

A Multiplex Social Contagion Dynamics Model to Shape and Discriminate D2D Content Dissemination

Marialisa Scatà¹, Member, IEEE, Alessandro Di Stefano², Member, IEEE, Aurelio La Corte³, and Pietro Liò⁴

Abstract—5G network technology is growing fast, thus the number of devices and the traffic are likely to pose impressive challenges. A new paradigm called “Internet-of-People” (IoP) represents a valid approach to include the social aspect. Following an IoP perspective, we believe that the knowledge of social multiplex interactions and dynamics could drive more sustainable growth. By merging this with the Device-to-Device communication (D2D), we originate a new paradigm presented in this work. We propose a novel bio-inspired approach for quantifying the impact of the social multiplex structure on D2D contents’ dissemination. Through rigorous mathematical modelling, we have shaped the D2D data dissemination process as a social contagion dynamics of two co-evolving spreading processes. We weigh the dynamic interactions by including the concepts of homophily and awareness. We have measured the effect of homophily, awareness and network heterogeneity on information diffusion. The bio-inspired mechanism is evaluated through a rigorous mathematical and algorithm analysis, and a meaningful simulation. We show that this mechanism is effective in tuning network awareness and alertness, breaking the “echo chambers” effect. Through our model, we have defined and proposed the guidelines to discriminate the nature of the contents based on contents’ dissemination.

Index Terms—D2D data dissemination, multiplex networks, social contagion dynamics, epidemic spreading, bio-inspired, Internet of People.

I. INTRODUCTION

THE ONGOING process of telecommunications evolution within 5G networks along with the increasing number of mobile users, high data-rate applications and demands of growing bandwidth-intensive services, is creating a large volume of traffic, making a compelling and complex dare that

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Marialisa Scatà and Aurelio La Corte are with the Department of Electrical, Electronic and Computer Engineering, University of Catania, Catania 95125, Italy, and also with Consorzio Nazionale Interuniversitario per le Telecomunicazioni, 43124 Parma, Italy (e-mail: lisa.scata@dieei.unicit.it; aurelio.lacorte@unicit.it).

Alessandro Di Stefano is with the Department of Computer Science and Technology, Computer Laboratory, University of Cambridge, Cambridge CB3 0FD, U.K., and also with the School of Computing, Engineering and Digital Technologies, Department of Computing and Games, Teesside University, Middlesbrough TS1 3BX, U.K. (e-mail: a.distefano@tees.ac.uk).

Pietro Liò is with the Department of Computer Science and Technology, Computer Laboratory, University of Cambridge, Cambridge CB3 0FD, U.K. (e-mail: pl219@cam.ac.uk).

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still lies ahead [1]–[3]. Mobile data traffic is growing so fast that it is foreseen that it will reach a monthly global size of 77 exabytes by 2022 [3]–[5]. Some schemes have been proposed to offload the data traffic through groundbreaking paradigm such as Device-to-Device communication (D2D), which tackles content distribution [6], [7]. In the modern information society, given that we are turning to heterogeneous, cognitive and constantly-changing connected systems of things (Internet of Things) and people (Internet of People) [8], [9], information dissemination has become one of the most important services of communication networks. D2D-based mechanisms can solve the mobile traffic offloading by avoiding to reduce both the quantity and quality of information or minimize data diffusion [6], [7]. Direct D2D communication with device controlled link formation represents a successful approach where terminals or user equipments (UEs) interact with each other without the base station [1]. Although it is well-known that hand-held mobile user devices are typically carried by human-beings, these technologies overlook how a deeper analysis based on correlations and dynamics of multiple levels of social interactions could be crucial [10], [11]. To this aim, an interesting point to untangle, introducing the social multiplex representation of users, is the knowledge mining of the network structure and its dynamics. Moreover, this is in line with the future requirements of 5G networks that are headed straight towards cognitive heterogeneous environments characterised by the co-existence, interdependence and social connectivity of people and things. Indeed, it is fundamental to design models allowing us to build smart cognitive IoP environments [8], [10], [12] with specific topological properties, capable of spotting collective behaviours, envisioning dynamics of communication networks. Despite in some cases the dissemination issue in D2D has been addressed embracing the awareness on social properties [13]–[15], it has left aside the potential gain of applying complex systems theory in terms of network structure, social contagion and collective behaviours [16]–[19]. It is widely known that many complex systems in social science, physics, biology, and engineering can be modelled as evolving networks of interacting heterogeneous entities [17], [20], [21]. By introducing complex systems and networks theory including the multiple social representation levels of users, we are therefore able to strengthen and broaden grades of knowledge, deepening the social network dynamics of users’ behaviours. In a D2D communication scenario, treated as a complex relational system, we are interested in detecting emerging behaviours, determined by non-trivial networks of interactions. Thus, we start from multiplexity of

networked users [17], leveraging the heterogeneity, homophily and awareness which represent unexplored innovative bio-inspired perspectives, typical of the complex systems and complex networks theory applied to various scientific fields [22]. “Heterogeneity” represents the different willingness to receive information, “homophily” is the tendency to interact with similar nodes and “awareness” is the knowledge about information received. The introduced multiplex dimension, which represents the coexistence of various types of interactions among users on a complex network [23], allows us to unveil hidden behaviours that this kind of network can exhibit.

In this context, we focus on content dissemination on D2D, targeting at efficiently improving the communication among users and discriminating the nature of contents shared between them. Indeed, in the era of digital misinformation and fake news’ invasion [24], [25], considering the potential impact of shared contents on human society, it becomes vital to deepen and discriminate content dissemination dynamics. In [25], the author defines the “echo chambers” effect as a phenomenon of network polarization when an opinion bounces in a cluster of nodes. This can make a misinformation viral due to a complex contagion process that starts from an initial bandwagon effect and leads to a reinforcing diffusion. In a people-centric perspective detecting the role of awareness may allow the system to react becoming increasingly robust. Since, D2D, IoT environment and 5G network hold to improve our lives by introducing innovative services conceived for a wide range of application domains, this will provide a great opportunity for health-care including use cases, such as ambient assisted living and patient monitoring based on telemedicine, integrated monitoring systems of smart homes and advanced multimedia surveillance of smart cities [26]. To the best of our knowledge, in this work, for the first time, we introduce multiplexity jointly with social contagion dynamics to explore content dissemination in D2D. To this aim, we propose a bio-inspired approach which shows and unveils the interplay between the weighted multiplex network of different UEs, represented as nodes, and the content dissemination dynamics, modelled as two co-existing and co-evolving spreading processes, namely information and awareness diffusion, on D2D communications. We analyze the diffusion dynamics disclosing the impact of heterogeneity, homophily, and awareness, on data dissemination. The co-evolution of these two interdependent and not disjoint processes follows the social contagion dynamics. Moreover, the model is able to distinguish the dynamical patterns of different types of contents: useful and useless (fake or malicious) information.

A. Contributions of This Article

Once explained the motivations behind the proposed methodology, the main contributions of this article are summarized below.

- We redefine the content dissemination issue on D2D by introducing multiplexity and shaping the D2D content dissemination as a social contagion dynamics of two co-evolving spreading processes, information and awareness diffusion.

