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Is the Self-Evaluation of Resilience a Valid Assessment to Measure Resilience in Healthcare? A Confirmatory validation Study in Italian Healthcare Settings

Annalisa Pennini[1], Rosario Caruso[2,3], Gianluca Conte[3], Maddalena De Maria[4], Lauren Nirta[5], Arianna Magon[3], and Giampaolo Armellin[1]

Abstract

Although the Self-Evaluation of Resilience (SEOR) scale is a promising tool for assessing resilience in healthcare, its psychometric structure has not yet been confirmed. This study aimed to assess and validate the four-factor psychometric structure of the SEOR. Between September 2020 and January 2021, cross-sectional data were collected from randomly selected healthcare workers, managers, and administrators from a predefined network of 70 healthcare facilities in 12 Italian regions. The sample size was based on a Monte Carlo simulation using estimates from the SEOR developmental study. Two confirmatory factor models (first-order and second-order) were predefined. The responders (n = 199, response rate, 81%) were healthcare workers (n = 99; 49.7%), managers (n = 86; 43.2%), and administrators (n = 14; 7%). The two confirmatory factor models each showed a good fit in explaining sample statistics, corroborating the capacity of the scale to provide a total score of resilience and sub-scores for organizational resilience, network-based resilience, skill-based resilience, and individual-based resilience. The Molenaar-Sijtsma coefficients (internal consistency) ranged between 0.889 and 0.927. The SEOR enables managers and policy-makers to comprehensively screen resilience in healthcare from an epidemiological perspective.

Keywords

healthcare, health system, policy-making, psychometric, resilience, resilient healthcare, scale, validation

Introduction

Healthcare systems are under constant and considerable pressure resulting from the COVID-19 pandemic and the economic crisis (Arsenault et al., 2022; Haldane et al., 2021; Zhong et al., 2015). In today's rapidly evolving healthcare environment, resilience is a key requirement for the performance of healthcare systems and is crucial to the planning and delivery of high-quality health-related services (Agnello et al., 2017; Aristodemou et al., 2021). Resilience in healthcare is a multidimensional phenomenon defined by the proactive capacity of healthcare organizations, units, teams, and individuals to adjust to changes and potential problems in daily practices rather than oppose them (Aase et al., 2020).

The foundation for resilience in healthcare lies in healthcare systems' ability to utilize both internal and external resources to promptly adapt to changes in daily organizational functioning and to effectively address burgeoning issues so that healthcare delivery continues to be of a high standard (Braithwaite et al., 2015). Thus, resilience leads organizations to adapt their function in a very short period and guarantees continuing endurance of high-quality performance in challenging situations. The attributes of resilience include internal resources, such as 'sense-making' and 'experience', and external resources, such as available networks and regulations (Aase et al., 2020). Stakeholder engagement and collaborative learnings are antecedents of resilience in

[1]CBA Zucchetti, Rovereto, Trento, Italy
[2]Department of Biomedical Sciences for Health, University of Milan, Milan, Italy
[3]Health Professions Research and Development Unit, IRCCS Policlinico San Donato, San Donato Milanese, Italy
[4]Department of Biomedicine and Prevention, University of Rome Tor Vergata, Rome, Italy
[5]MediSpeak Communications, Bukgu, Busan, South Korea

Corresponding Author:
Rosario Caruso, PhD, RN Head of Health Professions Research and Development Unit, IRCCS Policlinico San Donato, San Donato Milanese and Researcher Department of Biomedical Sciences for Health, University of Milan, Milan, Italy.
Email: rosario.caruso@grupposandonato.it

healthcare (Wiig et al., 2020). Contrary to the majority of current research on healthcare quality, which tends to focus on healthcare failures, resilience research focuses on analyzing healthcare processes with positive outcomes to show how high-quality healthcare processes can be deployed in healthcare systems (Aase et al., 2020; Braithwaite et al., 2015; Wiig et al., 2020).

