC and CLC evaluate how 'information' propagates through the network. Other centrality metrics, such as PRC aim to fill the gaps of basic nodal metrics such as ODC and IDC, as it includes 'information' (such as a node influences) whilst also describing the connectivity as degree centrality evaluates. Given these three perspectives, this could possibly explain why typically studies returned in this review adopt an average of three metrics. This would therefore assume that there is a minimum number of characteristics required to evaluate a network. Morrison et al. (2022) also conclude from their review that more metrics are not necessarily better, as this runs the risk of redundancy if the results of the chosen metrics are correlated. Therefore, an important step in validating the five metrics chosen for our analysis is a correlation analysis to minimise this risk (see Section 5.2.2 and Figure 8).

It is important to be explicit about what is being meant by a node being "central" and what the centrality measure of choice entails to make sure there is a match between the process under study and the centrality measure being used. In particular, BTC and CLC may be problematic in certain applications, given they have more complex assumptions about the manner in which things flow in a network. Both metrics count only geodesic paths (Freeman, 1978), assuming that whatever flows through the network moves only along the shortest possible paths. In most networks, however, and particularly in the maps we analyse in this paper, causation between contextual and psychosocial factors (or anything else) does not necessarily flow only along geodesic (shortest) paths. Flow betweenness (Freeman et al., 1991) counts all paths that carry information when a maximum flow is pumped between each pair of vertices. However, in numerous networks, neither of these situations is practical. Both only consider a minor fraction of potential routes between points, and both presuppose some form of efficiency in the transmission of information (either through shortest paths or maximum flow). In this paper we use a more general pair of measures—current-flow betweenness and current-flow closeness—that count essentially all paths between vertices (it excludes those that don't lead from the designated source to the target), and which make no assumptions of optimality. For simplicity, in the following we will refer to current-flow betweenness and current-flow closeness metrics as BTC and CLC, respectively. We applied the weighted versions of these algorithms, using the strength of causal relationships (weak, medium, low) as weights.

To answer our first research question "*What drives LT-SA?*", we computed and combined these centrality measures with the aim to identify and categorise the functional roles of the different factors that were elicited during the PSM process. This categorisation was achieved using the *clustermap()* method of the Seaborn Python library on the five centrality metrics described above. Seaborn's clustermap method was used to create a clustered heatmap—a graphical representation of a matrix in which the values in the matrix are represented by colours. The clustermap method shows the hierarchical clustering (as a dendogram) of both the rows (factors) and columns (centrality metrics) of the matrix, in addition to the heatmap itself. Hierarchical clustering groups similar items together based on their similarity, where items that are more similar are placed in the same group. The resulting plot shows the factors (rows) and centrality metrics (columns) reordered based on their similarity, so that groups of similar rows and columns are placed closer together. This allows patterns and relationships within the data to become more apparent that might not be immediately apparent from simple visual inspection of the network. The colours in the heatmap represent the values in the matrix, where different colours correspond to different centrality values, normalised to a [0,1] scale (see Figure 9). The results of this analysis are presented in Section 5.2.2.

WHERE TO INTERVENE?

Controllability analysis

Controllability analysis is a quantitative technique used to understand and predict the controllability of complex systems represented as networks. Controllability refers to the ability to steer a system from any initial state to any desired state in a finite amount of time, using external inputs. Figure 3 provides an illustrative example of the three types of controllability analysis that will be applied in this paper.

The first and simplest application of controllability analysis, based on **Classic Control Theory** (Figure 3A), consists of determining the proportion of system nodes that can be (theoretically) controlled and/or reached by intervening a specified set of nodes (intervention nodes are selected manually by the analyst). A second and more sophisticated suite of controllability analysis methods survey the significance of each node in a network in terms of its contribution to the network's ability to be fully controlled by an external input (Figure 3B-C). The concept of controllability is based on identifying "driver nodes," which are the key components of the network that must be manipulated to achieve complete control of the system. The Hopcroft-Karp algorithm is used to identify these driver nodes, which are nodes that are not receiving control from neighbouring nodes and therefore require external input to be controlled. The minimum input set (MIS) is the smallest group of driver nodes that can fully control the network, and there can be multiple possible MISs depending on the size of the network. After identifying the MIS, there are two methods of categorising the controllability of each node. In the concept of **Robust Controllability** (Figure 3C), the minimum input set (MIS) is recalculated (as ND') after removing each node from the network. This allows the classification of the node's effect on the network's controllability, based on whether the removal of the node increases or decreases the size of the MIS. An *indispensable* node increases the number of driver nodes needed for control, while a *dispensable* node reduces the number, and a *neutral* node has no effect. This method has been applied to various network types to understand their dynamics better, however, it only considers one possible MIS. **Global Controllability** (Figure 3B) categorises nodes based on their role across all possible MISs. A *critical* node is included in all MISs, an *intermittent* node is included in some, and a *redundant* node is not included in any. This approach provides a broader view of the node's contribution to the network's controllability.

Additional factor attributes

We used subjective information about the key factors (i.e. what is important to stakeholders, what is vulnerable, observable, or controllable) to complement and incorporate qualitative dimensions to the centrality and controllability analyses. This information, when combined with centrality and controllability analysis, provides more nuanced insights about where the most effective levers might be in the system. For example, an influential (high out-degree) factor, which impacts many important factors, is obviously significant. However, if it is vulnerable to change or controlled by a contextual or uncertain factor,

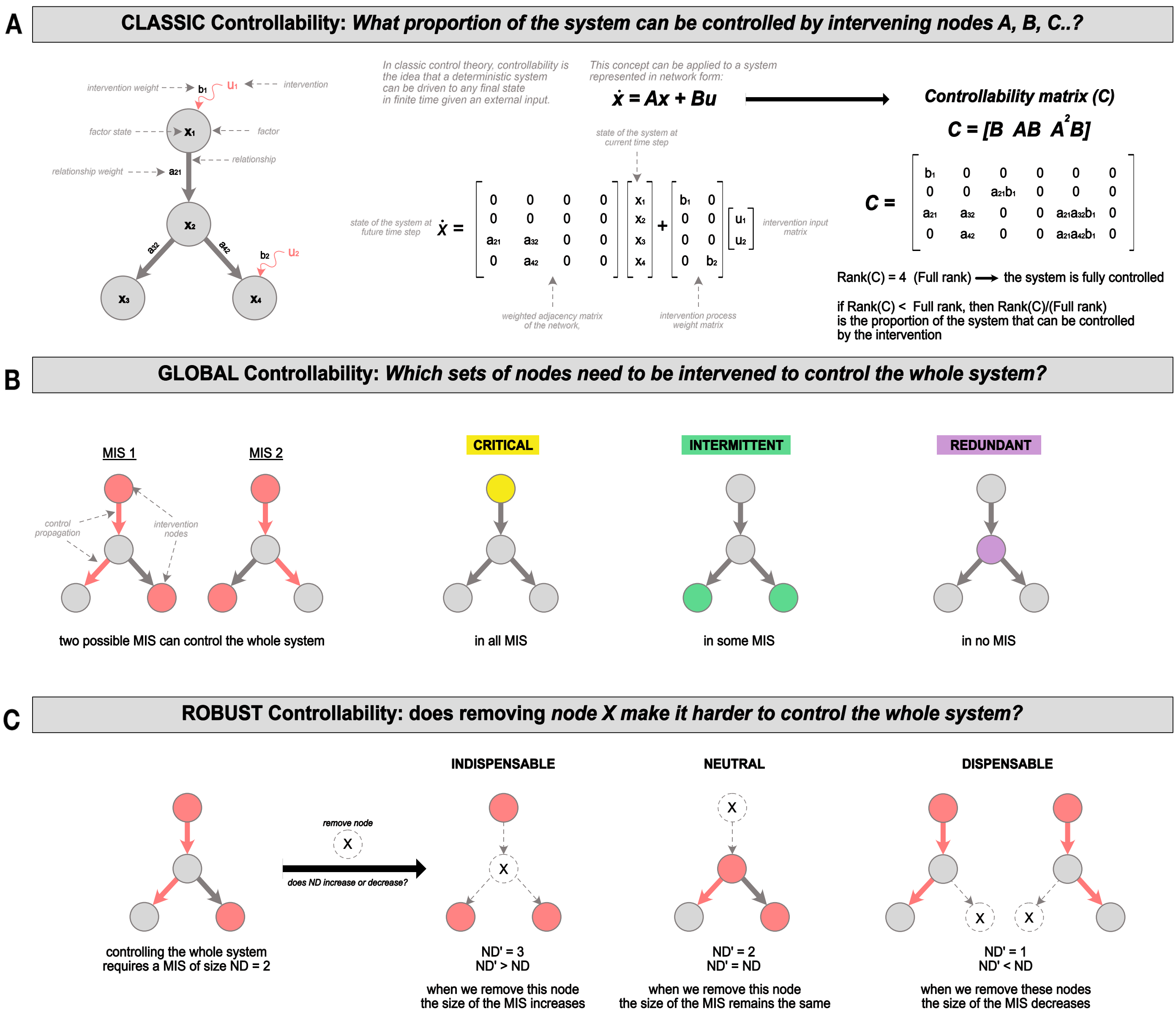


FIGURE 3. Example of a causal map with four factors, three relationships, and two intervention points (u1, u2). (A) classic controllability analysis shows that this system is fully controllable by the proposed intervention and could, therefore, be driven to any possible state in every factor. (B) Example application of global controllability, which assesses the importance of a factor to all methods of network control (i.e., minimum input sets, MIS). (C) Example application of robust controllability, which determines the robustness of the network after the removal of a factor.

it may be a vulnerability. If it is manageable, it could present a chance to induce change, often referred to as a system lever. Various forms of data can be gathered based on what is pertinent to the system and the parties involved.. Ideally the process of eliciting additional factor attributes occurs during participatory stakeholder workshops, which was only partly the case in this study as we did not have the time to elicit this information for a large proportion of the factors in our map (our aim and priority in each of the three workshops was to elicit and validate the factors and relationships of the map, and less so to elicit additional factor attributes). To garner this information, the research team deliberated on and subsequently labelled (based on their expertise and knowledge of the subject matter) the key factors identified from the centrality analysis on the following dimensions: strategic importance, difficulty/cost to intervene, and difficulty/cost to measure/observe. These three attributes were evaluated by the research team using a (low, medium, high) scale.

Tradeoff analysis

We used parallel coordinate plots to compare factors side by side. In a parallel coordinate plot, each significance dimension is assigned an axis, and all of these axes are aligned in parallel. Each axis can have its unique scale, given that every variable operates based on a different measurement unit, or all axes can be normalised to maintain uniform scales. The values are represented as a sequence of lines that are interconnected across all axes. This implies that each line is a set of points located on each axis that are all linked together. The sequence in which the axes are organised can influence the reader's comprehension of the data. One rationale for this is that the correlations between neighbouring variables are more readily discernible than those between non-neighboring variables. Consequently, rearranging the axes could aid in identifying patterns or relationships among variables.