- We measure the impact of network properties and human-related factors, such as homophily and awareness, on the social contagion dynamics. To this aim, we define weighted connections between nodes, where weights are defined by taking into account both the concept of homophily and awareness in the multiplex structure. We point out how these weights influence the contagion dynamics on the social multiplex network.
- We explore and quantify the role of network structural heterogeneity on the social contagion dynamics. Thus, we unveil and measure the role of heterogeneity, homophily and awareness, on D2D data dissemination.
- We analytically define a bio-inspired control mechanism able to increase the alertness of nodes, breaking the “echo-chambers” effect in the case of misinformation. It is based on a η -score and it acts on user behaviours.
- We quantify the social multiplex dynamics for D2D data dissemination, by defining the network structure more able to efficiently disseminate information. We also detect the subset of nodes corresponding to the most central nodes, assigning them the role of cluster heads. These nodes regulate the alertness of nodes, increasing their awareness on correlated information.
- We identify as a possible application domain health-care innovative services for people with recognised frailty syndromes in case of ambient assisted living and patient monitoring, represented as a D2D scenario where its needed to manage the content dissemination and discrimination detecting the actual state of patient.
- Our novel modelling approach constitutes the core of a cognitive IoP-based D2D and opens up a novel way to deal with heterogeneous 5G networks considered as complex interdependent systems. We include dynamical, socially-aware and human-related aspects in the design of this kind of networks.

This article is organised as follows: in Section II we overview literature works on socially-aware D2D communications and models exploring social contagion dynamics on multiplex networks. In Section III we present our modelling approach. In Section IV we show and discuss the results through conducted simulations. Finally, in Section V we conclude the work discussing the findings and possible future works.

II. RELATED WORK

Recent literature works have shed light on the role of multiplex networks, homophily and awareness on social contagion dynamics. In this section, we review the existing works, other than some proposed socially-aware models of D2D data dissemination. In Tables I and II we include a comparison of network structures and social-based methods used respectively in D2D communications and social contagion.

A. Multiplex Networks and Social Contagion Dynamics

The connectivity of a complex system is described by the network representation. Nodes in the network are linked to each other via multiple edges. A standard approach

TABLE I
COMPARISON OF NETWORK STRUCTURES AND SOCIAL-BASED
METHODS USED IN D2D COMMUNICATIONS

Ref.	Keywords	Network Structure - Social based methods
[13]	Ad hoc networks; Resource management; D2D communication; Mobile communication; Base station; Energy consumption; Social Network services.	Community Detection; User Importance as centrality; User similarity; Single layer Networks; Neighbor discovery method (SOCA); Community aware network.
[14]	Streaming media; Resource management; Mobile Communication; Radio transmitters; Wireless communication; Knowledge engineering; Mobile computing; D2D communication.	Social and Communication Features in D2D networks, Social Ties; Clustering; Single layer Network.
[71]	Analytical models; Mathematical model; Mobile communication; Mobile computing; Mobile handsets; Wireless communication; Performance evaluation.	D2D information diffusion through population processes; SIR model; basic epidemic model; single layer network.
[72]	D2D communication; Content dissemination; Social aspects of user mobility; Mobile communications.	Centrality; Single layer network; social-aware decision-making (SADM) scheme.
[73]	D2D communication; Social ties; Priority scheme; System capacity.	Social tie-driven decision scheme; decision modeling; single layer network.
[74]	D2D communication; Social aspects; IoT; 5G.	D2D direct-link communication; Relay Discovery and Peer Selection through social ties; Single layer network; Social Aware metrics.

TABLE II
COMPARISON OF NETWORK STRUCTURES AND SOCIAL-BASED METHODS
USED IN LITERATURE ON SOCIAL CONTAGION

Ref.	Keywords	Network Structure - Social based methods
[34]	social contagious model; obesity epidemic.	Social Contagion Dynamic; SW Network; single layer network.
[36]	complex social contagion; disease outbreak.	SW Network; single layer network.
[49]	awareness and epidemic spreading; multiplex networks.	ER and SF Networks; Multiplex Networks; Epidemic and Awareness spreading in separate layers.
[50]	epidemic spreading; transmission network dynamics.	SF Networks; Epidemic spreading on single layer network.
[52]	awareness and disease spreading; multiplex networks.	SF Networks; Epidemic spreading on multiplex network.
[53]	epidemic spreading; risk perception, multiplex networks; percolation.	SF Networks; Epidemic spreading on multiplex network; Risk analysis and prediction.
[55]	epidemic spreading; activity driven awareness; multiplex networks.	SF networks; Epidemic spreading on multiplex network.
[56]	awareness; epidemic spreading.	SF Networks; Epidemic spreading and Awareness spreading on multiplex network in separated layers.
[57]	disease spreading; information diffusion; multiplex networks.	Information diffusion as disease on multiplex; ER networks; SF networks.
[58]	epidemics; multiplex networks; overlapping.	Overlapped Multiplex network structure with ER hypothesis.
[59]	epidemics; multiplex networks.	Transmission of an epidemic in multiplex network; ER and SF network cases metrics.

for network description generally consists of analyzing the aggregation of all links between nodes. The resulting aggregate graph includes many useful aspects but neglects some

important information about structural complexity and connectivity. The relationships and interactions between nodes in many real-world systems can be different for relevance, context and meaning [17], [23]. Each type of interaction is characterised by a given cost, distance or weight, proving that treating all the links as equivalent in an aggregate structure, results into losing knowledge [17], [23], [27]. To better quantify information encoded in terms of social behaviours and connectivity in the considered scenario, we need to introduce the multiplex dimension. It allows to preserve information related to the different interactions among the constituents of a complex system. The scientific interest in multiplex networks ranges between different areas: biological, social and technological systems, social networks and relationships, epidemic and social contagions, air transportation networks and brain computing [10], [11], [18], [28]–[31]. These systems are characterised by the fact that elements, represented as nodes, are connected through multiple types of links embedded on distinct layers. Nodes can be adjacent to each other through intra-layer edges and each node can be connected to its counterpart on another layer through inter-layer edges [17], [23]. Multiplex networks represent the most suitable structure for studying dynamics of spreading phenomena depending on the nature of social ties [10], [22]. The main belief behind the investigation of a multi-dimensional network representation is that having full information about the structure of a system under analysis is fundamental to fully characterise its behaviour. For this reason, multiplex networks have helped unveiling interesting structural properties and understanding emerging phenomena and behaviours in various systems, such as cascading failures, super-diffusion, spreading and epidemic dynamics [10], [28]–[32]. A deeper level of analysis in structural terms can be achieved by exploring connectivity through weighted multiplex networks [27] and, with regards to the dynamics, through social contagion processes (see Fig. 2). Indeed, real-world multiplex networks include weighted connections or links between nodes, so that links between the nodes not only are distinguished by the kind of interaction linking the nodes, but also by the intensity reflecting the importance of these interactions. In our work, since we are interested in capturing the coevolution in a realistic scenario, we investigate the role of weighted multiplex networks by defining specific weights of the ties (see Section III). Social contagion, modelled as an infectious disease spreading [11], is based on classical epidemiological models [16], thoroughly used in network science, social behavioural analysis, misinformation diffusion, infectious disease and emotions spreading [18]. Since the social networking is a form of content dispersal, which adds complexity in the understanding how information is disseminated through interactions and inside communities, some models are very helpful in predicting information spreading patterns. In [19], the authors model, in a single-layer network, how people learn and spread different types of information, taking into consideration also the lack of exposure to the information and the loss of continued interest or awareness. The interplay between social contagion and collective awareness dynamics has allowed to shed light on the role of awareness in the spreading process [10], [11]. In particular,

it has been found that the more the networked individuals are aware about the spreading content, the more they may be able to adopt strategies to quickly disseminate or slow diffusion. In recent years, a vast amount of literature has investigated the social contagion, suggesting the key role of the nature of social ties in a phenomenon spreading on a social network [18], [33]. It has been underlined how social behaviours, misinformation or rumors [34], infectious diseases and emotions [35] spread inter-personally [18], [33], [36]. These works pushed research towards modelling social contagion as an infectious disease spreading [18], [35]–[38]. All these models have been obtained starting from the classical epidemiological models [16], [39], [40], involving several research fields in network science [41]–[48]. Furthermore, various processes have been used to model social contagion as diffusion models [49] and threshold models [18], [36]–[38], [50]. The interplay between infectious diseases and awareness dynamics has allowed to underline the role of awareness in the spreading process of a disease [51]–[54]. The more the networked individuals are aware of the likely disease spreading, the more they may be able to adopt strategies targeted at self-protecting [11]. Most of these studies have explored the spreading and competition of both phenomena using different layers of propagation [52], [55]–[59]. Multiplex networks, that consider the same set of nodes in all the layers, constitute the most suitable network structure for studying such dynamical processes and their complex coevolution [60], [61]. Although having considered multiplexity, all the previous models have separated and constrained each of the processes to only one of the layers. By contrast, in [11] it has been investigated and quantified the impact of the coevolution of the two processes in all the layers of a multiplex network. Coherently with the real nature of multiplex networks [22], [62], [63], it has been taken into account heterogeneity and its impact along with awareness on the epidemic spreading [11], [64].

