A systems perspective on promoting sustainable food systems

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Abstract

Global food systems are at the center of some of the most pressing modern societal challenges: They are significant contributors to a range of systemic issues, including health problems and chronic diseases, greenhouse gas emissions and general environmental degradation, and increasing financial burdens on healthcare and economies. Within these complex systems, final sustainable consumption, which refers to the adoption of diets that are both healthy and environmentally friendly, plays a critical role. Significant changes in contemporary dietary patterns are essential to address the rising burden of chronic diseases and public health outcomes and the escalating climate crisis. Achieving these shifts requires coordinated action from policymakers, consumers, and the scientific community in an effort to support the development, implementation, and evaluation of advertising and policy instruments that promote healthier and more sustainable dietary choices. However, driving changes in dietary behavior is a complex challenge, shaped by the interplay of heterogeneous influences, including biological, social, cultural, environmental, political, and economic factors, and further complicated by the difficulty of validating proposed approaches in ways that are both efficient and ethically sound. This vision paper presents the problem of promoting healthy and environmentally friendly diets and their implications for environmental sustainability. In particular, it discusses a systems approach based on social network dynamics and social interventions, illustrating recent findings that demonstrate the potential of influence strategies to drive dietary change. Finally, key scientific challenges and emerging research opportunities are highlighted.

Keywords: healthy diets, environmentally friendly diets, meat reduction, sustainability goals, GHG emissions, human behavior, social networks

1. Introduction

Encouraged by global sustainability goals, the cyber-physical human systems (CPHS) research area has gained significant interest in recent years (Annaswamy and Yildiz, 2020; Annaswamy et al., 2023; Hirche et al., 2023). The term CPHS emerges from the need to capture the integration of humans into cyber-physical systems (CPS), and refers to the interconnection of physical systems, computing devices, and humans, with time-varying and complex interactions (Hirche et al., 2023). With a foundation in engineering applications focused on the interaction between automation and human systems, including smart mobility and transportation, robotics, and manufactur-

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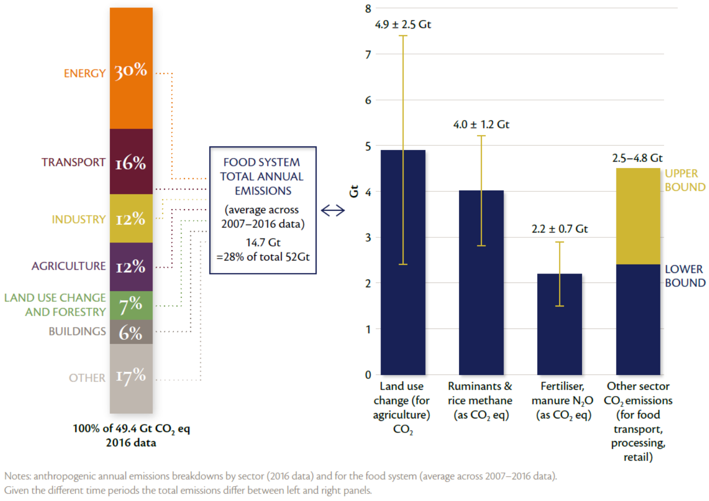
ing (Annaswamy and Yildiz, 2020), recent efforts have been directed toward addressing broader societal challenges, including climate change (Romanello et al., 2023), sustainable development and environmental management (Bibri and Krogstie, 2017; Karvonen et al., 2021), shared mobility services for disadvantaged communities (Annaswamy and Venkataramanan, 2024), energy efficiency in smart homes (Xu et al., 2023), and real-world social diffusion processes, including policy design as well as the study of behavioral and social dynamics (Frieswijk et al., 2025; Fontan et al., 2024; Ravazzi et al., 2025). Addressing these complex challenges increasingly requires interdisciplinary collaboration across scientific communities, including systems and control researchers (Lamnabhi-Lagarrigue et al., 2017).

This vision article focuses on a specific CPHS application within the broader domain of food systems: The promotion of sustainable dietary behaviors, i.e., behaviors towards healthy and environmentally friendly diets. Dietary choices are increasingly recognized as critical determinants of human health, economic stability, and environmental sustainability. The transition toward sustainable diets, characterized by reduced environmental impact, cultural acceptability, nutritional adequacy, and economic viability, poses complex challenges that include technological and digital communication infrastructure, individual behavior and societal norms, and policy frameworks. As such, these interdependencies exemplify a social influence process within the CPHS paradigm, with dietary behaviors at its center. Social diffusion processes in a CPHS can be represented as closed-loop control architectures with humans-in-multiagent loops (Samad, 2023), where the goal is to influence the final collective outcome via direct control measures (such as policies) or incentive mechanisms (Zino and Cao, 2023). To study these processes, network-theoretic frameworks have been introduced that model CPHS as multiplex networks, with each layer representing a distinct component: social networks of humans, networks of optimization and control paradigms, information and cyber networks, and physical networks (Zino and Cao, 2023). In our application of interest within the context of food systems, the overall goal is to promote sustainable diets through social diffusion. The human social network represents interpersonal interactions and peer influence within a population: each individual holds an opinion about adopting the sustainable diet, which evolves over time according to predetermined dynamics that define their decision-making mechanisms. Monitoring the collective behavior can inform the design of effective control policies, which policymakers (e.g., governments) can implement to influence individual opinions within the social network. However, these strategies also need to account for physical network infrastructures (representing, e.g., networks for transportation and distribution of food) and other constraints, such as resource availability, economic viability, and nutritional intake, which may in turn also influence individual behaviors. To summarize, representing these complex systems as (multilayered) CPHS provides a powerful framework for understanding their dynamic and coupled interdependencies.

Outline of the paper. The remainder of this paper is organized as follows: Section 2 introduces the societal and environmental challenges related to complex global food systems. Section 3 presents approaches to modeling sustainable diets within food systems, and Section 4 illustrates a preliminary case study focused on the problem of influencing public opinion in the UK regarding meat consumption. Finally, future directions and opportunities are discussed in Section 5.

2. Promoting a sustainable diet

A critical area within the broader context of societal and environmental challenges is that of *food systems*, which includes all processes related to the production, processing, distribution, preparation, and consumption of food (Willett et al., 2019). Food systems are widely recognized as significant contributors to a range of systemic issues, with substantial collective impacts on the en-



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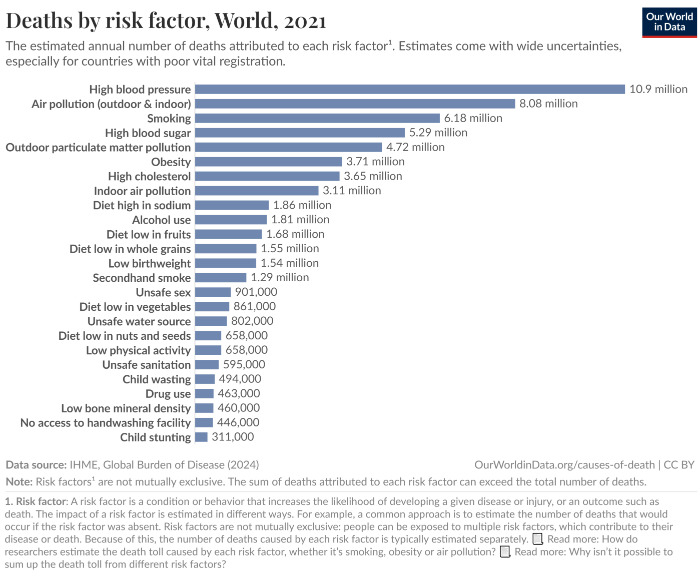


(b)

