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Investigating the link between teachers' burnout and technology through the network psychometrics analysis: A survey of educators from diverse schools and grade level

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1. Introduction

The era of information technology has brought about swift technological progress, significantly influencing our daily lives. The widespread and rapid adoption of technology has compelled people to adopt a digital lifestyle, which can impact their professional productivity and psychosocial well-being (Erten et al., 2020). In the education context, the incorporation of technology has undergone changes over time, with teachers emphasising the necessity for specialised training to effectively utilise technology in the classroom. Several studies have shown that there is a connection between the well-being of teachers and that of their students. Therefore, it has been established that, given the contagious nature of teachers' well-being, it should be ensured and protected over time. This is not only in the interest of the teachers themselves but also of the entire educational system.

It is widely demonstrated in the literature that the introduction of technology in education can evoke mixed responses among teachers, with some facing difficulty in managing external demands, increasing the risk of burnout. The burnout syndrome observed in caring professions, particularly among health, social workers, and educators, is characterised by prolonged exposure to emotionally taxing work conditions resulting in physical and emotional exhaustion, depersonalization, and a low sense of personal accomplishment (Maslach et al., 1981). Research on the impact of technology use by teachers suggests that there are both potential risks and benefits. On the one hand, extensive technology use may contribute to burnout due to increased workload, lack of training, and difficulties in managing technology-related issues. On the other hand, technology can provide advantages such as greater work flexibility, personalized learning opportunities for students, and support for teachers' professional development. The relationship between technology use and teachers' well-being and job satisfaction is complex and varies across different studies.

Driven by the interest to further explore these topics, we conducted a study specifically aimed at investigating the link between burnout and the use of technology by teachers. To achieve this, we reached out to both support teachers and teachers from various disciplines in primary, lower secondary, and upper secondary schools across Italy. To gather data from teachers residing in different regions of the country, we employed a web-survey as our primary data collection method. Through a network psychometrics analysis (Epskamp et al., 2012), we checked if three group-teachers from primary, middle and high school differ in terms of the relationship between burnout and knowledge and pedagogical competencies about technology and its effective use during classroom activities. The remainder of the paper is organised as follows. After this introduction, Section 2, gives insights about participants, instruments and methodology for data analysis. Section 3, presents the main results of the empirical analysis carried out to investigate the link between teachers' burnout and technology, while the final Section offers the main conclusions from the paper.

2. Materials and methods

2.1 Participants

In this research, 430 Italian teachers were involved. After obtaining the initial approval from their school principals, we reached out to the teachers through social networks. We gathered data from schools situated throughout the entire national territory. Out of the 430 participants, 90% are female. The majority of teachers are aged between 46 and 55 years old (34.5%) with only 3 participants below the age of 25 and 6 individuals above the age of 65. We collected data in schools located across the whole national territory. Campania, Lombardy, Abruzzo, and Lazio are the most represented regions. When considering the school level where they teach, 26.7% of the teachers are employed at the primary school level (1st–5th grade, N = 115, 98.3% females), 48.8% at the middle school level (6th–8th grade, N = 214, 90.1% females), and 23.5% at the high school level (9th–13th grade, N = 101, 86.8% females).

2.2 Instruments

To evaluate the burnout levels among teachers, we utilised the Italian version of the Copenhagen Burnout Inventory (CBI) (Kristensen et al., 2005), which was validated by Avanzi et al. (2013). This inventory consists of 19 self-reported items, and respondents rated their experiences on a 5-point Likert scale. The CBI measures three dimensions of burnout: personal burnout, work-related burnout, and student-related burnout. The personal and work-related subscales focus on emotional and physical exhaustion, both in personal and workplace domains. The third subscale specifically examines the experience of professional fatigue concerning students. Furthermore, we administered eight ad hoc items specifically designed to assess teachers' interactions with technology during lessons. These items covered the use of devices in the classroom, reflections on whether they use technologies excessively for work-related reasons, efforts to reduce technology usage, perceptions of how technologies may affect the conduct of lessons, and beliefs about how devices can aid students' understanding of explanations. Additionally, teachers were asked about their opinions regarding the presence of devices in the classroom, including considerations about removing devices if possible, and the potential impact of personal and collective device usage on students' attention. Items description is listed in Table 1.