B. Socially-Aware D2D Data Dissemination

Recently, due to the increasing popularity of high data rate applications (e.g., mobile social networking, etc.), it becomes crucial to support these service among users, thus a lot of research efforts have been devoted to D2D communications. In particular, social attributes and aspects of mobile devices that impact on this kind of communications have attracted the scientific interest of various research communities, aiming at exploring the role of social networks on D2D communications [65]. In this line of research, in [13] authors have underlined the importance of dealing with multiple social attributes of D2D devices. Indeed, a proper perception of these attributes can significantly enhance the efficiency of D2D communications. In [13] the authors have proposed a dynamic method for detecting overlapping communities, which allows enhancing both the neighbour discovery, data delivery ratio and the overall efficiency of the system.

Some other authors have addressed the problem of content delivery in D2D communications [66], by proposing a social network-based solution for joint peer discovery and resource allocation which leverages social and physical layer information. This is in line with some other works

which take into account physical location information, social information or interests on mobile applications, etc. [67], [68]. Specifically, in [69] the authors proposed a socially-aware peer discovery scheme for D2D communications where mobile users are clustered by using location, interest and background information deriving from social networks. Social information derived from interactions on social networks and clustering information have been exploited to enhance various performance metrics of D2D communications, such as system rate, throughput and energy efficiency [66], [69]. In [70] it has been highlighted how sharing communication and computation resources with other users can improve the cooperation in the network.

The concept of socially-aware communication has been also proposed for knowledge extraction in mobile networks [14]. Given that any socially-aware communication scheme is based on the involvement of users with their devices, in [71] the authors have addressed this issue by analysing the creation of trusted socially-aware direct connections between devices. Other authors have focused on communications in mobile opportunistic networks among mobile nodes using direct communication [72]. They have proposed an analytical model able to explore data dissemination and the role of infrastructure in the diffusion of contents. The dissemination of the content through D2D represents an efficient way of offloading cellular traffic, as well as to reduce cost, increasing spectral efficiency and providing robustness. Thus, in [73], it has been proposed a socially-aware D2D content dissemination scheme based on social aspects of user mobility, social structural metrics, such as centrality, contact rate and inter-contact time. Starting from social patterns, they have been able to enhance data dissemination performance. In fact, in [15], the authors underline how social networking could be the key for enabling D2D Communications in 5G wireless networks, shedding light how the investigation of the social networks properties leads to an increasing in efficacy of trustworthiness, resulting in the necessity of including this analysis in different aspects of D2D.

Furthermore, the key role of social ties has been also demonstrated for content priority scheme for D2D communications [74], where authors have included the impact of social relationship on data transmission. One of the most interesting aspects is that they consider the interplay between social and physical D2D networks in the design of a novel efficient priority scheme. The priority is related to the increment of strength of social ties based on social trust and social reciprocity. All the previous works have shed light on the increasingly need for including social aspects in data dissemination between devices by means of D2D communications. Socially-driven D2D communications are able to deal with some of the most challenging issues for this kind of communications, such as throughput, spectral efficiency, latency and fairness [75]. The authors in [75] provide a comprehensive survey of how social networking can enhance various aspects of D2D communications, ranging from relay discovery and peer selection, to communication mode selection, spectrum resource allocation and management. However, none of the previous works has included a complex network perspective and a social contagion dynamics modelling approach with two co-evolving processes

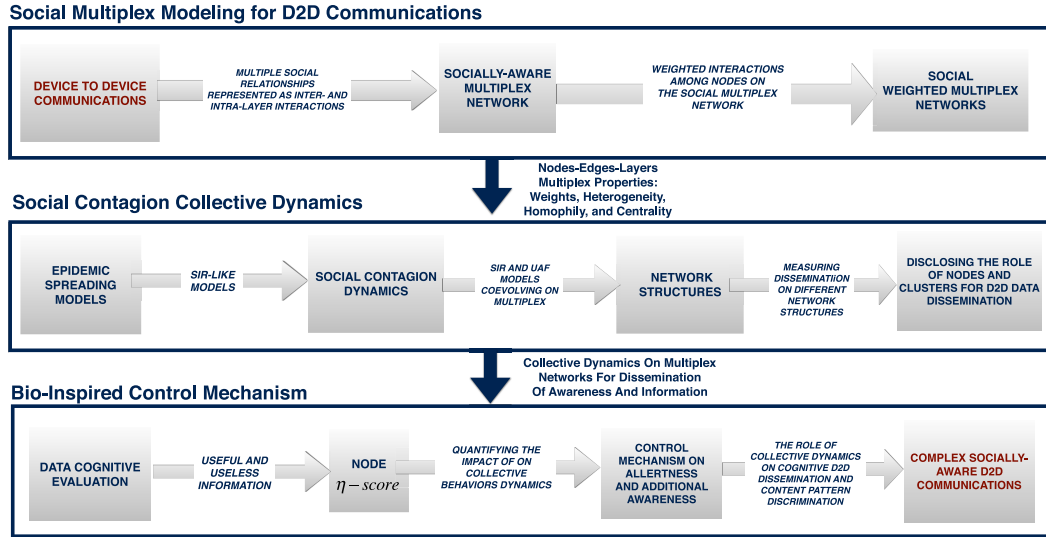


Fig. 1. **Modelling approach.** The figure schematically describes the various steps and aspects of the modelling procedure. Starting from D2D communications it allows us to define complex socially-aware D2D communications. In the first step, we define the social weighted multiplex network, with a measure of weight which is function of the discrepancy of users' knowledge about the shared content and homophily. In the second step, we analyse the D2D data dissemination as the social contagion collective dynamics which consists of the coevolution of the two spreading processes, detecting the role of network structures in the contents' dissemination. The last step of the proposed modelling approach defines a bio-inspired control mechanism deriving from the social contagion dynamics. Finally, in the last step we define a bio-inspired control mechanism deriving from the social contagion dynamics and a data cognitive evaluation which allows us to distinguish the two types of contents, namely useful and useless information, in the weighted multiplex network. This cognitive mechanism, based on nodes heterogeneity, allows tuning the awareness and alertness on the whole multiplex network.

to characterise the data dissemination on D2D communications (see Section II-A). Thus, other than a socially-aware paradigm, a dynamical, complex model, embodying also human-related aspects, is needed to deeply understand how social issues impact on the dynamics of data dissemination.

III. MODEL

The assumed scenario is an open congested area where mobile users devices (UEs) in a D2D communication environment can enter to share contents. Devices, represented as social network nodes, are linked with each other through social ties in different contexts. Considering the case of D2D communication with device-controlled link formation [1], we assume that there is the simultaneous diffusion of information and awareness. Information is divided into contents of two types, useful or useless and it is shared, stored and kept updated. Useless content refers to either malicious information or fake news, where malicious information represents a security threat, while fake news are false or misleading content intentionally dressed up to look like useful information (news, articles, etc.) [24]. Information is disseminated using interactions between mobile devices on a weighted multiplex network [27].

