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Are Resilient Occupational Therapists at Low Risk of Burnout? A Structural Equation Modeling Approach Combined with Latent Profile Analysis in a Greek Sample

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Abstract

This study focused on the following research objectives: 1) to examine how resilience is related to personal accomplishment of Occupational Therapists; 2) to examine the relationship between personal accomplishment, depersonalization, and emotional exhaustion; 3) to profile Occupational Therapists based on resilience, personal accomplishment, emotional exhaustion, and depersonalization. The sample included 315 Greek Occupational Therapists. Data was collected on resilience (CD-RISC 10), personal accomplishment, emotional exhaustion, and depersonalization (MBI-HSS). A Structural Equation Model (SEM) was successfully specified with the two-step approach to examine how resilience is related to personal accomplishment and how personal accomplishment, emotional exhaustion, and depersonalization interact. The measurement and full SEM model showed a good fit and adequate model-based reliability. The SEM analysis suggested that increased resilience predicted a major increase in personal accomplishment with a standardized direct effect > 0.70, $p < 0.001$ (49% explained variance). Additionally, there was a mediation effect of depersonalization in the relationship between personal accomplishment and emotional exhaustion with a significant indirect and total effect, $p < 0.001$. Then, Latent Profile Analysis (LPA) followed to describe the Occupational Therapists based on their score on resilience, personal accomplishment, emotional exhaustion, and depersonalization. During the LPA the optimal profile model was selected using an integrative model fit calculation approach based on the Analytic Hierarchy Process (AHP) and 4 profile groups of Occupational Therapists emerged. The scoring patterns of the 4 groups that emerged from PLA suggested that high-resilient Occupational Therapists are at lower burnout risk and low-resilient Occupational Therapists are at higher burnout risk.

Keywords

Burnout, Resilience, Emotional Exhaustion, Structural Equation Modeling, SEM, Latent Profile Analysis, LPA, Occupational Therapy, Occupational Therapists

1. Introduction

In the last twenty years, there was a dramatic increase in the prevalence of burnout in all Western societies (Glasberg, Eriksson, & Norberg, 2007). Relevant Scholarship argues that occupational therapy is generally a challenging, highly stressful, and burnout-causing health profession (Gupta, Paterson, Lysaght, & Von Zweck, 2012). This makes occupational therapists (OTs)—like all health professionals—prone to burnout (Lloyd & King, 2001; Scanlan & Hazelton, 2019; Sturgess & Poulsen, 1983).

Why is this a problem? Burnt out OTs are more likely to offer low-quality care or quit their job limiting institutional knowledge, raising training budgets, or discontinuing the therapeutic relationship (Scanlan & Still, 2013). Furthermore, they can spread burnout and discontentment to peers, contaminating the entire staff (Scanlan, & Hazelton, 2019). However, OTs "do not choose to burn out" (Schlenz, Guthrie, & Dudgeon, 1995: p. 986). The prolonged, unrelieved work stress in a highly demanding workplace and the complexity of healthcare expose OTs to burnout (Derakhshanrad, Piven, & Ghoochani, 2019; Maslach, 1976). However, a unique feature of burnout in comparison to stress is that the social interactions between the OT and the recipient are the major source of stress (Schlenz et al., 1995), and this relevancy to the work environment is one of its major differences from depression (Maslach, Jackson, & Leiter, 1996).

1.1. Review of Relevant Scholarship

Job burnout is the inability to use coping resources in the face of work-related stressful situations, causing a sense of helplessness (Derakhshanrad et al., 2019). Individuals suffering from burnout may also experience diminished personal health resources, recurrent minor health problems, boredom, and inflexibility (Maslach, 1978; Sturgess & Poulsen, 1983). In the context of occupational therapy burnout is the physical, emotional, and mental exhaustion caused by the loss of OTs' interest in providing the expected healthcare services (Hendrickson, 1979).

After consistent research results, burnout is described as a syndrome (Maslach, Jackson, & Leiter, 1996) OTs and all health professionals may commonly experience in response to job stress, developing: 1) emotional exhaustion; 2) depersonalization; and 3) reduced perceived personal accomplishment (Pines & Maslach, 1978). As a result, burnout OTs emotionally withdraw from previously enjoyable work tasks, lose work meaning and professional effectiveness (Sturgess & Poulsen, 1983). Emotional exhaustion refers to losing psychological and physical "zest" (Maslach, Jackson, & Leiter, 1996; Schlenz et al., 1995). Depersonalized OTs no longer show empathy or respect for clients and low personal accomplishment is perceived as low self-appraisal and efficacy regarding work performance (Maslach et al., 1996; Schlenz et al., 1995). Although the three dimensions of the burnout syndrome are discrete, combined they can have cumulative effects, generating gradually more severe symptoms (Reis, Vale, Camacho, Estrela, & Anjos, 2018). Moreover, the interaction of burnout with personal and organizational resources also moderates the severity of symptoms (Lasalvia, et al., 2009; Lloyd & King, 2001; Maslach et al., 1996).

In contrast to emotional exhaustion, personal accomplishment is associated with high personal engagement, activation, identification, and absorption (high activation and high identification at the same time; see Demerouti, Mostert & Bakker, 2010). Engaged OTs are more likely to feel pleasantly tired after a workday than emotionally drained ones (Poulsen, Meredith, Khan, Henderson, Castrisos, & Khan, 2014). Whereas the mediating effect of external resources between job demands and emotional exhaustion is heavily researched (see Lloyd & King, 2001), the effect of internal resources is less researched (Derakhshanrad et al., 2019; Schmitt, Zacher, & Frese, 2012). E.g. the studies on the resilience of OTs are limited. The same is true for studies on the effect of resilience on the personal accomplishment of the OTs. Crucially, resilience is an important internal resource associated with personal accomplishment (Rivard & Brown, 2019), the positive component of Maslach's burnout model (Maslach et al., 1996).