The study of resilience in healthcare has roots in sociology, psychology, and ecology, which has led to the development of different appraisal tools (Pennini & Armellin, 2021; Wiig et al., 2020). The sociological perspective evaluates the organization and recovery capabilities of system stability in the wake of major disasters (Pennini & Armellin, 2021). The psychological perspective focuses on investigating individuals' psychological ability to deal with challenges, and this approach is frequently connected with resilience in vulnerable populations. The ecological perspective concentrates on how biological systems adapt to deal with unforeseen changes to preserve system stability (Pennini & Armellin, 2021; Wiig et al., 2020).

Pennini and Armellin recently developed and performed a preliminary evaluation of the Self-Evaluation of Resilience (SEOR) tool, which is a self-reported scale for assessing resilience in healthcare settings (Pennini & Armellin, 2021). Using a broad, multidimensional definition of resilience with multiple levels with a framework that integrates several theoretical models (Aase et al., 2020), the SEOR overcomes the drawbacks of several existing assessment tools rooted in narrower fields (Bruneau et al., 2003; Kantur & İşeri-Say, 2012; Kotnour & Mallak, 2009; Kruk et al., 2015; Martinelli & Tagliazucchi, 2018; Weick & Sutcliffe, 2007). In the SEOR, levels of resilience are organized and scaffolded in four domains: organizational resilience, network-based resilience, skill-based resilience, and individual-based resilience (Pennini & Armellin, 2021).

Organizational resilience, which comprises nine items, gauges how well an organization is able to modify its operations in response to pressures and challenges and has previously shown good internal consistency. Network-based resilience, which comprises four items, assesses the capacity of an organization to use its network and engage stakeholders to support adaptations to specific contextual challenges. Likewise, skill-based resilience, which comprises six items, focuses on determining an organization's capacity to use the competencies of its employees to sustain collaborative learning. Finally, individual-based resilience, which comprises three items, focuses on assessing individuals' ability to use the resources of an institution to learn from their mistakes, rely on others, and deal with unexpected problems (Engelsberger et al., 2022).

The main advantages of the SEOR scale are conferred by its psychometric structure, which reflects domains that are not otherwise measurable by a single scale and would therefore require multiple assessments (Ahern et al., 2006; Hoffman & Hancock, 2017). A multidimensional assessment of resilience in healthcare allows managers and policy-makers to screen organizational resilience, recognize weaknesses, and identify each aspect that contributes to the successful adaptation of healthcare organizations in response to internal or external pressures and challenges (Pennini & Armellin, 2021).

Validation of the psychometric characteristics of a self-report scale measures the appropriateness of the scale for assessing the particular construct of interest (Mueller & Hancock, 2001). Assessment of validity and reliability requires several studies using different samples and analytical approaches. An exploratory study determined the dimensionality of the SEOR. Despite satisfactory evidence of both psychometric validity and reliability (internal consistency), further evidence of dimensionality in a broader context than the one in which the scale was developed is needed to enable wide and systematic utilization adoption of the SEOR for the assessment of resilience in a range of healthcare contexts. For this reason, the current study aimed to assess and validate the psychometric structure of the SEOR.

Materials and methods

Design

This study has an observational design with a cross-sectional data collection approach. It follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines for reporting observational studies (see Supplementary file 1) (von Elm et al., 2008). The Institutional Review Board of the coordinating center (CBA Zucchetti) approved the study protocol (*n*. 6/20) developed under European and domestic regulations for conducting observational studies (Orel & Bernik, 2018). Prior to enrollment in the study, all participants signed an electronic informed consent form as well as a disclaimer acknowledging the data protection policy.

Samples, sample sizes, and procedures

Sampling followed a stepwise procedure based on the following six steps: definition of the population, definition of the sampling frame, selection of sampling technique, determination of sample size, collection of data, and evaluation of response rate (Taherdoost, 2016).