The final target is to quickly disseminate the most relevant information and awareness among users and eventually delay the not relevant ones. Specifically, we quantify contents' dissemination unveiling the patterns related to fake news and distinguishing them from malicious contents.

The proposed modelling approach is schematically described in Fig. 1. In this section we describe each block of the framework.

A. Social Multiplex Modelling for D2D Communications

In this section, we describe the first step of our modelling procedure which consists of defining a social weighted multiplex network. Thus, starting from simple D2D communications' network, first we highlight the importance of including multiple relationships between users. Therefore, we define a socially-aware multiplex network, where each layer corresponds to a different type of social interaction between human users. Then, we define a novel measure of weight, so that we get a social weighted multiplex network defined as follows.

Let us consider a multiplex network of M layers $\alpha = \{1, \dots, M\}$ and N nodes $i = \{1, \dots, N\}$. A multiplex network is a set of M weighted networks (or layers) $G_\alpha = (V, E_\alpha)$ (see Fig. 2). The set of nodes V is the same for each layer, whereas the set of links E changes according to the layer [27]. Each network G_α is described by the adjacency matrix, denoted by A^α with elements a_{ij}^α , where $a_{ij}^\alpha = w_{ij}^\alpha > 0$, if there is a link between i and j with a weight w_{ij} , otherwise $a_{ij}^\alpha = 0$. We include a definition of weights as function of the discrepancy of users knowledge about the shared content (Δaw) and homophily, namely the tendency of interacts with similar users (h_{ij}^α).

Definition 1: *Weights*, denoted as w_{ij}^α , are given by:

$$w_{ij}^\alpha = h_{ij}^\alpha \cdot |\Delta aw| \quad (1)$$

where h_{ij} is the homophily between nodes/human users i and j , that is the tendency to associate and interact more with similar people [22], [63], given by:

$$h_{ij} = \frac{1}{1 + \delta_{ij}} \quad (2)$$

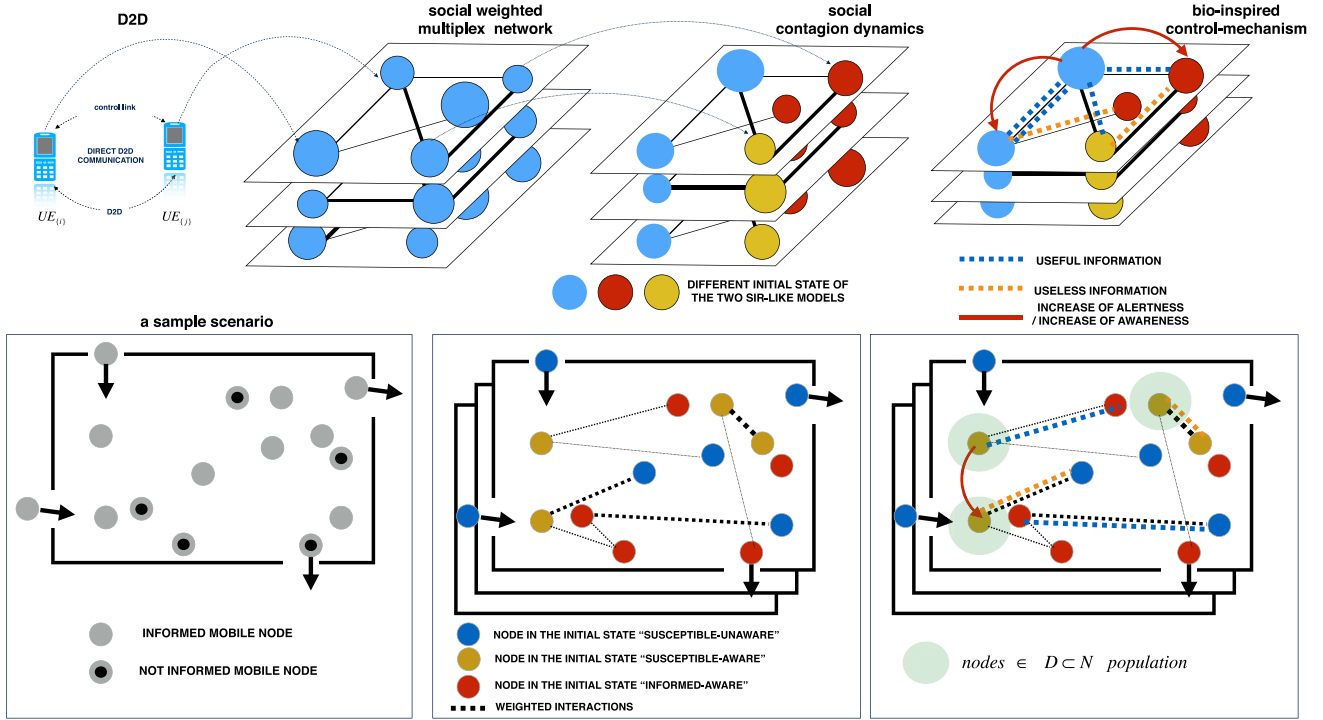


Fig. 2. **Mapping multiplexity, social contagion dynamics and bio-inspired control mechanism in a sample D2D data dissemination scenario.** The figure illustrates the modelling approach, showing the different social representation levels and linking them with each step of the model in a sample D2D data dissemination scenario. The upper part depicts the social representation levels and the control mechanism, while in the lower part we map the various steps of the model with a sample D2D data dissemination scenario. In the lower-left panel, we show a sample scenario, where UEs can be only informed or not informed mobile nodes. By applying our modelling approach, in the lower-central panel we illustrate the possible initial states of nodes in the dynamic MMCA of the social contagion dynamics (dot lines indicate weighted interactions between nodes). Finally, in the last panel on the lower-right we show the cluster heads' selection for each cluster and we apply the bio-inspired control mechanism (see Sections III-A and III-B).

While, Δaw is equal to the absolute difference of awareness, $|aw_i - aw_j|$, between nodes i and j , where awareness is the knowledge about information received.

Nodes centrality, given by X_i and z^α , is defined according to [10], [76], which is a measure of centrality of both nodes and layers, where X_i and z^α capture the heterogeneity of the network structure in terms of weights. X_i and z^α are defined as follows:

$$X_i = \bar{\alpha} \sum_{j=1}^N \frac{G_{ij}}{\kappa_j} X_j + \beta v_i \quad (3)$$

and

$$z^{[\alpha]} = \frac{1}{N} W^{[\alpha]} \sum_{j=1}^N B_{\alpha i}^{in}(X_i) \quad (4)$$

where $\bar{\alpha}$ is taken to be $\bar{\alpha} = 0.85$, G_{ij} represents the element of the weighted matrix G , dependent from weights, that in our model depend on awareness and homophily, β , v_i and κ_j are given by equations expressed in [76]. $W^{[\alpha]}$ represents a quantity that, in our case, indicates the total weights of the links at layer α , instead $B_{\alpha i}^{in}(X_i)$ is the normalised in-strength of node i in the layer α , and N is a normalised constant. These measures are coupled and define an overall ranking of nodes and layers in the multiplex structure. In our model, its definition is function of the weights of the multiplex network, so it includes awareness and homophily. We exploit this kind

of measures in order to select a subset of nodes $D \subset N$ characterised by higher centrality values and electing them as Cluster Heads (CHs) [14] (see Fig. 2). We assign to these nodes the key role of disseminating the contents following the most disseminating network structure (see algorithm 1).