1.2. The Professional Resilience of OTs

The American Psychological Association (2015) defined resilience as the ability to adapt well when facing adversity, trauma, or serious stress. In a similar vein, high resilient OTs can face adversity and use it to thrive and develop personal growth (Rivard & Brown, 2019). All resilience definitions focus on the ability to bounce back from adversity or stress, adapting successfully (Kyriazos, Stalikas, Prassa, Galanakis, Yotsidi, & Lakioti, 2018).

Crucially, professional resilience is a learnable internal resource (de Witt, Monareng, Abraham, Koor, & Saber, 2019; Tugade & Fredrickson, 2007), promotable through emotion regulation strategies (Tugade & Fredrickson, 2007). Strategies promoting OTs' resilience include self-reflection, building work-related purpose and meaning, highlighting personal achievements, cultivating professional skills, and acting upon professional values in the face of contextual pressures (McAllister & McKinnon, 2009). Preserving a personal value system can sometimes be challenging but it seems to be effective when dealing with organizational aspects beyond personal control, and can help an OT build professional accomplishment, engagement, and efficacy. Finally, a strong professional identity (Ashby, Ryan, Gray, & James, 2013) and sense of personal accomplishment (Lloyd & King, 2001) was reported to protect from burnout, and to build resilience (see Rivard & Brown, 2019 for more details). Moreover, to cope with burnout, effective coping strategies are setting limits, selecting tasks, balancing homework requirements, managing time to raise effectiveness, receiving social network support, prioritizing, setting goals, and self-care (Gupta et al., 2012). In contrast, in a mixed OT sample from Greece and Cyprus the effect of resilience and organizational factors like working days, years in the current position, quality of relationships with colleagues, holding a managerial position, age and total years of professional experience on burnout levels was limited (Katsiana et al., 2021). Therefore, at an organizational level, policymakers, and health organizations are encouraged to cultivate resilience-building environments and adopt policies and procedures to foster OTs' professional resilience (Rivard & Brown, 2019). The present study focuses on providing evidence to this end.

1.3. The Present Study

The core and essential property of resilience is the ability to bounce back from stress and adversity (Smith, Tooley, Christopher, & Kay, 2010). On the contrary, the core effect of burnout is the inability to use coping resources in the face of work-related stressful contexts like occupational therapy and healthcare (Derakhshanrad et al., 2019). Some questions that arise are: What is the effect of resilience on personal accomplishment—the positive burnout component—and the other dimensions of burnout? What is the interrelation of the three burnout components that make up this complex burnout mechanism? Could resilient OTs be at low risk of burnout?

Five primary hypotheses arise from the above questions and a causal modeling design was used to test them, by specifying a Structural Equation Model (H1 - H5, **Figure 1**).

H1: *Personal Accomplishment has a significant, direct negative effect on Depersonalization* (*path a*).

H2: *Depersonalization has a significant, direct positive effect on Emotional Exhaustion* (*path b*).

H3: *Persona Accomplishment has a significant, direct negative effect on Emotional Exhaustion* (*path c*).

H4: *Resilience has a significant, direct positive effect on Personal Accomplishment* (*path d*).

H5: *Depersonalization mediates the relation between Personal Accomplishment and Emotional Exhaustion* (*path a * b*).

Furthermore, if high-resilient OTs are at less risk of burnout in comparison to low-resilient, then distinct psychological OT profiles are hypothesized to exist. Therefore, two secondary hypotheses arise, and to test them, we carried out a

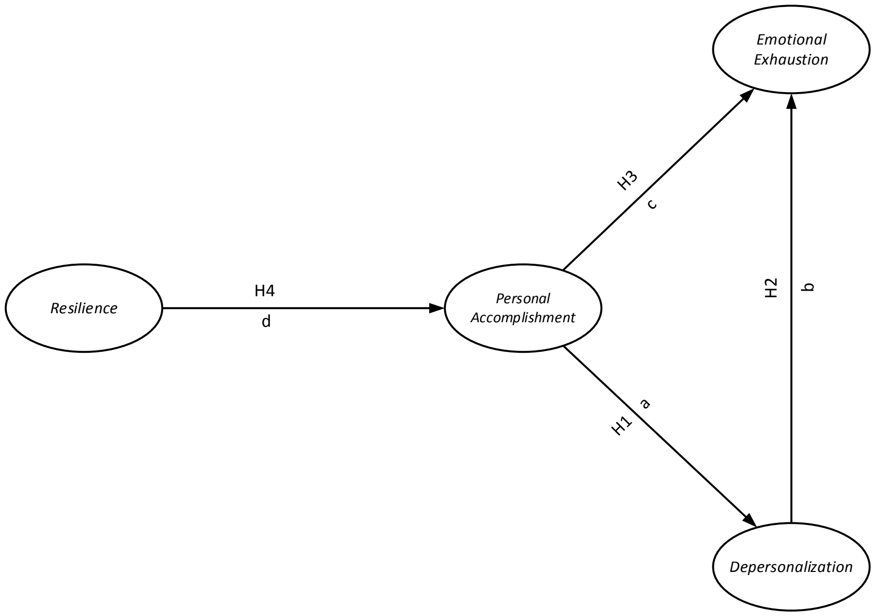

Figure 1. The research model tested with SEM (N = 315). An indirect path (mediation) was also tested (a * b).

Latent Profile Analysis (LPA) based on resilience, and burnout (i.e. personal accomplishment, depersonalization, and emotional exhaustion).

