Monitor, anticipate, respond, and learn: developing and interpreting a multilayer social network of resilience abilities

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Abstract

Resilient performance is influenced by social interactions of several types, which may be analysed as layers of interwoven networks. The combination of these layers gives rise to a "network of networks", also known as a multilayer network. This study presents an approach to develop and interpret multilayer networks in light of resilience engineering. Layers correspond to the four abilities of resilient systems: monitor, anticipate, respond, and learn. The proposal is applied in a 34-bed intensive care unit. To map relationships between actors in each layer, a questionnaire was devised and answered by 133 staff members, including doctors, nurses, nurse technicians, and allied health professionals. Two multilayer networks were developed: one considering that actors are 100% available and reliable (work-as-imagined) and another considering suboptimal availability and reliability (work-as-done). The multilayer networks were analysed through actor-centred (Katz centrality, degree deviation, and neighbourhood centrality) and layer-centred metrics (inter-layer correlation, and assortativity correlation). Strengths and weaknesses of social interactions at the ICU are discussed based on the adopted metrics.

Keywords: resilience engineering; social network analysis; multilayer network; complexity; intensive care unit.

1. Introduction

Resilience is a characteristic of complex socio-technical systems, explaining why and how these systems do not break down, by adjusting their performance in face of constraints and opportunities (Hollnagel, 2017). Resilience is also emergent, which means that it is a new property that arises at system level from interactions between individual parts of the system, such as people, software, and hardware (Cilliers, 1998).

This paper explores a particular type of interaction that gives rise to resilience, namely social interactions in the workplace. The modelling of how these interactions influence resilience is challenging as they have different purposes (e.g. advice-seeking, nurturing friendship), and all may be influential depending on the context (Koirala and Hakvoort, 2017).

Four general types of social interactions are discussed. They are associated with the four abilities of resilient systems (Hollnagel, 2017), which have been used in resilience engineering (RE). RE is the discipline concerned with finding, assessing, and influencing resilience through design, in socio-technical systems (Nemeth and Herrera, 2015). These abilities are (Hollnagel, 2017): (*i*) *monitoring,* which implies in knowing what to look for, or being able to monitor what could seriously affect the system's performance in the near term, positively or negatively; (*ii*) *responding*, which implies in knowing what to do, or being able to respond to regular and irregular changes, disturbances, and opportunities in the system; (*iii*) *learning*, which implies in knowing what has happened, or being able to learn from experience, in particular to acquire the right lessons from the right experience; and (*iv*) *anticipating*, which implies in knowing what to expect, or being able to prepare for developments further into the future, such as disruptions, constraints or opportunities in the system.

Social interactions are one of the possible ways to boost those four abilities. As social interactions take place in messy real-life situations, it is reasonable to expect that an interaction may simultaneously target at two or more abilities. Also, interactions focused on a certain ability (e.g. monitor) may trigger other ability-centred interactions (e.g. respond) at a later moment in time. However, while dependence between resilience abilities is expected in theory (Patriarca, et al., 2018a), empirical data supporting the understanding of what that looks like in practice is scarce.

In this study, Social Network Analysis (SNA) (Wasserman and Faust, 1994) is used to model interactions between the four abilities of resilient systems. In our proposal, interactions related to each resilience ability are modelled as layers of a multilayer network. Each layer consists of nodes (i.e. people) and edges (i.e. purpose of the interaction). Although sharing the same nodes, each layer conveys different information on the edges. If the same actors are present in every layer the network is denoted as multiplex (Nicosia et al. 2013), which is the type investigated in this study. While some previous studies adopted SNA for modelling resilience in socio-technical systems (Bertoni et al. 2020; Long et al., 2014; McCurdie et al., 2018), none of them took a multilayer perspective. That is a drawback as the multilayer network is effectively a new network, and therefore it offers insights that are not observable at the single-layer level – e.g., it makes it clear, in a concise way, the extent to which actors interact with the same people regardless of the purpose of the social interaction (Dickinson et al., 2016).

Our perspective is aligned to Wood's (2015) view of resilience as layered interwoven networks that adapt to surprises as conditions evolve. While sound in principle, such perspective of resilience has remained mostly at a conceptual level (Berg et al., 2018). We aim at bridging such gap in the literature by investigating two research questions (RQs), as follows:

RQ1: How can a multilayer social network be developed to map resilience in a socio-technical system?

RQ2: How can traditional metrics used in multilayer social networks, at both actor and layer levels, be interpreted in light of resilience engineering?

These questions are investigated through an application of SNA to the modelling of social interactions in the ICU of a tertiary care teaching hospital located in Brazil. A number of problems in today's healthcare systems are influenced by social interactions, such as silo-working, poor communication, and professional isolation (Pomare et al., 2020). Healthcare has been one of the top studied sectors in RE, which may be justified by the sector's high complexity (Braithwaite, 2018).

A survey questionnaire was devised to gather information related to social interactions between caregivers at the ICU. Data on four types of interactions corresponding to the resilience abilities were collected and used to develop a multilayer social network, thus addressing RQ1. Next, selected actor-centred and layer-centred metrics derived from the multilayer network were calculated and interpreted from an RE lens, thus addressing RQ2. The study reported in this paper expands the data analysis conducted by Bertoni et al. (2020) at the same ICU, which focused on the identification of key resilient players in ability-based layers.

2. Background

2.1 Resilient healthcare: concept and previous studies in ICUs

When applied to healthcare, resilience engineering has been referred to as resilient healthcare, which is the "ability of the healthcare system to adjust its functioning prior to, during, or following changes and disturbances, so that it can sustain required performance under both expected and unexpected conditions" (Hollnagel et al., 2013, p. xxv).

A core idea of resilient healthcare is the distinction between work-as-imagined (WAI) and work-as-done (WAD). WAI is commonly defined top-down, prescribing rules, procedures, and policies that define what is expected to occur, in various levels of detail. WAD represents what actually occurs in the workplace, stressing the adaptations needed to adjust to real work conditions (Hollnagel, 2014). In complex systems, such as healthcare, there is inevitably a gap between WAI and WAD; however, none is intrinsically superior over the other (Braithwaite, 2018). The adaptive capacity to fill out gaps in WAI arises from formal organizational structures (e.g., training programs, built-in slack resources, such as extra capacity) as well as from self-organization of employees, trial and error, and experience (Provan et al., 2020; Wachs et al., 2016).

In line with the emergent nature of resilient performance, Anderson et al. (2020) argue that resilient healthcare research and practice should account for the prominence of social, cultural and organizational factors in healthcare work – this further justifies the approach adopted in our paper. In addition, those authors stress the need for giving visibility to the linkages between resilience at different scales of time and space across the whole healthcare system. Berg et al. (2018) refer to these scales as the micro (e.g., front-line clinical work), meso (e.g., hospital), and macro levels (e.g., national regulations and public health policies).