B. Social Contagion Collective Dynamics

The information spreading process is thought as a “composed” classic “Susceptible-Infected-Recovered” (SIR) model [16], where the transition rate β_i^α is different for each node and for each layer of multiplex network contributing to the network heterogeneity (see 5). The awareness spreading process, denoted by UAA^* , co-existing and co-evolving with the first one, is a “Unaware-Aware-Faded”(UAF)-like model [11]. The meaning of the various states of the two interdependent spreading processes is explained in Table III. Fig. 2 graphically illustrates the social representation levels (see upper part of the figure) and the corresponding various steps of the model in a sample D2D data dissemination scenario where, as showed in the lower-left panel, UEs can be informed or not informed mobile nodes. In the lower-central panel we illustrate the possible initial states in the dynamic MMCA of the social contagion dynamics, where dot lines indicate the weighted interactions between nodes. Finally, the last panel on the lower-right represents the output of the phase 1, where we select the cluster heads for each cluster and we apply the bio-inspired control mechanism.

TABLE III
MMCA—STATES. DEFINITION OF THE DIFFERENT STATES
IN THE MMCA (SEE TEXT)

States	Definition
S	Susceptible - An entity does not have updated information
I	Informed - An entity is carrying useful information
R	Recovered - An entity leaves or interrupts connections
U	Unaware of received information
A	Aware of received information
N_i	Not interested on received information
Aoc	Aware on correlated information

TABLE IV
MMCA—RATES. DEFINITION OF THE TRANSITION
RATES IN THE MMCA (SEE TEXT)

Rates	Definition
β_i^α	Informed rate
μ	Exit Rate
λ_i^α	Awareness rate
δ	Loss of Alertness
ϵ	Additional Awareness rate

The state A leads to A^* , which represents two possible alternative states, N_i and Aoc (see 6). The N_i state derives from a non-zero probability δ , while the Aoc state derives from a non-zero probability ϵ (see Table III and Table IV). The N_i state represents the probability of losing the interest in having a high alertness. It means that if the rate δ decreases, there is the interest to maintain a high alertness about the nature of information disseminated. The state Aoc represents an alternative state to N_i , meaning an interest of having an additional awareness correlated to the received information (see (6)).

Information and awareness spreading processes are described in terms of reaction-diffusion equations as follows:

$$SIR \Rightarrow S \xrightarrow{\beta_i^\alpha} I \xrightarrow{\mu} R; \quad (5)$$

$$UAA^* = \begin{cases} U \xrightarrow{\lambda_i^\alpha} A \xrightarrow{\delta} N_i \\ U \xrightarrow{\lambda_i^\alpha} A \xrightarrow{\epsilon} Aoc \end{cases} \quad (6)$$

In each of the two SIR-like processes, indicated in (5) and (6), we have indicated the transition rates between the various states of the $SIR - UAA^*$ model. These transition rates are summarised in the Table IV.

The Dynamic Microscopic Markov Chain Approach (MMCA) enables us to explore the dynamics of the co-evolution of information and awareness spreading on the weighted multiplex network. In the next subsection we give a more detailed explanation of the MMCA used in our model.

1) *Dynamic Microscopic Markov Chain*: At the beginning, each node can occupy only one of the following states: susceptible and unaware (SU), informed and aware (IA), and susceptible and aware (SA) (see Fig. 2). Some states are not reachable or do not exist, such as IU (Informed Unaware), IN_i (Informed Not interested), $SAoc$ (Susceptible - Additionally aware) and N_iAoc (Not interested - Additionally aware) (see Fig. 3). Thus, at time step t each node i is in one of the initial three states, with probabilities $p_i^{SU}(t)$, $p_i^{SA}(t)$ and $p_i^{IA}(t)$ respectively. Let us denote by $q_i(t)$ the probability of node i not being informed at time step t and $r_i(t)$ the probability of

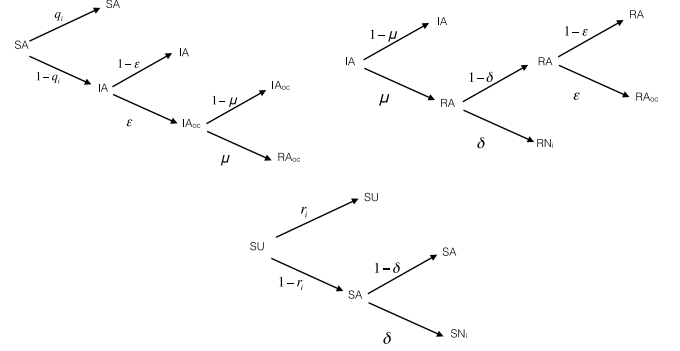


Fig. 3. **Probability tree.** We illustrate the MMCA method using a probability tree, representing all the possible states and their transitions in our model at each time step. Roots in the transition tree represent the initial states (time step t), SA , SU and IA , and leaves are all the possible states at the subsequent time step. Arrows are labeled with the corresponding transition probabilities.

an unaware node i staying unaware at time step t , as follows:

$$q_i(t) = (1 - \bar{\beta}_i) \prod_j \left[1 - a_{ji} p_j^I(t) \bar{\beta}_i \right] \quad (7)$$

$$r_i(t) = (1 - \bar{\lambda}_i) \prod_j \left[1 - a_{ji} p_j^A(t) \bar{\lambda}_j \right] \quad (8)$$

where a_{ij} are the elements of the adjacency matrix of each layer of the weighted multiplex network. $\bar{\beta}_i$ and $\bar{\lambda}_i$ are the “elected informed rate” and the “elected rate of awareness” of the node i , respectively. Once calculated the centrality measures of nodes and layers X_i and z^α , from this heterogeneous ranking we extract the “elected” layer, that is the most central layer, namely the most influential in the evaluation of the transition dynamics. The following MMCA equations represent the probability of each node of being in one of the states at time step $t + 1$, as showed in Fig. 3:

$$\begin{aligned} p_i^{SA}(t+1) &= q_i(t) p_i^{SA}(t) + (1 - r_i(t))(1 - \delta) p_i^{SU}(t); \\ p_i^{IA}(t+1) &= (1 - q_i(t))(1 - \epsilon) p_i^{SA}(t) + (1 - \mu) p_i^{IA}(t); \\ p_i^{IAoc}(t+1) &= \epsilon(1 - q_i(t))(1 - \mu) p_i^{SA}(t); \\ p_i^{RAoc}(t+1) &= \mu \epsilon(1 - q_i(t)) p_i^{SA}(t) + \mu \epsilon(1 - \delta) p_i^{IA}(t); \\ p_i^{SU}(t+1) &= r_i(t) p_i^{SU}(t); \\ p_i^{SN_i}(t+1) &= \delta(1 - r_i(t)) p_i^{SU}(t); \\ p_i^{RA}(t+1) &= \mu(1 - \delta)(1 - \epsilon) p_i^{IA}(t); \\ p_i^{RN_i}(t+1) &= \mu \delta p_i^{IA}(t); \end{aligned} \quad (9)$$

To obtain the contagion threshold, we investigate the steady state solution of the system constituted by the previous equations. When time $t \rightarrow +\infty$, there exists a contagion threshold β_C for the two coevolving processes, so that the contagion can outbreak only if $\beta \geq \beta_C$. Following the same conditions of [11], the contagion threshold is given by the order parameter ρ_i and it is defined as follows:

$$\rho^I = \frac{1}{N} \sum_{i=1}^N p_i^I = \frac{1}{N} \sum_{i=1}^N p_i^{IA} \quad (10)$$