Figure 1: The global food system is a key contributor to anthropogenic emissions, and dietary behaviors have a key societal impact. (a): Anthropogenic annual emissions breakdowns by sector (2016 data) and for the food system (average across 2007–2016 data). Food systems are responsible for approximately a third of global anthropogenic GHG emissions (28% on average, with a likely range of 21% to 37%, for the period 2007–2016); they are generated by crop and livestock production activities within the farm gate, land use and land-use change dynamics associated with agriculture, and in pre- and post-production processes (manufacturing, retail, household consumption, and food disposal). The estimate includes emissions of 9%–14% from crop and livestock activities within the farm gate and 5%–14% from land use and land-use change (including deforestation and peatland degradation) (Masson-Delmotte et al., 2019; Crippa et al., 2021). Visualization by Global Panel on Agriculture and Food Systems for Nutrition (2020) (Fig. 3.5). (b): Annual number of deaths attributed to a wide range of risk factors. Poor diets have become the biggest contributor to the global burden of disease (Swinburn et al., 2019). In particular, unhealthy diets can lead to obesity (defined as having a high body mass index), which is a risk factor for several of the world's leading causes of death, including heart disease, stroke, diabetes, and various types of cancer. In 2015, excess body weight was estimated to affect 2 billion people worldwide and to account for approximately 4 million deaths (Swinburn et al., 2019); by 2019, obesity was estimated to contribute to around 5 million premature deaths (Brauer et al., 2024). Visualization by Ritchie and Roser (2024), based on data from Brauer et al. (2024).

vironment and the society, see Fig. 1. These include high levels of avoidable mortality and morbidity from chronic diseases and financial burdens (Tilman and Clark, 2014; Springmann et al., 2016; Willett et al., 2019; Masson-Delmotte et al., 2019; Ruiz Mirazo, 2022). Moreover, it is estimated that food systems account for approximately one-third of global anthropogenic greenhouse gas (GHG) emissions, with agricultural practices (all farming activities, including livestock production and associated land use activities) contributing to roughly a quarter of all GHG emissions (Poore and Nemecek, 2018; Masson-Delmotte et al., 2019; Crippa et al., 2021; Tubiello et al., 2022). Among the processes within global food systems, final consumption, namely, the *adoption of a sustainable diet (environmentally friendly and healthy)*, plays a crucial role and stands out due to its associated significant economic, environmental, and human health impacts. Suboptimal diets, low in whole grains, legumes, fruits and vegetables, and high in red and processed meat, sugar, salt and calories (Tilman and Clark, 2014; Afshin et al., 2019), are indeed directly linked to both environmental impacts, including increased anthropogenic GHG emissions (Springmann et al. (2016, 2020); Clark et al. (2022); Fig. 1a), and negative human health outcomes (Tilman and Clark (2014); Swinburn et al. (2019); Fig. 1b). A sustainable diet would instead be "protective and respectful of biodiversity and ecosystems, culturally acceptable, accessible, economically fair and affordable; nutritionally adequate, safe and healthy" (FAO, 2012, p. 83). In recent years, considerable efforts have been made towards setting scientific targets, both for the intake of specific food groups and sustainable food production. These targets aim to define a (universal) *safe operating space for food systems*, within which human health is optimized while environmental impact is minimized.

Within this space, it becomes possible to identify and subsequently promote dietary shifts toward *sustainable win-win diets*, i.e., diets that are both environmentally friendly *and* healthy, while also needing to remain affordable, one noteworthy example being the EAT-Lancet diet (Willett et al. (2019); Fig. 2a). Notably, Willett et al. (2019) also highlights the high potential for local adaptation and scalability of such a safe operating framework for food systems. Additional scientific efforts demonstrating the health and environmental benefits of *reducing the animal products intake while increasing the consumption of plant-based foods* include the studies by Milner et al. (2015); Springmann et al. (2018); Eustachio Colombo et al. (2021); Scheelbeek et al. (2020) in high-income countries and Fanzo and Davis (2019); Springmann et al. (2021) in high- to low-income countries. These studies also highlight key constraints and important concerns. In particular, Springmann et al. (2021) provide an estimate of the global costs of sustainable diets, showing that limited affordability poses a significant challenge to the adoption of these dietary patterns in lower-middle-income to low-income countries. Nonetheless, they note that reductions in food waste and future socioeconomic changes could make these diets more accessible. Beyond affordability concerns, dietary inequity (defined as the lack of access to a nutritious, affordable, and culturally acceptable diet) can restrict the adoption of sustainable diets and contribute to multiple forms of malnutrition (Fanzo and Davis, 2019). In particular, the double burden of malnutrition, referring to the coexistence of undernutrition (i.e., energy and micronutrient deficiencies) and overnutrition (i.e., dietary access, overweight, obesity) individuals, households, and populations (WHO, 2017), is increasingly prevalent in low- and middle-income countries (Seferidi et al., 2022).

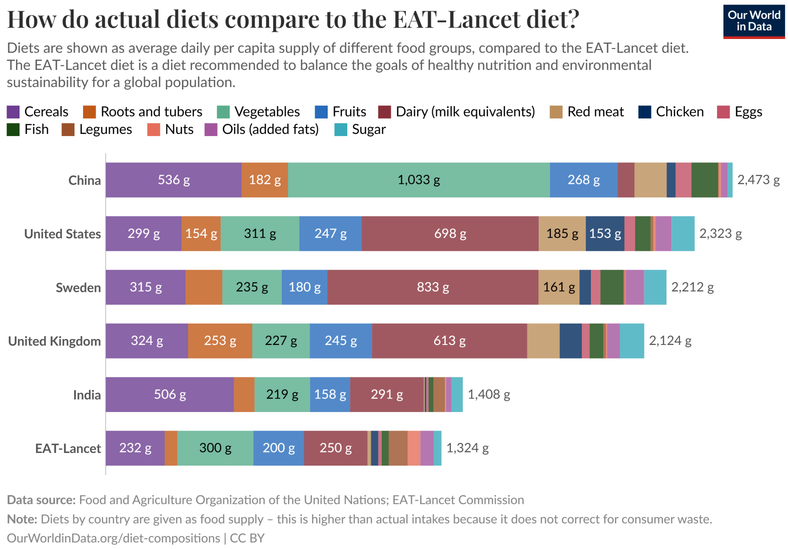
Therefore, promoting dietary shifts requires considerable efforts not only from the scientific community, but also from policy-makers and citizens. Accordingly, significant initiatives involve providing food-based dietary guidelines for citizens (FAO et al., 2024; Willett et al., 2019), for instance by offering recommendations on what constitutes a healthy and nutritious diet from a sustainable food system viewpoint (Fig. 2b), and by sharing resources such as climate-calculated recipes, weekly menus, and food calculators (Fig. 2c). These efforts are complemented by strategies for policymakers (e.g., governments, countries), including the establishment of dietary targets (Blomhoff et al., 2023; Swedish National Food Agency (Livsmedelsverket), 2015; Bergman et al., 2020) and the setting of ambitious public health goals and climate commitments, such as reducing or achieving net-zero emissions (FAO, 2012; Climate Change Committee, 2020; Swedish Environmental Protection Agency, 2012; Ministry of the Environment Sweden, 2020; Norwegian Environment Agency, 2014). In this context, proposed global food-based dietary strategies should align with established guiding principles (Martini et al., 2021) such as the one proposed by FAO and WHO (2019).

Understanding how to effectively promote sustainable dietary behaviors is a complex challenge, and limited knowledge persists regarding the design of policies to implement the desired changes at the population level, as well as their practical realization. Indeed, numerous factors pose constraints to the broader challenge of promoting dietary shifts and to the adoption of healthy diets.

Among the most influential are affordability and economic barriers to accessing healthy food, particularly in disadvantaged or low-income communities (FAO et al., 2024). In general, adopting a healthy diet can represent a large household expense, with some estimates exceeding 30% of income, and is therefore often deemed "unaffordable" ((Russell et al., 2022, p. 601); Fig. 3a). As a way to mitigate these affordability barriers, fiscal policies (including taxes and subsidies) have been proposed as viable strategies (Mozaffarian et al., 2014). In an effort to provide a quantitative assessment of their effectiveness, Afshin et al. (2017) conducted a meta-analysis to investigate the prospective impact and empirical effects of food pricing on dietary consumption. In particular, their findings indicate that subsidizing healthy foods significantly increases their consumption, while taxing unhealthy foods leads to a reduction in their intake. Crucially, there must be an understanding and support from policy-makers. For instance, in the context of the environmental impacts of animal-based technologies, Vallone and Lambin (2023) recently showed that the existing animal farming system continues to receive the majority of financial subsidies allocated to food producers, and its products are still recommended in official nutrition guidelines. These behaviors contribute to an active resistance against the transformation required for sustainable food systems.