In the context of ICUs, in addition to Bertoni et al. (2020), a few other works have explicitly adopted a resilient healthcare lens. Paries et al. (2013) investigated the merger of two separate ICU services in a university hospital, describing how resilience contributed to the improved performance of the new unit in terms of quality and safety of care. Clay-Williams et al. (2015) proposed improvements in clinical guidelines in an ICU, making them more compatible with WAD. Rosso and Saurin (2018) proposed the joint use of the Functional Resonance Analysis Method (FRAM) and value stream mapping to understand how resilience played out in the patient flow from an emergency department to an ICU. Bueno et al. (2019) conducted a systematic literature review, analysing how guidelines for coping with complexity were accounted for in 91 improvement interventions at ICUs. Ransolin et al. (2020) explored the influence of the built environment on the resilient performance of caregivers in an ICU.

In most of the aforementioned studies, theoretical and practical implications were discussed in light of the four abilities of resilient systems. Alders' (2019) study was the only fully focused on the four abilities in ICUs, by assessing them through the resilience assessment grid proposed by Hollnagel (2017). One of the findings was that resilient performance strongly benefited from social interactions between care providers. In a similar vein, Horsley et al. (2019) presented a framework for the improvement of ICU team resilience.

2.2 Multilayer social networks analysis: definitions and metrics

A single-layered social network (SSN) is defined by a tuple $\langle V, E \rangle$, where V is a set of actors and E is a set of edges defining relations between actors. In a multilayered social network (MSN), pairs of actors are connected by multiple edges and the network is defined by a tuple $\langle V, E, L \rangle$, where L is a set of distinct layers, each associated with a different type of relationship between actors (Magnani and Rossi, 2011).

At each layer l information on actors and edges may be summarized in an adjacency matrix $\mathbf{A}_l$, with element a_{ij} signalizing the existence of a relationship between actors i and j, through a binary value, or the strength of this relationship though a continuous non-negative value. A common approach to MSN analysis is to merge layers of the SSN through flattening of matrices $\mathbf{A}_l$ (Dickinson et al., 2016). Several metrics at the actor and layer level may be calculated for MSNs. Next, we briefly review the five metrics used in our case study. These metrics reflect key attributes of complex systems, which therefore have implications for resilient performance. Three of the metrics are actor-centred: Katz centrality, degree deviation, and neighbourhood centrality.

Katz centrality $C_i^{(katz)}$ relates the centrality of an actor i to centralities of the incoming neighbours, taking into account immediate neighbours and those reachable through a larger number of steps. Thus, Katz centrality assumes that nodes increase their centrality if they are connected to central nodes. It is worth noting that, since the multilayer network considers every edge, it represents a different network with a new topology; this may result in Katz scores substantially different from those obtained for the individual layers. A decay parameter α is used to assign larger weights to closer neighbours, through the following expression (Katz, 1953):

$$C_i^{(katz)} = \sum_{k=1}^{\infty} \sum_{j=1}^{N} \alpha^k \left(\mathbf{A}^k\right)_{ji} \quad (1)$$

where $\mathbf{A}^k$ is the adjacency matrix from a given layer or from the flattened network, and N is the total number of actors in V. The value of α is usually set to $^1/_{\lambda_{max}}$, where λ_{max} is the largest eigenvector associated with $\mathbf{A}$.

Katz centrality is relevant for resilient performance since it accounts for the number of interactions with central nodes, which refers to the number of interacting elements, acknowledged to be a proxy measure of complexity (Perrow, 1984).

Degree deviation, G_i of actor i, is the standard deviation of i's centrality measurements on a subset $\mathcal{L}$ of network layers, which may include all layers in the network (Bródka et al., 2011). A low value of G_i may indicate that i is either homogenously active or inactive on the layers. When calculating G_i in a directed network with weighted edges, two approaches could be considered: (*i*) use Katz as centrality measure, or (*ii*) use the degree centrality measure given by the sum of edges leaving and arriving at i, ignoring weights. We used approach (*ii*) since degree reflects a local property less dependent on the graph's topology and corresponds to the neighbour concept presented next.

Degree deviation reflects the diversity of actors' interactions, which is another key attribute of complexity that influences resilience (Dekker, 2011). Thus, it is reasonable to expect that actors do not have a uniform participation across the four ability-based networks – i.e. their degree deviation would be higher than zero.

Neighbours of an actor i are defined as all actors directly connected to i. In directed networks, incoming and outgoing connections are considered in the determination of neighbours. **Neighbourhood centrality** of actor i is defined as the total number of i's neighbours in the subset $\mathcal{L}$ of layers of interest, such that each neighbour is only computed once (Bródka and Kazienko, 2018); i.e.,

$$Neighbourhood\ (i, \mathcal{L}) = |neighbours(i, \mathcal{L})| \quad (2)$$

Similarly to degree deviation, neighbourhood centrality also reflects diversity. However, it is concerned with the diversity of neighbours across the network layers, which may be useful in providing diverse perspectives for decision-making (Page, 2010).

In addition to the actor-centred measures, two layer-centred measures are used in our analysis: interlayer correlation and interlayer assortativity. **Interlayer correlation** is calculated determining the proportion of edges that are common to pairs of layers, regardless of the weights assigned to them. It is a measure of similarity, and therefore redundancy between layers. As such, this metric also explores diversity at the layer level.

Assortativity correlation between a given pair of layers is obtained by first generating for each layer a vector with entries given by the strength of edges in that layer (incoming, outgoing or both) and organizing entries such that they refer to the same edges in both vectors. Then, Pearson's correlation between those vectors is calculated (Nicosa and Latora, 2015). At a single layer level, assortativity measures the preference of actors to attach to others that are similar in some way. Thus, a network is assortative if edges connect actors with similar degrees, high with high and low with low (Karrer and Newman, 2009). In MSNs, this metric assesses whether these preferences remain the same across all layers. Thus, assortativity correlation is yet another metric that reflects diversity of interactions between actors.

As a support to the explanation above, Figure 1 depicts a multilayer network comprised of four layers, namely monitor, anticipate, respond, and learn. Each single layer (on the left side) renders a specific kind of directed relationship between five actors (A, B, C, D, E). Depending on the chosen criteria, an actor may be central in a layer and peripheral in the multilayer network (on the right side), in which the maximum possible network density is quadrupled in relation to any individual layer. The thickness of an arc is depicted as proportional to the frequency of the interactions between the corresponding dyad, which helps to highlight the difference between degree and Katz centrality. The former depends only on the number and values of incident arcs, whereas the second depends on the topology of the entire network.