H1: *OT groups that have high resilience will have low burnout.*

H2: *OT groups that have low resilience will have high burnout.*

2. Method

2.1. Participants

The inclusion criteria were 1) to be an occupational therapist working in Greece; 2) to have at least 6 months of working experience. A total of 315 Greek occupational therapists participated in this study (80% female). They were aged between 21 - 60 years (that is 40% from 21 - 30 years, 30% from 31 - 40 years, 20% from 41 - 50 years, 9% from 51 - 60 years). Most therapists were married (42%) or in a permanent relationship (28%, 27% unmarried, 3% other) without children (61%). Almost 1 in 3 therapists (27%) had postgraduate qualifications or an additional university degree (13%). The vast majority of them (76%) were private health-care workers, in metropolitan areas (75%), with 1 - 14 years tenure (80%) or ≥15 years (20%), working mostly with children/teenagers (84%. 13% adults, 3% elderly). This sample was used before (Katsiana et al., 2021).

2.2. Procedure

Respondents were involved in the study with voluntary response sampling. Specifically, the registered members of the Panhellenic Occupational Therapists Association (N = 700) received an email inviting them to participate. Respondents received no inducement to participate. The study was available online from November 2019 to March 2020. Three hundred and forty-five voluntarily took the online survey (response rate 49%). In March 2020 Greece entered a lockdown period to control the COVID-19 pandemic and the survey was discontinued to avoid response bias because the achieved subjects per variable ratio for the two measuring instruments combined (=9.8) was sufficient for robust SEM model parameters (Schumacker & Lomax, 2015: p. 39). Note that a response rate of 49% is good for an on-line survey, with the average return rate of online surveys on convenience samples being 33% (Nulty, 2008). The response rate of some OT surveys was comparable, i.e. 40.5% (Poulsen et al., 2014), 42% (Derakhshanrad et al., 2019), or 50% (Devery, Scanlan, & Ross, 2018).

Sample Size, Power, and Precision

Thirty cases were excluded for not meeting the inclusion criteria (they did not work in Greece) leaving a final sample of $N = 315$. A priori power analysis based on population RMSEA of the full SEM model (MacCallum, Browne, & Sugawara, 1996), suggested that a sample size of $N = 72$ ($< N = 315$) was necessary for achieving a power of about 80% to reject a wrong model ($df = 457$) with an amount of misspecification corresponding to RMSEA = 0.05 on alpha = 0.05.

2.3. Measures

***Maslach Burnout Inventory—Human Services Survey* (*MBI-HSS*; Maslach Jackson, & Leiter, 1996).**

The MBI is a 22-item self-assessment questionnaire measuring perceived burnout with 22 items (e.g. "I feel burned out from my work") The items are rated on a 7-point frequency scale (from 0 = *Never* to 6 = *Every Day*). MBI-HSS evaluates the 3 facets of the burnout syndrome in 3 factors: Emotional Exhaustion (EE; 9 items), Depersonalization (DP; 5 items), and Personal Accomplishment (PA; 8 items). The items for each factor are aggregated separately to generate 3 scores, one for each factor—where a high EE score indicates high Burnout, a high DP score indicates high Burnout and a high PA score indicates low Burnout. Each score is coded as low, average, or high by using the numerical cutoff points (Maslach, Jackson, & Leiter, 1996). Maslach et al. reported internal consistency reliability of α = 0.90 (EE), 0.79 (DP), and 0.71 (PA). The Greek version of MBI-HSS was used in this study (Galanakis, Moraitou, Garivaldis, & Stalikas, 2009; Kokkinos, 2006).

***Connor-Davidson Resilience Scale*, 10*-item version* (*CD-RISC* 10; Campbell-Sills, & Stein, 2007; Connor & Davidson, 2003)**

This is a short version of the original CD-RISC (Connor & Davidson, 2003). It is a self-report, unidimensional measure of resilience with 10 items (e.g. "Coping with stress can strengthen me") rated on 5-point Likert scale (0 = *Not True at All*; 4 = *True Nearly All of The Time*). The higher the score, the higher the perceived resilience. The scale internal consistency reliability in a Spanish sample was α = 0.85 (Notario-Pacheco et al., 2011).

Data collected for some additional variables (like peer relationships) were not used in the present study.

2.4. Data Diagnostics

The fields of the online survey form were set as required to eliminate missing values. Outliers were detected separately for each study measure and for the SEM measurement model too using the Mahalanobis distance criterion. Multivariate normality of the burnout and resilience scale scores was examined using Mardia's multivariate kurtosis and skewness test, Henze-Zirkler's consistent test, Doornik-Hansen omnibus test, and Energy test. Only multivariate normality tests were evaluated. A normal multivariate distribution, suggests that each data variable has also a normal univariate and bivariate distribution (Wang & Wang, 2020).

2.5. Analytic Strategy

Initially, a CFA confirmed the factor structure of MBI-HSS and CD-RISC 10 separately, to ensure that the hypothesized structure was tenable in this special population of OTs because MBI-HSS structure was previously verified on different, special populations (Galanakis et al., 2009; Kokkinos, 2006), and CD-RISC 10 was unverified.

Next, a Structural Equation Model (SEM) was specified with the latent variables of EE, DP, PA, and resilience to test the study's main hypotheses. The SEM measurement and the full SEM model (Byrne, 2012) were evaluated (two-Step Approach; Anderson & Gerbing, 1988). We estimated all models with a robust estimator (MLR) to correct the chi-square and standard errors for non-normality. Model fit criteria (Hu & Bentler, 1999) were RMSEA [90% CI ≤ 0.06] ≤ 0.06, SRMR ≤ 0.08, CFI ≥ 0.95, TLI ≥ 0.95. A priori and post hoc power analysis evaluated the sample size adequacy of the full SEM model with the population the RMSEA (MacCallum, Browne, & Sugawara, 1996), with an alpha level of 0.05. Internal consistency reliability of all measures was evaluated with Cronbach's alpha [95% CI] (Feldt, Woodru, & Salih, 1987) and model-based reliability with Omega coefficient (McDonald, 1999).