2.3 Psychometric Networks

Psychometric network analysis, introduced as a distinct methodological approach by Epskamp et al. (2012), represents a novel method for modeling the interrelationships between psychological constructs and their items in a measurement instrument. In contrast to conventional psychometrics, which treats items as mere indicators of some latent constructs, network analysis considers both items and constructs as interconnected nodes within a network. In this context, nodes represent various psychological variables such as mood states, symptoms, or attitudes, while the links between nodes signify the underlying statistical relationships that necessitate estimation. As a result, this distinctive feature presents novel challenges for statistical inference, differentiating it from traditional social network analysis, where links between nodes are readily observable.

In this study, our emphasis lies on a specific network model known as the pairwise Markov random field (PMRF; Lauritzen, 1996). PMRF belongs to the category of undirected network models where variables are depicted as nodes linked by edges. These edges indicate the strength of the conditional association between two variables, considering the influence of all other variables within the network. The prevailing approach to building a psychological network is by estimating a network of partial correlation coefficients (McNally, 2016; Borsboom et al., 2013).

Table 1: Teacher Burnout and Technology Interaction Items

Item	
How often do you feel tired?	B1
How often do you feel physically exhausted?	B2
How often do you feel emotionally exhausted?	B3
How often do you think, "I can't take it anymore"?	B4
How often do you feel worn out?	B5
How often do you feel weak and susceptible to illness?	B6
Is your work emotionally exhausting?	B7
Do you feel burnt out because of your work?	B8
Does your work frustrate you?	B9
Do you feel worn out at the end of the working day?	B10
Are you exhausted in the morning at the thought of another day at work?	B11
Do you feel that every working hour is tiring for you?	B12
Do you have enough energy for family and friends during leisure time?	B13
Do you find it hard to work with students?	B14
Do you find it frustrating to work with students?	B15
Does it drain your energy to work with students?	B16
Do you feel that you give more than you get back when you work with students?	B17
Are you tired of working with students?	B18
Do you sometimes wonder how much longer you will be able to work with students?	B19
Do you use technologies during classroom lessons?	D1
Have you thought about using technologies excessively for work-related reasons?	D2
Have you tried to reduce your usage of technologies?	D3
Do technologies (devices and digital tools) hinder the conduct of the lesson?	D4
Do devices help students understand explanations?	D5
If it were up to me, I would remove devices from the classroom.	D6
Does the presence of personal and collective devices negatively affect students' attention?	D7
Have various devices facilitated interactions with students' families?	D8

These networks are also referred to as Gaussian graphical models (GGMs; Lauritzen, 1996). In a GGM, the main idea is to represent each variable as a node in the graph, and the absence or presence of edges between nodes indicates conditional independence or dependence between the corresponding variables. An edge between two nodes implies that the two variables are conditionally dependent, given all the other variables in the model. The variables are assumed to follow a multivariate normal (Gaussian) distribution. This means that the joint distribution of all variables can be fully characterised by their mean vector and covariance matrix. From a formal standpoint, let us denote by $\mathbf{Y}$ a vector containing n responses from a random subject, and $\mathbf{y}$ as a specific realisation of this vector. We will make the assumption that $\mathbf{Y}$ follows a normal distribution with a mean vector $\boldsymbol{\mu}$ and a variance-covariance matrix $\boldsymbol{\Sigma}$. Particular significance assumes the variance-covariance matrix Σ as it captures both the marginal and conditional relationships among variables in $\mathbf{y}$. In the GGMs, we do not directly model $\boldsymbol{\Sigma}$ itself, but instead, we focus on modeling the standardised elements of

$$\boldsymbol{K} = \Sigma^{-1} \tag{1}$$

Each element in the standardised precision matrix represents the partial correlation between two variables, controlling for all other variables in the model:

$$\omega_{ij} = \frac{-k_{ij}}{\sqrt{k_{ii}k_{ij}}} \tag{2}$$

If the partial correlation is zero (no edge), then there is no link between the corresponding variables in the network. As recommended by Epskamp et al. (2017), to achieve a clearer modeling and interpretation of the network parameters, the inverse variance-covariance matrix can be framed in this form:

$$\Sigma = \Delta(I - \Omega)^{-1}\Delta, \tag{3}$$

where Ω contains partial correlation coefficients on off-diagonal elements and zeroes on the diagonal, and Δ is a diagonal scaling matrix. Estimating the GGM involves estimating the precision matrix. Various estimation methods can be used. More details can be found in Isvoranu et al. (2022). Since we are working with responses evaluated on a 5-point Likert scale, a potential approach involves building a model in which a GGM is hypothesized to underlie a collection of ordered categorical responses. Drawing from Epskamp et al.'s (2018) methodology, we employed polychoric correlations as input for GGM estimation tools that operate on a correlation matrix.

3. Results

Psychometric network analyses were performed on partial correlation matrices derived from both the burnout inventory and items related to teachers' technology interactions during lessons. It is worth noting that prior to conducting the analyses, the items B10, D1, D5, and D8 were reversed. The analysis employed the *qgraph*, the *bootnet*, and *igraph* packages (Isvoranu et al., 2022), within the R programming environment. The networks generated were subsequently visualised using the qgraph package.

The psychometric network analysis was carried out in accordance with the steps described by Epskamp et al. (2018). We combined the data into three group-teachers' responses, representing primary, middle, and high school levels. We initially constructed distinct networks for each of the three datasets and for each scale that was taken into account. The nodes in these networks corresponded to the variables listed in Table 1, with then interconnections between nodes depicted by partial correlation coefficients. Then, we utilised the Network Comparison Test (NCT; van Borkulo et al., 2021) from the R NetworkComparisonTest package to assess whether the underlying structure could be consistent across these three groups. Results of the test for both burnout scale and the investigation of teacher's device interactions suggest no significant disparities in the three network structures. Consequently, we merged the datasets for all subsequent analyses. For each scale, we also determine a partition of nodes. To this end, we perform a community detection analysis. The results of *louvain* community detection algorithm (Blondel et al., 2008) are displayed in Figure 1. The *louvain* algorithm supported the selection of 4-cluster solution for the burnout network. The colors employed in the plot correspond to the community identifiers

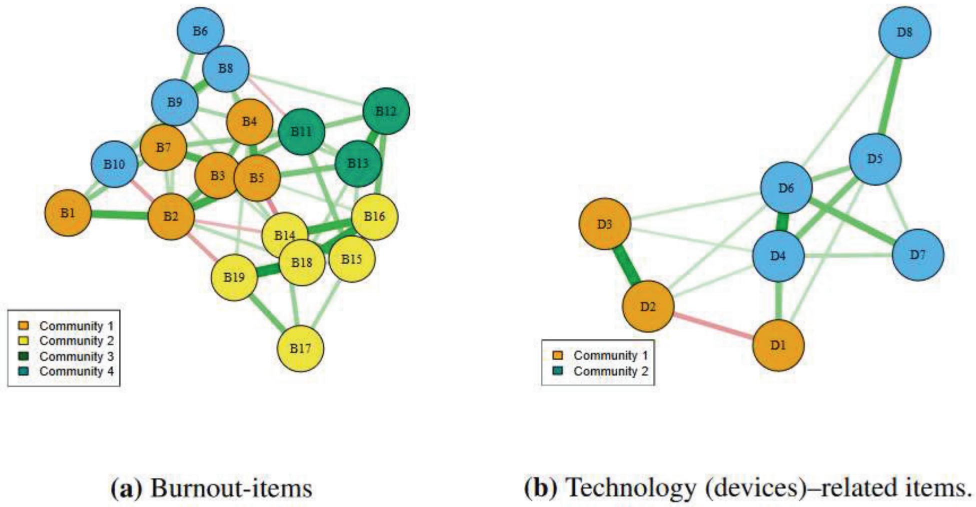
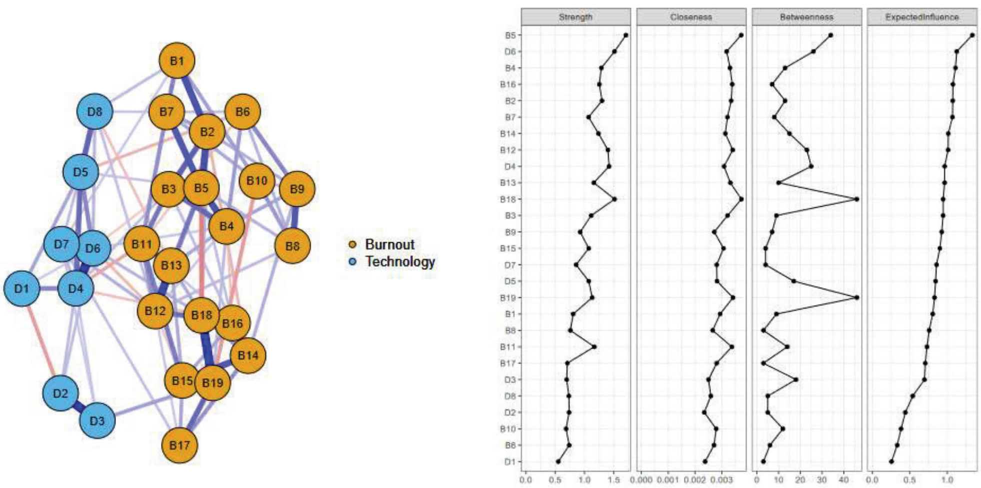