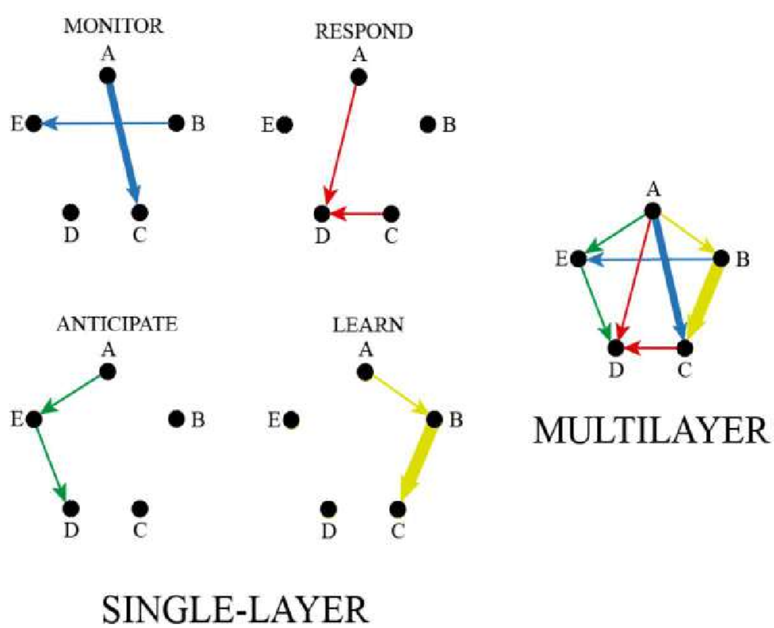

Figure 1. Examples of single and multilayer networks

3. Method

3.1 Research stages

The ICU chosen for this study is part of a teaching hospital in Southern Brazil, which has around 5,000 employees and 850 inward beds. The ICU has 34 beds and it has two adjacent pods: one of them with 21 beds and another with 13 beds. Other recent resilience engineering studies have been carried out at this same ICU by the same research group involved in the present work (e.g., Ransolin et al., 2020).

Figure 2 presents the three main research stages: data collection, multilayer modelling, and data analysis. There are two major sub-stages in the multilayer modelling, which need to be justified upfront. Initially, a WAI network was devised by simply considering the frequency of interactions between actors. An expanded definition of WAI was used by not limiting it to explicit knowledge. Indeed, there were no standardized procedures specifying what the interactions should look like. Thus, the WAI network, in our context, should read as the network of interactions under ideal circumstances, when the contacted person is 100% available and 100% reliable. However, as these assumptions do not necessarily hold true in practice, the development of a WAD network was necessary by considering less than ideal availability and less than ideal reliability of the information provided. The use of the terms WAI and WAD maintains their original key message, namely that there is an idealized work system and a real one.

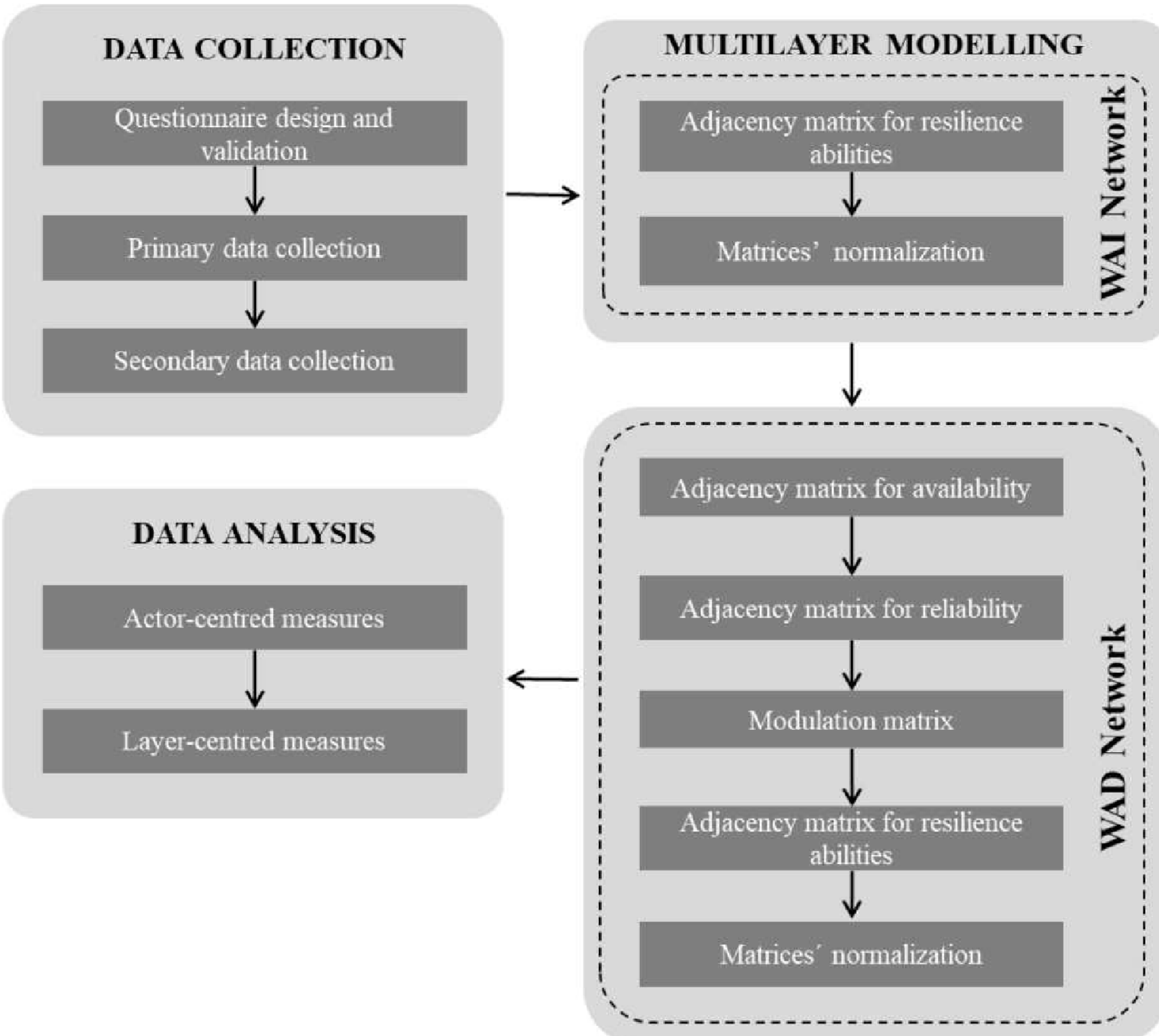

Figure 2. Stages of the research method

3.2 Data collection

To obtain data for the development and interpretation of the MSN, we (*i*) designed and validated a survey questionnaire, (*ii*) applied the questionnaire to the target population (primary data collection), and (*iii*) carried out semi-structured interviews with some actors (secondary data collection). The same data collection procedures were used by Bertoni et al. (2020) at the same ICU. Therefore, the same database supported the study in Bertoni et al. (2020) – focused on actor-centered metrics at layer level, and the study described in this paper. Furthermore, the previous study included semi-structured interviews with five actors (two doctors and three nurses) that stood out based on actor-centered metrics at the layer level. Some of those interviews were re-interpreted in this paper for the purpose of the MSN.