A disadvantage of parallel coordinate plots is that they can become overcrowded, making them unreadable when they contain a lot of data. The most effective solution then is through interactivity and a method referred to as "brushing", which emphasises a chosen line or group of lines while dimming the rest. This enables a reader to separate and focus on the portions of the plot that are of interest to the reader, while minimising distraction from irrelevant parts. Interactive parallel coordinate plots were implemented using Python scripts and the HiPlot library.

To answer our second research question "*Where to intervene?*", we combined controllability analysis, additional factor attributes, and tradeoff analysis to identify the critical factors that prevent individuals from becoming self-sufficient and exiting social assistance programs. These factors might include, for example, lack of education or job skills, limited access to job opportunities, or other socio-economic factors that impact their ability to secure gainful employment. Once these critical factors have been identified, policymakers can design targeted interventions to address them. For example, they may develop education and training programs to equip individuals with the skills necessary to obtain and maintain employment. They may also implement policies to encourage businesses to locate in areas with high rates of social assistance use, thereby creating job opportunities for individuals in these areas. The results of this analysis are presented in Section 5.3.

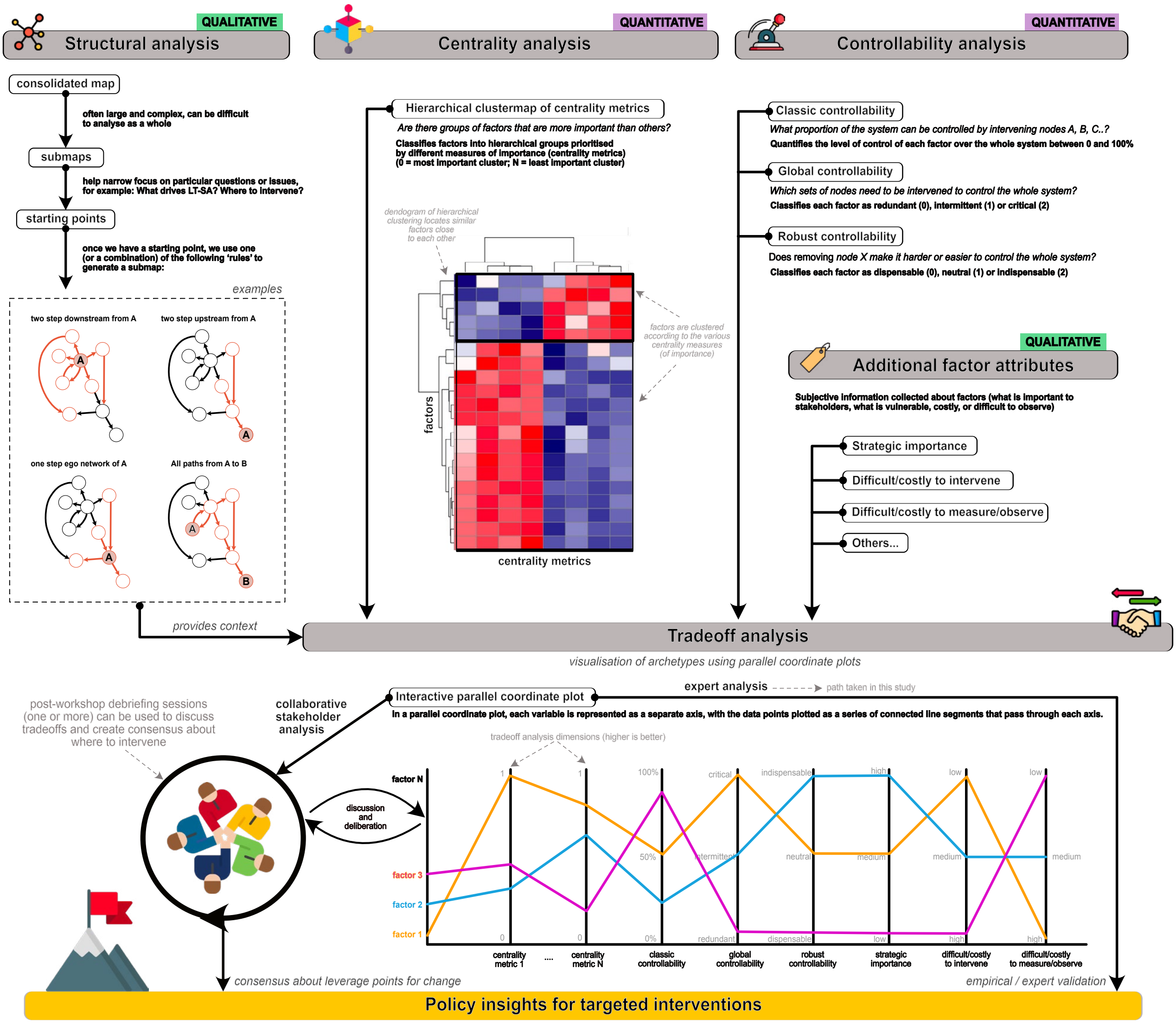


FIGURE 4. Detailed graphical representation of the qualitative and quantitative workflow and approaches used to answer our two research questions: "What drives LT-SA?" and "Where to intervene?"

5 Results

5.1 NETWORK TOPOLOGY

In this section, we describe the basic topology of the constructed network. The final consolidated map consisted of 95 factors that were mentioned and discussed by participants during the three workshops. These factors were divided into seven domains: focal factor, that is, LT-SA, parental variables (16 factors), service sector (27 factors), health (7 factors), wellbeing (19), social environment (14), social security (14). These domains were selected prior by the research team while they were also influenced by a survey for the first, researcher workshop participants. We did not collect any personal information in the workshop, thus it is not possible to disentangle which groups constructed selected relationships.

The map consisted of a total of 429 relationships. Each factor had thus an average of 4 outgoing links with a median of 4 and range of 1 and 18 (parental education). While excluding the focal factor, the mean of incoming links was 5 with median of 4 and range of 1 and 29 (access to services). The map consisted of 152 weak, 177 medium and 100 strong in strength relationships. The wellbeing domains were overrepresented and the parental domain under-represented in the factors from which weak relationships originated. In medium strength relationships, parental and social environment factors were overrepresented as the origin factors. The origins of the strong relationships were fairly equally distributed across the six domains. Some 29 percent of the relationships were intra-domain relationships, that is, the origin and destination factor shared the same domain. This share was highest (79%) in the parental domain and lowest in the health domain (13%). Figure 5 shows the maps in a chord diagram representation.

There were 45 factors with direct influence on LT-SA. Strong relationships were overrepresented in direct influences and weak links were underrepresented. The direct links originated from all domains while social security and health domains were overrepresented.

5.2 WHAT DRIVES LT-SA?

5.2.1 Structural analysis

Figure 6 presents a submap filtered by the strength of relationships that drive long-term social assistance (LT-SA). In the following, we focus on strong relationships, aiming to recognize the crucial policy points of LT-SA.

Factors exhibiting a direct, strong connection to LT-SA — such as education, substance use, and mental disorders — align much with previous studies. Simultaneously, several novel factors were recognized, such as future orientation and a sense of agency. These direct predictors fall under “soft factors”, which are challenging to quantify through conventional survey or registry data, and thus lacking in the previous studies.

Looking at the strong indirect drivers, we identified factors like a positive attitude towards education (which, through improved educational attainment, influences LT-SA), hobbies (contributing to better mental and physical health), and self-awareness (enhancing mental health and future orientation, marked A on the map). The map also embraces traditional indirect influencers from existing literature, like health services (improving overall health), bullying (leading to mental health disorders), and childhood trauma (through child welfare involvement). The most innovative causes were detected in the outer layer of the map, pointing to root factors like access to services, structural and everyday discrimination, and parental social capital.

To illustrate, everyday discrimination significantly impacted the study environment, fostering positive attitudes towards education. These attitudes directly influenced educational attainment, thus affecting LT-SA.

Intermediate factors, strongly driving LT-SA, encompassed aspects related to services and mental well-being. Health services (A marked on the map) have a robust influence on physical health, substantially affecting LT-SA. Homelessness (B marked on the map) strongly associates with substance abuse issues, thus increasing LT-SA dependency.

Additionally, experiences like bullying (C on the map) and violence (D) contribute significantly to mental health disorders, enhancing the propensity for LT-SA. Personal characteristics and activities also play a vital role. For instance, self-awareness (E) considerably improves mental health, reducing LT-SA dependency. Engagement in hobbies (F) similarly benefits mental health and mitigates LT-SA reliance. Peer support forms a crucial link, mitigating substance abuse issues and thus reducing LT-SA dependency. Furthermore, ineffective support systems contribute to unemployment rates, triggering a significant surge in LT-SA reliance.

Collectively, these strong relationships provide a nuanced understanding of the causal factors influencing LT-SA in Finland.