Then a Latent Profile Analysis (LPA) followed to classify the sample based on their scores on EE, DP, PA, and resilience. LPA is a model-based approach that classifies individuals into distinct groups (i.e. latent profiles) based on their scores on a set of continuous observed variables by using statistical tests and model fit indicators to identify the number of profiles (see Masyn, 2013). It differs from Latent Class Analysis (LCA) which clusters categorically observed variable sets (Wang & Wang, 2020). For comparisons between the latent profile models, we used the following model fit indicators: the mean probability for maximum profile membership likelihood (entropy; Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Bootstrapped Likelihood Ratio Test (BLRT). For deciding on the optimal profile model to be retained we implemented the calculation proposed by Akogul and Erisoglu (2017) integrates several fit indices to choose the optimal profile model using the Analytic Hierarchy Process (AHP;

Saaty, 1990). Data were analyzed with R version 4.0.2. (R Development Core Team, 2020), with the packages "tidyLPA" (Rosenberg, Beymer, Anderson, Van Lissa, & Schmidt, 2018), "lavaan" (Rosseel, 2012), and "semPlot" (Epskamp, 2019). See all the steps of the analytic strategy listed in **Table 1**.

3. Results

3.1. Preliminary Analysis

There were no missing values. We examined MBI-HSS, CD-RISC10 and the measurement model for multivariate normality and outliers (**Table 2**). Multivariate skewness, kurtosis, and all other tests were statistically significant ($p < 0.001$). Outliers (**Table 2**) were not inaccurate data entries and did not weaken findings (see Kyriazos, 2018). Therefore, they were not removed ($N = 315$).

Subsequently, a CFA confirmed the factor structure of MBI-HSS and CD-RISC 10 separately to ensure there were no misspecifications in the SEM measurement

Table 1. An overview of the study analyses.

Analysis	Description	Rationale
1	Multivariate Normality Test	To test for the multivariate normality assumption with Mardia's multivariate kurtosis and skewness, Henze–Zirkler's consistent test, Doornik–Hansen omnibus test, and Energy test.
2	Detecting outliers	To detect outliers with Mahalanobis distance.
3	CFA on each study measures	To confirm the factor structure of MBI-HSS and CD-RISC 10 in this special Greek population (OTs), ensuring no misspecifications in the SEM model.
4	Cronbach's alpha & McDonald's omega (1999)	To calculate the internal consistency reliability and the model-based reliability of MBI-HSS and CD-RISC 10, before the SEM measurement model with ωt coefficient (McDonald, 1999).
5	Spearman rho Correlations, and means	Descriptive statistics and burnout scores.
6	Test the SEM measurement model and model-based reliability	To evaluate the measurement model fit with a CFA and to evaluate reliability of the measurement variables and the reliability latent variables with ωt coefficient (McDonald, 1999).
7	Test the full SEM model fit	To evaluate if the structural model fit is adequate.
8	A priori & post hoc power analysis of the full SEM model	To calculate the required sample for achieving a power of 80% to reject a wrong model. An alpha level of 0.05 was assumed with an RMSEA misspecification of 0.05 (MacCallum, Browne, & Sugawara, 1996).
9	Primary Hypotheses testing (Primary hypotheses H1 - H5)	To test the hypothesized relationships between 4 latent variables with 4 direct associations, and 1 mediation. No covariates were used.
10	Latent Profile Analysis (LPA) (Secondary Hypotheses H1 - H2)	Use the scores of the latent variables of the SEM model to profile the sample and check if the profiles that emerged confirm the hypotheses tested with the SEM model.

Table 2. Multivariate normality tests, outliers and critical value for Mahalanobis distance (χ^2) for each study measure and for the measurement model, ($N = 315$).

Measure	Outliers	D^2 C.V. χ^2 (df)*	Mardia's Skew*	Mardia's Kurtosis*	Doornik-Hansen (df)*	Energy Test*	Henze-Zirkler*
MBI-HSS ($k = 22$)	12	48.27 (22)	5294.88	30.52	245.199 (44)	6.31	1.22
CD-RISC10 ($k = 10$)	6	29.59 (10)	495.97	11.05	60.07 (20)	2.41	1.10
Measurement Model ($k = 22$)	11	62.49 (32)	10,504.41	29.06	275.30 (64)	4.70	1.02

*$p < 0.001$.

model. The model fit for the 3-factor MBI-HSS model (Maslach et al., 1996) was adequate, χ^2 (203) = 403.19, $p = 0.000$, CFI = 0.929, TLI = 0.920, RMSEA = 0.056 90% CI [0.048, 0.064], SRMR = 0.079 with 3 residual covariances added (between PA items 4 and 7, PA items 7 and 9, and DP items 10 and 11). Loadings ranged from 0.332 to 0.920 and the inter-factor correlations from |0.41| to |0.48|. More specifically, the correlation between DP and PA was (as expected) negative (−0.41) and between DP and EE positive (0.48). Equally, the correlation between PA and EE was negative (−0.44). The internal consistency reliability of this solution was α = 0.92 95% CI [0.91, 0.94] (EE), α = 0.70 95% CI [0.65, 0.75] (DP), α = 0.81 95% CI [0.78, 0.84] (PA). And the model-based reliability based on McDonald's ω was ω = 0.93 (EE), 0.61 (DP) and 0.77 (PA). This is the original 3-factor structure of the MBI-HSS postulated by Maslach et al. (1996) and confirmed with CFA by Boles et al. (2000).

The unidimensional structure of CD-RISC10 (Campbell-Sills & Stein, 2007) had a good model fit, χ^2 (35) = 70.62, $p = 0.001$, CFI = 0.947, TLI = 0.931, RMSEA = 0.057 90% CI [0.039, 0.075], SRMR = 0.048. Loadings ranged from 0.408 - 0.704, α = 0.83 95% CI [0.80, 0.85], and McDonald's ω = 0.83. The unidimensional structure of CD-RISC 10 (Campbell-Sills & Stein, 2007) is easier to handle in an SEM model and it was preferred over the original (Connor & Davidson, 2003).