A pilot survey was initially designed and tested with 8 of the 201 professionals working in the ICU. Feedbacks were incorporated in the survey and a final version was applied to the target population, comprised of four groups of care providers with at least one year of experience in the ICU. They are: doctors (DR), nurses (N), nurse technicians (NT), and allied health professionals (AH), such as psychologists, pharmacists, nutritionists, speech and occupational therapists. Residents were not included in the target population.

There are three main sections to the survey questionnaire, which are summarized in Table 1. An overview of the sections is given next.

Section 1 (questions 1 to 7) – designed to collect information on respondents, such as professional group, age, experience, and working shift. Questions 7.1 and 7.2 refer to two contextual information (i.e. frequency of interruptions and participation in daily rounds) explored by Bertoni et al. (2020), and out of scope in the present study.

Section 2 (questions 8 and 9) – designed such that respondents were given the complete list of 201 ICU staff members and asked to indicate those they search for advice (face-to-face or through electronic means). Then, peers shortlisted from the full roster were scored regarding their availability ("likelihood of peer being available") and reliability ("frequency in which the peer provides exactly the information requested"), using a five-point scale, with the following descriptors: 1 – never; 2 – rarely; 3 – sometimes; 4 – frequently; and 5 – always. Availability relates to time and reliability relates to precision. These are the two main criteria for assessing variability (in time and precision dimensions, respectively) when modelling socio-technical systems in resilience engineering (Hollnagel, 2012).

Section 3 (questions 10 to 13) – a customized list of sought-after peers was generated for each respondent based on names indicated in section 2. In this section, they were asked to score the frequency of their interactions with those peers to monitor, anticipate, respond, or learn. For that, a 5-point scale was presented with the following anchors: 1 – never; 2 – less than once a month; 3 – one to three times a month; 4 – one to three times a week; and 5 – daily.

Table 1 - Overview of the survey questionnaire (Bertoni et al., 2020)

Section name	Question #	Question name	Possible responses
Survey Starts		Opening remarks	
Demographic Data	1	Name	Full name
	2	How old are you?	Number of years
	3	What is your gender?	Male/female
	4	Profession	Physician, nurse, nursing technician, pharmaceutical, nutritionist, physiotherapist, speech therapist, social assistant, psychologist
	5	5.1 Indicate number of years since graduation	Number of years
		5.2 Time working in ICUs (including other hospitals)	
		5.3 Time working at this ICU	
		5.4 Worked in other areas prior to the ICU? List them	Writing
	6	Work Shift	Morning, afternoon, morning and afternoon, night shift 1, night shift 2, night shift 3, sixth shift
	7	7.1 Frequency of participation in multidisciplinary rounds	Marks on a 5-point scale: 1 – never; 2 – less than once a month; 3 – one to three times a month; 4 – one to three times a week; 5 – daily
		7.2 Frequency in which interruptions take place during work (phone calls, answering to peers, etc.)	
Roster	8	From the list of peers below, choose those you interact for advice or information	Marks on names
Non-network attributes	9	9.1 Score the list of peers shortlisted in Question #8 regarding their likelihood of being available when needed	Marks on a 5-point scale: 1 – never; 2 – rarely; 3 – sometimes; 4 – frequently; 5 – always
		9.2 Score the list of peers shortlisted in Question #8 regarding the frequency in which they provide exactly the information requested	Marks on a 5-point scale: 1 – never; 2 – rarely; 3 – sometimes; 4 – frequently; 5 – always
Ability to Monitor	10	From the list of peers shortlisted in Question #8, identify those you consult to understand what is happening or has occurred in real-time in the ICU and how often that occurs	Marks on a 5-point scale: 1 – never; 2 – less than once a month; 3 – one to three times a month; 4 – one to three times a week; 5 – daily
Ability to Anticipate	11	From the list of peers shortlisted in Question #8, identify those you consult to anticipate short, medium and long-term trends concerning the ICU and how often that occurs	Marks on a 5-point scale: 1 – never; 2 – less than once a month; 3 – one to three times a month; 4 – one to three times a week; 5 – daily
Ability to Respond	12	From the list of peers shortlisted in Question #8, identify those you consult to know what to do when an event occurs (either expected or unexpected) and how often that occurs	Marks on a 5-point scale: 1 – never; 2 – less than once a month; 3 – one to three times a month; 4 – one to three times a week; 5 – daily
Ability to Learn	13	From the list of peers shortlisted in Question #8, identify those you consult to learn during regular days and in the occurrence of positive or negatives events, and how often that occurs	Marks on a 5-point scale: 1 – never; 2 – less than once a month; 3 – one to three times a month; 4 – one to three times a week; 5 – daily
Survey Ends		Closing remarks	

The online platform Qualtrics was used to apply the survey. All ICU staff members listed in the roster were invited to answer the questionnaire. Three follow-up reminders were e-mailed to non-respondents; ICU team leaders and managers sent additional e-mails requesting them to complete the survey. There were 133 (out of 201) staff members who completed the questionnaire, yielding a 66.2% response rate. Respondents included nurses (78.1% of the total nurses), nurse technicians (72.2%), allied health professionals

(64.3%), and doctors (40.0%). Respondents were mostly female (72.9%) and experienced. The share of respondents from each professional group is fairly similar to their participation in the total population. The wider gap refers to doctors, who correspond to 20% of the population and 12% of the respondents.

Regarding the secondary data collection, Bertoni et al. (2020) conducted semi-structured interviews with five actors (DR198, DR190, N12, N94, and N135) positioned among the top ten highest ranked in at least one of the ability-based networks – among the top ten, they were randomly selected for the interviews. Interviews were audio recorded, lasted on average 30 minutes, and were conducted in-person at the ICU premises, in a room that allowed privacy for the conversation. A script with four questions was followed: *(i)* could you provide examples of everyday situations in which you interact with others in terms of monitoring, anticipating, responding, and learning? *(ii)* Could you provide examples of typical information requests from your colleagues? *(iii)* Is your central role linked to interruptions in your everyday work? How do you cope with interruptions? *(iv)* How does participation in the interdisciplinary rounds affect the four resilience abilities? For the purpose of this paper, only questions *(i)* and *(ii)* were useful. The other two questions related mostly to the study by Bertoni et al. (2020).

All data collection and analysis procedures were granted approval by the hospital's ethics committee. According to that approval, interviewees signed a form of informed consent and SNA survey's respondents were made aware that their names would not be disclosed when presenting this study's results – this warning appeared on the top of the questionnaire. Only the researchers had access to data that identified respondents, which was necessary for the follow-up interviews. Although ICU managers received a report with the main findings, respondents were coded in the same way as presented in this paper (see results, in which doctors are coded as DR, nurses as N, and so on).

3.3 Multilayer modelling

3.3.1 Work-as-Imagined (WAI) network

As previously mentioned, a questionnaire was designed customising a roster of actors to each respondent and using the list to collect data on six relational variables (henceforth denoted as the six dyads). Raw dyadic data may be represented as six directed graphs: the ability-based networks (monitoring, anticipating, responding, learning), in addition to reliability and availability networks.