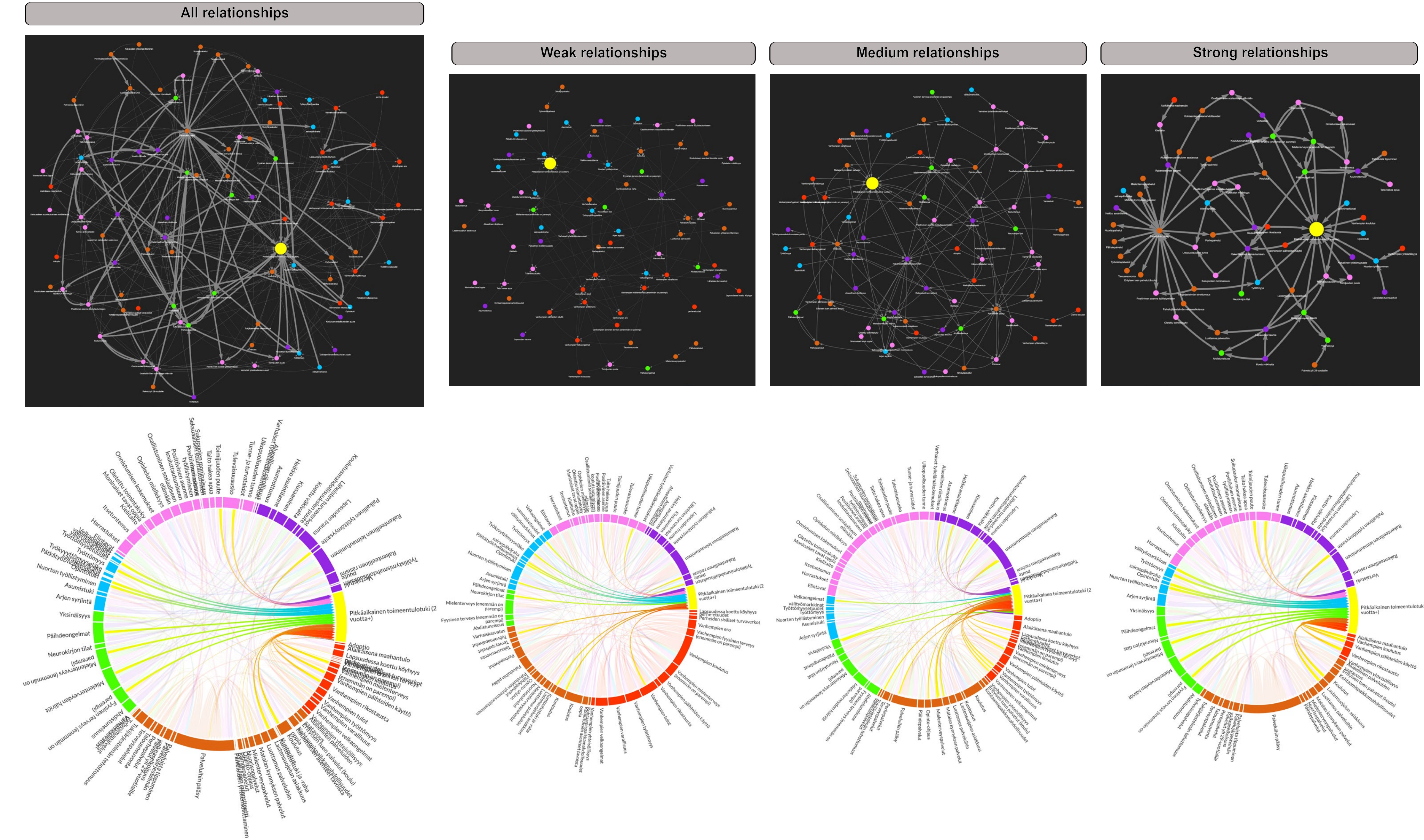


FIGURE 5. Chord diagram representations of the causal map elicited in this study. A) all relationships, B) weak relationships, C) medium relationships and D) strong relationships only

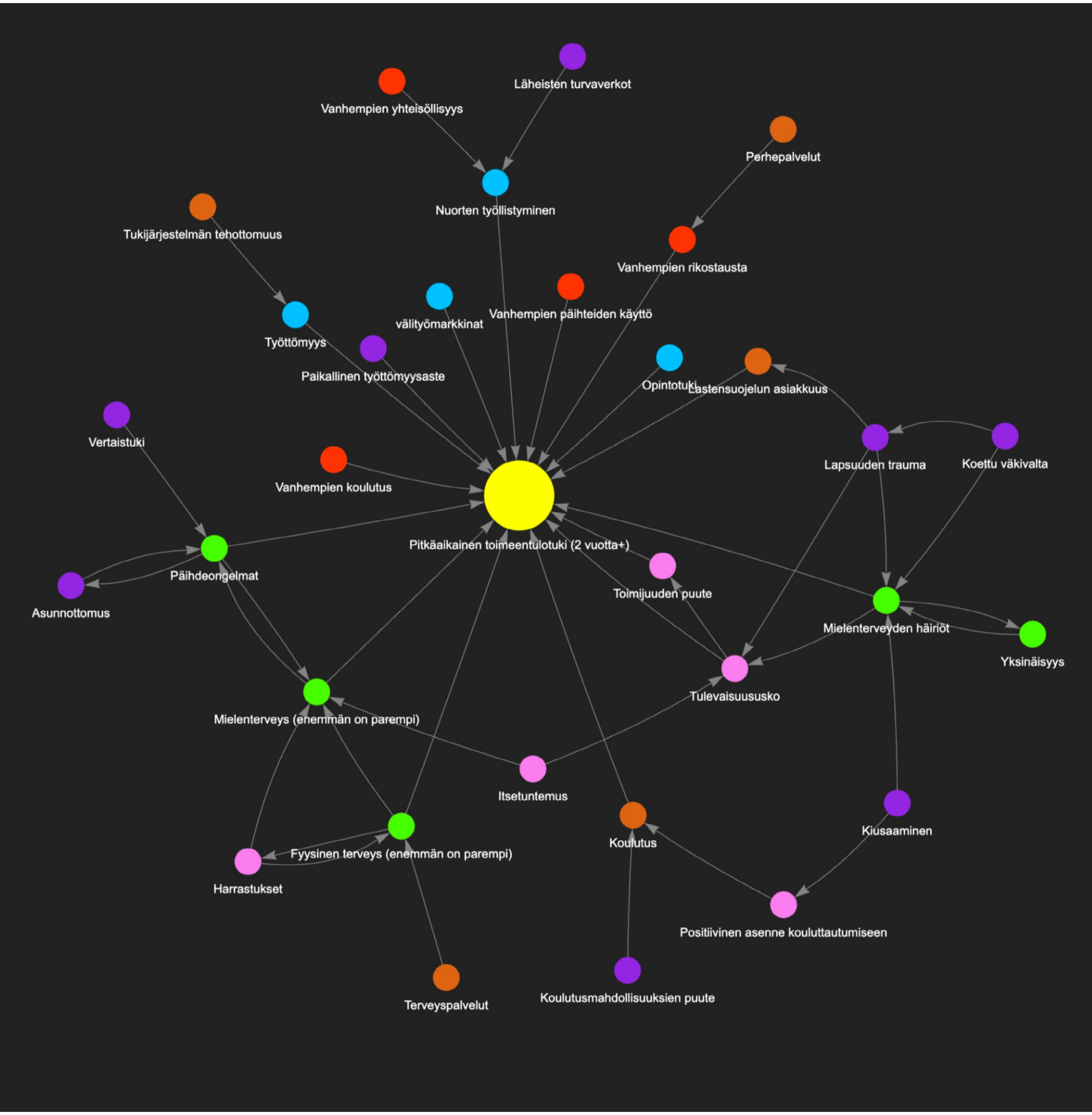


FIGURE 6. Structural analysis: submap of factors and relationships (strong only) two steps upstream from LT-SA

5.2.2 Centrality analysis

Figure 7 summarises the results of the centrality analysis: for each factor we report the centrality value (Figure 7A), the relative ranking (Figure 7B) and the average rank across the five centrality metrics (Figure 7C). Factors with identical centrality metrics were allocated equal ranks. To avoid distorting the numerical results (and colour coding), the focal factor (LT-SA) was excluded from the table.

Figure 7A offers an initial "birds-eye" view of the key drivers of LT-SA. Among the five centrality metrics, all but CLC highlight a small set of important factors (light blue and white shading) among the universe of 95 factors. CLC does however identify 20 or so "less important" factors (dark blue shading)—topologically, these are peripheral factors in the map. The relatively high CLC scores for the majority of factors supports our thesis of systemic complexity around the focal factor (LT-SA) as this indicates that the map displays a high level of connectivity between factors (see Figure 5). Two factors clearly stand out from the rest, scoring highly across all five metrics: Access to Services (Palveluihin pääsy) and Structural Stigma (Rakenteellinen leimautuminen).

To extract more information from this data, we used rank transformation. Rank transformation replaces the data by their ranks, or average ties in the case of ties, prior to performing statistical procedures on the data. Ranks can cope with nonlinear (albeit monotonic) input-output distributions and mitigate the impact of outliers, allowing the use of linear regression techniques. Rank transformed statistics are more robust, and provide a useful solution in the presence of long tailed input and output distributions (it puts data into the same type of distribution and scale). The rank transformation for the data in Figure 7A is presented in Figure 7B and, when compared to the raw data, rank transformation displays a greater capacity to discriminate on the relative importance of factors (i.e., the question of how important a factor is under each centrality metric is unambiguous). Rank transformation also allows interpretation and comparison of factors *across* the five centrality metrics. Figure 6C presents the average ranks, from which it is possible to expand the list of important drivers of LT-SA. Besides Access to Services and Structural Stigma, the top then drivers by rank are: Mental health disorders (Mielenterveyden häiriöt), Mental health (Mielenterveys), Training (Koulutus), Faith in the future (Tulevaisuususko), Everyday discrimination (Arjen syrjintä), Substance abuse problems (Päihdeongelmat), A positive attitude towards training (Positiivinen asenne kouluttautumiseen) and The feeling of being outside (Ulkopuolisuuden tunne).

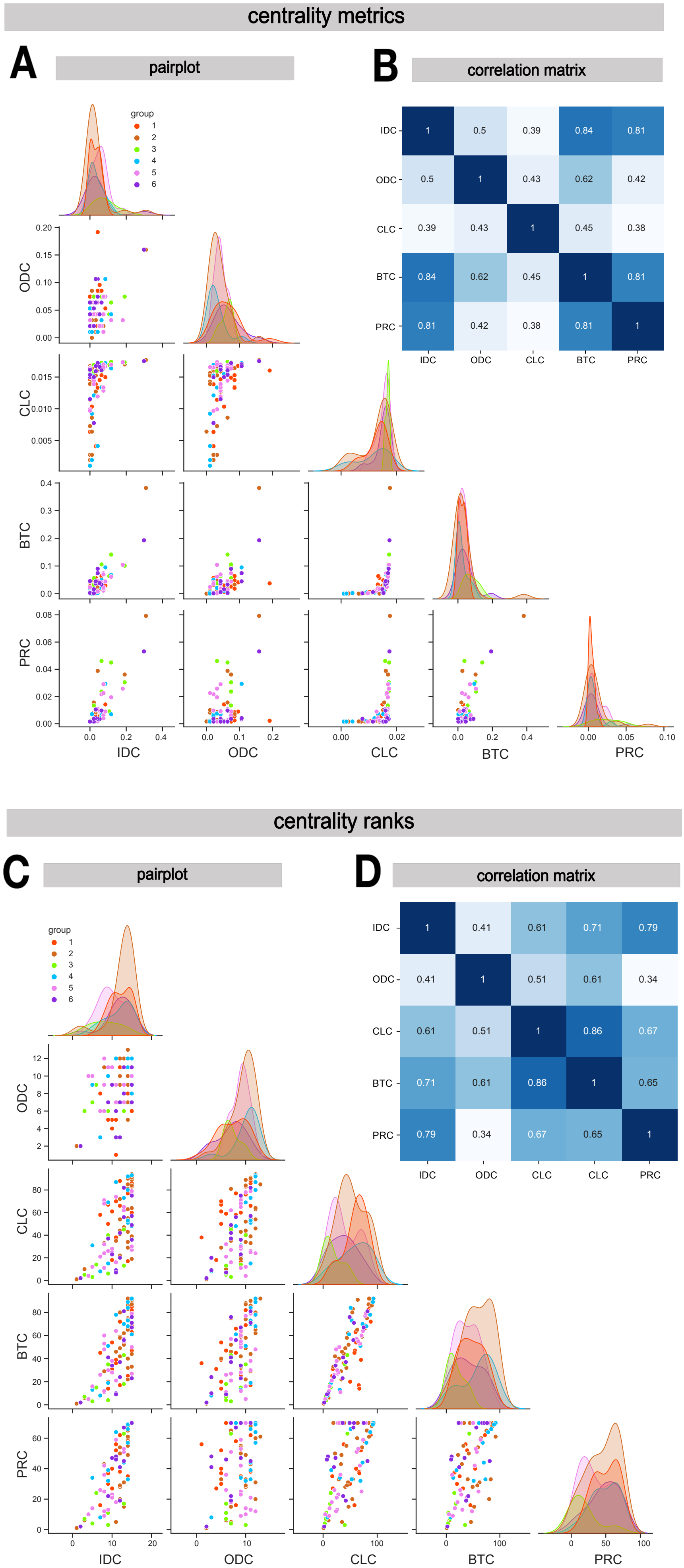
Pair Plots are a powerful tool to further explore distributions and relationships in our causal map. A Pair Plot allows us to see the distribution of single variables and relationships between two variables. Figures 7A and 7C present the Pair Plots for the raw centrality metrics and centrality ranks, respectively. These plots also show a breakdown of the centrality analysis across the six factor domains (excluding LT-SA as a domain: parental variables, service sector, health, wellbeing, social environment, social security). The density plot on the diagonal shows the distributions of a single centrality metric for each domain while the scatter plots on the lower triangle show the relationship (or lack thereof) between centrality metric pairs.