The target population was defined as the network of facilities working with the authors for educational purposes (70 healthcare facilities in 12 Italian regions: Emilia, Romagna, Friuli Venezia Giulia, Lazio, Liguria, Lombardy, Marche, Piemonte, Apulia, Tuscany, Trentino Alto Adige, Umbria, and Veneto). The sampling frame was defined as the 'professional role' ('healthcare worker', 'manager', or 'administrative staff'). The sampling technique was selected to ensure a balanced number of responses from multiple relevant perspectives within the predefined target population (Taherdoost, 2016). In small clinics (<80 beds), one representative from each professional category of the sampling frame was invited to participate; in medium facilities (81–350 beds) and in large hospitals

(>351 beds), two representatives from each professional category were invited to participate.

The sample size was determined using a Monte Carlo simulation based on each item-level statistic published in the SEOR developmental study's exploratory factor analysis (Pennini & Armellin, 2021). We performed the Monte Carlo simulation following the recommendations of Muthén and Muthén for determining a minimum of 80% power to reject the null hypothesis of a factor correlation equal to zero (i.e., the matrix resulted from the model is statistically identical to the input matrix) (Muthén & Muthén, 2002). Not accounting for missing data, the simulation indicated 175 responders were required to show adequate goodness-of-fit in explaining the simulated sample statistics of the simulated datasets. Accounting for 5% missing data (skipped answers in the questionnaire) in the simulation, we determined that 205 responders were required. We anticipated a response rate of 80% based on published studies validating self-reported scales (Magon et al., 2021). Finally, a target of 246 participants was selected as the target sample size.

Between September 2020 and January 2021, a total of 246 individuals were invited to participate in the current study. Following a systematic random selection method, all 70 hospitals in the target population were invited to participate in the study by email, followed by a discussion meeting. Following voluntary approval by each hospital Director based on a local evaluation of feasibility, relevant staff members were stratified by professional category and randomly selected from within each stratum to receive an invitation to participate. The principal investigator sent one invitation to each candidate via web-based email. The email contained a description of the study by including its aims and an impact statement, the estimated approximate time for completing the questionnaire (15 minutes), that participation was voluntary and confidential, and that there was an option to 'opt out' without any direct or indirect negative consequence. It also explained the mandated data protection and storage requirements, and respondents were required to electronically sign a disclaimer form acknowledging the data protection policy. Respondents who did not choose to opt-out were then directed to fill in the SEOR questionnaire directly embedded in the email. In accordance with the requirements of the General Data Protection Regulations in Europe, a cloud-based system was used to collect data (Orel & Bernik, 2018). The response rate was evaluated by calculating the difference between the number of invitations sent and the number of total responses. Partial responses were not permissible.

Measurements

Participants were asked to provide minimal socio-demographic information, indicating their professional group (healthcare worker, manager, administrative staff), the system of accreditation of the hospital (public, private), the region of the hospital, and the size of the hospital (number of beds and number of employees). Data about sex, age, and years of employment were not collected to ensure the anonymity of respondents, particularly in small facilities where even a few demographics could be used to identify the responder.

The version of the SEOR used in the current study was the same as the previous developmental study (Pennini & Armellin, 2021). Thus, the SEOR encompassed 22 items measuring four domains, all of which showed at least adequate internal consistency. In the developmental study (Pennini & Armellin, 2021), the domain of organizational resilience comprised nine items (Cronbach's alpha, 0.916), network-based resilience comprised four items (Cronbach's alpha, 0.863), skill-based resilience comprised six items (Cronbach's alpha, 0.903), and individual-based resilience comprised three items (Cronbach's alpha, 0.812). Each item was represented by a statement describing a specific attribute of perceived resilience, which was answered by selecting a point on a 5-point Likert scale (from 1 "completely disagree" to 5 "completely agree"). The domains were standardized into a score ranging from 0 to 100, where higher scores indicate higher levels of resilience, following the procedure described in the developmental study (Pennini & Armellin, 2021).

