One Factor SEM and Multilevel SEM Model for Patient Satisfaction Data

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Authors’ contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Structural equation models are very common in medical, social, management and behavioral sciences where researchers established some causal relations between observed variables and latent variable. In structured populations the assumption of independence of observations is often violated and had been ignored by the researchers. As a result with the correlated structure of the error terms, biased estimates of the parameters have been produced that leads towards incorrect statistical inference. Multilevel structural equation model under one factor model has been proposed, estimated and compared with the traditional structural equation model on patient satisfaction data. Multilevel structural equation model produced better estimates than the structural equation models.

Keywords: Causal relation; path diagram; SEM; multilevel SEM.
1. INTRODUCTION

Structural equation modeling (SEM) was first developed from econometrics and then from latent variable models for factor analysis. The theory studies the causal relations between observed and latent variables. SEM is a common and useful framework for statistical analysis that covers as special cases numerous customary multivariate techniques. Structural equation models are frequently seen by a figure named path diagram [1,2]. Structural equation modeling has its origins in path analysis and it is usual to begin a SEM analysis by sketching a path diagram. A path diagram contains circles and rectangles, which are linked by arrows. Observed (or measured) variables are signified by a square box or rectangle, and latent (or unmeasured) features by a circle or ellipse. One-headed arrows or ‘paths’ are used to describe assumed causal associations in the model, with the variable at the tail of the arrow being the cause of the variable at the point. Statistically, the one headed arrows or paths characterize the regression coefficients [3].

As the path coefficients in a SEM model are like the regression weights in a Multiple Regression analysis which means that they control the correlations among multiple causes of the same variables. Path Coefficients represent the direct or indirect effect of an indicator or observed variable to the Latent Variable. So the violation of independence of observations in a SEM model from a structured population is pretty common. In this case, the estimates of the coefficients of a SEM model will be biased and misleading [4-7].

Behavioral, social and medical scientists often use structural equation modeling in their researches and the correlated structure of the data from a structured population must be taken into account while applying structural equation models on their data. Under clustered populations, multilevel structural equation models (MLSEM) can be used for the proper estimation of the model because MLSEM are considered the generalization of the SEM for structured populations [6,8,9].

Patient satisfaction plays a pivotal role in a consistent use of medical services in sustaining relationships with certain care-givers, and in compliance with medical rules and treatments [10-13]. Apart from that, patient or consumer satisfaction with health care services is considered to be a principal importance with regard to quality enhancement programs from the patients’ perspective; total quality management and the expected consequence of care [14,15]. With this regard, studies related to patient satisfaction can be used to increase medical audit programs. However, the significance of patient satisfaction researches is also probed on the basis of theoretical and operational complications. Theoretically, most investigators consider patient satisfaction as a tool of prospects and involvements of the users of health care facilities [16,17]. Dissimilarities in patient satisfaction are due in part to patient preferences and approaches toward health care and the health care transferring practice, and in part to outdoor conditions, such as practice setting or the way health care services are systematized [18,19]. Most studies are “data driven,” and concentrating on patient satisfaction scores as a regressor for subsequent performance or as the outcome variable for evaluating health care services and the behavior of health care providers. Compared with the vast amount of patient satisfaction studies that link predictor variables at the patient level to differences in patient satisfaction, the number of studies relating quality of care scores to more objective measures of service delivery or to perceived differences between care providers is relatively small [20,8].

Satisfaction of patient is greatly affected by the physician’s communication with the patient [21-23]. In present study we apply both SEM and MLSEM models on patient satisfaction with the doctor’s communication data (Table 1). Patient satisfaction measured on 13 items from 1650 patients admitted in leading hospitals of Lahore was considered level-1 units and the 14 hospitals were taken as level-2 units.

2. LEVEL STRUCTURAL EQUATION MODEL

Let $y_{ijk}$ be the $j^{th}$ patient satisfaction reading ($i = 1,2,\ldots,1650$) within $j^{th}$ hospital ($j = 1,2,\ldots,14$) on $k^{th}$ observed variable ($k = 1,2,\ldots,13$). The patient readings are treated as level-1 units and the hospitals are taken as level-2 units. We did not take any regressor along level-2 units and allow the variation of the level-1 units only at intercept. The observed data from a $j^{th}$ hospital can be written as,
Let $y_{ij}$ can be written as

$$y_{ij} = S_{ij}v_j + S_{ij}u_{ij} \quad (1)$$

where, $v_j \sim N(0, \Sigma_v)$ is the variation of patient satisfaction readings between the hospitals and $u_{ij} \sim N(0, \Sigma_u)$ is the variation of patient satisfaction readings within the hospitals. Also, $\text{Cov}(v_j, u_{ij}) = 0$ for $j = 1, 2, \ldots, 14$ & $i = 1, 2, \ldots, 1650$. $S_{ij}$ is a selection matrix having a subset of $p_{ij}$ rows of the identity matrix $I_p$, where the rows of $S_{ij}$ correspond to the response measurements available for the $(ij)^{th}$ unit.