In the WAI network, dyads represent idealised social interactions that give rise to *adjacency matrices for resilience abilities*. The WAI network has four layers, one for each resilience ability, with corresponding intra-layer adjacency matrices obtained from answers to questions 10 to 13 in Table 1. In each layer, the weights on actor i's outgoing edges correspond to the Likert scores obtained from the actor's questionnaire. Since all matrices share the complete list of 201 professionals in the ICU, some entries will be nulled, corresponding to non-existent connections between pairs of actors.

Next, we carry out the *WAI matrices' normalization*. Each adjacency matrix is normalized dividing their respective Likert scores by the maximum scale value (5). Therefore, possible WAI weights span between 0 (i.e. $0/5$) and 1 (i.e. $5/5$).

3.2.2 Work-as-Done (WAD) network

We used the two remaining sets of dyads – availability and reliability – to obtain a more realistic representation of working conditions at the ICU and build the WAD network. Availability is an estimate of likelihood (in Bayesian terms) to receive support from actor j as rated by actor i. Reliability is a score reflecting actor i's confidence that actor j is providing exactly the information requested. Availability and reliability scores have been used, after some manipulations, to build the modulation matrix $\mathbf{F}$.

The *adjacency matrix for availability* uses scores from question 9.1 in Table 1. We assumed that respondents were biased to a negligible extent when asked to evaluate others' physical or behavioural availability. This assumption is reasonable since others' openness may be viewed as an acceptable estimate of both accustomed relationship and reciprocity. Therefore, the only data manipulation performed when modelling availability consisted in converting the lowest Likert score 1 into 0, to represent the dyadic unavailability (i.e. Null dyad).

The *adjacency matrix for reliability* uses results from question 9.2 in Table 1. Since reliability judgements have a potentially biased moral connotation, its assessments required a more careful data handling. For that, we took advantage of the reliability's adjacency matrix structure in which actors in rows assess the reliability of actors in columns. We thus calculated a mean reliability value for the j-th actor adding scores in the j-th column of the adjacency matrix and divided it by the total number of judgements. Entries in all non-null cells in column j are replaced by the mean reliability value. Such approach is intended to compensate for individual liking or aversion biases.

To obtain the *modulation matrix* **F** used to adjust the adjacency matrices for resilience abilities considering actors' availability and reliability, we multiplied the assessment in cell (i, j) of the availability matrix by the mean reliability value of actor j from the reliability matrix.

The WAD network is finally obtained adjusting the WAI network by the modulation matrix **F**, yielding the *adjusted adjacency matrices for resilience abilities*, which result from performing the Hadamard product between each ability adjacency matrix and **F**.

The final result in this step is the WAD adjacency matrices for the resilience abilities, which are obtained through *normalization* of the adjusted adjacency matrices, dividing each matrix score by the maximum value (5). Possible WAD weights also span between 0 and 1. Note that both WAI and WAD networks will have the same nodes. However, the WAD network will be less connected (with no or weaker connections), proportional to the entries in **F**, in which availability and reliability scores are manipulated.

3.4 Data analysis

In this stage, we analysed two sets of information from the multilayer network: (*i*) *actor-centred metrics*, and (*ii*) *layer-centred metrics*. Measures in (*i*) include Katz centrality, neighbourhood centrality, and degree deviation. Actors were ranked according to their scores in each of these metrics. Metrics in (*ii*) include interlayer correlation and assortativity. Algorithms used for calculating all metrics are mostly based on De Domenico et al. (2014), Azimi-Tafreshi et al. (2014), and De Domenico et al. (2015), and were implemented using R language. They are grounded on a compact tensorial representation of the entire network, i.e. the adjacency tensor. A tensor is a mathematical object that generalizes the notion of a matrix, which is a 2nd order tensor. A tensor may sometimes be represented by a supra-matrix, i.e. a flattened matrix structured to retain all information distributed over the layers.

As for the interviews, the corresponding transcripts were subject to a thematic analysis (Pope, 2000). Researchers looked for excerpts of text related to practical instances of social interactions that operationalized one or more of the resilience abilities. It is worth reinforcing that these interviews were primarily conducted for the study by Bertoni et al. (2020). For the purpose of this paper, we had a more limited interest in those interviews, and they were useful to a lower extent, mostly for the contextualization of some findings associated with the multilayer analysis.

4. Results

4.1. Actor-centred measures

Tables 2 and 3 display Katz centrality results for the multilayer WAI and WAD networks as well as for each ability-related layer, respectively. Only the ten best ranked actors are listed in these tables. Results show that only actor N94 appears among the top ten, both in the multilayer and the single layer, for both WAI and WAD. This means that this actor is well-connected to other central actors regardless of the resilience ability.

In fact, N94 is also a key player herself as she has the largest degree (in and out-degrees) in both multi (67) and single layers. The following report from N94 suggested that her prominent role in the networks is partly due to her past managerial position in the ICU: *"I have been working in this hospital for 12 years, always in the ICU. I served as chief-nurse during two different periods. Thus, people refer to me for advice on care activities and administrative issues"*. According to her report, N94 is also a reference for certain care activities, such as puncturing and extracorporeal membrane oxygenation. It seems to be beneficial that an actor is central herself and is also well-connected to other central actors. This tends to produce rich exchanges of information between those involved, supporting the four resilience abilities.

By contrast, other actors displayed high Katz scores in the individual layers, while being poorly ranked in the multilayer network. An exemplar case is DR169, which at worst was the 4th in one of the WAD layers. However, in the correspondent multilayer, the Katz score of DR169 was 0.19, ranking at the 112nd place. This is consistent with the fairly low overall degree of that actor in the WAD multilayer network (i.e. 34, ranked 35th). This reflects the lower diversity of DR169 contacts across the four layers, in comparison to N94. Therefore, DR169 is probably surrounded by a relatively small and stable number of co-workers who do not necessarily have very high central roles. This aligns with the expected everyday work of busy and specialized doctors. Table 2 conveys a similar pattern for other doctors as there was only one doctor (10th place) among the top ten Katz scores at the multilayer. Another way of interpreting these findings is that nurses and nurse technicians work closely with several different central doctors, which do not interact that much with others central doctors.

In turn, the ten best ranked actors are mostly the same at both the WAI and WAD multilayer networks. However, DR142 is ranked 30th in WAI, while being the 10th in

WAD. This means that he is available and/or reliable, despite being well-connected to a relatively low number of central actors. This type of actor, significantly better ranked in WAD in comparison to WAI, may in principle play a bigger role in the ICU by being connected to a wider number of central actors.

By contrast, DR190 was fairly well-ranked in WAI (13^{th}), but less central in WAD (25^{th}). This means that her good connections with central actors have been underexploited, as she is not much available and/or reliable. As such, this actor may need organizational support to make the most from her good connections – e.g. less administrative tasks, making her more available for adding-value social interactions.