3.2. Descriptive Statistics

Table 3 displays the raw correlations and means of MBI-HSS and CD-RISC10 scores. Cutoffs outlined in the MBI test manual suggested that the OTs in this sample experienced average EE levels, low DP levels, and average PA levels.

3.3. The SEM Measurement Model

The measurement model had four latent variables (resilience, PA, DP, and EE) and 32 observed variables and it showed a good model fit, χ^2 (455) =806.00, $p = 0.000$, CFI = 0.909, TLI = 0.900, RMSEA = 0.049 90% CI [0.044, 0.055], SRMR = 0.072 (MLR estimator). The standardized factor loadings remained above the 0.40 threshold (Brown, 2015), ranging from 0.406 to 0.812, and they were higher on their assigned latent variable than on the other latent variables of the measurement model. Also, all the 32 observed variables significantly loaded on their latent variable, suggesting robustness (**Table 4**). Omega coefficient (McDonald,

Table 3. Descriptive statistics and raw correlations (Spearman rho) for the CD-RISC10 and MBI-HSS Scores.

Measures	*M*	*SD*	1	2	3	4
1. CD-RISC10	26.83	0.49	—			
2. MBI-HSS EE	19.76	0.62	−0.39**	—		
3. MBI-HSS DP	5.09	0.27	−0.18**	0.41**	—	
4. MBI-HSS PA	38.85	0.47	0.58**	−0.35**	−0.28**	—

DP = Depersonalization, PA = Personal Accomplishment, EE = Emotional Exhaustion. ** $p < 0.01$.

Table 4. Standardized loadings (λ), and R squared for the SEM measurement model (N = 315).

Latent Variable	Observed Variable	λ*	R^2	Latent Variable	Observed Variable	λ*	R^2
MBI-HSS DP	DP5	0.594	0.353		EE6	0.744	0.554
	DP10	0.559	0.312		EE8	0.92	0.846
	DP11	0.513	0.263		EE13	0.747	0.558
	DP15	0.648	0.420		EE14	0.526	0.277
	DP22	0.428	0.183		EE16	0.729	0.531
MBI-HSS PA	PA4	0.353	0.125		EE20	0.793	0.629
	PA7	0.507	0.257	CD-RISC 10	CDRISC 1	0.493	0.243
	PA9	0.61	0.372		CDRISC2	0.646	0.417
	PA12	0.718	0.516		CDRISC3	0.547	0.299
	PA17	0.607	0.368		CDRISC4	0.425	0.181
	PA18	0.672	0.452		CDRISC5	0.564	0.318
	PA19	0.596	0.355		CDRISC6	0.516	0.266
	PA21	0.611	0.373		CDRISC7	0.508	0.258
MBI-HSS EE	EE1	0.852	0.726		CDRISC8	0.713	0.508
	EE2	0.74	0.548		CDRISC9	0.672	0.452
	EE3	0.848	0.719		CDRISC10	0.661	0.437

Note. DP = Depersonalization, PA = Personal Accomplishment, EE = Emotional Exhaustion, Model Estimator = MLR. * $p < 0.001$.

1999) for each latent variable was ω = 0.93 (EE), 0.78 (PA), 0.61 (DP) and 0.83 (CD-RISC 10), suggesting adequate model-based reliability (Kline, 2016; Kyriazos 2017a). The R^2 ranged from 0.125 to 0.846, i.e. the latent variables accounted for a variance from 13% to 85% by each observed variable (**Table 4**). The interfactor correlations of the measurement model were in the expected directions, ranging from |0.24| to |0.69|. More specifically, the interfactor correlations of resilience (CD-RISC) with DP, PA, and EE were −0.24, 0.692, and −0.41 respectively. The interfactor correlation of DP with PA was −0.42, and DP with EE 0.48. Equally, the intercorrelation of PA with EE was −0.43.

3.4. The Full SEM Model

The full SEM model to study the relationship of resilience and personal accomplishment, emotional exhaustion and depersonalization showed a god fit, χ^2 (457) = 812.54, p = 0.000, CFI = 0.908, TLI = 0.900, RMSEA = 0.050 90% CI [0.044, 0.055], SRMR = 0.075.

Post-hoc power analysis based on population the RMSEA of the full SEM model (MacCallum, Browne, & Sugawara, 1996) suggested that N = 315 was associated with >99.99% power to reject a wrong model (df = 457, RMSEA = 0.05 on alpha 0.05).

***Hypotheses testing* (*Primary hypotheses H*1 - *H*5)**

The structural results for the relationship of resilience (CD-RISC 10), and PA, EE, and DP are presented in **Table 5** (path coefficients and their 95% CI) and in **Figure 2** (structural model). Standardized path coefficients (**Table 5**) showed

Table 5. Structural results for the primary hypotheses H1 - H4 regarding the direct effects in the full SEM model (N = 315).

H (path)	Path Description	β	*B*	95% CI for B		*SE*	*z*	*P*	A/R
				LL	LU				
H1 (a)	PA → DP	−0.405	−0.686	−1.067	−0.306	0.194	−3.534	0.000	A
H2 (b)	DP → EE	0.348	0.588	0.287	0.889	0.154	3.826	0.000	A
H3 (c)	PA → EE	−0.328	−0.941	−1.664	−0.217	0.369	−2.547	0.011	A
H4 (d)	CD-RISC 10 → PA	0.701	0.872	0.470	1.275	0.205	4.250	0.000	A

Note. CI = Confidence Interval, LL = Lower Limit, UL = Upper Limit, z = z-value, DP = Depersonalization, PA = Personal Accomplishment, EE = Emotional Exhaustion, H = Hypothesis, A = Hypothesis Accepted, R = Hypothesis Rejected, Model Estimator = MLR.