In addition, correlation heatmaps—a two dimensional plot of the amount of correlation (measure of dependence) between variables represented by colours—can be used to ascertain if the five centrality metrics are correlated, to what degree, in which direction and alert about potential multicollinearity problems in our analysis. Figures 8B and 8D present the correlation heatmaps for centrality metrics and centrality ranks, respectively. With a few exceptions—IDC/BTC, IDC/PRC, BTC/PRC in Figure 7B and IDC/BTC, IDC/PRC, CLC/BTC in Figure 8D (correlations > 0.8)—correlation coefficients indicate that the centrality metrics chosen for our analysis exhibit low (0.3-0.5) to moderate (0.5-0.7) correlation. These correlation heatmaps also show the absence of multicollinearity between centrality metrics (i.e., correlations of +1 or -1). This means that all centrality metrics are contributing (varying degrees of) information to the analysis.

Figures 9A and 9B present the clustermap analysis for centrality metrics and centrality ranks, respectively. These cluster maps reveal groups of factors which are similar in their importance and ability to drive the flow of causality within the network. These cluster maps show which factors are highly central and which are peripheral, as well as the relationships between different nodes and clusters (this is encoded in by the dendogram on the y-axis of each clustermap). Figure 8 reveals that certain factors or clusters or factors are central to the overall structure and dynamics of the network, while others are more isolated or peripheral. To facilitate this understanding, for each clustermap we scored the clusters identified by the algorithm in order of importance according to the number of centrality metrics in which a cluster scores highly. We assigned a rank of 1 to the most important cluster (i.e., which scores highly on all metrics), a rank of 2 to the next most important cluster (i.e., scores highly in most but not all metrics), and so on. Following this classification rule, the cluster with the lowest ranking exhibits low scores across all metrics. Overall, this information helps better understand the overall organisation and function of the system's causality chains, as well as identify key nodes or clusters that may be particularly influential or amenable for intervention, as will be shown in the following section.

FIGURE 7. Centrality metrics (A), centrality ranks (B) and average ranks (C).

FIGURE 8. Pair plots and correlation matrices for centrality metrics (A and B) and centrality ranks (C and D).



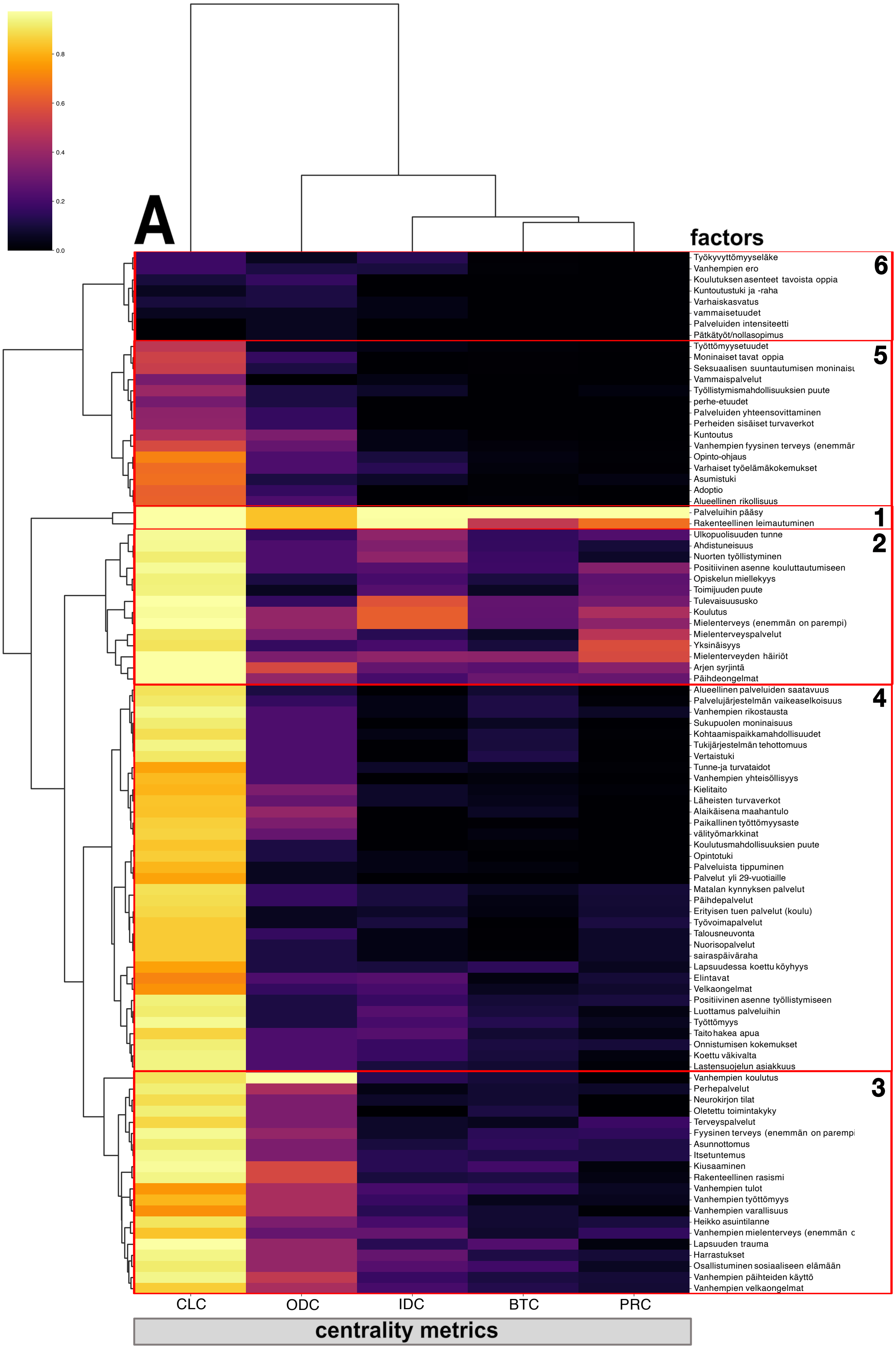
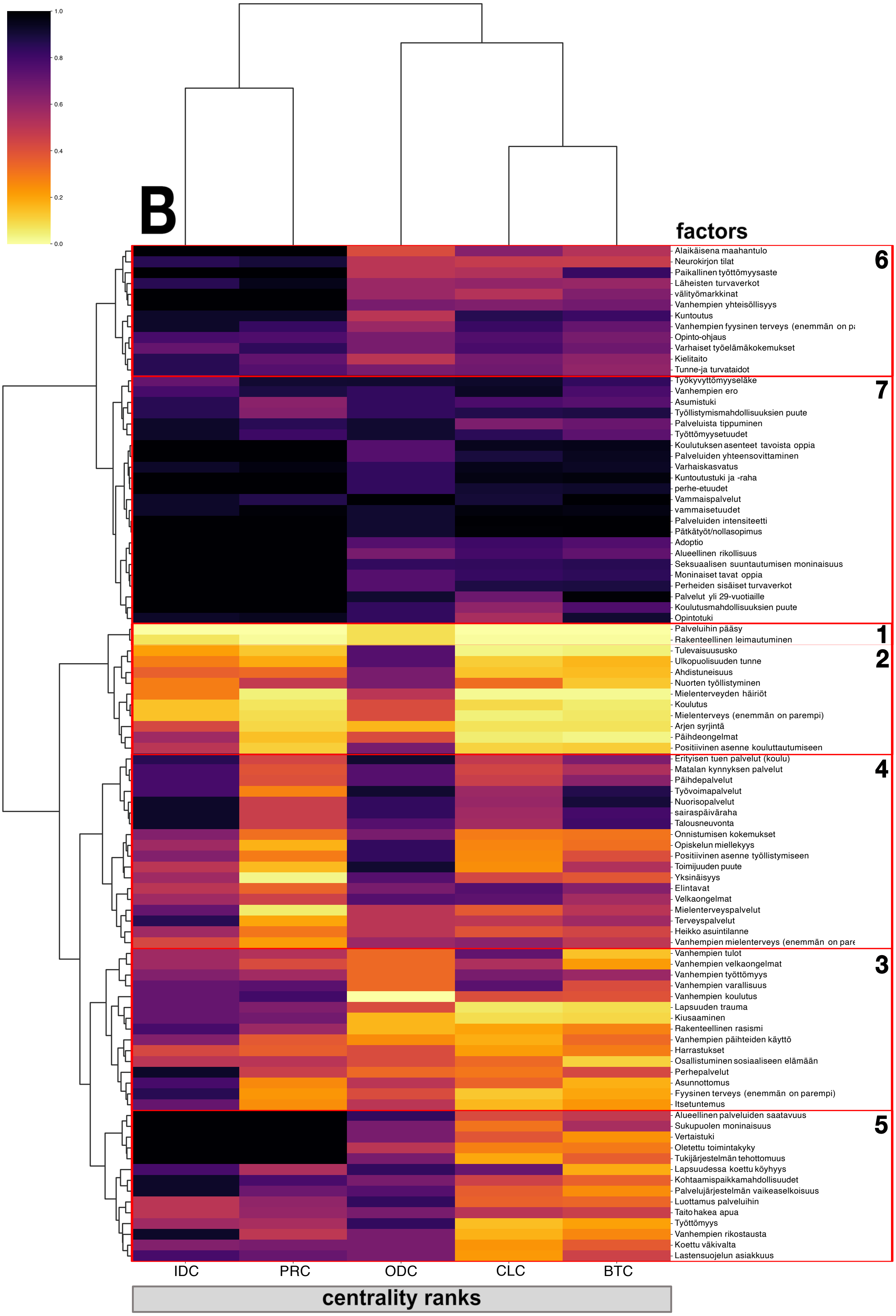