Table 2. Katz centrality results for WAI. Notes: actors in blue appear in the multilayer and single layer results. Actors in red appear in all single layer results.

Multilayer WAI			Monitor			Respond			Anticipate			Learn		
Actor	Katz	Degree	Actor	Katz	Degree	Actor	Katz	Degree	Actor	Katz	Degree	Actor	Katz	Degree
NT128	1.00	43	**DR169**	1.00	37	**N94**	1.00	67	**DR169**	1.00	33	**DR169**	1.00	34
N104	0.99	45	**N68**	0.87	42	**DR169**	1.00	33	**N94**	0.89	66	**N94**	0.91	67
N186	0.93	52	NT20	0.86	47	**N73**	0.99	42	**N135**	0.75	54	**DR108**	0.75	34
NT4	0.92	39	**N94**	0.81	70	**N68**	0.95	40	NT193	0.75	35	AH156	0.72	29
N94	0.85	70	**N73**	0.77	47	NT20	0.92	41	**N73**	0.73	43	DR48	0.72	37
NT53	0.82	38	**N135**	0.75	55	NT28	0.90	40	**DR108**	0.72	33	**N68**	0.71	40
NT164	0.82	46	NT152	0.74	40	**N135**	0.86	52	**N68**	0.70	40	**N73**	0.70	42
NT32	0.76	41	NT28	0.72	42	NT152	0.81	38	DR198	0.67	32	**N135**	0.68	54
NT145	0.74	36	**DR108**	0.70	36	NT193	0.73	33	DR48	0.66	37	DR198	0.62	32
NT72	0.74	30	NT101	0.64	31	**DR108**	0.72	34	DR36	0.57	28	DR36	0.60	28

Table 3. Katz centrality results for WAD

Multilayer WAD			Monitor			Respond			Anticipate			Learn		
Actor	Katz	Degree	Actor	Katz	Degree	Actor	Katz	Degree	Actor	Katz	Degree	Actor	Katz	Degree
N186	1.00	50	**DR169**	1.00	33	**N73**	1.00	42	**NT193**	1.00	35	**DR169**	1.00	34
NT128	0.98	42	**NT193**	0.83	34	NT28	0.93	40	**DR169**	0.91	33	**N94**	0.82	67
NT4	0.89	39	**N73**	0.82	43	**NT193**	0.91	33	**N94**	0.74	66	**N73**	0.71	42
N104	0.88	40	NT28	0.79	41	**DR169**	0.90	33	**N135**	0.70	54	**NT193**	0.71	35
N94	0.84	67	**N135**	0.78	54	**N135**	0.83	52	**N73**	0.67	43	**N135**	0.70	54
NT145	0.78	35	N68	0.78	40	**N94**	0.83	67	DR108	0.61	33	DR108	0.69	34
NT72	0.76	30	**N94**	0.74	64	N68	0.80	40	N172	0.60	28	DR48	0.67	37
NT164	0.75	44	NT152	0.72	39	NT152	0.74	38	DR48	0.60	37	N68	0.61	40
NT32	0.74	40	NT20	0.68	41	NT20	0.74	41	NT112	0.58	30	NT28	0.59	41
DR142	0.71	26	NT47	0.68	29	N172	0.64	27	NT47	0.58	29	DR198	0.57	32

Tables 4 and 5 present results for degree deviation (G_i) of WAD and WAI multilayer networks, respectively. Low G_i values indicate actors that are either homogeneously active or inactive on layers – actors with low G_i values and active on layers were assumed to be in a more favourable position for resilient performance.

Only the top 10 actors according to degree deviation and degree centrality are shown. Several actors had a homogeneous and relevant centrality in the four layers in both WAI and WAD, such as NT4 and N68. These actors could be assigned formal and standardized roles related to the four types of social interactions, as they can be trusted to be fairly available and reliable. For example, these actors could be regular members that attend ward rounds, or they could take part in committees that assess the ICU performance and devise action plans.

It is important to note that the lowest possible degree deviation (i.e. zero) not always goes hand in hand with the highest degree centrality. For instance, in the WAD network, actor N94 had the highest degree centrality (67) and the 7th highest degree deviation (1.4). Similarly, actor N186 had the third highest degree centrality (50) and the highest degree deviation (3.4). While these actors' contributions to resilience are relevant, they have unbalanced participation in the layers. This is not necessarily a weakness provided those actors have a relevant centrality in the individual layers, which is the case of N94 and N186. Another way of putting that is that these actors are strong assets for resilience in general, but even stronger in some abilities. This might be more a strength than a weakness, depending on the role these actors play in the workplace.

Tables 6 (WAI) and 7 (WAD) present, for the top ten best ranked, the last actor-centred metrics of interest for the multilayer network: neighbourhood centrality. Results indicate a wide amplitude in neighbourhood centrality values. This metric conveys in a concise way that some actors, such as N94, have a much wider diversity of neighbours across the four layers. From the out-degree viewpoint, a possible interpretation is that N94 requests information from people specialized in each ability. From the in-degree viewpoint, a possible interpretation is that N94 is a reliable and available source of information related to all four abilities as she is sought by a number of different people, each interested in ability-specific information.

Table 4. Partial view of degree deviation and centrality values for WAI

Actor	Degree Dev. WAI	Degree Centrality WAI
N68	0	42
NT4	0	39
AH156	0	39
NT44	0	38
NT144	0	37
AH102	0	35
NT38	0	33
NT91	0	31
N39	0	30
N65	0	30

Table 5. Partial view of degree deviation and centrality values for WAD

Actor	Degree Dev. WAD	Degree Centrality WAD
NT66	0	46
N68	0	40
NT4	0	39
NT44	0	34
N34	0	30
N39	0	30
NT38	0	29
NT47	0	29
N65	0	29
NT60	0	28

Table 6. Neighbourhood centrality – WAI

Actor	Neighborhood Centrality
N94	70
N135	55
N186	52
NT66	48
NT20	47
N73	47
NT164	46
N104	45
NT128	43
NT28	42

Table 7. Neighbourhood centrality – WAD

Actor	Neighborhood Centrality
N94	56
N135	52
N186	43
NT66	42
NT164	38
NT4	36
NT10	36
DR48	36
N104	36
AH161	35

4.2. Layer-centred measures

Figure 3 shows a representation of single-layer and multilayer networks. In the WAD networks, weights on edges are deflated according to availability and reliability assessments. As a result, WAI networks are denser than their WAD counterparts, i.e. although sharing the same edges, they are thicker on the WAI network. Actors are also the same across all layers, although at different positions. Actors' spatial positioning is optimized to allow better visualization using the layout algorithm developed by Fruchterman and Reingold (1991). Graphs were obtained using the igraph package in R software.