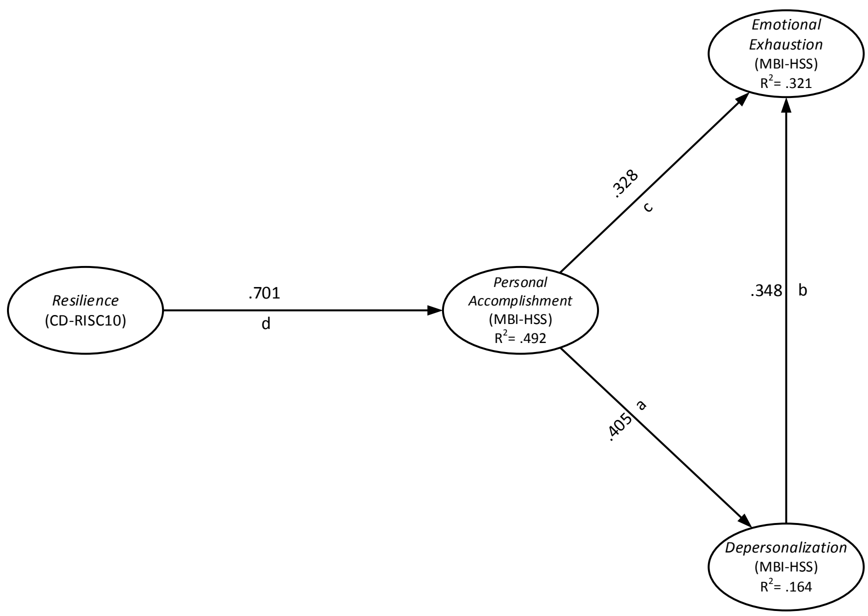

Figure 2. The path diagram of the SEM structural model (standardized coefficients, all p < 0.001).

that resilience had a significant positive effect on PA (β = 0.701, $p < 0.001$), 49% explained variance (see all the explained variances in **Figure 2**). The effect of PA on EE was significantly mediated by DP, total effect = −0.981, and indirect effect = −0.141 (**Table 6**).

See the full SEM model in **Figure A1** of the **Appendix**.

3.5. Latent Profile Analysis (LPA; Secondary Hypotheses H1 - H2)

Then, LPA followed to group the OTs based on their scores on resilience, EE, DP, and PA, i.e. the latent constructs of the SEM model. EE, DP, PA and CD-RISC 10 scores were scaled (z scores; $M = 0$; $SD = 1$) to make them comparable before profile estimation. We compared 4 profile models with different variance-covariance specifications. Model 1 had equal variances and covariances fixed to zero. Model 2 had varying variances and covariances fixed to zero. Model 3 had equal variances and equal covariances and Model 4 had varying variances and varying covariances. For each model specification, profiles with 1 - 4 groups were tested (a total of 16 group solutions). Model fit comparison based on the integrative function of multiple fit indicators (Akogul & Erisoglu, 2017; Saaty, 1990) suggested that Model 2 (varying variances and covariances fixed to zero) with 4 groups was the optimal solution. The model fit for each solution is listed in **Table 7**.

The OTs in Group 4 had the highest resilience scores, the lowest EE and DP scores combined with the highest PA scores (presented with the line connecting the cross symbol across bars). Group 3 had the second-highest resilience scores, the second-lowest EE and DP scores, and the second-highest PA scores (presented with the line connecting the square symbol across bars). Group 2 had the lowest resilience scores of all groups, the highest EE scores, equally high DP scores with Group 1, and the lowest PA scores (presented with the line connecting the triangle symbol across bars). Group 1 had the third-highest resilience scores, the second-highest EE, and equally high DP scores with Group 2 and equally high PA scores with Group 3 (presented with the line connecting the circle symbol across bars). **Figure 3** contains a plot with the 4 distinct OTs' profiles based on their resilience, EE, DP and PA.

Table 6. Indirect and total effects of personal accomplishment on emotional exhaustion through depersonalization in the full SEM model ($N = 315$).

Effect (path)	Estimate	95% CI for B		*SE*	*z*	*p* (>|z|)	SD_{ALL}
		LL	LU				
Indirect = (a * b)	−0.141	−0.639	−0.168	0.120	−3.362	0.000	−0.205
TOTAL = c + (a * b)	−0.981	−1.344	−0.618	0.185	−5.295	0.000	−0.310

Note. CI = Confidence Interval, LL = Lower Limit, UL = Upper Limit, Estimator = MLR. z = z-value = Wald statistic, p (>|z|) = p value for testing that the parameter equals zero in the population (H0), Std_{ALL} = Solution standardizes the factor loadings by the *SD* of both the predictor and the outcome.

Table 7. Model fit statistics for the 1 to 4 profiles solutions estimated with 1 - 4 groups each based on the EE, DP, PA and resilience scores of the OTs to test secondary hypotheses H1 - H2 secondary hypotheses H1 - H2 ($N = 315$).

Model	Groups	AIC	BIC	Entropy	*n* min	*n* max	BLRT *p*
1	1	3587.72	3617.74	1	1	1	
1	2	3398.08	3446.87	0.72	0.37	0.63	0.01
1	3	3358.77	3426.31	0.71	0.15	0.44	0.01
1	4	3312.65	3398.96	0.72	0.12	0.42	0.01
2	1	3587.72	3617.74	1	1	1	
2	2	3323.43	3387.22	0.73	0.45	0.55	0.01
2	3	3239.68	3337.25	0.74	0.15	0.51	0.01
2	**4**	**3197.61**	**3328.95**	**0.74**	**0.09**	**0.33**	**0.01**
3	1	3351.93	3404.46	1	1	1	
3	2	3312.58	3383.88	0.8	0.24	0.76	0.01
3	3	3280.37	3370.43	0.81	0.08	0.71	0.01
3	4	3290.53	3399.36	0.55	0.09	0.43	0.97
4	1	3351.93	3404.46	1	1	1	
4	2	3234.11	3342.94	0.73	0.32	0.68	0.01
4	3	3199.04	3364.15	0.73	0.12	0.53	0.02
4	4	3180.64	3402.04	0.77	0.09	0.48	0.06

Note. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, BLRT = Bootstrapped Likelihood Ratio Test. Bold typeface indicates the best model.