Beyond economic or financial factors, several other drivers are known to influence food-related attitudes and beliefs (Steg et al., 2016; Monterrosa et al., 2020). These can be conceptualized through a multilevel socioecological framework (Fig. 3b), which emphasizes the significant role of interactions between individuals and their social and physical environments in shaping food choices (Monterrosa et al., 2020). Finally, eating behavior is affected by various complex trade-offs. For example, dietary choices aimed at improving human health, such as increasing fish consumption, may conflict with environmental sustainability goals, including concerns related to fish welfare and aquaculture impacts (Röcklinsberg, 2015). Similarly, switching from one animal-based food source to another (e.g., from beef to chicken) may reduce certain environmental impacts, such as GHG emissions, while increasing others, such as water pollution, and raising additional ethical concerns, including those related to animal welfare (Ritchie, 2024). These trade-offs can contribute to delayed action or indecision among both consumers and governments or policymakers.

In summary, promoting sustainable dietary behaviors requires addressing the complex interplay of biological, social, cultural, demographic, environmental, political, and economic factors that influence the adoption of both unhealthy and healthy diets (Drewnowski and Kawachi, 2015). At the same time, it is equally important to account for the different timescales involved within the broader challenge of promoting dietary shifts, and associated, for example, with biological responses and health outcomes, shifts in cultural norms or so-



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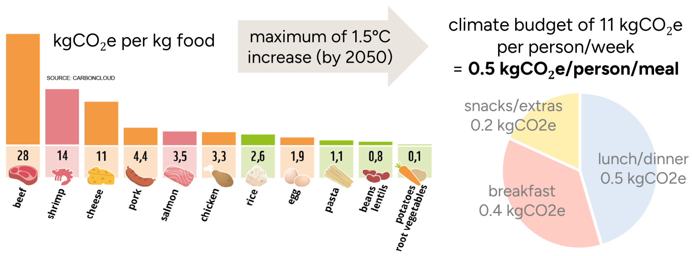

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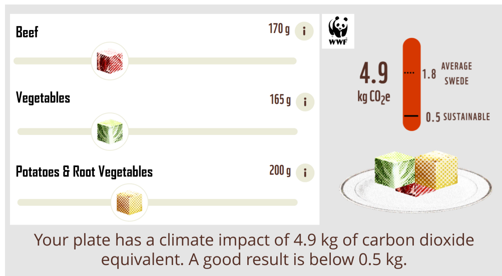
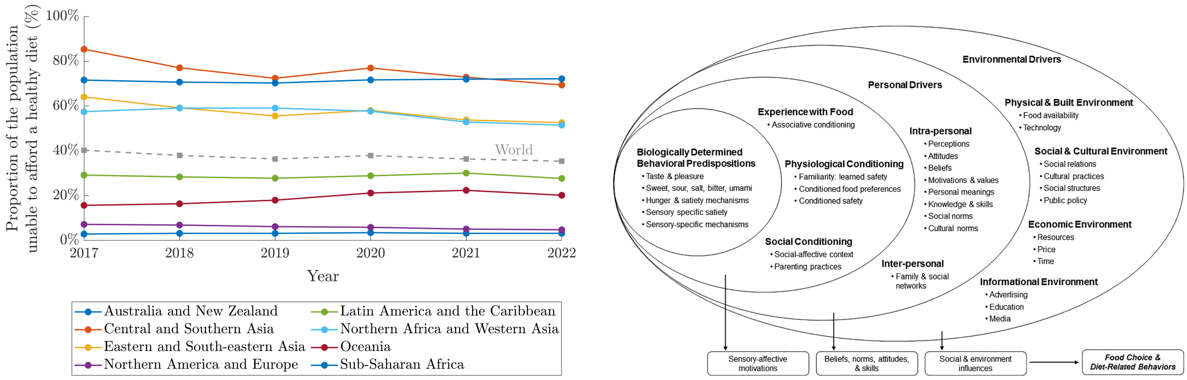


(c)

Figure 2: (a): What constitutes a sustainable diet? The EAT-Lancet report (Willett et al., 2019) represents one of the first scientific reviews of what constitutes a healthy diet from a sustainable food system. The EAT-Lancet diet is defined using food groups in a balance between nutritional adequacy and environmental sustainability, and its widespread adoption could place the global food system on a sustainable trajectory by 2050. However, current dietary patterns (in high- and middle-income countries) do not align with the EAT-Lancet diet. Source: ourworldindata.org/grapher/eat-lancet-diet-comparison. (b): Selecting guidelines based on an adequate climate budget to respect planetary boundaries represents a critical step toward achieving a sustainable diet (in high- and middle-income countries). As an illustration, in Sweden, a core framework for evaluating the emissions and climate impacts related to food systems (final consumption in particular) is provided by the WWF Sweden One Planet Plate Model (WWF Sweden, 2021), which helps assess individual emissions budget for food in line with the 2018 Report by the Intergovernmental Panel on Climate Change, IPCC (2018). In particular, WWF Sweden has developed criteria for meals to stay within planetary boundaries with regard to two aspects of sustainability: Climate and biodiversity. They calculate and allocate the climate impact a meal could generate in order to stay within the limit of maximum 1.5°C global warming, using data from the report IPCC (2018). Assuming that food accounts for 50% of an individual's GHG emissions, WWF Sweden (2021) establishes a global weekly climate budget for food of 11 kgCO_2e per person, which translates to 0.5 kgCO_2e per meal per person. Source: WWF Sweden (2021). (c): WWF Sweden has produced various tools to facilitate the transition to more sustainable meals. For example, WWF Sweden's Food Calculator shows how much GHG emissions a meal causes. The example shows a meal consisting of a piece of beef tenderloin, one pepper, and two potatoes. The associated climate impact is 4.9 kg of carbon dioxide equivalent (kgCO_2e), well above the "average Swede" (1.8kgCO_2e) and the recommended 0.5 kgCO_2e. Source: https://matkalkylatorn.se/en (edited).



(a) (b)

Figure 3: (a): Affordability of a healthy diet by world regions (defined according to the SDG framework of the United Nations), 2017–2022. Visualization based on data from FAO et al. (2024) (Table A1.6), which defines the cost of a healthy diet (CoHD) indicator as national level estimates of the cost of acquiring the cheapest possible healthy diet in a given country. (b): Social and environmental influences at multiple levels on food choice and diet-related behaviors. Source: Contento (2008).

cioeconomic conditions, and the implementation of policy interventions. Finally, significant challenges emerge related to the monitoring of food systems, e.g., via cross-sectional studies for identification of the most critical data for comparing progress and changes towards sustainability in different regions of the globe (Schneider et al., 2023), or related to the collection of longitudinal data to evaluate how specific large populations or groups of individuals respond to social pressure and policy interventions over extended periods of time–while being able to track individual outcomes, in ways that can capture the heterogeneity in food choices within the population, while still being cost-efficient, ethical, and non-intrusive.

3. Modeling changes in sustainable diets through social dynamics

An increasingly relevant approach to modeling sustainable diets within complex food systems is the use of agent-based models (ABMs), which capture the collective behavior of systems composed of heterogeneous agents (individuals or groups of individuals) whose behaviors evolve over time through mutual influence and interaction. Recent relevant applications of ABMs within food systems include studying group decision-making problems on essential nutrients allocation distributions (Friedkin et al., 2019), investigating food consumption behavior under social marketing campaigns and time-varying meat prices (Scalco et al., 2019), assessing the impact of policies (Zhang et al., 2014; Fontan et al., 2024), and identifying optimal interventions aimed at, for instance, promoting sustainability (Calisti et al., 2019) or reducing income-based inequalities (Blok et al., 2015) in healthy food consumption.

Within this framework, opinion formation models offer a promising approach to capturing how social network dynamics influence individual and collective dietary choices, and to studying the short- and long-term impacts of socially determined consumption behaviors. Their potential is particularly relevant given that food choices are significantly influenced by the social environment and emerge through social interaction with others (Meiselman and Bell, 2003; Monterrosa et al., 2020). In the following sections, we present a modeling approach based on social dynamics. We begin with a brief overview of opinion dynamics models (Section 3.1), followed by an introduction to social network interventions (Section 3.2).