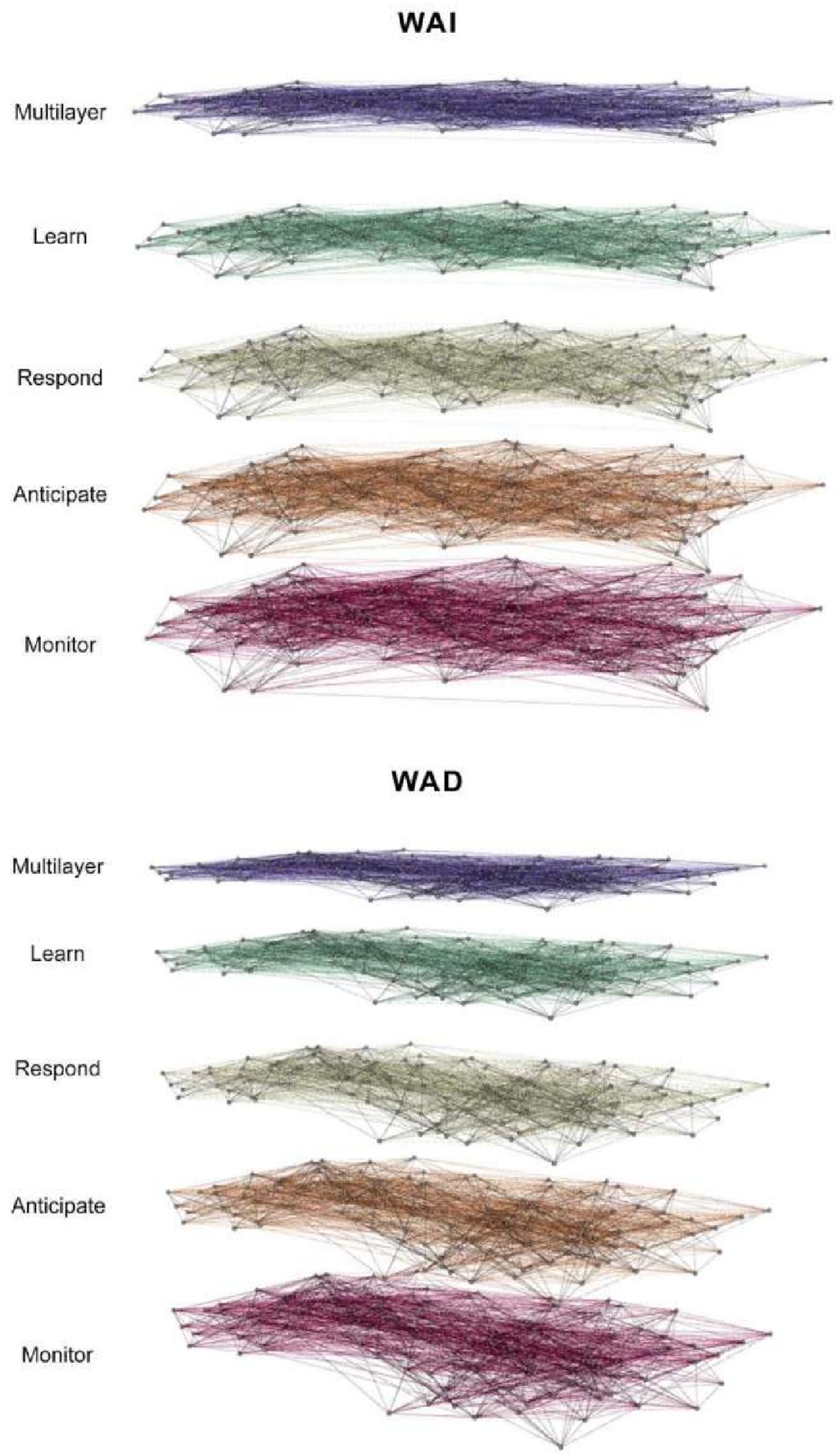

Figure 3. Schematic representations of the WAI and WAD networks.

As for interlayer correlations, which measure the similarity or redundancy between pairs of layers, all correlation values are in the interval [0.78; 0.79]. These strong correlations are expected in real-world multiplex networks, as actors are the same in all layers (Nicosia and Latora, 2015).

In turn, all assortativity correlations were in the interval [0.98; 0.99]. This suggests that actors have a clear preference for connecting with similar degree actors in all four layers. That can imply the formation of clusters of high degree and low degree actors, hindering diverse perspectives when monitoring, anticipating, responding, and learning. For example, it may be useful to make a high degree actor in the monitor network more connected to low degree actors in the learn network.

The similar assortativity correlations for WAI and WAD convey that actors are not discouraged from interacting with the same peers despite their occasional low availability and low reliability. Possible reasons for that might be highly specialized knowledge and skills of many actors, individual preferences, and strict organizational structures, which leave actors with limited realistic options. Another interpretation is that, in face of the unavailability of preferred co-workers, there is no social interaction at all, and actors fill out information gaps on their own. This point is revealed in the report from N12: *"we take many actions and decisions on our own, because sometimes the doctors are sleeping…so we end up having to take the responsibilities"*.

Lastly, the benefits of having preferential actors for interactions is illustrated by the following report from DR169: *the nurses know how I work, they know my way…for example, some topics that I approach during the multidisciplinary round, a break in the administration of sedation. The nurses I work with know that I will arrive in the morning and I will pause the sedation…some exams that the nurse collects, some of their attitudes…so they don't even ask me what to do"*. This report also raises the question of whether low frequency social interactions can still be effective, as they can be partly replaced by tacit knowledge and assumptions.

5. Discussion

The proposed steps for developing a multilayer social network of resilience abilities (see Figure 2) proved to be workable and insightful. Although these steps are not healthcare specific, adaptations for other contexts might be necessary in some portions of the questionnaire – e.g. relevant demographic information on the respondent, and examples of what counts as a monitor, anticipate, respond, or learn social interaction. As a minor drawback, to generate MSN measures it is necessary to integrate the computing environment with specific libraries developed for dealing with multiplex networks; e.g. multinet, MUNA, Py3plex and Pymnet (McGee et al., 2019; Škrlj et al., 2019).

The most distinctive aspect of our approach is the development of separate WAI and WAD networks, which in addition to the four ability-based layers translate RE ideas into the practice of social network analysis. Our findings pointed out that there were relevant differences between WAI and WAD at the actor-centred level. This means that the frequency of interactions between pairs of actors, *per se*, is not representative of the effectiveness of these interactions. However, since actors normally insist on contacting the same people, the structure of the WAI and WAD networks is similar.

The ICU study shed light on how some multilayer metrics may be interpreted in light of resilience engineering (Table 8). Results suggest that the ICU has a number of actors that have effective interactions across the four layers, which is an asset for resilient performance – e.g. there were 37 actors (27.1%) with a Katz score higher than the 75-th percentile, 23 actors (17.3%) with neighbourhood centrality higher than the 75-th percentile, and 47 actors (35%) with zero degree deviation and high centrality.