Statistical analysis

Data were preliminary assessed using frequency analyses for possible errors, outliers, and missingness. Normality was assessed by univariate analysis using the Shapiro-Wilk tests, and sample statistics were summarized by employing descriptive analysis according to the level of measurements of each analyzed variable and data distribution.

The SEOR developmental study assessed the most plausible factor structure of the SEOR using an exploratory approach (Pennini & Armellin, 2021). An unconstrained confirmatory factor analysis model using the maximum likelihood robust estimation method was used to validate the factor structure derived from the developmental study (Pennini & Armellin, 2021). In the pre-specified model, organizational resilience predicted items 1–9, network-based resilience predicted items 10–12 and 19, skill-based resilience predicted items 13–18, and individual-based resilience predicted items 20–22.

In order to determine possible avenues for improvements in χ^2 and to explain sample statistics, modification indices from the model were examined by evaluating χ^2 behaviors when a single parameter was removed. Overall, the following criteria for establishing a goodness-of-fit were considered: χ^2 statistics [χ^2 and χ^2/degrees of freedom (df)], comparative fit index (CFI), Tucker and Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). CFI and TLI values of .90–.95 suggested a good fit, and RMSEA and SRMR values under .08 indicated a good fit (Xia & Yang, 2019).

Given that organizational resilience, network-based resilience, skill-based resilience, and individual-based resilience were previously described as moderately inter-correlated (Pennini & Armellin, 2021), a model including a second-order factor was tested and compared with the model including only first-order factors. A comparison was performed by employing an χ^2 difference test involving the determination of a p-value for the χ^2 difference (TRd) and accounting for the comparison of the difference between the degrees of freedom (Δdf). We determined that the model with the best-fit indices and the more accurate factor loading estimates based on standard errors was the most appropriate for explaining the data suggestive of discriminant validity.

Because the SEOR is a multidimensional scale, we selected Molenaar-Sijtsma coefficients (MS statistics), which are estimates of reliability, for assessing the internal consistency of each domain (Tavakol & Dennick, 2011). MS statistics were computed using the package MSP5 in the R environment (R Foundation for Statistical Computing, Vienna, Austria) (Molenaar et al., 2000).

The scores of each domain in the SEOR were standardized on a scale of 0–100 using the method described in the development study (Pennini & Armellin, 2021). In brief, we summed all the items for each domain and subtracted the lowest possible score for that domain. We then multiplied the resulting value by the values resulting from dividing 100 by the difference between the maximum possible score and the number of items in that domain. This process was also applied to calculate the total score of the SEOR.

All statistical analyses were performed using IBM SPSS Statistics for Windows, Version 27.0 (IBM Corp., Armonk, NY), Mplus version 8.1 (Muthén & Muthén, 1998–2017), and R 4.2.1 (R Foundation for Statistical Computing, Vienna, Austria, http://www.R-project.org/) with two-sided null hypotheses and a significance level set to 5%.

Results

Sample

There were 199 responders from 70 hospitals (Table 1), with a response rate of 81%. The majority of responders were

Table 1. Characteristics of the respondents (n = 199) and facilities (n = 70).

		N	%
Type of facility			
	Tertiary-level hospital	12	17.1
	Secondary-level hospital	32	45.7
	Community and primary care facilities	26	37.1
Hospital beds			
	Small (≤80 beds)	18	25.7
	Medium (81-350 beds)	38	54.3
	Large (>351 beds)	14	20.0
	Median, interquartile range (IQR)	110	50–418
Region (respondents)			
	Emilia romagna (central northern region)	13	6.5
	Friuli venezia giulia (northeast region)	4	2
	Lazio (central region)	1	0.5
	Liguria (northwest region)	2	1
	Lombardy (northwest region)	37	18.6
	Marche (central region)	3	1.5
	Piemonte (northwest region)	6	3
	Apulia (southern region)	1	0.5
	Tuscany (central region)	5	2.5
	Trentino alto adige (northeast region)	46	23.1
	Umbria (central region)	1	0.5
	Veneto (northeast region)	80	40.2
Hospital			
	Public	26	37.1
	Private	44	62.9
Number of employees			
	Median, interquartile range (IQR)	80	42–1250
Profession			
	Healthcare worker	99	49.7
	Manager	86	43.2
	Administrative worker	14	7