3.1. Opinion dynamics and dietary behaviors

Models of opinion formation typically represent agents' opinions as real-valued states and describe their evolution over time using linear or nonlinear dynamical systems. A social network, typically modeled as a weighted directed graph, encodes the interactions among agents. These models aim to capture how opinions evolve as a result of social influence and potentially external or exogenous factors, with typical analyses investigating the conditions for convergence and stability, and the emerging behavior, such as consensus, polarization, or clustering. There is a rich literature dedicated to models of opinion formation and there are several comprehensive tutorials and surveys reviewing models of opinion dynamics, including Castellano et al. (2009); Acemoğlu and Ozdaglar (2011); Flache et al. (2017); Proskurnikov and Tempo (2017, 2018); Molavi et al. (2018); Anderson and Ye (2019); Shi et al. (2019); Tian and Wang (2023); Bernardo et al. (2024); Zino and Cao (2023). Moreover, the study by Groeber et al. (2014) has shown that a wide range of opinion formation models, ranging from the classical ones such as the DeGroot or Friedkin-Johnsen (FJ) models to more recent such as the Deffuant-Weishbuch model and the Hegselmann-Krause bounded confidence model (see Proskurnikov and Tempo (2017, 2018) for an overview), can be represented as best response dynamics, hence providing a microfoundation based on the the principle of dissonance minimization. While most findings reflect and demonstrate the theoretical behavior of these models, recent efforts show empirical evidence supporting the models, e.g., the works by De et al. (2019); Chandrasekhar et al. (2020); Friedkin et al. (2021); Kozitsin (2022, 2023).

In the context of dietary behaviors, opinions may represent agents' levels of concern regarding specific aspects of meat consumption (e.g., health, environment, or animal welfare) (Zhang et al., 2014; Scalco et al., 2019; Fontan et al., 2023), their ideal intake percentages for different food groups (e.g., fruits or vegetables, grains, and meats), or their preferred proportions of meat consumption in their diet (Fontan et al., 2024). Social networks may refer, at a small scale, to co-workers or household members (Scalco et al., 2019; Fontan et al., 2023), or, at a large scale, to the population of an entire country (Fontan et al., 2024; Frieswijk et al., 2025). Models of social influence within these dietary social networks often seem to rely on consensus-based mechanisms, where individuals adapt their opinions to align with those of their peers (Zhang et al., 2014; Scalco et al., 2019). One of the most widely used frameworks for capturing such dynamics is the DeGroot model (DeGroot, 1974), along with its continuous-time counterpart, the Abelson model (Abelson, 1964, 1967). These linear models, like many of their later extensions, are grounded on the principle that individuals' opinion updates occur through some weighted average of the opinions held by their neighbors within the community. When certain connectivity assumptions on the social network describing the community are met, the DeGroot model exhibits consensus, or, equivalently, it converges towards unanimous agreement on opinions (Proskurnikov and Tempo, 2017). The DeGroot model can also be viewed as a non-Bayesian social learning algorithm (Proskurnikov and Tempo, 2017; Molavi et al., 2018). In such models, agents iteratively update and share their beliefs about an unknown *true state of the world* with their neighbors using a social learning rule satisfying "imperfect recall": each agent treats their neighbors' current beliefs as sufficient statistics of all their past information. Under suitable conditions, agents can eventually successfully achieve full learning (Jadbabaie et al., 2012; Molavi et al., 2018): in our context, this could correspond to identifying a sustainable diet, such as the EAT-Lancet reference diet (Willett et al., 2019).

Building on the DeGroot original model, there is now a rich literature on opinion dynamics models capturing more complex behaviors, including disagreement, clustering, and polarization. For instance, they can incorporate cognitive features such as prejudices or stubbornness, as in the FJ model (Friedkin and Johnsen, 1999); capture antagonistic vs cooperative relations among individuals (Altafini, 2013; Fontan and Altafini, 2022; Bizyaeva et al., 2025); account for homophily behavior, i.e., the tendency of individuals to interact and form connections more with those who hold similar opinions than with dissimilar ones, as in bounded confidence models where agents are influenced only by neighbors whose opinions lie within their confidence interval (Hegselmann and Krause, 2002; Blondel et al., 2009; Bernardo et al., 2024); describe the coevolution of opinions and decision-making (Zino et al., 2020; Raineri et al., 2024); or use nonlinearities to describe how agents express their opinions (Bizyaeva et al., 2023; Gray et al., 2018; Fontan and Altafini, 2018, 2022).

This literature introduces (nonlinear and/or time-varying) opinion dynamics models that can be difficult to analyze, but at the same time provide non-trivial insights into strategies for persuading stubborn individuals to change their behavior and for promoting sustainable diets collectively. In the following, we present the well-known Friedkin–Johnsen model and a recent extension known as the concatenated Friedkin–Johnsen model, as they serve as the foundation for the illustrative example presented later in this paper.

Example 1 (The Friedkin-Johnsen model)**.** *The discrete-time (DT) FJ model postulates that the vector of the agents' opinions* $x(k) = [x_1(k) \ \cdots \ x_n(k)]^T$*, where* $x_i(k) \in \mathbb{R}$ *describes the opinion of agent i at time k, evolves following*

$$x(k+1) = \Lambda W x(k) + (I - \Lambda)u. \qquad (1)$$

The constant vector $u = [u_1 \ \cdots \ u_n]^T$ *represents the agent's prejudices. The parameter* $\lambda_i \in [0,1]$ *represents agent's i susceptibility to interpersonal influence, or, equivalently,* $1 - \lambda_i$ *indicates attachment to their prejudice* u_i*. An agent i is called prejudiced, fully prejudiced, and fully susceptible if* $\lambda_i \in (0,1)$, $\lambda_i = 0$, $\lambda_i = 1$*, respectively. The matrix* $\Lambda = \operatorname{diag}(\lambda_1, \ldots, \lambda_n)$ *is the diagonal matrix of the agents' susceptibilities. The matrix W describes the social network of interactions between the agents. For simplicity, we consider scalar-valued agent opinions, but the extension to higher-dimensional agent states can be handled analogously.*

An individual's prejudice can be viewed as an internalized opinion shaped either by personal experiences or by external influences. Indeed, the traditional assumption (e.g., Friedkin and Johnsen (1999); Friedkin (2015); Proskurnikov and Tempo (2017)) is that $u = x(0)$*, i.e., the prejudice of each agent is given by their initial option, which is the result of past exogenous conditions and captures the group's history. An alternative perspective is to consider the prejudice* $u \neq x(0)$ *as the result of exogenous sources, let it be social/mass media, leaders or social influencers, or other external communication sources.*

There are several continuous-time (CT) counterparts of the FJ model. First of all, the Taylor model (Taylor, 1968; Proskurnikov and Tempo, 2017)

$$\dot{x}_i(t) = \sum_{j=1}^{n} a_{ij}(x_j(t) - x_i(t)) + \gamma_i(u_i - x_i(t)) \qquad (2)$$

where $\gamma_i \geq 0$ *and* $A = [a_{ij}] \in \mathbb{R}^{n \times n}$ *is the adjacency matrix of the graph describing the social network. Another (equivalent) representation is the one proposed in Altafini (2022)*

$$\dot{x}_i(t) = \lambda_i \sum_{j=1}^{n} a_{ij}(x_j(t) - x_i(t)) + (1 - \lambda_i)(u_i - x_i(t)), \qquad (3)$$

which, in compact form, can be rewritten as

$$\dot{x}(t) = -(\Lambda L + I - \Lambda)x(t) + (I - \Lambda)u, \qquad (4)$$

where L is the Laplacian of the social network. Assuming strong connectivity of the social network and the existence of at least one partially or fully prejudiced agent (i.e., $\lambda_i < 1$ *for at least one agent i), it is well-known that the system (3) has a unique asymptotically stable equilibrium point* $x(\infty) := \lim_{t\to\infty} x(t) = Vu$*, where* $V := (\Lambda L + I - \Lambda)^{-1}(I - \Lambda)$*. Notably,* $x(\infty)$ *is in general not a consensus state.*

Example 2 (Concatenated FJ model)**.** *Several models have been proposed to evaluate the formation of opinions across different issues (Tian and Wang, 2018), a negotiation process held by sequential discussions (Wang et al., 2023), or a sequence* *of campaigns. In the following, we present a version of the concatenated CT FJ model, modified from the concatenated DT FJ model introduced in Tian and Wang (2018), and illustrate it within the context of social influence campaigns.*

Assume that interconnected agents are participating in a sequence of campaigns. Let $s \in \mathbb{N}$ indicate the campaign instants, where the (start and end of the) s-th campaign is captured by the interval $[s-1, s]$. To model opinion propagation in sequential issues, the CT FJ model (4) can be concatenated as

$$\dot{x}(s,t) = -\Lambda L x(s,t) + (I-\Lambda)x(s,0) \quad (5a)$$

$$x(s,0) = x(s-1,\infty) := \lim_{t\to\infty} x(s-1,t). \quad (5b)$$

Eq. (5a) means that during each issue the opinion of each agent evolves according to the CT FJ model (4) (here, $\dot{x}(s,t) := \frac{\partial x}{\partial t}(s,t)$). Eq. (5b) indicates the concatenation rule between initial and final opinions of subsequent campaigns.