Thus, starting from equation $p_i^{IA}(t+1)$ (see (9)), at steady state we have:

$$p_i^{IA} = (1 - q_i)(1 - \varepsilon)p_i^{SA} \quad (11)$$

Since around the contagion threshold β_C , the informed probability is close to zero ($p_i^{IA} = \eta_i \ll 1$), the probabilities of being informed can be approximated as follows:

$$q_i = (1 - \bar{\beta}_i) \left[1 - \bar{\beta}_j \sum_j a_{ij} \eta_j \right] = (1 - \bar{\beta}_i)(1 - \omega_i) \quad (12)$$

where:

$$\omega_i = \bar{\beta}_j \sum_j a_{ij} \eta_j \quad (13)$$

Furthermore, close to the contagion onset we have that the fading rate is approximately close to zero ($\delta \simeq 0$). Considering this approximation into (11), and omitting higher order items, (11) is reduced to the following form:

$$\mu \eta_i \simeq (1 - \varepsilon) p_i^{SA} \bar{\beta}_i \bar{\beta}_j \sum_j a_{ij} \eta_j \quad (14)$$

The contagion threshold is obtained starting from the following condition:

$$\sum_j \left| (1 - \varepsilon) \bar{\beta}_i p_i^{SA} a_{ij} - \frac{\mu}{\beta_j} t_{ji} \right| \eta_j = 0 \quad (15)$$

where t_{ji} are the elements of the Identity matrix. By defining the matrix H whose elements are given by: $h_{ij} = [(1 - \varepsilon) \bar{\beta}_i p_i^{SA}] a_{ij}$, the contagion threshold β_C is the value corresponding to the largest eigenvalue of the matrix H , which is given by $\Lambda_{\max}(H) = \mu / \bar{\beta}_j$, so finally we get: $\beta_C = \mu / \Lambda_{\max}(H)$.

2) *Network Structures*: In our work, each of the layers of the multiplex network is characterised by an underlying graph where nodes are connected according to one of the following network structures: the Scale-free (SF) network [77] and the Small-World (SW) network [78]. We have considered in our analysis two of the most popular network structures, which are two ideal examples of network topologies but easily distinguishable in samples of real-world population. Indeed, even though many real-world networks are thought to be scale-free in terms of topology, there is no evidence, mainly due to the developing awareness of more rigorous data analysis techniques. For this reason, we have decided to consider also the SW network, which allows us to take into account another realistic network topology. These networks exhibit a different level of heterogeneity. Specifically, SW networks are small heterogeneous networks, characterised by a high clustering and modularity, so that there are groups of nodes that are more highly connected than the rest of the network, and there is an over-abundance of hubs high-degree nodes (or hubs) that mediate the shortest path length. In SW networks, degree distributions exhibit a fast typically Gaussian decaying tail. Instead, SF networks are highly heterogeneous networks, characterised by a power-law degree distribution. They exhibit a high degree correlation between nodes and degree distribution has a long tail, which means that there are a few hubs in the network.

C. Bio-Inspired Control Mechanism

In our model, the last step of the proposed modelling approach defines a bio-inspired control mechanism deriving from the social contagion dynamics. To this aim, for each node we introduce a statistical parameter η -score that is function of the shared content as in (16). It hinges on the number of interactions and information shared between nodes at each layer. We distinguish two types of contents: useful information, indicated by c_{uf} , and useless information, indicated by c_{ul} . According to the concentration of the two types of contents received and shared by each user, at each layer of the weighted multiplex network, a bio-inspired control mechanism, based on nodes heterogeneity, is able to tune the awareness and alertness on the whole multiplex network. In fact, it is well-known that there is a strict interplay between ‘‘echo chambers’’ and the spread of misinformation [25]: strongly homogeneous groups tend to prefer contents that confirm their shared beliefs, polarizing rumors and misinformation. In presence of both a high useful contents dissemination and highly homophilic clusters of users, it is very likely having fake news masqueraded as useful contents. Thus, the bio-inspired control mechanism increases the alertness of nodes, which means pushing them towards a higher awareness on correlated information, with the final aim to break the ‘‘echo chambers’’ effect. The η -score is defined as follows:

$$\eta_i = \sum_{\alpha} \sum_j \frac{c_{ulij}^{\alpha} - c_{ufij}^{\alpha}}{c_{ufij}^{\alpha} + c_{ulij}^{\alpha}} \quad (16)$$

The two spreading processes are interdependent and linked to the network structure and both are characterised by the rates, the ‘‘informed rate’’ β_i^{α} , and the ‘‘awareness rate’’ λ_i^{α} , defined for each node i at each layer α of the multiplex as follows:

$$\lambda_i^{\alpha} = \left(\frac{s_i^{\alpha}}{1 + s_i^{\alpha}} \right) \lambda, \quad \beta_i^{\alpha} = \left(\frac{1}{1 + (\lambda_i^{\alpha})^{\eta^{\alpha}}} \cdot \frac{1}{Y_i^{\alpha}} \right) \beta \quad (17)$$

where s_i^{α} and Y_i^{α} are respectively the strength measure of the node i and the inverse participation ratio of node i [27], [79] given by:

$$s_i^{\alpha} = \sum_{j=1}^N a_{ij}^{\alpha}, \quad Y_i^{\alpha} = \sum_{j=1}^N \left(\frac{a_{ij}^{\alpha}}{s_i^{\alpha}} \right)^2 \quad (18)$$

The various steps of our modelling approach and procedure allow us to quantify the social multiplex dynamics for D2D data dissemination. In particular, starting from the social multiplex network of *UEs*, we are able to define the network structure G^* where contents are efficiently disseminated using a social contagion mechanism as previously explained in Section III-B. By defining the nodes centrality, given by X_i and z^{α} , we detect the subset of nodes corresponding to the most central nodes, assigning them the role of cluster heads. These nodes regulate the alertness of nodes, increasing their awareness on correlated information. The pseudo code of the model is shown as Algorithm 1.

IV. SIMULATION RESULTS AND DISCUSSION

Simulations have been conducted by taking into account a weighted multiplex network of $M = 3$ layers and $N = 100$

Algorithm 1 Social Multiplex Dynamics for D2D

Input: UEs as population of nodes N in the M layers of the multiplex network, $\alpha = 1, \dots, M$, where nodes $i, j \in N$, G_α is the graph of each layer, A^α the adjacency matrix, w_{ij} weights, function of awareness aw_i , and homophily h_{ij} ; μ , δ and ϵ are the transitions rates.

Output: G^* network structure, dissemination as social contagion (β_C), X_i and z^α nodes centrality, bio-inspired control mechanism (η_i, h_{ij}) \Rightarrow (δ, ϵ).

1: Case 1: $G_\alpha =$ Scale-Free Multiplex Network.

2: Phase 1: Multiplexity and Social Contagion.

3: $\forall i \in N$, assign to i one of the initial states $SU - IA - SA$.

4: at time step t , calculate $\lambda_i^\alpha, \beta_i^\alpha, q_i(t), r_i(t)$.

5: MMCA method.

6: Calculate β_C

7: Repeat Phase 1 for Case 2, $G_\alpha =$ Small-World Multiplex Network.

8: Thresholds

if β_C (CASE 1) $<$ β_C (CASE 2) **then**

$G^* =$ Scale-Free Multiplex Network.

else

$G^* =$ Small-World Multiplex Network.

end if

9: Calculate centrality X_i and z^α , and select a subset of nodes $D \subset N$ with the higher values of centrality, as Cluster Heads.

10: Cluster Heads disseminate the content following the G^* network structure.

11: Phase 2: Bio-Inspired Control Mechanism.

12: $\forall i \in N$: $aw_i, \eta_i, s_i^\alpha, Y_i^\alpha$.

13: Repeat Phase 1 for $G_\alpha = G^*$.