healthcare workers (n = 99; 49.7%), followed by managers (n = 86; 43.2%) and administrative workers (n = 14; 7%). The majority of the enrolled facilities were secondary-level hospitals (n = 32; 45.7%), followed by community and primary care facilities (n = 26; 37.1%) and tertiary-level hospitals (n = 12; 17.1%). There were 18 (25.7%) small facilities (≤80 beds), 38 (54.3%) medium-sized hospitals (81–350 beds), and 14 (20.0%) large hospitals (>351 beds). Most respondents were from the northern regions of Italy (Veneto, Trentino, Alto Adige, Friuli Venezia Giulia) (n = 130; 65.3%). Most facilities (n = 44, 62.9%) were privately owned, even if they delivered both public and private health services. The median number of employees per hospital was 80 workers, with an interquartile range (IQR) between 42 and 1250.

Confirmatory factor analysis and reliability

The unconstrained model well explained the sample statistics ($\chi^2_{(203)}$ = 504.305; p < .001; χ^2/DF = 2.5; CFI = 0.927; TLI = 0.917; RMSEA = 0.079, 90% CI = 0.074–0.091, p < 0.001; and SRMR = 0.54). Correlations between first-level factors ranged from 0.494 to 0.710. All factor loadings in the posited model were positive, indicating a positive relationship between each observed variable and its corresponding latent factors. The magnitude of factor loadings reflected the strength of the relationship between the observed variables and the latent factors and ranged from 0.546 to 0.898, indicating that the latent factors explained a significant amount of variance in each observed variable (Table 2). Specifically, the organizational resilience factor explained 63.3% of the variance of the observed items (items 1–9), the network-based resilience factor explained 49.3% of the variance of the observed variables (items 10–12, and 19), the skill-based resilience factor explained 65.1% of the variance of the observed variables (items 13–18), and the individual-based resilience factor explained 54.7% of the variance of the observed variables (items 13–18). The standard errors for the factor loadings ranged from 0.023 to 0.092, indicating some variability in the estimated factor loadings. A large standard error suggests a less precise estimate, while a small standard error indicates a more precise estimate. Thus, the variability in the estimated factor loadings suggests the need for additional modifications to the model. In this regard, given the theoretical structure of the SEOR, a second-order factor was tested in a second model to explain the first-level factors.

The model, which included a second-order factor predicting the first-level factors, adequately explained sample statistics as well ($\chi^2_{(205)}$ = 542.722; p < .001; χ^2/DF = 2.6; CFI = 0.927; TLI = 0.917; RMSEA = 0.078, 90% CI = 0.074–0.090, p < 0.001; and SRMR = 0.53). The second-order factor was positively correlated with organizational resilience (0.865), network-based resilience (0.788), skill-based resilience (0.880), and individual-based resilience (0.848). All factor loadings in the tested model were positive, indicating a positive relationship between each observed variable and its corresponding latent factors. Specifically, the factor loadings ranged from 0.546 to 0.897, indicating that the latent factors accounted for a significant amount of variance in each observed variable (Table 2). The organizational resilience factor explained 63.3% of the variance of the observed items (items 1–9), the network-based resilience factor explained 49.3% of the variance of the observed variables (items 10–12 and 19), the skill-based resilience factor explained 65.1% of the variance of the observed variables (items 13–18), and the individual-based resilience factor explained 54.6% of the variance of the observed variables (items 13–18). The standard errors for the factor loadings ranged from 0.05 to 0.059, indicating that the estimates (factor loadings) were more precise than the ones without a second-order factor and represented reliable estimates of the true underlying relationships between the measured variables and the latent factors. Even if the scaled χ^2 difference with Δdf = 2 showed non-significant differences, the comparison of standard errors between the two models indicates that the model that included a second-order factor showed a better discriminant validity for explaining sample statistics.