As we explore in the next sections, the potential benefits of applying an opinion dynamics approach, although based on a theoretical framework, include estimating individual food-consumption outcomes over time despite data gaps, studying environmental impacts under different influence scenarios, and exploring how to design or modify an intervention (Hennessy et al., 2016). Indeed, networked dynamical models (such as models of opinion formation) can be extended to include control designs, referred to as *social network interventions* in this manuscript. These interventions may represent, for instance, environmental constraints, subsidies, and awareness campaigns, and are designed to guide the collective system toward a desired state. This modeling framework thus presents an opportunity to gain unique insights into how policies can impact people's dietary behaviors to the benefit of both human and planetary health.

3.2. Social network interventions

The problem of interventions in social networks, such as guiding the collective opinion of a group of agents connected in a social network towards a desired state, has broad significance with applications that extend well beyond the control community. It finds relevance not only in common viral marketing contexts (Varma et al., 2018; Morărescu et al., 2020) and influence maximization problems (Kempe et al., 2003; Rasoul Etesami, 2022; Bastopcu et al., 2025), but also in negotiation processes (Bernardo et al., 2021; Wang et al., 2023), social power games (Wang et al., 2024), political decision-making (Leonard et al., 2021; Fontan and Altafini, 2021), recommender systems (Burke, 2002; Sprenger et al., 2024; Kühne et al., 2025), and social media effects in online social networks (Li and Zhu, 2020; Tu and Neumann, 2022). Recent applications extend to the context of public health (Ancona et al., 2022), sustainable behaviors in smart homes (Farjadnia et al., 2023; Fontan et al., 2023), and dietary choices (Fontan et al., 2024).

The problem of social network interventions has been addressed from multiple perspectives, which we briefly review below. Independent of the specific intervention strategy, most existing studies model the evolution of social dynamics using the DeGroot model (Grabisch et al., 2018; Varma et al., 2017, 2018, 2019; Rasoul Etesami, 2022; Bastopcu et al., 2025; Morărescu et al., 2018, 2020), the FJ model (1) (Bindel et al., 2015; Gionis et al., 2013; Ancona et al., 2022; Chen et al., 2018; Musco et al., 2018; Matakos et al., 2017; Zhu et al., 2021; Chitra and Musco, 2020; Tu and Neumann, 2022; Kühne et al., 2025; Kareeva et al., 2023; Sprenger et al., 2024), or the Hegselmann–Krause model (Hegselmann et al., 2015). Other works adopt nonlinear models (Leonard et al., 2021; Ancona et al., 2023), such as those introduced in Gray et al. (2018); Fontan and Altafini (2018); Bizyaeva et al. (2023).

One extensively studied intervention approach focuses on modifying the network structure, typically by editing its connectivity or adjusting edge weights, e.g., Bindel et al. (2015); Chen et al. (2018); Chitra and Musco (2020); Zhu et al. (2021); Kühne et al. (2025) and references therein. Such network interventions have typically been applied with the aim of reducing polarization, minimizing social cost, or mitigating the risk of conflict in social networks.

Beyond targeting the social network, an alternative strategy involves intervening directly in the opinions of agents in the network, typically through influence campaigns conducted by external entities. These *campaigns* may have either a positive or a negative connotation, with applications ranging from product marketing and spreading political messages to advocating for public health and behavioral change initiatives. Influence maximization has been widely studied through seed selection problems (Kempe et al., 2003; Gionis et al., 2013; Aslay et al., 2017; Sathanur et al., 2018; Matakos et al., 2017; Musco et al., 2018; Tu and Neumann, 2022), which focus on identifying a subset of target individuals whose full adoption of a campaign's message can lead to its widespread diffusion throughout the social network. Motivated by growing evidence of polarization in online social networks (see, e.g., Bakshy et al. (2015); Bail et al. (2018)), and its potential to disrupt collective decision-making within social communities, recent studies have shifted attention from maximizing positive influence to minimizing polarization (Matakos et al., 2017; Musco et al., 2018; Tu and Neumann, 2022). Another set of approaches addresses pinning control problems (Leonard et al., 2021; Ancona et al., 2022, 2023), in which one or more influencers directly influence the opinions of selected pinned nodes, leveraging the network structure to spread influence (see, e.g, Wang and Chen (2002); Sorrentino et al. (2007); Wang and Su (2014); Della Rossa and De Lellis (2022); D'Souza et al. (2023) for comprehensive reviews on pinning-based control). Game-theoretical formulations model competition among multiple strategic external entities attempting to control consumer opinions, particularly in viral marketing and word-of-mouth contexts. These settings include static games (Grabisch et al., 2018; Varma et al., 2017, 2018) and dynamic or long-term campaigns (Varma et al., 2019; Bastopcu et al., 2025), both with (Kareeva et al., 2023) and without (Veetaseveera et al., 2021) stubborn agents. Budget constraints are considered in several of these works (Varma et al., 2018, 2019; Fabiani et al., 2022; Fabiani and Simonetto, 2024; Rasoul Etesami, 2022; Bastopcu et al., 2025), while others analyze unconstrained settings (Grabisch et al., 2018; Varma et al., 2017; Kareeva et al., 2023). Finally, optimal control approaches examine how a single influencer can guide the network's average opinion toward a target value, often under budget limitations (Hegselmann et al., 2015; Morărescu et al., 2018, 2020; Fontan et al., 2024; Ravazzi et al., 2025).

Related to this last approach, Hegselmann et al. introduce the *campaign problem*, where "a strategic agent tries to control an opinion dynamics, such that in a certain period, known in advance, there are as much as possible opinions of normal agents in a certain interval of the opinion space" (Hegselmann et al., 2015, p. 3). In other words, by the end of a campaign led by the strategic agent, as many opinions of the (non-strategic, normal) agents in the network as possible should fall within a certain desired range. At each campaign, agents update their opinions according to a bounded confidence mechanism, in which the strategic agent can participate by optimally placing its opinion. In this setting, *control* corresponds to the public expression of an opinion, which may either have a positive connotation (e.g., dissemination of information, raising awareness) or a negative one (e.g., spreading misinformation). Recent contributions reformulate the campaign problem as one in which an influencer aims at guiding the overall opinion of the social network as close as possible to a desired target, possibly subject to specific influence budget constraints (Morărescu et al., 2018, 2020; Fontan et al., 2024). In particular, the studies by Ancona et al. (2022); Morărescu et al. (2018, 2020) illustrate how intervention strategies based on opinion dynamics models can be applied to real-world problems, such as public health and viral marketing, while also highlighting key practical challenges such as uncertainty in network parameters, resource or budget constraints, scalability, and timescales. In general, targeted (marketing or awareness) campaigns have been proven to outperform broadcasting campaigns, representing traditional mass-media efforts, with the most effective strategy varying according to the available total campaign resources or constraints. Importantly, these approaches require varying levels of insight and face several practical challenges. These include limited knowledge of the social network and difficulties in accurately estimating various centrality measures. Additionally, effective implementation may depend on the ability to collect data on individual agents' attitudes or beliefs and to perform nuanced psychological profiling to identify the most susceptible agents. Beyond these informational constraints, there are also computational limitations, particularly in scenarios involving large populations or extended sequences of intervention campaigns, which can significantly increase the complexity of strategy design and optimization.