FIGURE 9. Hierarchical cluster heatmap of calculated centrality metrics (A) and centrality ranks (B). Numbers indicate the functional groups of factors identified by the cluster analysis; the cluster number indicates its functional importance (1=most important, N=least important). Rows are the causal factors and columns are the five centrality metrics used in the analysis. Centrality metrics have been normalised using a [0-1] scale. Brighter colours indicate higher centrality values/ranks, while darker colours correspond to low centrality values/rank


B
factors
1.0
0.8
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Alaikäisena maahantulo
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Paikallinen työttömyysaste
Läheisten turvaverkot
välityömarkkinat
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Työkyvyttömyyseläke
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Asumistuki
Työllistymismahdollisuuksien puute
Palveluista tippuminen
Työttömyysetuudet
Koulutuksen asenteet tavoista oppia
Palveluiden yhteensovittaminen
Varhaiskasvatus
Kuntoutustuki ja -raha
perhe-etuudet
Vammaispalvelut
vammaisetuudet
Palveluiden intensiteetti
Pätkätyöt/nollasopimus
Adoptio
Alueellinen rikollisuus
Seksuaalisen suuntautumisen moninaisuus
Moninaiset tavat oppia
Perheiden sisäiset turvaverkot
Palvelut yli 29-vuotiaille
Koulutusmahdollisuuksien puute
Opintotuki
7
Palveluihin pääsy
Rakenteellinen leimautuminen
1
Tulevaisuususko
Ulkopuolisuuden tunne
Ahdistuneisuus
Nuorten työllistyminen
Mielenterveyden häiriöt
Koulutus
Mielenterveys (enemmän on parempi)
Arjen syrjintä
Päihdeongelmat
Positiivinen asenne kouluttautumiseen
2
Erityisen tuen palvelut (koulu)
Matalan kynnyksen palvelut
Päihdepalvelut
Työvoimapalvelut
Nuorisopalvelut
sairaspäiväraha
Talousneuvonta
Onnistumisen kokemukset
Opiskelun mielekyys
Positiivinen asenne työllistymiseen
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Vanhempien tulot
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Vanhempien työttömyys
Vanhempien varallisuus
Vanhempien koulutus
Lapsuuden trauma
Kiusaaminen
Rakenteellinen rasismi
Vanhempien päihteiden käyttö
Harrastukset
Osallistuminen sosiaaliseen elämään
Perhepalvelut
Asunnottomuus
Fyysinen terveys (enemmän on parempi)
Itsetuntemus
3
Alueellinen palveluiden saatavuus
Sukupuolen moninaisuus
Vertaistuki
Oletettu toimintakyky
Tukijärjestelmän tehottomuus
Lapsuudessa koettu köyhyys
Kohtaamispaikkamahdollisuudet
Palvelujärjestelmän vaikeaselkoisuus
Luottamus palveluihin
Taito hakea apua
Työttömyys
Vanhempien rikostausta
Koettu väkivalta
Lastensuojelun asiakkuus
5
IDC
PRC
ODC
CLC
BTC
centrality ranks

5.3 WHERE TO INTERVENE?

5.3.1 Controllability analysis

The maps shown in Figure 5 provide a snapshot of the chains of causality that contribute to LT-SA. We applied controllability analysis tools (described in Section 4) first to quantify what proportion of the map (system) can be theoretically controlled by each individual factor, and second to identify a minimum set of driver nodes (i.e., nodes through which we can achieve control of the whole network). Note that the identified minimum driver node set (MDS) is not unique, but its size, denoted as ND, is uniquely determined by the network topology. Given that the controllability calculations do not discriminate between relationship strengths (weak, medium, high), we performed these calculations on the submap of strong relationships (Figure 5D). By focusing on these strong relationships—i.e., well-known mechanisms and causal relationships—we also reduce the dimensionality and complexity of the analysis and facilitate its interpretation.

The results of **classic control calculations** for individual factors are presented in Figure 10A. This analysis identifies two groups of factors: those with a marginal contribution to system controllability (32 factors can control 11% of the system or less) and those with a substantial contribution to system controllability (30 factors can control 30-38% of the system). The key factors previously identified using the clustermap analysis (Section 5.2) are not necessarily the ones that provide the highest controllability—individually, Access to Services (Palveluihin pääsy) and Structural Stigma (Rakenteellinen leimautuminen) can control 32% of the system and rank 27 and 28 among the 30 factors that provide this level of controllability. This result suggests that controllability calculations provide an additional and independent line of evidence to the process of designing potential interventions (Figures 2 and 4).

We found that the MDS of our consolidated map contains 50% of nodes (ND=32). From a controllability point of view, we consider this to be a high number—theoretically, 50% of the nodes in the map need to be intervened to steer the factors leading to LT-SA to a desired state. This result, again, supports our thesis of systemic complexity and the need to apply complex systems methodologies to adequately analyse the LT-SA issue.

Using **robust controllability**, we classified the nodes as *indispensable*, *neutral*, or *dispensable*, based on the change of ND upon their removal. A node is (i) indispensable if removing it increases ND, (ii) neutral if its removal has no effect on ND, and (iii) dispensable if its removal reduces ND. In our map, 6 (10%) of nodes are indispensable, (30) 48% are neutral, and the remaining (27) 42% are dispensable. The results of this analysis are presented in Figure 10B.

Using **global controllability**, we classified the nodes as *critical*, *intermittent*, or *redundant* based on their role across all possible MISs. A critical node is included in all MISs, an intermittent node is included in some, and a redundant node is not included in any. In our map, 22 (35%) are critical, 12 (19%) are intermittent, and 29 (46%) are redundant. The results of this analysis are presented in Figure 10C.

The results of our controllability analyses lead to three complementary views to answer the *"Where to intervene?"* question. **First, the view of classic controllability** which quantifies the level of systemic control that can be attributed to each individual factor—i.e., the proportion of factors in the system (map) that can be theoretically controlled by a single-factor intervention. This analysis discriminates against 32 of the factors (controllability < 11%; light blue in Figure 10A) and suggests that by controlling any one of the remaining 30 factors (dark blue in Figure 10A) it is possible to influence between 31% and 38% of the system's overall state.

Classic controllability calculations can also be performed for more than one factor. One could select different sets of factors—each representing an intervention package—and subsequently compute the level of systemic control triggered via each multi-factor intervention. Calculating the systemic controllability of all possible factor combinations is, however, computationally intractable and beyond the scope of this study (there are no efficient algorithms to solve them, except brute force search of all possible combinations). There are many ways in which a decision maker could design intervention packages and compare them using classic controllability calculations. In this study, we follow a systematic and bespoke process of analysis (Figures 2 and 4) which evaluates individual factors using qualitative concepts and quantitative measures of importance, visualises this data using multivariate graphical methods (radar plots) and finally uses tradeoff analysis tools (parallel coordinate plots) to deliberate, select, and combine factors for inclusion into one or more intervention packages. The systemic controllability of different sets of factors can then be used to benchmark and compare the efficiency of each proposed intervention package.

Robust and global controllability classifications offer complementary views to the classic controllability calculations. These approaches address the intractability of classic control calculations by assuming that the goal of intervention is full system control—i.e., the system (represented by the causal map of LT-SA) can be driven from any initial state to any desired state in finite time. In the context of policy interventions, completely controllable systems are the most desirable, as they can be easily influenced and controlled by policymakers. However, many if not all complex policy systems—and LT-SA is no exception—are only partially controllable, meaning that some aspects of the system may be influenced, while others are beyond the control of policymakers. In these cases, it is important to identify which aspects of the system are controllable and which are not (see Additional Factor Attributes subsection below). With this information at hand, we can take further steps towards designing interventions that focus on the controllable aspects and that maximise the level of control that decision makers have on the system.

The second view is the robust controllability classification, which provides information to design interventions that are robust to uncertainty. This classification determines whether and how well a system (more specifically, its institutions and decision makers) can maintain its controllability after the removal of singular nodes. The removal of a node from the map implies a structural uncertainty in a factor—meaning the causality associated with that factor is either unobservable or unknown. Recalculating the controllability of the system after the removal of a node is assumed to be a proxy of the effect that this uncertainty has on maintaining full control of the system.

In this context, we aim to identify the factors that are essential or indispensable for an individual's dependence on social assistance and those that are dispensable. For example, factors such as lack of education or job skills may be indispensable, as they are critical for an individual's ability to find gainful employment and become self-sufficient. Factors such as lack of access to transportation or affordable childcare may be dispensable, as they can be addressed through targeted interventions such as providing transportation vouchers or subsidising childcare. Additionally, identifying the neutral factors, or those that do not significantly impact an individual's reliance on social assistance, can help in prioritising interventions and resources towards more impactful solutions. In this context, our analysis has identified six indispensable factors: Childhood Trauma (Lapsuuden trauma), Faith in the Future (Tulevaisuususko), Access to Services (Palveluihin pääsy), Experiences of Success (Onnistumisen kokemukset), Physical Health (Fyysinen terveys), and Language Skills (Kielitaito). Neutral and dispensable factors are shown on Figure 10B.

The third view is the global controllability classification, which provides information to identify a minimal set of nodes that, if controlled independently, could be used to control the state of the entire network. The rationale is that it should be easier to manipulate a given system using the smallest number of points of intervention possible. The identification of a minimal set of nodes offers a set of plausible options for system intervention. This classification also favours nodes in the periphery of the map—i.e., root causes rather than direct determinants of LT-SA. Under this classification, twenty-two factors were labelled as critical: Peer Support (Vertaistuki), Weak Living Situation (Heikko asuintilanne), Assumed Operational Capability (Oletettu toimintakyky), Neurospectrum states (Neurokirjon tilat), Services for over 29-year olds (Palvelut yli 29-vuotiaille), The Complexity of the Service System (Palvelujärjestelmän vaikeaselkoisuus), Dropping Services (Palveluista tippuminen), Perceived Violence (Koettu väkivalta), Ability to Seek Help (Taito hakea apua), Diversity of Gender (Sukupuolen moninaisuus), Study Support (Opintotuki), Support System Ineffectiveness (Tukijärjestelmän tehottomuus), Harassment (Kiusaaminen), Safety Nets for Loved Ones (Läheisten turvaverkot), Local Unemployment Rate (Paikallinen työttömyysaste), Intermediate Labor Market (välityömarkkinat), Regional Availability of Services (Alueellinen palveluiden saatavuus), Parent's Sense of Community (Vanhempien yhteisöllisyys), Older Substance Abuse (Vanhempien päihteiden käyttö), Parent Education (Vanhempien koulutus), Entry as a Minor (Alaikäisena maahantulo), and Lack of Educational Opportunities (Koulutusmahdollisuuksien puute). Intermittent and redundant factors are shown on Figure 10C.