On the other hand, actors interact mostly with others with similar degrees, as indicated by the high assortativity correlations. That may point to organizational structures (e.g. stable and self-contained teams) and rigid social and professional hierarchies that either discourage or impede actors' access to a broader set of co-workers. Although healthcare settings are known for communication barriers between professional groups (Creswick et al. 2009; Bate, 2000), our results suggest that this can also be a relevant issue within professional groups – e.g. high degree nurses communicating mostly with other high degree nurses. Organizational structures can also explain the finding that 9 out of the 10 top Katz scores were either nurses (3) or nurse technicians (6). These professionals, especially nurse technicians, play a key role as second-order resilient actors (see definition in Table 8) as they work closely under the guidance of central doctors and central nurses. It also points out that many doctors do not strongly interact with highly central actors, which may stem from the greater autonomy and decision-making responsibilities of these professionals.

As a drawback for an extended analysis of how well the ICU is performing, there is a lack of benchmarks from other ICUs. Another difficulty in this respect refers to the ambiguity of some metrics from the viewpoint of resilience (e.g. neighbourhood and assortativity), which makes it difficult to generalize what counts as a desirable value.

Considering this background, and whether or not benchmarks are available, the presented analysis can also play a role as a starting point for qualitative investigations that shed light on the underlying mechanisms that gave rise to the quantitative findings – e.g. to which extent is actors' centrality influenced by organizational structures or personality traits?

Table 8. Selected multilayer metrics and their connections to resilience engineering.

Metrics	Logical connections to RE	ICU performance
Katz centrality	Actors with high Katz centrality can be those that display resilient performance first-hand, after getting advice or information from central actors. Thus, high-scored Katz actors can be ***second-order*** resilient actors, while those central actors around them can be ***first-order*** actors. High-scored Katz actors can enjoy a certain status by being close to powerful actors, besides being in a favourable position to learn from them.	27.1% of the actors had a Katz centrality score higher than the 75-th percentile score (0.369) in the WAD multilayer network.
Degree deviation	Actors that strongly contribute to resilient performance can have low degree deviation, provided this is ***associated with*** a high centrality in all four layers	For WAD, 35% of the actors had a degree deviation score equal to zero and at the same time had a high centrality (higher than the average) in each of the four layers.
Neighbourhood centrality	A high neighbourhood centrality indicates that an actor has different neighbours in each layer. This can stem from specialized neighbours in certain abilities. Diversity of perspectives is normally accepted as beneficial to resilience (Page, 2010). However, low neighbourhood centrality is not necessarily detrimental, provided the same actors are available and reliable for different types of interactions.	For WAD, 17.3% of the actors had a neighbourhood centrality score higher than the 75-th percentile score (32.0).
Interlayer correlation	A high interlayer correlation tends to be desirable to resilience. It suggests that social interactions are rich in terms of contributing at the same time to the four abilities.	Inter-layer correlations were strong for both WAI and WAD.
Assortativity correlation	A high assortativity correlation suggests clusters of high degree actors and low degree actors. As a downside, actors can lose sight of the context and miss out different perspectives. As an upside (Kazawa and Tsugawa, 2020), it makes the network more robust with respect to node removal, as they tend to be similar within each cluster.	Assortativity correlations were very strong both for WAI and WAD, suggesting that both the downside and the upside of high correlations tend to be amplified.

Both researchers and professionals on top leadership roles are the main potential users of the aforementioned metrics and analysis. Researchers might use the proposed approach for the investigation of research questions related to the role of social interactions in resilient performance (e.g., whether network metrics correlate with patient safety and workload of caregivers). Depending on the nature of these questions, complementary tools might be necessary, while at the same time the steps adopted in this study do not need to be followed strictly. In turn, managers might use our proposal as a basis for the revision of work organization structures and allocation of staff in the ICU. Some of these possibilities were presented in the Results section. In addition, there could be created routines that allowed professionals to interact with a broader set of co-workers, which would be relevant in the studied ICU. One such routine could be based on the RPET method, which has been tested in hospitals. According to it, at the end of each shift, professionals meet and reflect on what went right and what went wrong, based on a checklist of probing questions (Hollnagel 2019).

Lastly, it is worth reinforcing that there is more to resilient performance than social interactions. As previously mentioned, resilience is an emergent property of socio-technical systems. Our approach addresses the social portion, emphasizing the four resilience abilities. Other types of interactions, such as those involving people and technological artefacts (e.g., consultation of information on patient dashboards) were not considered, even though earlier studies indicated that they have an influence on ICU resilience (Bueno et al., 2019).

6. Conclusions

This paper presented an approach for the development and interpretation of multilayer networks, using the lens of RE. The steps for the development of the network encompass core concepts of RE: the four resilience abilities, work-as-imagined, work-as-done, and performance variability (Patriarca et al., 2018b). These RE concepts have been translated into the practice of social network analysis, offering a new perspective for the analysis of resilient performance. The multilayer network provided an emergent yet concise representation of the interactions between the four ability-based layers, being complementary rather than a replacement for the traditional analysis layer by layer.

The five metrics adopted in this work pointed out strengths and weaknesses of social interactions at the ICU, which had not been identified by Bertoni et al. (2020) at the same setting. However, some of these metrics were ambiguous from the RE viewpoint (i.e. neighborhood and assortativity), and some findings were counterintuitive at a cursory view. For example, two actors had very high degree deviations and very high degree centralities, while also being key assets for resilience. That background, when jointly considered with the lack of benchmarks for comparison, makes it difficult to establish generalizable and simple rules for the interpretation of the multilayer metrics from an RE standpoint – the proposal in Table 8 is a starting point. Despite these limitations, the richness of information stemming from the multilayer network is valuable by itself, in addition to raising questions for further investigation.

Some further limitations of this study should be mentioned. First, there was no primary qualitative data collection, which could have offered additional insight into the underlying reasons for the observed performance. Second, the pioneer nature of this research in terms of applying multilayer network analysis in resilient healthcare, hindered comparative analysis with other contexts. Third, while the response rate to the questionnaire survey was high (66.2%), some important actors may have been missed out. Fourth, social interactions have other dimensions not explored in this study, such as their timing, duration, and workload implications.

As for future studies, some opportunities may be highlighted, as follows: (*i*) to investigate whether actors' centrality and network structures change in face of prolonged crisis and growing use of virtual interactions, as observed during the COVID-19 pandemic; (*ii*) to develop other multilayer approaches for investigating resilient performance, e.g. by considering interactions between layers composed by nodes at the individual, team, and organizational levels – in this study, the nodes in all layers corresponded to individuals; (*iii*) to assess the value of using other metrics at the multilayer level; (*iv*) to apply the proposed approach to other settings, not only in healthcare; (*v*) to use the results of the multilayer analysis as a basis for qualitative investigations that further explore the consultation experience and explain the observed results; and *(vi)* to map social interactions onto functions carried out by actors, through the joint use of SNA and FRAM – this could shed light on interactions' impacts on functions and networks of functions that display resilient performance, following early results where FRAM itself has been interpreted as a multi-layer network (Falegnami et al., 2020).

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