The Molenaar-Sijtsma coefficients ranged between 0.889 and 0.927 (organizational resilience, 0.927; network-based resilience, 0.899; skill-based resilience, 0.901; and individual-based resilience, 0.889). These coefficients of reliability, used to estimate the reliability of the latent variable scores based on the factor loadings and error variances in the measurement model, suggested that the latent factors in the model measured the underlying constructs with a high degree of accuracy and consistency. The adequate reliability of the Molenaar-Sijtsma coefficients provided confidence in the validity of the model and its ability to accurately represent the underlying concepts of organizational resilience.

Supplementary file 2 depicts the synthesis of the total SEOR score and the scores for each domain. The bivariate linear relationships among first-order and second-order factors (labeled 'total resilience score') are shown in Figure 1.

Discussion

The results of the current study corroborated the factor structure of the SEOR reported in the SEOR developmental study (Pennini & Armellin, 2021). The main finding of the current study is the adequate fit to sample statistics of the two previously posited models, which confirm that the SEOR is a reliable composite tool for measuring organizational, network-based, skill-based, and individual-based resilience in healthcare. The findings of this study have important implications for measuring and understanding resilience in healthcare. Specifically, our results indicate that the SEOR is a reliable and valid tool for measuring resilience across multiple domains, including organizational, network-based, skill-based, and individual-based resilience. Our study also provides evidence for the internal consistency reliability of the SEOR in healthcare. The presence of a second-order factor is consistent

Table 2. Factor loadings and reliability coefficients.

		First-Order Factors		Second-Order Factor and First-Order Factors	
		Factor loadings (standardized)	Standard error	Factor loadings (standardized)	Standard error
Organizational resilience					
I1	My organization is determined to affirm its vision in challenging situations and preserve pursuing the core values of its vision	0.546	0.546	0.546	0.059
I2	My organization manages to generate several solutions for the current challenges	0.827	0.827	0.827	0.026
I3	My organization resists in every situation maintaining a good quality in the work environment	0.750	0.750	0.750	0.035
I4	My organization continues its mission in every challenging situation	0.701	0.701	0.701	0.042
I5	My organization acts (takes action) quickly	0.827	0.827	0.828	0.027
I6	My organization is capable of generating opportunities even under unfavorable circumstances	0.862	0.862	0.862	0.024
I7	My organization is agile in taking action when needed	0.875	0.875	0.876	0.021
I8	My organization respects its employees and works efficiently	0.874	0.874	0.874	0.024
I9	My organization uses its network of relationships as resources (sources) of knowledge	0.898	0.898	0.897	0.022
Molenaar-sijtsma coefficient 0.927					
Network-based resilience					
I10	I can use the networks of my organization to facilitate my daily activity	0.701	0.701	0.699	0.050
I11	The relationships among employees are an important source of information for the organization	0.596	0.596	0.595	0.051
I12	My organization uses relationship networks to positively influence the context in which it operates	0.890	0.890	0.892	0.040
I19	My colleagues have a variety of informal contacts that they sometimes use to solve problems	0.622	0.622	0.622	0.048
Molenaar-sijtsma coefficient 0.899					
Skill-based resilience					
I13	Resources are continuously allocated for training and retraining personnel who work with the technical system	0.833	0.833	0.833	0.025
I14	The staff has more than enough training and experience for the work they do	0.696	0.696	0.696	0.040
I15	My organization is actively interested in developing the skills and knowledge of the people who work here	0.870	0.870	0.871	0.023
I16	My organization promotes tasks that allow me to face challenges	0.799	0.799	0.799	0.029
I17	The people who work at this organization are known for their ability to use knowledge in new ways	0.750	0.750	0.750	0.034
I18	This organization is committed to developing the competence of employees	0.892	0.892	0.892	0.022
Molenaar-sijtsma coefficient 0.901					
Individual-based resilience					
I20	In this organization, people learn from their mistakes	0.643	0.643	0.639	0.050
I21	In this organization, people rely on each other	0.719	0.719	0.721	0.041
I22	In this organization, most people have the skills to deal with unexpected problems that arise	0.856	0.856	0.857	0.035
Molenaar-sijtsma coefficient 0.889					