A marketing-based framework has also been applied, though only to a limited extent, in the context of promoting sustainable dietary behaviors, from the studies by (Zhang et al., 2014; Scalco et al., 2019) to the recent work by Fontan et al. (2024), described in the next section.

4. Influencing opinion dynamics to promote sustainable food choices

Our initial study Fontan et al. (2024) explores how a sequence of targeted campaigns can be used to shift public opinion within a social network toward a desired dietary behavior, as defined by an external entity representing a policy-maker or planner. The goal of the external entity is to guide the collective opinion of a population toward healthier and more sustainable diets, specifically, a reduction in meat consumption, by strategically allocating influence efforts to individual agents in the social network while working within budget constraints for each campaign. Notably, the agents interact with one another in a social network and are prejudiced, meaning that they tend to resist change due to habitual dietary patterns.

As a practical example, we focus on the United Kingdom's climate targets set by the Climate Change Committee (2020) (UK CCC), which call for significant reductions in the average consumption of meat and dairy products by 2030 and 2050. To model baseline consumption patterns, we use data from the 2019 National Diet and Nutrition Survey (NDNS) (Bates et al., 2019), mapping the population's reported consumption levels onto the initial opinions of agents representing the UK population. By exploring various influence strategies under budget constraints, we aim to illustrate the potential effectiveness of repeated influence campaigns in shifting dietary behaviors toward sustainable diets, which align with public health and environmental goals. Preliminary findings on the case study, primarily focused on broadcasting strategies, are reported in Fontan et al. (2025).

4.1. Modeling approach

In our framework, n agents and an external (strategic) entity interact over a sequence of campaign opportunities. We formalize this process using a modified concatenated FJ model (5) across a sequence of campaigns. During each campaign, agents update their opinions using the CT FJ model with prejudices (4). A concatenation rule dictates that the agents' initial opinions at the start of each campaign are determined by their final opinions at the end of the previous campaign. At the end of each campaign period, the external entity observes the average opinion in the social network and, to minimize its deviation from the target state, (impulsively) controls the agents' prejudices. Specifically, each agent's prejudice is defined as a convex combination of their initial opinion and the external entity's target opinion. The relative weight assigned to the opinion of the external entity is agent-specific, bounded, and reflects the intensity of influence or receptiveness to it. Finally, the individuals' prejudices remain constant between consecutive campaigns.

Remark 1. *The use of a CT FJ model (rather than its DT counterpart) and of a two-timescale approach is motivated by a reasoning based on the* *separation between fast dynamics (external influence efforts) and slow dynamics (social diffusion), inherent to the dietary shifts problem. Specifically, external influence occurs only when the observed behavior of the social network is stationary, which may require a meaningful amount of time.*

The rationale for this choice stems from practical considerations and builds on the approach proposed in Morărescu et al. (2020), where a CT model is adopted for opinion dynamics and an impulsive model for the marketing strategy. As remarked by Morărescu et al., advertising campaigns are typically of much shorter duration relative to timescale over which public opinion evolves regarding the promoted product. This two-timescale modeling approach is not only appropriate in the context of market regulation on social networks but, as noted in Fabiani and Simonetto (2024), is fairly general and can be extended to other applications, such as energy flexibility markets (Heinrich et al., 2021; Evangelopoulos et al., 2022).

To summarize, campaigns are modeled in a concatenated FJ model (5), adapted to include external influence as follows:

$$\dot{x}(s,t) = -(\Lambda L + I - \Lambda)x(s,t) + (I-\Lambda)u(s) \quad (6a)$$

$$u(s) = (I - H\Gamma(s))x(s,0) + H\Gamma(s)\, d\mathbb{1} \quad (6b)$$

$$x(s,0) = x(s-1,\infty) := \lim_{t\to\infty} x(s-1,t) \quad (6c)$$

Equations (6a)–(6c) describe, respectively, the intra-campaign opinion update dynamics, the external entity's control of agents' prejudices, and the concatenation rule between initial-final opinions of subsequent campaigns (in the initial study, to simplify the analysis, we assume a complete timescale separation). The parameter $s \in \mathbb{N}$ indicates the campaign instants, where the (start and end of the) s-th campaign is captured by the interval $[s-1, s]$. The vector $x(s,t) = [x_1(s,t) \ \cdots \ x_n(t)]^T \in [0,1]^n$ represents the (normalized) opinions of the n agents in the social network at time t of campaign s, while $x(s-1,\infty)$ indicates the opinion state at the end of the $(s-1)$-th campaign. The scalar $d \in \{0,1\}$ represents the declared opinion of the strategic entity, which is assumed to be linked to all the agents in the network. The influence (or control) effort of the external entity towards each agent i at campaign s is represented by a parameter $\gamma_i(s) \in [0,\bar{\gamma}]$, and $\Gamma(s) = \mathrm{diag}\,(\gamma_1(s),\ldots,\gamma_n(s))$ is the corresponding diagonal matrix of all the influence efforts at campaign s. The parameter $h_i \in [0,1]$ represents how much an individual i can be persuaded by or is susceptible to the external entity; $H = \mathrm{diag}\,(h_1,\ldots,h_n)$ is the diagonal matrix obtained from the h_i. As an extreme case, fully stubborn agents i (with $\lambda_i = 0$), having $h_i = 0$ and $x_i(0) \in \{0,1\}$ such that $x_i(0) \neq d$, can represent "anti-campaign" (non-strategic) zealot agents. Note that the parameter $0 < h_i \ll 1$ could alternatively indicate that selected agents require more resources to change their habits.

4.2. *Case study: Meeting the target for meat intake in the United Kingdom*

We consider the problem of influencing public opinion in the UK regarding meat consumption, involving influence campaigns to guide the UK population towards achieving the consumption target for meat set by the UK CCC. The CCC's recommended Widespread Engagement Pathway represents a transition to net zero across all sectors of the economy and involves ambitious and substantial behavioral changes from consumers. One of the targets is to achieve a 35% reduction in the average consumption of all meat products (and dairy products, which we do not consider here) by 2030.

Data description. We derived dietary data from the National Diet and Nutrition Survey (NDNS) 2019, designed to collect comprehensive and quantitative information on the food consumption and nutrient intake of the general UK population (Bates et al., 2019) In particular, the NDNS data provides quantities in grams of items eaten or drunk over 4 consecutive days, categorized by main food groups, subfood groups, and individual food items. The processed data considers a sample of $n = 1841$ individuals and intakes of four food groups, i.e., meat (red/processed and poultry meat), meat alternatives (e.g., tofu, tempeh, Quorn), pulses (dry

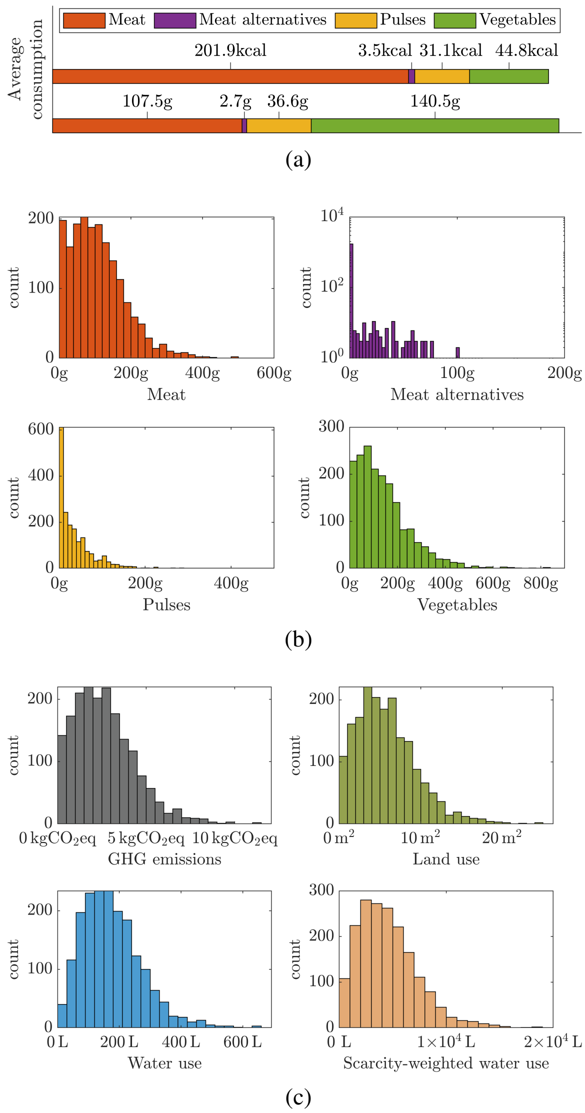


Figure 4: Illustration of the data obtained from the 2019 National Diet and Nutrition Survey in the UK (Bates et al., 2019), from a sample of $n = 1941$ individuals. (a): Average daily per capita consumption of four food groups (meat, meat alternatives, pulses, and vegetables), in grams and kcal. (b) Histograms of the recorded daily per capita consumption of four food groups, in grams (similar plots can be obtained for kcal). (c): Recorded daily per capita environmental impacts from food consumption (including consumption of meat, meat alternatives, pulses, and vegetables). The environmental impacts are measured in terms of GHG emissions, land use, water use, and scarcity-weighted water use.