14: Control Mechanism

if $C_{uf} > C_{ul}$ with high values of h_{ij} **then**

nodes $\in D \subset N$ with higher values of centrality, increase the alertness to clusters \Rightarrow decrease of δ , increase of ϵ .
Nodes require additional awareness with probability ϵ .

end if

15: Repeat Phase 2.

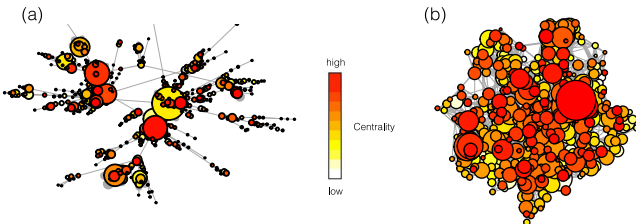


Fig. 4. **Awareness and Centrality on Weighted Multiplex Network.** The figure illustrates a representative layer for each network topology: (a) Scale-Free Network; (b) Small-World Network. The size of nodes represent the centrality measure and the colour corresponds to awareness.

nodes, following the analytical model described in Section III. Each layer is modelled by varying network topologies considering Scale-Free network (SF) and Small-World Network (SW) [16]. Thus, we are able to investigate how such synthetic networks, characterised by controlled topological properties,

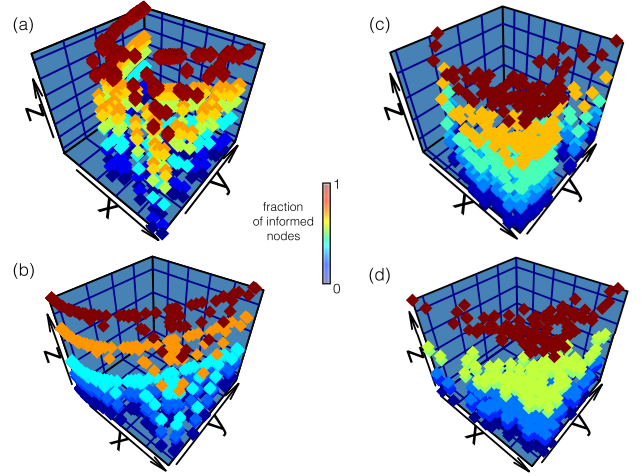


Fig. 5. **Fraction of Informed nodes.** We show the fraction of informed nodes (z -axis, ρ_i) as function of awareness rate (x -axis, λ_i^α) and informed rate (y -axis, β_i^α). In (a)-(b) respectively, we illustrate the useless contents spreading and the useful contents spreading in the case of Scale-Free network. In (c)-(d) we illustrate the same cases for the Small-World network topology.

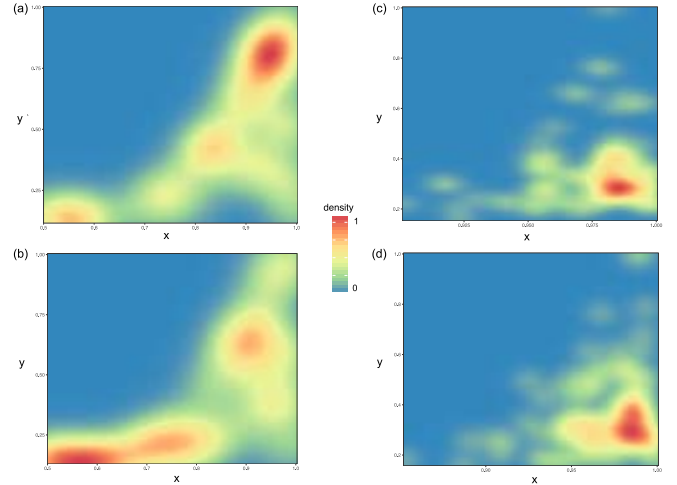


Fig. 6. **Colour map in the $\lambda - \beta$ plane.** We show the density of informed nodes in the case of useful contents spreading in the condition of high homophily. In (a)-(b), respectively, we illustrate the two cases of $\delta = 0.9$, $\epsilon = 0.1$ and $\delta = 0.1$, $\epsilon = 0.9$ in the Scale-Free network. While in (c)-(d), respectively, we show the same cases for the Small-World network topology.

allow us to derive the potential gain in data dissemination for a D2D scenario. In Fig. 4 we can observe how heterogeneity, in terms of awareness and centrality, between nodes is more evident in the scale-free network case. This result is what we expected by reasoning in terms of connectivity patterns of the different topologies. Indeed, SF is inherently heterogeneous, strictly resembling real-world networks displaying a skewed statistical distribution deriving from the preferential attachment rule (“rich get richer”) [16]. In Fig. 5 we display the impact of different network structures on the fraction of informed nodes according to the co-evolving processes of information and awareness. Notably, when useless contents are predominant (see Fig. 5 (a) and Fig. 5 (c)), an increase of awareness rate results in a decrease of information rate, up to a specific value of awareness rate. In fact, when values of awareness rate exceed a threshold derived from network features,

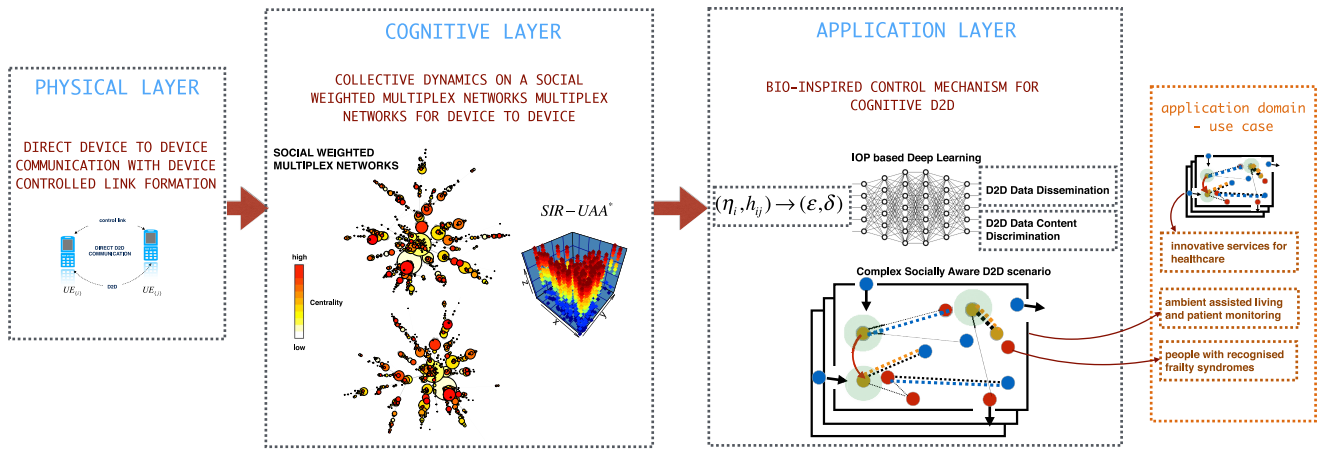


Fig. 7. **Modelling Architecture.** We illustrate the three-layer architecture characterising our modelling procedure towards a novel Cognitive IoP-based D2D. In the physical layer, devices directly communicate with other devices by following a classical D2D communication paradigm. The cognitive layer includes the quantification of collective dynamics on a social weighted multiplex network through the social contagion dynamics. Finally, the application layer consists of the bio-inspired control mechanism and the IoP-based Deep learning method, allowing us to improve D2D data dissemination and discriminating the patterns' dissemination of the different types of contents, useful and useless (fake or malicious) information. As use case in the application domain, we detect an innovative healthcare service for community of people in an ambient assisted living with recognised frailty syndromes.

this leads to a new willingness to receive other information. This occurs more quickly in the SF case due to its more heterogeneous nature, rather than in SW topology. Instead, when useful contents are mostly spread in the network (see Fig. 5 (b) and Fig. 5 (d)), an increasing awareness rate produces a corresponding growing of information rate. Also in this case SF is the network structure where the highlighted trend is more evident. Thus, if from one hand SF network topology is able to give a boost to useful contents spreading, on the other hand it is also able to slow the spreading of useless contents. For the same values of awareness rate, the SW network exhibits a lower information rate than the SF network topology, in both cases of predominance of useful or useless contents. This trend is due to the inherent properties of the SW network structure, which displays a high clustering coefficient, thus bordering the dissemination within communities. These clusters in networks hinder the spread of diffusion, as they lead to a decrease in the number of the weak ties that assume a crucial role in cascade diffusion [80]. Thus, information remains bounded within clusters, having not the time of spreading out of clusters, since these are less connected to the surrounding network, reducing the probability for a widespread diffusion.