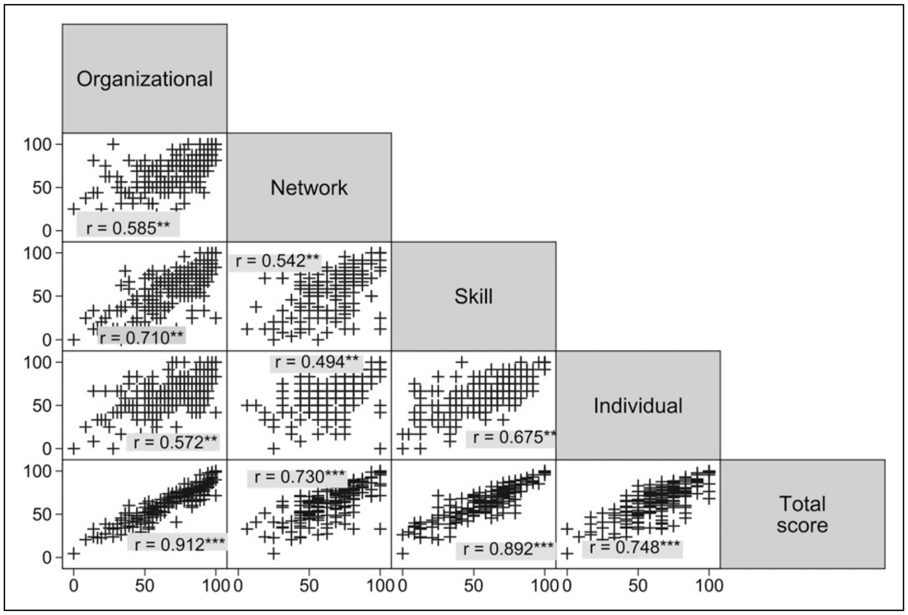

Figure 1. Correlations between the SEOR's domains.

with the indications provided in the developmental study to compute a total score (Pennini & Armellin, 2021). Broadly, the four domains of the SEOR are consistent with recent frameworks published to guide research on resilience in healthcare (Aase et al., 2020).

Organizational resilience is critical to any healthcare organization's ability to adapt and recover from disruptive events such as natural disasters, pandemics, and unexpected changes. The SEOR reflects the level of managerial commitment to the delivery of essential health services during challenging times such as the COVID-19 pandemic (Finucane et al., 2020). Our study demonstrates that the SEOR is a reliable and valid tool for measuring an organization's capacity to anticipate, manage, and learn from disruptions, as well as its ability to resist challenging situations by innovating and finding solutions for growth in response to such events. Planning for business continuity and worst-case scenario recovery is a key pillar of organizational resilience. Ultimately, foresight and preparation for worst-case scenarios facilitate the management of any challenge an organization faces, making the SEOR an invaluable tool for healthcare organizations looking to build and maintain their resilience (Margherita & Heikkilä, 2021).

Network-based resilience is the ability of individuals and organizations to establish and maintain robust relationships and networks, enabling effective information sharing, resource allocation, and collaborative problem-solving. Through collaboration, organizations can leverage each other's strengths, resources, and knowledge to better navigate uncertainty. Assessment of network-based resilience in terms of network building and collaborative problem-solving can help identify an organization's strengths and areas which require improvement (Lyng et al., 2021). Our study shows that the SEOR is a reliable and valid tool for measuring this construct by evaluating the level and quality of individuals' and organizations' connections with other healthcare ecosystem stakeholders. The internal consistency of network-based resilience demonstrated in the current study was in agreement with earlier exploratory research and the literature advocating for robust stakeholder engagement and collaborative learning within organizations (Braithwaite et al., 2015). Thus, our findings further emphasize the importance of fostering strong relationships and networks to increase organizations' ability to respond to and recover from disruptions (Pennini & Armellin, 2021).