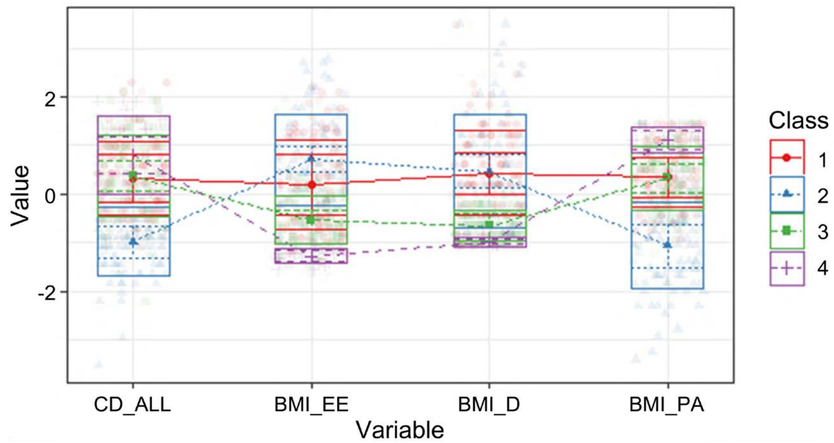

Figure 3. The 4 groups of the optimal profile model (Model 2) based on the EE, DP, PA and resilience scores of the OTs ($N = 315$). *Note*. Bars indicate the confidence interval for the group centroids; Each bar indicates the *SD* within each group, incorporating +/− 64% of the cases in a normal distribution; Each raw datapoint becomes most visible for the group with the highest membership probability, i.e. data transparency is weighted by the posterior group probability.

4. Discussion

The purpose of this study was: 1) to test the effect of resilience on personal accomplishment and the inter-relation between personal accomplishment, emotional exhaustion, and depersonalization with an SEM model and 2) to test if distinct psychological profiles of Occupational Therapists emerge based on resilience, personal accomplishment, emotional exhaustion and depersonalization by profiling OTs with Latent Profile Analysis (LPA). All primary and secondary research hypotheses tested with SEM and LPA respectively were confirmed.

For the interpretation of the SEM model results, for standardized direct effects Kline (2016) suggested that standardized direct effects are small when they are less than 0.10, medium when they are around 0.30, and large when they are around 0.50 Adopting Kline's criteria, the estimates of the SEM model suggested that increased PA predicted decreased EE with a moderate–large standardized direct effect. Increased DP predicted an increase in EE of a moderate magnitude. In contrast, increased personal accomplishment predicted a decrease in EE with a moderate standardized direct effect. Lastly and most importantly, an increase in resilience predicted a major increase in PA with a standardized major direct effect > 0.70. Alternative SEM models with direct paths from resilience to depersonalization and emotional exhaustion had an unacceptable model fit and they were not retained. The same was true for models tested with all the work-related demographic variables of the sample.

Generally, the tripartite model of burnout used is well documented in OT literature, postulating that healthcare professionals like OTs experience chronic work-related stress (Maslach, 1993): EE, DP (i.e. cynicism), and low PA. Therefore, the negative relationship of PA with DP and EE is well-documented (Maslach et al., 1996; Lloyd & King, 2004). However, findings from structural models proposed that PA was unrelated to EE, rather they were reported to move in parallel (Maslach et al., 1996).

A sense of accomplishment (competence) was reported to work separately from EE, as a protective factor (Lloyd & King, 2004), confirming the results of this study. Interestingly, resilience explains half of the variance of PA with a very strong, significant positive effect. PA of OTs contributes to resilience and effective coping strategies (Sweeney, Nichols, & Cormack, 1993; Lloyd & King, 2001), confirming our findings. Actually, OT literature proposed that OT students can counterbalance stress and burnout by building professional resilience and self-care (de Witt et al., 2019). However, according to our findings, PA was related to EE through the significant mediation of DP. Relevant literature suggests that OTs may become depersonalized and detached, in an effort to protect themselves from EE, and they contact less and more distantly with their recipients, becoming more needlessly bureaucratic (Maslach, 1976; Sturgess & Poulsen, 1983).

Furthermore, distinct psychological profiles of Occupational Therapists were hypothesized (secondary hypotheses) based on resilience, personal accomplishment, emotional exhaustion, and depersonalization: 1) OT groups with high resilience and low burnout and 2) OT groups with low resilience and high burnout. These secondary, exploratory hypotheses were evaluated with a Latent

Profile Analysis (LPA). This could answer the question whether high-resilient OTs are at lower risk of emotional exhaustion and depersonalization, and have increased personal accomplishment than low-resilient OTs—as the SEM model implicitly suggested.

Four groups emerged that directly demonstrate that high-resilient OTs have less emotional exhaustion and depersonalization and higher personal accomplishment in comparison to low-resilient OTs. Specifically, the OTs in Group 4 were the most resilient, and they experienced the lowest emotional exhaustion and depersonalization along with the highest personal accomplishment. The OTs of Group 3, showed an identical pattern. They were the second most resilient and they experienced the second-lowest emotional exhaustion and depersonalization and the second-highest personal accomplishment. Group 2 showed the inverse pattern. They were the least resilient of all groups, and they experienced the highest emotional exhaustion, equally high depersonalization, and the lowest personal accomplishment. OTs in Group 1 had all scores above and below average. They ranked third in resilience, second in emotional exhaustion, and as highly depersonalized with OTs of Group 1 but as high personal accomplishment of OTs in Group 3. In sum, Groups 4, and 2 confirmed the secondary hypotheses that resilient OTs are at low burnout risk and that low resilient OTs are at high burnout risk. OTs in Group 1 experience average burnout and low resilience. Unfortunately, no similar LPA studies exist to compare these findings.