peas, beans, lentils, and chickpeas), and vegetables (fresh, canned, or frozen vegetables, excluding potatoes), see Fig. 4a and Fig. 4b. These four food groups were selected as the most realistic substitutes for meat following methods from a previous work (Eustachio Colombo et al., 2021). Environmental impacts of meat, meat alternatives, pulses, and vegetables are based on data from a meta-analysis of food product Life Cycle Assessments (LCA) compiled from published literature related to UK-specific emission data (Clark et al., 2022). These data are used to quantify the changes in diet-related GHG emissions (measured in kg carbon dioxide equivalents), land use, which is an estimate of how much arable land and pasture land is occupied to produce food product without biodiversity impacts (measured in square meters), water use (measured in liters of blue water), and scarcity-weighted water use, which refers to weighted blue water used to produce food products by regional water availability (measured in liters), see Fig. 4c.

Target on consumption of meat for a healthy diet. Given the desired 35% reduction set by the UK CCC, and the data collected in the 2019 NDNS (Fig. 4a), the target for average meat consumption is given by $(1 - 0.35)201.9\,\text{kcal} = 131.2\,\text{kcal}$.

Opinion dynamics modeling of food consumption. In the case study, agents are individuals in the UK population. Their opinion is indicated by a real number between 0 and 1, representing the preferred proportion of meat consumption in relation to their total energy intake. Total energy intake is defined as the sum of the four above-mentioned food groups (meat, meat alternatives, pulses, and vegetables), and it is assumed to remain constant. Based on previous research (Bentham et al., 2020) and for simplicity, we model only meat consumption opinion formation, presuming the other food groups adjust to maintain constant energy intake.

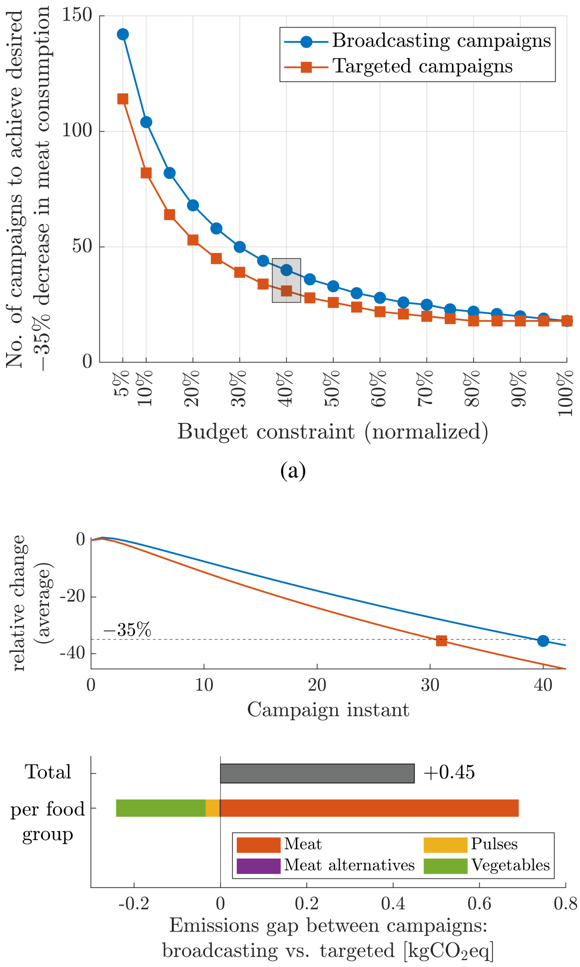
To model the evolution of opinions, we use the model (6), with the 2019 NDNS data as initial opinions. We assume that vegetarians and carnivores (individuals whose percentage of meat consumption is 0% and 100%, respectively) are fully prejudiced ($\lambda_i = 0$), while omnivores (individuals that are neither carnivores nor vegetarians) are partially prejudiced ($\lambda_i \in (0, 1)$). From the survey data, we obtain 129 vegetarians and 31 carnivores. In general, insights into large-scale social structures could be obtained given comprehensive population data, including demographic, socioeconomic, and geographic information (Bokányi et al., 2023). In our case, the UK social network is modeled as a weighted undirected graph of interactions, where edge weights are determined by age and socioeconomic status (related to income), attributes known to act as environmental influences on food choices (Larson and Story, 2009). This modeling choice reflects the intuition that individuals who are more similar in age and socioeconomic background are more likely to trust each other, and vice versa. Finally, we assume that $d = 0$, which follows naturally from the dietary choices application where the influence efforts of the external entity (e.g., a government) aim towards achieving a meat-free diet.

Impact of social network interventions. To evaluate the impact of the external entity on opinion dynamics, we consider two influence scenarios under budget constraints, compared against a baseline in which equal influence is applied to all agents.

The first setting we consider is that of a homogeneous (in time) broadcasting among the agents, i.e., $\Gamma(s) = \bar{\gamma} I$ for all $s \in \mathbb{N}$ in (6). In general, the average deviation between agents' opinions and target d converges to zero (after a potentially infinite number of campaigns) only if all fully prejudiced carnivore agents are susceptible to the influence efforts of the external entity. Advantages of broadcasting campaigns include their simplicity and scalability: they do not require knowledge of the social network or individual psychological traits (such as agents' prejudices). Limitations, however, include the potential need for a substantial number of campaigns to observe a meaningful shift toward a meat-free diet. Moreover, if the external influence diminishes over time, i.e., its impact weakens with each campaign, the resulting average decrease in meat consumption may remain limited within a realistic time frame.

However, the proposed modeling approach can be extended to address a broader range of scenarios, centered around the key question: How can the external entity optimally allocate its influence efforts $\Gamma(s)$ to achieve the desired reduction in meat consumption, possibly under budget constraints? Two specific scenarios can be analyzed. (i) Broadcasting influence with budget constraints: The external entity can influence all agents equally in each campaign, but a budget constraint limits the total number of campaigns where this influence can occur; and (ii) Targeted influence with budget constraints: For each campaign, a budget constraint limits the total number of agents that can be influenced. In the first case, we want to find a sequence $\Lambda(1) = \gamma(1)I, \Lambda(2) = \gamma(2)I, \ldots, \Lambda(s) = \gamma(s)I$ that minimizes the cost at the end of the s-th campaign, defined as the (absolute value) difference between the average opinion at the end of the s-th campaign $\mathbb{1}^T x(s, \infty)/n$, where $x(\cdot,\cdot)$ evolves according to (6), and the desired opinion d, under a total budget constraint B. The constraints are $\gamma(k) \in [0, \bar{\gamma}]$ for all $k = 1, \ldots, s$ and $\sum_{k=1}^{s} \gamma(k) \leq B/n$. In the second case, each diagonal matrix $\Gamma(s)$ is designed to minimize the cost at the end of the s-th campaign, defined as the (absolute value) difference between the average opinion $\mathbb{1}^T x(s, \infty)/n$, where $x(\cdot,\cdot)$ evolves according to (6), and the desired opinion d, given the observed opinions at the end of the $(s-1)$-th campaign, and under a budget constraint imposed for that specific campaign and denoted by B_s. The constraints are $\Gamma_{ii}(s) \in [0, \bar{\gamma}]$ for all $i = 1, \ldots, n$ and $\sum_{i=1}^{n} \Gamma_{ii}(s) \leq B_s$. Similar to the findings in Morărescu et al. (2020), theoretical analysis for each scenario reveals water-filling solutions for the optimal influence strategies: (i) When equal influence across agents is feasible, the available resources should be used as early as possible; and (ii) In targeted campaigns, resources should be allocated to agents with the highest social power, defined as the weight of an agent's initial opinion in determining the group's final average opinion (Proskurnikov and Tempo, 2017), taking into account each agent's proximity to the external entity's opinion on meat consumption (a one-step-ahead solution).