Figure 1: Network of the nodes listed in Table 1, with communities estimated using the *louvain* algorithm.



a b

Figure 2: Estimated global network (a) and centrality indices of the nodes ordered by expected influence (b)

The initial cluster, encompassing items B1:B4 and B7, corresponds to the underlying construct referred to as "personal burnout" in the CBI by Kristensen et al. (2005). On the other hand, item B6 was situated within a different cluster, as demonstrated in Figure 1. Predictably, item B1displays a significant connection with B2. Additionally, we observe a strong correlation between item B5 and both B2 and B4. The second *louvain* community accurately captures the student-related burnout dimension of the CBI. Strong positive edges are found in most of the items of this cluster. On the other hand, the algorithm has divided the initial work-related burnout dimension of the CBI into two separate communities, which can be interpreted post-hoc as: "EmotionalStrain" (Community 3) and "Physical Exhaustion and Energy Depletion" (Community 4).

Figure 1 also provides a two-cluster solution for the technology network. The first community, containing the items D1:D3, can be termed "Technology utilisation and management", whereas the second community is associated with "Technology influence on Teaching and Engagement." To explore the connection between teacher's burnout and technology interaction, we complemented the analysis by constructing a psychometrics network that incorporates both dimensions. Figure 2 illustrates the network configuration, where the edges are represented by partial correlation coefficients. A careful examination of Figure 2 uncovers an adverse association between the item that explores the perception of teachers' fatigue during their work hours (B12) and desire to remove devices from the classroom if given the choice (D6). Likewise, negative relationships are observed between the items addressing potential obstacles due to technology usage in lessons (D4) and emotional exhaustion (B11). D4 also exhibits a negative correlation with B12.

Additionally, for each node, we present in Figure 2 its estimated strength (direct connections to other nodes), its closeness (indirect connections to other nodes), its betweenness (importance in linking other nodes together), and its expected influence (potential influence on other nodes within the network). Notably, concerning betweenness and closeness, items D1 and D2 were positioned at the periphery of the network. Conversely, the items B5 and B18 were among the most central nodes with respect to strength and betweenness. In other words, these nodes had strong direct connections to other nodes. Regarding the expected influence metric, it is evident that B5, D6, B4, B16 and B2 are the items that significantly influence the overall network dynamics.

4. Concluding remarks

Our psychometric network analysis has unveiled a consistent foundation for both teachers' burnout and technology interaction. Unlike structural equation modelling, which relies on predefined relationships grounded in theory, psychometrics network analysis allows for a more data-driven exploration, revealing patterns and connections not initially hypothesized. The centrality indices provide valuable insights into overall network dynamics, guiding future investigations into teachers' exhaustion, career longevity concerns, and energy depletion. Notably, adverse associations were discovered between indicators of teachers' fatigue and their inclination to remove devices from the classroom. Additionally, negative correlations emerged between technology-related obstacles and emotional exhaustion.

In conclusion, these findings contribute to a deeper understanding of the complex interplay between teachers' well-being and their interactions with technology in an educational setting.

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