Skill-based resilience is a subtype of individual-based resilience, which reflects an individual's ability to manage and cope with stressors and challenges in their work environment, is a critical aspect of an organization's overall resilience. While other scales have been developed to measure individual-based resilience in relation to disasters, the SEOR is the only scale that places individual-based resilience in the context of organizational resilience by adding emphasis to skill-based resiliance (Khan et al., 2022). This domain evaluates an individual's self-efficacy, problem-solving skills, and ability to manage emotions and maintain positive attitudes in the face of adversity. The inclusion of skill-based resilience as a domain in the SEOR is novel and underscores the importance of individual-based resilience in contributing to an organization's overall resilience. Our study demonstrates that the skill-based resilience domain is reliable and valid.

Individual-based resilience refers to individuals' ability to withstand and recover from personal or professional challenges, such as burnout, work-life balance issues, and job dissatisfaction.

The individual-based domain is unique in that it takes into account the broader context of organizational wellbeing, which provides the foundation for developing individual-based resilience (Caruso et al., 2016). Notably, this domain showed strong reliability based on its internal consistency coefficients, indicating its robustness as a measure of individual-based resilience. Our study demonstrates that the SEOR can effectively measure this construct by evaluating an individual's psychological flexibility, coping strategies, and self-care practices.

The current study has several limitations that influence the interpretation and generalizability of the results. By design, we excluded partial responses. The electronic case report form was developed to record complete responses only. The form indicated that a valid recorded answer was required for each item before moving to the next. Thus, no items could be missed, and we recorded a full dataset for our analysis. However, we are unsure if any participants withdrew from completing the questionnaire after starting it. In this case, it is likely that we lost partial information either at random (in cases where the respondent was interrupted while responding to the questions and did not return to complete the form) or not at random, in cases where the responder did not perceive the questionnaire as attractive. The main purpose of corroborating the results of the SEOR developmental study was to involve the viewpoints of different groups of employees from several organizations within a predefined hospital network. The lack of representation of various other professional groups from within each organization limits the internal validity of the study. In this sense, future studies are required to determine if the SEOR is invariant across different professional groups, organizations, and networks. The specific period of data collection (September 2020–January 2021), which were the months of the second wave of the COVID-19 epidemic in Italy, resulted in specific requests from multiple stakeholders and the Institutional Review Board to ensure the full anonymity of respondents to avoid placing additional unnecessary stress on any individual who provided negative answers. Thus, the sociodemographic data collection was restricted, limiting the study's external validity. Therefore, we urge caution in generalizing the results of the psychometric performance of the SEOR because the circumstances may have inflated the viewpoints of the responders. On the other hand, the descriptive data (Figure 1) of the scores indicate a highly challenging situation for every employee within the healthcare setting (Manara et al., 2021). Other limitations include the absence of longitudinal information on the SEOR (its stability over time) and its relationships with other measures to assess criterion-related validity.

Conclusions

The SEOR is a valid and reliable tool for evaluating resilience in healthcare systems, providing a comprehensive assessment of organizational, network-based, skill-based, and individual-based resilience. The results of this study support the psychometric validity of the SEOR, which may be applied in various contexts to identify areas of strength and weakness and promote sustained resilience. Policy-makers, senior managers, and the scientific community can confidently use the SEOR to develop solutions and support resilient healthcare systems.

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ORCID iDs

Rosario Caruso https://orcid.org/0000-0002-7736-6209
Gianluca Conte https://orcid.org/0000-0002-8171-8203
Arianna Magon https://orcid.org/0000-0003-0440-6940

Supplemental Material

Supplemental material for this article is available online.

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