Overall, the proposed modeling approach for



(a)

(b)

Figure 5: (a): No. of campaigns required to reach the UK CCC's 35% reduction in kcal meat consumption, using different social influence strategies under increasing campaign-specific budget constraints. In particular, we define a broadcasting strategy where the campaign-specific budget is distributed equally among the agents, and we compare the proposed targeted strategy against it (details in Fontan et al. (2024)). The impact of influence campaigns is evaluated in terms of % average relative change w.r.t. the initial opinions. (b): For the particular case of a normalized budget of 40% (as shown in panel (a)), the top panel illustrates the average relative change in meat consumption, while the bottom panel shows the additional GHG emissions resulting from the adoption of a broadcasting strategy instead of a targeted strategy. The predicted environmental impacts of meat, meat alternatives, pulses, and vegetables, in terms of diet-related GHG emissions, measured in kg carbon dioxide equivalents (CO_2eq) are estimated based on previous research by Eustachio Colombo et al. (2021).

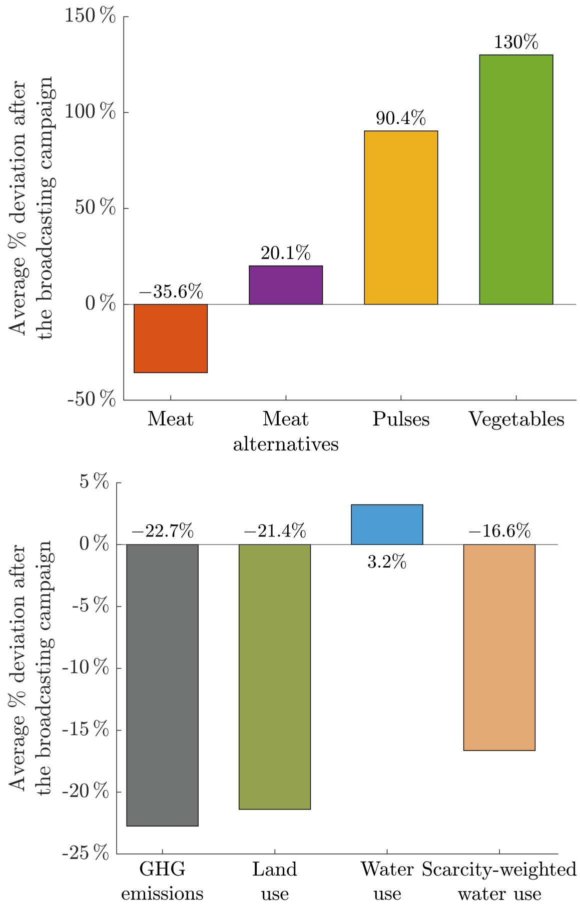


Figure 6: Average percentage deviation after a broadcasting campaign, in grams consumption (top panel) and environmental impacts (bottom panel). Observe that influencing only meat consumption to achieve the desired −35% decrease may not be sufficient to achieve a healthy *as well as* environmentally friendly diet. In this illustrative example, we assume that the other food groups (meat alternatives, pulses, and vegetables) adjust to maintain constant energy intake, according to observed baseline dietary patterns, without influence or control by the external entity. As a result, many individuals tend to redistribute their reduced meat intake primarily through increased vegetable consumption, rather than opting for meat alternatives (top panel). The observed average increase in water use (+3.2%, bottom panel) results from an increase in vegetables and pulses, which are food groups that have a relatively high demand for freshwater (Springmann et al., 2018). Details in Fontan et al. (2025).

social interventions in opinion dynamics can be used to evaluate the effectiveness of optimal policies in comparison to standard broadcasting campaigns, which serve as benchmark scenarios. The analysis shows that targeted campaigns, while requiring more information such as agents' social power, whose perception is not a trivial challenge (Tian et al., 2025), typically achieve the desired healthy diet outcomes in fewer campaigns (Fig. 5a) and, consequently, result in lower cumulative GHG emissions w.r.t. broadcasting campaigns (Fig. 5b). Finally, while the proposed approach in Fontan et al. (2024) (with a concrete application presented in Fontan et al. (2025)) is intentionally simplified, it effectively serves to highlight the complexity of promoting diets that are sustainable, i.e., both healthy and environmentally friendly. Focusing exclusively on one aspect, such as reduction in meat consumption, while disregarding other aspects of an individual's diet, may lead to desired health outcomes and reductions in GHG emissions, but could still result in other unintended negative environmental impacts (Fig. 6). Therefore, a general limitation of this analysis is that it does not consider potential trade-offs with dimensions such as nutritional adequacy (and considered number of food groups), health outcomes, and other environmental impacts.

5. Future directions and opportunities

This vision paper aims to invite the control community to contribute to and explore the potential benefits of influencing dietary behavior, both in alignment with dietary goals for health benefits and to promote environmental sustainability. The methods discussed here primarily focus on network-based social interventions, building on an opinion dynamics approach. In the following, we outline emerging research directions and open challenges.

First of all, as dietary-related behaviors are increasingly shaped by digital interactions and peer influence within online platforms, among future challenges related to the theoretical aspect of designing adaptive social interventions for complex networks in the context of food consumption, recent emerging directions in modeling and control include:

- The study of open multiagent systems, in which agents may dynamically enter or leave the social network and where relationships can continuously be formed, changed, or dissolved (Dashti et al., 2022; Oliva et al., 2024; Vizuete et al., 2024; Sekercioglu et al., 2025);
- The extension to higher-order network representations, where interactions occur not just pairwise but in groups, along with the study of their influence on social dynamics and collective decision-making (Battiston et al., 2020; Neuhäuser et al., 2022; Fontan and Zhang, 2025);
- The inclusion of AI-agents (as bots, recommender systems, and virtual influencers) in the social dynamics, and the analysis of how these entities, often indistinguishable from human actors, can influence the decision-making of human agents (La Cava and Tagarelli, 2025; Jain and Krishnamurthy, 2025), through both intentional influence and unintended manipulation;
- The extension of social diffusion models to include health and environmental feedback loops (e.g., Tilman et al. (2020); Frieswijk et al. (2025) and references therein).

A key strength of some of the proposed modeling approaches based on social interventions is their ability to evaluate the impact of both social and external influences on dietary behavior. Additionally, these models can incorporate constraints such as fairness/diversity and privacy, which are essential to consider when planning interventions (Dörfler et al., 2024; Sprenger et al., 2024).

Future research will need to complement model-based designs with scalable, data-driven approaches to account for uncertainties and constraints inherent in human behavior and to adapt to changing environments. This includes learning networks from dynamical systems (Wai et al., 2020; Xing et al., 2024) as well as learning social influences from data (Ravazzi et al., 2021), and learning dynamics and agents' objectives to successfully apply control strategies (Hewing et al., 2020). Advances in the digitalization of smart cities can facilitate these studies by providing extensive data, ranging from large-scale collection efforts to controlled experimental studies. For these approaches to be effective in real-world scenarios, they must be developed in close coordination with available data and resources, which range from municipalities (small scale), to regional (medium scale), and national authorities (large scale). In the short term, proposed approaches must consider, and eventually, adapt to typically information-poor, sparse, and noisy datasets. Indeed, the available data often fail to fully capture the heterogeneity within a population, and may not adequately represent and keep track of the different relevant factors (including biological, social, economic, and geographical) needed for a comprehensive analysis; examples include Bates et al. (2019) for the UK and Bremberg et al. (2015, 2024) for the city of Stockholm. In general, current methodologies for data collection lack longitudinal analysis, real-time availability, and testbeds for implementing feedback strategies. In the medium to long term, it is essential to work with stakeholders to build trust in the effectiveness of these approaches, advocate for the implementation of longitudinal experimental studies at different scales, and identify which types of data are most relevant and necessary to collect while considering practical constraints.

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