Implications & Limitations

The generalizability of the findings is relatively safe to make due to their statistical validity (see Kyriazos, 2017b). That is, the SEM research model to study the relationships between resilience, personal accomplishment, emotional exhaustion, and depersonalization showed a good fit, robust loadings, highly significant effects and power analysis indicated enough sample size. The same was true for the LPA analysis, which strengthened the SEM results.

Interpretation of the findings however should be made cautiously because the voluntary response sampling is a non-probability sampling method, similar to ad hoc samples. Furthermore, cross-cultural comparisons are a challenge because OT literature has unique variability due to differences in OT specializations, in MBI measures used (HSS, GS, etc.), and wide differences in healthcare settings and other work-related factors. However, the response rate was satisfactory, comparable to similar studies, and the sampling frame very narrow permitting safe interpretation of the results.

One of the study limitations was the imbalanced sample in terms of gender. Another limitation was that the study was disrupted by the early COVID-19 quarantine, so the initial response to the quarantine may have some sort of impact (if any). Lastly, the cross-sectional, design of this study cannot permit causal inference (Stalikas & Kyriazos, 2019). Causal inference is a matter of study design (Kline, 2020), although this rigid view on causality with SEM can be somewhat problematic (Bollen & Pearl, 2013; Kline, 2020). Future research could explore if resilience of OTs is associated to a number of positive work-related constructs like flow (for Greece see Kyriazos, Stalikas, Prassa, Galanakis, Flora & Chatzilia, 2018), hope (for Greece see Yotsidi, Pagoulatou, Kyriazos, & Stalikas, 2018), flourishing (for Greece see Kyriazos, Stalikas, Prassa, Yotsidi, Galanakis, & Pezirkianidis, 2018) and life meaning (for Greece see Stalikas, Kyriazos, Yotsidi, Prassa, 2018). However, personal and family relationships may also affect OTs' resilience therefore, another future research possibility could be to explore the association of OTs' resilience to constructs like interpersonal anxiety (for Greece see Giotsa, Kyriazos, & Mitrogiorgou, 2018; Kyriazos & Giotsa, 2019) or family-related constructs like parental behaviors (for Greece see Kyriazos & Stalikas, 2019a) and positive parenting (for Greece see Kyriazos & Stalikas, 2018; Kyriazos & Stalikas, 2019b).

5. Conclusion

This work hopefully offers useful insights into the effect of resilience in mitigating the vulnerability of the OTs to burnout, providing a base for more models of resilience, the burnout mechanism, and effective coping of OTs (Gupta et al., 2012), or OT students (de Witt et al., 2019) because resilience is a learnable resource (Tugade & Fredrickson, 2007).

Moreover, it extends the current research on the interaction of PA with resilience and other well-being constructs like work satisfaction (Devery et al., 2018; Scanlan & Still, 2013) flow and work engagement, or problem-solving and creativity (Derakhshanrad et al., 2019). By focusing more on the interaction of PA with DP and EE and the mediating role of DP between PA and EE more evidence is available to inform evidenced-based prevention and intervention strategies, offering more tools for policymakers and relevant organizations to build effective interventions that can boost resilience, and effective coping of OTs and OT students.

Finally, this study implements a new hybrid research cycle containing both SEM and LPA, two powerful techniques that effectively corroborate one-another.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

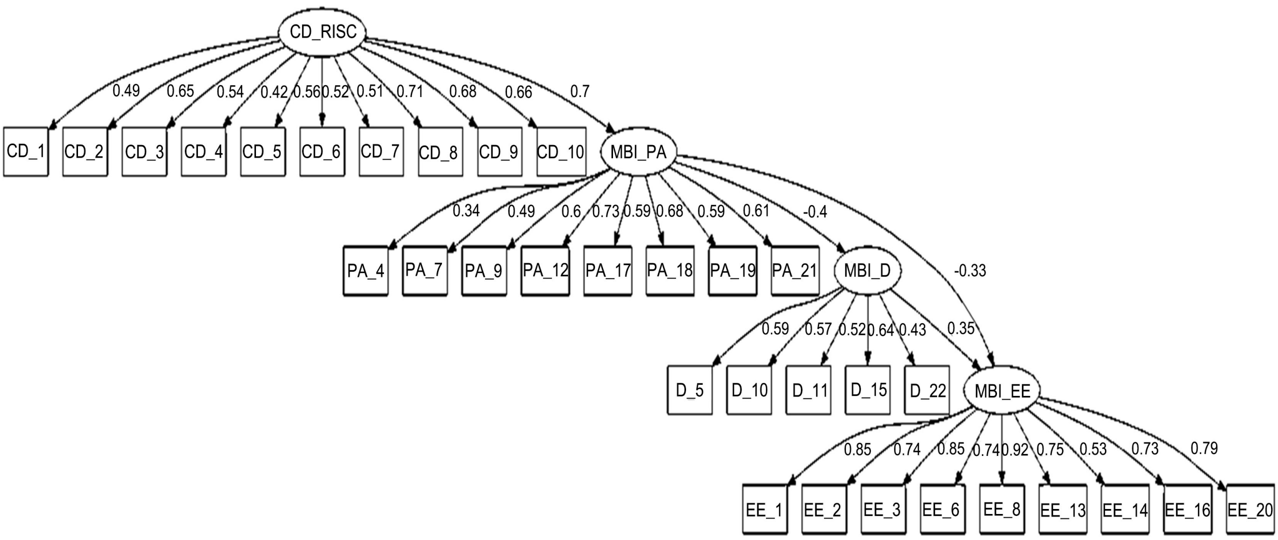

Figure A1. The path diagram of the proposed full SEM model (standardized coefficients, all *ps* < 0.001).