We acknowledge that the most effective factors for controlling a network, as determined mathematically based on their position within its structure, may not be the most manageable factors from the perspective of a specific group of system stakeholders. Some factors arise from the interplay of multiple large-scale effects, while others are influenced by various actors or organisations at different levels. To make this technique as practical as possible, it is necessary to assess the controllability of each control configuration in the "real world." Ideally, a workshop could be designed to create a process for evaluating the controllability of each factor and ranking control configurations based on their overall controllability as judged by the relevant stakeholders. This would involve the stakeholders rating each factor as easy, medium, or hard to control during group discussions. This approach was followed in (Penn et al., 2017), however in this study, due to time and resource constraints, this information was internally elicited by the research team (see Additional Factor Attributes subsection below).

A classic controllability

label	control_centrality
Tukijärjestelmän tehottomuus	0.37
Alueellinen palveluiden saatavuus	0.37
Palvelujärjestelmän vaikeaselkoisuus	0.35
Alaikäisena maahantulo	0.35
Vertaistuki	0.35
Oletettu toimintakyky	0.35
Sukupuolen moninaisuus	0.35
Perhepalvelut	0.33
Työttömyys	0.33
Vanhempien päihteiden käyttö	0.33
Matalan kynnyksen palvelut	0.33
Ulkopuolisuuden tunne	0.33
Terveyspalvelut	0.33
Rakenteellinen rasismi	0.33
Kielitaito	0.33
Harrastukset	0.32
Vanhempien rikostausta	0.32
Rakenteellinen leimautuminen	0.32
Onnistumisen kokemukset	0.32
Fyysinen terveys (enemmän on parempi)	0.32
Taito hakea apua	0.32
Heikko asuintilanne	0.32
Neurokirjon tilat	0.32
Mielenterveys (enemmän on parempi)	0.32
Asunnottomus	0.32
Arjen syrjintä	0.32
Itsetuntemus	0.32
Palveluihin pääsy	0.32
Palveluista tippuminen	0.32
Päihdeongelmat	0.32
Kiusaaminen	0.11
Koettu väkivalta	0.10
Palvelut yli 29-vuotiaille	0.10
Lapsuuden trauma	0.10
Yksinäisyys	0.08
Opiskelun mielekkyys	0.06
Mielenterveyden häiriöt	0.06
Positiivinen asenne kouluttautumiseen	0.05
Tulevaisuususko	0.05
Vanhempien yhteisöllisyys	0.05
Läheisten turvaverkot	0.05
Koulutusmahdollisuuksien puute	0.05
Paikallinen työttömyysaste	0.03
Vanhempien koulutus	0.03
välityömarkkinat	0.03
Opintotuki	0.03
Lastensuojelun asiakkuus	0.03
Koulutus	0.03
Toimijuuden puute	0.03
Kohtaamispaikkamahdollisuudet	0.03
Nuorten työllistyminen	0.03
Työvoimapalvelut	0.02
Ahdistuneisuus	0.02
Talousneuvonta	0.02
sairaspäiväraha	0.02
Positiivinen asenne työllistymiseen	0.02
Päihdepalvelut	0.02
Nuorisopalvelut	0.02
Mielenterveyspalvelut	0.02
Luottamus palveluihin	0.02
Erityisen tuen palvelut (koulu)	0.02
Osallistuminen sosiaaliseen elämään	0.02

B robust controllability

label	Liu_class	class_num
Lapsuuden trauma	indispensable	0
Tulevaisuususko	indispensable	0
Palveluihin pääsy	indispensable	0
Onnistumisen kokemukset	indispensable	0
Fyysinen terveys (enemmän on parempi)	indispensable	0
Kielitaito	indispensable	0
Pitkäaikainen toimeentulotuki (2 vuotta+)	neutral	1
Mielenterveyden häiriöt	neutral	1
Mielenterveys (enemmän on parempi)	neutral	1
Päihdeongelmat	neutral	1
Rakenteellinen rasismi	neutral	1
Arjen syrjintä	neutral	1
Nuorten työllistyminen	neutral	1
Harrastukset	neutral	1
Oletettu toimintakyky	neutral	1
Opiskelun mielekkyys	neutral	1
Osallistuminen sosiaaliseen elämään	neutral	1
Positiivinen asenne kouluttautumiseen	neutral	1
Toimijuuden puute	neutral	1
Ulkopuolisuuden tunne	neutral	1
Asunnottomus	neutral	1
Koettu väkivalta	neutral	1
Rakenteellinen leimautuminen	neutral	1
Itsetuntemus	neutral	1
Ahdistuneisuus	neutral	1
Yksinäisyys	neutral	1
Tukijärjestelmän tehottomuus	neutral	1
Alaikäisena maahantulo	neutral	1
Vanhempien rikostausta	neutral	1
Alueellinen palveluiden saatavuus	neutral	1
Kohtaamispaikkamahdollisuudet	neutral	1
Lastensuojelun asiakkuus	neutral	1
Luottamus palveluihin	neutral	1
Koulutus	neutral	1
Palvelujärjestelmän vaikeaselkoisuus	neutral	1
Perhepalvelut	neutral	1
Opintotuki	dispensable	2
Terveyspalvelut	dispensable	2
Paikallinen työttömyysaste	dispensable	2
Vanhempien koulutus	dispensable	2
Läheisten turvaverkot	dispensable	2
Koulutusmahdollisuuksien puute	dispensable	2
Vanhempien päihteiden käyttö	dispensable	2
Kiusaaminen	dispensable	2
Heikko asuintilanne	dispensable	2
Talousneuvonta	dispensable	2
Vanhempien yhteisöllisyys	dispensable	2
Neurokirjon tilat	dispensable	2
Erityisen tuen palvelut (koulu)	dispensable	2
Taito hakea apua	dispensable	2
Sukupuolen moninaisuus	dispensable	2
Positiivinen asenne työllistymiseen	dispensable	2
Työvoimapalvelut	dispensable	2
Palvelut yli 29-vuotiaille	dispensable	2
Matalan kynnyksen palvelut	dispensable	2
Mielenterveyspalvelut	dispensable	2
Nuorisopalvelut	dispensable	2
Päihdepalvelut	dispensable	2
välityömarkkinat	dispensable	2
Työttömyys	dispensable	2
sairaspäiväraha	dispensable	2
Palveluista tippuminen	dispensable	2
Vertaistuki	dispensable	2

C global controllability

label	Jia_class
Vertaistuki	critical
Heikko asuintilanne	critical
Oletettu toimintakyky	critical
Neurokirjon tilat	critical
Palvelut yli 29-vuotiaille	critical
Palvelujärjestelmän vaikeaselkoisuus	critical
Palveluista tippuminen	critical
Koettu väkivalta	critical
Taito hakea apua	critical
Sukupuolen moninaisuus	critical
Opintotuki	critical
Tukijärjestelmän tehottomuus	critical
Kiusaaminen	critical
Läheisten turvaverkot	critical
Paikallinen työttömyysaste	critical
välityömarkkinat	critical
Alueellinen palveluiden saatavuus	critical
Vanhempien yhteisöllisyys	critical
Vanhempien päihteiden käyttö	critical
Vanhempien koulutus	critical
Alaikäisena maahantulo	critical
Koulutusmahdollisuuksien puute	critical
Työttömyys	intermittent
Positiivinen asenne työllistymiseen	intermittent
sairaspäiväraha	intermittent
Talousneuvonta	intermittent
Terveyspalvelut	intermittent
Erityisen tuen palvelut (koulu)	intermittent
Matalan kynnyksen palvelut	intermittent
Työvoimapalvelut	intermittent
Nuorisopalvelut	intermittent
Päihdepalvelut	intermittent
Mielenterveyspalvelut	intermittent
Perhepalvelut	intermittent
Tulevaisuususko	redundant
Ulkopuolisuuden tunne	redundant
Lapsuuden trauma	redundant
Asunnottomus	redundant
Rakenteellinen leimautuminen	redundant
Positiivinen asenne kouluttautumiseen	redundant
Osallistuminen sosiaaliseen elämään	redundant
Toimijuuden puute	redundant
Opiskelun mielekkyys	redundant
Pitkäaikainen toimeentulotuki (2 vuotta+)	redundant
Kielitaito	redundant
Vanhempien rikostausta	redundant
Kohtaamispaikkamahdollisuudet	redundant
Koulutus	redundant
Lastensuojelun asiakkuus	redundant
Luottamus palveluihin	redundant
Palveluihin pääsy	redundant
Ahdistuneisuus	redundant
Onnistumisen kokemukset	redundant
Fyysinen terveys (enemmän on parempi)	redundant
Mielenterveys (enemmän on parempi)	redundant
Päihdeongelmat	redundant
Rakenteellinen rasismi	redundant
Arjen syrjintä	redundant
Nuorten työllistyminen	redundant
Harrastukset	redundant
Itsetuntemus	redundant
Mielenterveyden häiriöt	redundant
Yksinäisyys	redundant

FIGURE 10. Results of controllability analysis

5.3.2 Additional (Qualitative) Factor Attributes

To demonstrate how the quantitative (centrality and controllability) analyses can be complemented using qualitative dimensions, we incorporated additional factor attributes pertaining to the 69 factors on Figure 5D (i.e. the map of factors connected by strong relationships). We focused on the following three qualitative attributes: strategic importance, observability (difficulty/cost to measure and observe) and controllability (difficulty/cost to intervene). For each factor-attribute combination, factors were qualified as low, medium, and high via deliberation among the ITLA research team. These (and more) qualitative attributes could have been elicited and/or validated more openly in a follow-up workshop with participants (this was not possible due to time and budget constraints), yet our intention here is solely to demonstrate how these qualitative attributes can be combined with quantitative attributes (centrality and controllability) and subsequently used as inputs to the tradeoff analysis described in the following section. The qualitative attributes elicited by the research team are presented in Table 1.

5.3.4 Tradeoff Analysis

Tradeoff analysis was the final step and ultimate goal of our study—i.e., to develop a formal and practical means to answer our second and most important research question: *"Where to intervene?"*. To this end, a parallel coordinate plot (PCP) was developed to allow for iterative and interactive comparisons between multiple factors and deliberate on where the best points of intervention (levers) are likely to be.

In our PCP, each dimension is given a vertical axis, and values are plotted as a series of lines connected horizontally across all axes. To facilitate the interpretation of this tool by end-users, we renamed the different quantitative and qualitative attributes plotted on the PCP using a term that provides a clear and succinct description of what each attribute is highlighting about each factor. For example, the Pagerank attribute helps identify *effective* levers, the Global Control attribute helps identify *root cause* levers, and Betweenness Centrality identifies levers that may act as *bridges* to facilitate the flow of resources and/or information within the system (see table 2 for details). The PCP for all the factors linked by strong relationships is presented in Figure 12. It is important to note that the arrangement of axes can impact the reader's interpretation of the data, as adjacent variables have a more noticeable relationship than non-adjacent variables. Therefore, reordering the axes can aid in identifying any patterns or correlations between variables—this is possible using the interactive version of the parallel coordinate plot (download link).