In Fig. 6 we shed light on how the structural heterogeneity of the SF topology leads network to react against dissemination of fake news or misinformation dressed up as useful contents. Colour maps are obtained by taking into account both the network topologies (SF, SW) and we show the risky condition in which it is more likely to be in presence of “echo chambers”. This effect becomes critical when there is a high number of false positive jointly with an abundance of high-homophilic groups. The target is to better understand how the network exhibits a self-organised behaviour against this effect, reacting through the increase of alertness linked with the need to have additional awareness. This trend is evident in the SF network, where from Fig. 6 (a) to Fig. 6 (b) we observe that the highest densities of informed nodes correspond to lower

values of information rate. It demonstrates the power of the SF network, rather than SW network topology, in efficiently guiding the influence. SF introduces an additional awareness-based degree of robustness counterbalancing the “echo chambers” effect. SF network shows that varying the δ parameter we obtain larger differences (see positions of the red spots in Fig. 6 (a) and Fig. 6 (b)) than the SW network (see Fig. 6 (c) and Fig. 6 (d)). Overall both Fig. 5 and Fig. 6 highlight how our social multiplex contagion model and bio-inspired control mechanism are able to quantify the role of network structural properties and awareness in D2D data dissemination, also discriminating the type of contents and their dissemination in the weighted multiplex structure.

V. CONCLUSION

Our idea of embodying a social weighted multiplex network and social contagion dynamics to explore patterns of contents dissemination in D2D represents a major novelty and offers a novel bio-inspired methodological approach in a multidisciplinary vision. By analyzing and quantifying the impact of network topologies on D2D data dissemination, through social multiplexity and epidemic spreading modelling, we are able to shape and discriminate content dissemination in D2D communications. Our findings highlight how the scale-free network efficiently drives information spreading and distinguishes the type of content, increasing the network robustness and mitigating the “echo chambers” effect in the case of fake news. In a novel cognitive IoP-based D2D, as showed in Fig. 7, this approach sheds light on the way to include social multiplexity, nodes' cognitive abilities, human connectivity patterns and contagion dynamics in 5G networks. The novel modelling approach allows us to shift from a classical D2D communication network, where UE are simply connected to each other sharing information, to a network having cognitive abilities. Indeed, not only nodes disseminate information, but they are also able to discriminate the type of contents making

the whole multiplex network able to optimally disseminate the useful information. The impact of network heterogeneity along with the introduction of social and cognitive aspects, such as homophily and awareness, have allowed us to assign nodes and groups of nodes (or clusters) a different role in the D2D data dissemination. The proposed model, which encompasses collective and cognitive dynamics and a bio-inspired control mechanism, can represent an innovative method to design and implement innovative healthcare services for people with recognised frailty syndromes. A sample D2D scenario can be represented by a community of people with recognised frailty syndrome [81] which are in an ambient assisted living. Data can be transmitted between devices in short range without using the data transmission through base station (BS) from the cellular infrastructure, in which the UEs can be medical devices or hand-held user devices carried by frail people. This model allows us to optimally manage the dissemination and the discrimination of contents, detecting the actual state of the patient, exploiting users' awareness, homophily and expectations of the service based on their overall assessment. Our modelling procedure opens up a novel way to deal with heterogeneous 5G networks considered as complex interdependent systems, so that we propose to include dynamical, socially-aware and human-related aspects in the design of this kind of networks. We envision to consider also mesoscopic aspects, such as clustering methods and community detection algorithms, in order to better understand how to improve content dissemination in D2D.

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Marialisa Scatà (Member, IEEE) received the B.S. and M.S. degrees in telecommunication engineering from the Department of Electrical, Electronic and Computer Engineering (DIEEI), University of Catania, Italy, in 2008 and 2011, respectively, and the Ph.D. degree in computer science and telecommunication engineering from the University of Catania, in 2012. During the Ph.D. she attended several schools and conferences. She made an internship with Computer Laboratory, Department of Computer Science and Technology, University of Cambridge, U.K., under the supervision of Prof. Pietro Liò, with whom she has been collaborating since 2011. She currently works as a Postdoctoral Researcher with DIEEI, University of Catania. She keeps collaborating with the University of Cambridge other than other Universities in Europe and all over the world. She has an interdisciplinary approach to research and her interests include bio-inspired models, social networks, multilayer networks, mobile crowdsensing, epidemic models, social contagion, game theory, decision-making models, data mining, and ICT. She serves as a Reviewer for several top-tier journals, among them IEEE INTERNET OF THINGS JOURNAL, *Scientific Reports Nature*, and *PLoS ONE*.



Alessandro Di Stefano (Member, IEEE) received the B.Sc. and M.Sc. degrees in telecommunications engineering from the University of Catania, Italy, in 2009 and 2012, respectively, and the Ph.D. degree in systems engineering from the Department of Electrical, Electronic and Computer Engineering (DIEEI), University of Catania, Italy, in 2015, where he worked as a Postdoctoral Researcher. He is a Lecturer of Computer Science with the School of Computing, Engineering and Digital technologies, Department of Computing and Games, Teesside

University, Middlesbrough, U.K. He worked as a Research Associate with King's College London, U.K., and the Department of Computer Science and Technology, University of Cambridge, U.K., supervised by Prof. Pietro Liò, with whom he has been collaborating since 2012. He has published many peer-reviewed papers in high impact journals and leading international conferences. He has an interdisciplinary approach to research which incorporates engineering and computer science methodologies applied to socio-technological systems. His main research interests include game theory, network science, social dynamics, epidemic spreading, and machine learning.



Pietro Liò received the Ph.D. degree in complex systems and nonlinear dynamics from the School of Informatics, Department of Engineering, University of Firenze, Italy, and the Ph.D. degree in (theoretical) genetics, University of Pavia, Italy. He has an interdisciplinary approach to research and teaching. He is currently working as a Full Professor of Computational Biology with the Department of Computer Science and Technology, University of Cambridge, where he is a Member of the Artificial Intelligence Group. He has published more than 300

papers and organized several workshops and schools. His main research interests include artificial intelligence/machine learning and computational biology methodologies for health, focusing on modeling multiscale biological systems, machine learning methods for integration of multiscale, multiomics and multiphysics data, predictive models of comorbidities and inflammatory diseases, and the role of epigenetics.



Aurelio La Corte received the degree in electrical engineering and the Ph.D. degree in electronic engineering and computer science from the University of Catania in 1988 and 1994, respectively. He is an Associate Professor of Telecommunication Engineering. He has authored or coauthored more than 100 papers, published in international journals and conference proceedings. His scientific interests include digital signal processing, distributed systems, network and QoS management techniques, risk analysis of ICT systems, bio-inspired models

for information security, protocols and architecture for integrated communications, social networks, multilayer networks, game theory, epidemic spreading, decision-making models, and cloud/fog computing.