To demonstrate how the PCP can be used to identify points of intervention, we define so-called *intervention goals*. An intervention goal is a short statement that declares the intent of an intervention, in terms of design parameters such as those defined in Table 2. For example, an intervention goal might be to target *"highly influencing, effective, and controllable factors"* or *"factors that act as bottlenecks (bridges) in the flow of resources and information, that are observable, an important from a political or policy perspective"* or *"root cause factors that are also strategic in their causal proximity to other factors in the system"*. Any number of intervention goals could be constructed in this way and the process could also be undertaken collaboratively with the participation of stakeholder and decision makers. Once the intervention goal or goals have been identified, the PCP is queried by selecting or "brushing" the axes for the different attributes mentioned within each intervention goal as shown on Figure 11. The end result is the identification of a factor, or a set of factors, that are most likely to support the declared intent of a particular intervention goal (see Figures 11 and 12).

	Factor	Importance	Intervene	Observe
1	Ahdistuneisuus	High	Medium	Medium
2	Alaikäisena maahantulo	Low	High	Low
3	Alueellinen palveluiden saatavuus	High	Medium	Low
4	Arjen syrjintä	High	Medium	High
5	Asumistuki	Low	Low	Low
6	Asunnottomus	High	Medium	Low
7	Erityisen tuen palvelut (koulu)	Medium	Medium	Low
8	Fyysinen terveys (enemmän on parempi)	Medium	Medium	Medium
9	Harrastukset	High	Low	Low
10	Heikko asuintilanne	Medium	Medium	Low
11	Itsetuntemus	Medium	Medium	High
12	Kielitaito	High	Medium	Low
13	Kiusaaminen	High	Medium	High
14	Koettu väkivalta	High	Medium	Medium
15	Kohtaamispaikkamahdollisuudet	Medium	Low	Medium
16	Koulutus	High	Medium	Low
17	Koulutusmahdollisuuksien puute	High	Medium	Low
18	Läheisten turvaverkot	Medium	Medium	Medium
19	Lapsuuden trauma	Medium	High	High
20	Lapsuudessa koettu köyhyys	Low	Medium	Low
21	Lastensuojelun asiakkuus	High	High	Low
22	Luottamus palveluihin	High	High	High
23	Matalan kynnyksen palvelut	High	Low	Low
24	Mielenterveyden häiriöt	Medium	High	Medium
25	Mielenterveys (enemmän on parempi)	Medium	Medium	Medium
26	Mielenterveyspalvelut	Medium	Low	Low
27	Neurokirjon tilat	Low	NA	Medium
28	Nuorisopalvelut	Medium	Low	Low
29	Nuorten työllistyminen	High	Medium	Low
30	Oletettu toimintakyky	Low	NA	Medium
31	Onnistumisen kokemukset	High	Medium	High
32	Opintotuki	Low	Low	Low
33	Opiskelun mielekkyys	High	Medium	Medium
34	Osallistuminen sosiaaliseen elämään	Medium	Medium	Medium
35	Päihdeongelmat	Medium	Medium	Medium
36	Päihdepalvelut	Medium	Low	Low
37	Paikallinen työttömyysaste	Low	Medium	Low
38	Palveluihin pääsy	High	Medium	High
39	Palveluista tippuminen	High	Medium	Medium
40	Palvelujärjestelmän vaikeaselkoisuus	High	Medium	Medium
41	Palvelut yli 29-vuotiaille	Low	Medium	Low
42	Perhepalvelut	Medium	Low	Low
43	Positiivinen asenne kouluttautumiseen	High	Medium	Medium
44	Positiivinen asenne työllistymiseen	High	Medium	High
45	rakenteellinen leimautuminen	High	Medium	High
46	Rakenteellinen rasismi	High	Medium	High
47	sairaspäiväraha	Low	Low	Low
48	Sukupuolen moninaisuus	Low	NA	Medium
49	Taito hakea apua	High	Medium	High
50	Talousneuvonta	Medium	Low	Low
51	Terveyspalvelut	Medium	Low	Low
52	Toimijuuden puute	Medium	Medium	High
53	Tukijärjestelmän tehottomuus	High	Medium	High
54	Tulevaisuususko	High	Medium	High
55	Työttömyys	Medium	Medium	Low
56	Työvoimapalvelut	Medium	Low	Low
57	Ulkopuolisuuden tunne	High	Medium	High
58	välityömarkkinat	Medium	Medium	Low
59	Vanhempien koulutus	Low	High	Low
60	Vanhempien mielenterveys (enemmän on parempi)	Low	High	Medium
61	Vanhempien päihteiden käyttö	Low	High	Medium
62	Vanhempien rikostausta	Low	High	Low
63	Vanhempien tulot	Low	High	Low
64	Vanhempien työttömyys	Low	High	Low
65	Vanhempien varallisuus	Low	High	Low
66	Vanhempien velkaongelmat	Low	High	Medium
67	Vanhempien yhteisöllisyys	Low	High	High
68	Vertaistuki	High	Medium	High
69	Yksinäisyys	High	Medium	Medium

TABLE 1. Qualitative attributes elicited for each factor in the causal map

	Metric	Intervention attribute	Simple explanation
Quantitative	**In-degree centrality**	**Influenced**	Factors with high in-degree have many incoming relationships. Although an intervention on one of them is unlikely to trigger a systemic change, they can be useful points of measurement/observation of the effectiveness of interventions elsewhere in the system.
	Out-degree centrality	**Influencing**	Factors with high out-degree have many outgoing relationships. An intervention on one of these factors maximises the number of other factors that will be immediately affected by the intervention.
	Closeness centrality	**Strategic**	Factors with high closeness centrality are topologically located close to all other factors. An intervention on one of these factors is strategic as it is likely to percolate to a large number of other factors (which may or may not be important themselves).
	Pagerank centrality	**Effective**	Factors with high pagerank centrality are linked to other highly ranked nodes, therefore they are seen as more authoritative, central and important within the network. An intervention on one of these factors can be considered to be more effective at spreading influence and/or resources within the network.
	Betweenness centrality	**Bridge**	Factors with high betweenness centrality are connected by relationships that control the flow of resources and/or information within the system. An intervention on one of these factors has a "bridging" effect which increases the likelihood that an intervention will readily flow through a bottleneck and permeate to otherwise isolated parts of the system.
	Classic control	**Leverage**	Factors scoring highly on classic control are connected to a larger proportion of nodes via downstream relationships. An intervention on one of these factors is deemed to have leverage as it maximises the number of nodes that can be reached by a single-factor intervention.
	Global control	**Root Cause**	Factors identified as "critical" form part of a minimum set of root cause nodes that must be intervened if the goal is to gain full control of a system.
	Robust control	**Robust**	Losing control over factors identified as "indispensable" makes the system more difficult to control. An intervention on one of these factors therefore ensures that control over the system is robust.
Qualitative	**Importance**	**Important**	The factor is considered important from a social, political or economic perspective (by subject matter experts).
	Intervene	**Controllable**	The factor is considered easy to control or intervene (by subject matter experts)
	Observe	**Observable**	The factor is considered easy to measure or observe (by subject matter experts)

TABLE 2. Definitions of quantitative and qualitative variables used to analyse the causal map

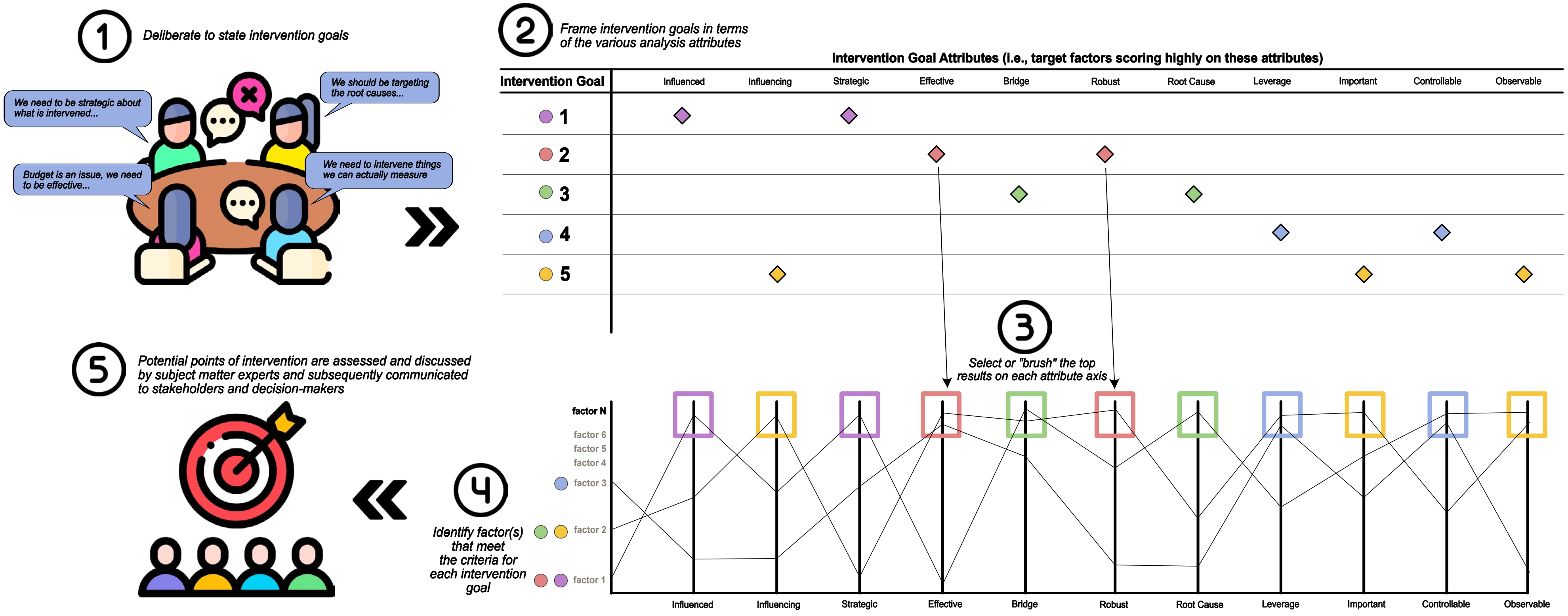

FIGURE 11. The PCP can be used to identify points of intervention by defining intervention goals. An intervention goal is a short statement that declares the intent of an intervention, in terms of design parameters such as those defined in Table 2. For example, an intervention goal might be to target “highly influencing, effective, and controllable factors” or “factors that act as bottlenecks (bridges) in the flow of resources and information, that are observable, an important from a political or policy perspective” or “root cause factors that are also strategic in their causal proximity to other factors in the system”. Any number of intervention goals could be constructed in this way and the process could also be undertaken collaboratively with the participation of stakeholder and decision makers (1,2). Once the intervention goal or goals have been identified, the PCP is queried by selecting or “brushing” the axes for the different attributes mentioned within each intervention goal (3). The end result is the identification of a factor, or a set of factors, that are most likely to support the declared intent of a particular intervention goal (4,5).

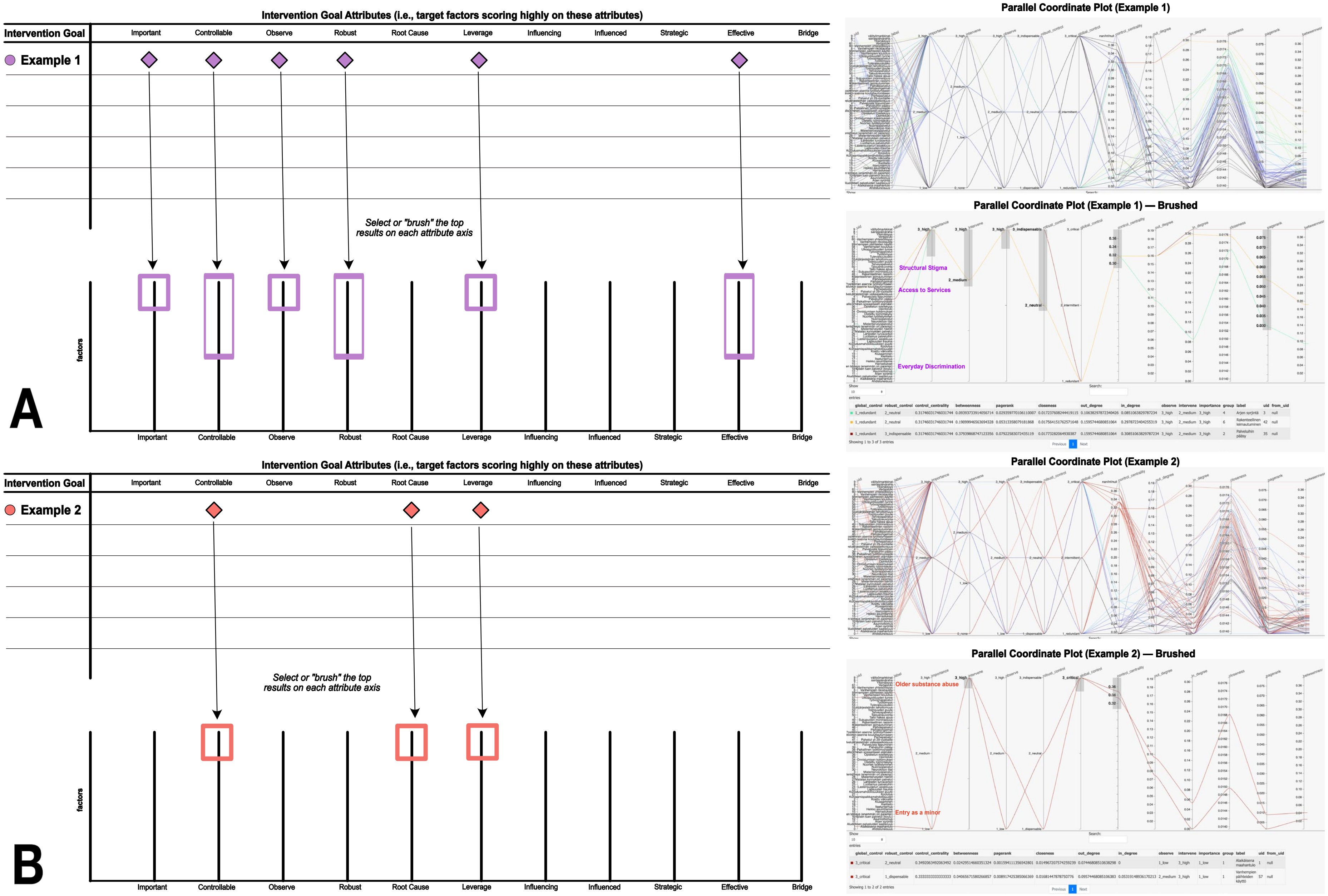

Figure 12. Two examples of tradeoff analysis using parallel coordinate plots (PCPs). Both examples begin with a PCP for all factors connected by strong relationships. Each line indicates how a single factor scores across the various measures of centrality (in-degree, out-degree, closeness, betweenness, pagerank), controllability (classic, robust, global) and additional factor attributes (strategic importance, ability to observe, ability to intervene). Panels A and B demonstrate the process of interactively selecting or “brushing” specific levels of factor attributes to design intervention packages. The brushing process is generally an open-ended exercise, undertaken in a collaborative environment (face-to-face or remote) where stakeholders and decision makers deliberate on what an intervention package aims to achieve and tradeoffs between factor interventions. For example, the factors that provide the highest controllability might not be the most important or could be difficult to measure/observe. The process of brushing the plot can help users debate on these tradeoffs and decide on the most effective points of intervention.

6 DISCUSSION AND CONCLUSION

LT-SA is a complex issue and comprises numerous interconnected contextual, policy and psychosocial factors. These factors are often invisible to researchers because there is little reliable data available on them. When facing the scarcity of register or other "hard" data, decision makers often adapt non-evidence-based approaches and rely heavily on judgement, anecdotal evidence, stereotypes, and established practices. Nevertheless, understanding the interactions between these factors is of great importance if the issue of LT-SA use among young adults is to be fully understood and mitigated. To do so requires advanced analytical methods that are able to quantify the importance of a constellation of factors and examine their role in the system with respect to other parts which they influence and are influenced by. For this purpose, network methods have significantly increased in their sophistication and popularity as the availability of data and software enables such analyses. The added value of network analyses demonstrated in this study is further enhanced by employing participatory approaches to elicit and encode knowledge about the system into a causal map with direct input from stakeholders. This paper, to the best of our knowledge, is the first attempt to apply the PSM approach and controllability analyses to social policy research. So far this approach has been applied in the areas of sustainability (Mercure et al., 2016), tourism (Baggio et al., 2010), and public health (McGill et al., 2021).

The first aim of the project was to demonstrate the use of participatory systems mapping in social policy research. We conducted a series of workshops to elicit expert knowledge on factors related to LT-SA. We further conducted extensive network analysis based on the map created from the workshops. Our key finding from these analyses is a strong interlink of factors related to LT-SA in different domains. Via a participatory project we identified some hundred factors that are linked via some 400 relationships to LT-SA. It is often acknowledged that long-term social assistance use is a complex, multifaceted phenomenon but our study is the first project to consolidate different sources of information and to quantify the complexity around LT-SA.

Our second aim was to complement existing literature by highlighting drivers of social assistance use not often discussed. The traditional research on social assistance use has focused on quantitative relationships between a predictor and social assistance use. For example, Kauppinen et al found that in Finland, Norway and Sweden, parental economic difficulties predict LT-SA (Kauppinen et al., 2014). Haula and Vaalavuo found that, in Finland, mental health problems were a strong predictor of social assistance recipients in young adulthood (Haula and Vaalavuo, 2021). Heggebø et al report that in Norway, substance abuse was linked to social assistance use (Heggebø et al., 2020). While the findings of these and many other studies on the topic were absorbed into the map via our researchers' workshop, we identified a number of novel determinants of LT-SA, such as childhood bullying, hobbies and positive early experiences. These perceived determinants would have left unidentified without the extensive engagement of multiple stakeholders in multiple workshops. Several novel factors are worth further discussion.

The overarching substantive finding is that the main drivers of LT-SA are not only related to hard policy areas such as education and employment as is often thought in policy circles. We also find that "soft" factors, that is, factors not easily measured e.g. via registers, such as self-awareness, experiences of successes and discrimination are vital determinants of LT-SA. This finding has implications for both research and practice. Research on social assistance use should adopt multidisciplinary methodologies, beyond traditional survey or register data collection, to capture and analyse these "soft" factors. In terms of practice, our findings call policy-makers to consider a broader set of socio-psychological factors in their policy solutions to reduce LT-SA. Policy solutions may include developing, for example, mentoring interventions that enhance self-awareness and resilience while addressing discrimination.

Our third aim was to contribute to the discussions in policy circles by identifying potential policy levers to reduce social assistance use among young adults. This paper underscores that multi-domain interventions, for example those addressing simultaneously childhood trauma, optimism, access to services, physical health, and positive early experiences as suggested by the robust controllability analysis, are most promising. Simultaneously targeting many areas highlighted above simultaneously is our key policy recommendation for designing interventions to reduce LT-SA. This is because there is no single causal factor of LT-SA and because there are no factors that control the full universe of upstream determinants of LT-SA. Nevertheless, we find that some factors are more important than others from a policy perspective. Our controllability analysis indicated that policy makers should keep in mind that interventions that target Childhood Trauma (Lapsuuden trauma) and promote Faith in the Future (Tulevaisuususko), Access to Services (Palveluihin pääsy), Experiences of Success (Onnistumisen kokemukset), Physical Health (Fyysinen terveys), and Language Skills (Kielitaito) are critical when reducing LT-SA in a sustained fashion.

Our findings prompt further discussion for suitable intervention packages to reduce social assistance use among young adults. By addressing the upstream factors contributing to LT-SA, we hope that these findings help to create sustainable and equitable policy changes, not related to the level and eligibility of the benefit. Nevertheless, we emphasise caution in implementing the policy changes—the causal maps elicited in this study represent a "snapshot" of the system at a given point in time, from the perspective of the stakeholders that contributed their views during the PSM exercise. The boundaries of the map are also arbitrary, as additional factors and relationships could be incorporated through follow-up stakeholder engagement. Given the inherent complexity of the policy system, unexpected outcomes or knock-on effects are possible and must be taken into consideration. Unexpected outcomes, often termed "knock-on" effects, are to some extent visible in your PSM exercise. An example could be the potential unintended effect of student counselling. Our analysis suggests that increasing student counselling may only have limited effect if it does not simultaneously address structural discrimination as student counselling can reinforce the downstream effects of stigma. Thus continual monitoring and adaptive management are crucial to adjust policy directions based on the observed effects over time.

While our participatory approach and the findings are embedded in the rather distinctive Finnish policy, there are several lessons to be generalised to other country contexts. Based on our experiences in this project, we recommend that researchers should embrace a participatory mapping approach in social policy research areas. We found the map drawing exercise highly beneficial to sensemaking and mutual learning among experts. The map, as separate products of this project, is intended as a basis—a living document—for future studies. The map can help future studies to formulate and make explicit their assumed causal structures on directed acyclic graphs. For example, researchers aiming to estimate the causal effect of substance use disorder on social assistance use may use the map to help to formulate their research question, structure their analytical strategy and contextualise their results. This map would guide them in deciding which variables to treat as control/pretreatment factors, that is, factors influencing substance use and LT-SA, and which to consider as potential mediators, that is, factors through which substance use affects social assistance use, in their causal analysis. The map could then help to contextualise their results and guide discussion about the potential implications of their findings. Additionally, policymakers can use controllability analysis to monitor the effectiveness of their interventions over time. By regularly assessing the controllability of the system using the approaches demonstrated in this study, policymakers can determine whether their interventions are producing the desired outcomes and adjust their strategies accordingly.

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