This means, the patient satisfaction data has been decomposed into two groups (Between hospitals component $Y^b_g$ and With in hospitals component $Y^w = Y_g - \overline{Y}_g$). In other words, for each patient we swap the observed total score $Y^T = Y_g$ with its partitioned scores $Y^b_g$ & $Y^w$. Both the two groups are assumed to be orthogonal and additive i.e., $Y^T = Y^b_g + Y^w$. We can compute satisfaction between hospitals covariance matrix $\Sigma_B$ and within hospitals covariance matrix $\Sigma_W$ by using above decomposition. These two covariance matrices are also additive and orthogonal i.e., $\Sigma_T = \Sigma_B + \Sigma_W$. Multilevel structural equation models between and within the hospitals are:

$$\Sigma_B = \lambda \psi \lambda' + D_B \quad \Sigma_W = \lambda \psi \lambda' + D_W \quad (2)$$

Where

$$\lambda' = (1, \lambda_{21}, \lambda_{21}, \lambda_{31}, \ldots, \lambda_{131})'$$

and $D_B$ & $D_W$ are diagonal matrices with diagonal elements equal to the unique (error) variances of observed variables. The variance of the latent variable is denoted by $\psi$. Also $\lambda_{21}, \ldots, \lambda_{131}$ are the factor loadings. We assume that the initial factor loadings between and within the hospital is same.

Maximum likelihood method is used to estimate the model parameters, factor loadings, path coefficients, and residual variances, between hospitals covariance matrix $\Sigma_B$ and within covariance matrix $\Sigma_W$.

Let $y_j \sim N(\mu_j, \Sigma_j)$ then the log-likelihood function of $y_1, y_2, \ldots, y_j$ is,

$$\ln L = \frac{1}{2} \sum_{j=1}^q \frac{1}{2} \sum_{ii} p_{ii} [\ln 2\pi + \ln |\Sigma_j| + \text{tr}(\Sigma_j^{-1}e_j)]$$

or,

$$\ln L = \frac{1}{2} \sum_{j=1}^q p_{ij} \ln 2\pi + \ln |\Sigma_j| + e_j' \Sigma_j^{-1} e_j \quad (3)$$

Where $e_j = y_j - \mu_j$ and $p_{ij} = \text{rank}(S_{ij})$. If there is no missing observation in $y_{ij}$ then $p_{ij} = p$ and $S_{ij} = I_p$.

In order to estimate the unknown values of the parameters one can minimize the $-\ln L$ with the constant term omitted i.e., by minimizing the function

$$F(\gamma) = \frac{1}{2} \sum_{j=1}^q \left[\ln |\Sigma_j| + e_j' \Sigma_j^{-1} e_j\right] \quad (5)$$

Where

$$e_j = e_{(1)j} \quad \text{and} \quad e_{(1)j} = (e_{1j}, e_{2j}, \ldots, e_{nj})' = (y_{1j} - \mu_{1j}, y_{2j} - \mu_{2j}, \ldots, y_{nj} - \mu_{nj}).$$
Table 1. Descriptive of patient satisfaction items with the physician's communication

| Items                                                                 | SD   | D    | N    | A    | SA   |
|-----------------------------------------------------------------------|------|------|------|------|------|
| I think that the doctor really knows how I think (Q7).               | 24(1.5) | 242(14.7) | 313(19.0) | 684(41.5) | 387(23.5) |
| I wonder if the doctor could have spent a little longer time with me (Q8). | 109(6.6) | 388(23.5) | 269(16.3) | 541(32.8) | 343(20.8) |
| The time of medical consultation with me was a little bit too short (Q9). | 101(6.1) | 416(25.2) | 292(17.7) | 547(33.2) | 294(17.8) |
| The doctor listened to what I want him/her to do (Q10).              | 28(1.7) | 135(8.2) | 303(18.4) | 689(41.8) | 495(30.0) |
| I don’t feel rush when I am with a doctor (Q15).                    | 34(2.1) | 154(9.3) | 286(17.3) | 752(45.6) | 424(25.7) |
| The doctor always ask about how my illness affects everyday life (Q16). | 84(5.1) | 194(11.8) | 247(15.0) | 639(38.7) | 486(29.5) |
| I some time feel I have not been given enough information by the doctor (Q17). | 326(19.8) | 644(39.0) | 342(20.7) | 220(13.3) | 118(7.2) |
| I do not feel confident discussing my problems with the doctors (Q18). | 250(15.2) | 537(32.5) | 292(17.7) | 431(26.2) | 294(17.8) |
| The doctor seems to want to get rid of me as soon as possible (Q19). | 220(13.3) | 504(30.5) | 358(21.7) | 352(21.3) | 216(13.1) |
| The doctor does not tell me enough about the treatment (Q20).         | 228(13.8) | 569(34.5) | 318(19.3) | 314(19.0) | 221(13.4) |
| The doctors sometimes fail to appreciate how ill I am (Q21).          | 259(15.7) | 496(30.1) | 352(21.3) | 333(20.2) | 210(12.7) |
| The doctor is always available over the telephone (Q22).              | 324(19.6) | 348(21.1) | 367(22.2) | 400(24.2) | 211(12.8) |
| It is easy to get advice over the phone (Q23).                        | 339(20.5) | 371(22.5) | 339(20.5) | 361(21.9) | 239(14.5) |

Table 2. Estimated between hospitals covariance matrix ($\hat{\Sigma}_B$) for doctor’s communication satisfaction data

|     | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 | 11 | 12 | 13 |
|-----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| 1   | 0.866 | |   |    |    |    |    |    |    |    |    |    |    |
| 2   | 0.306 | 1.258 |    |    |    |    |    |    |    |    |    |    |    |
| 3   | 0.294 | 0.725 | 1.245 |    |    |    |    |    |    |    |    |    |    |
| 4   | 0.219 | 0.168 | 0.211 | 0.846 |    |    |    |    |    |    |    |    |    |
| 5   | 0.276 | 0.082 | 0.099 | 0.191 | 0.791 |    |    |    |    |    |    |    |    |
| 6   | 0.311 | 0.243 | 0.147 | 0.296 | 0.194 | 0.990 |    |    |    |    |    |    |    |
| 7   | -0.210 | 0.265 | 0.242 | -0.209 | -0.150 | -0.422 | 1.254 |    |    |    |    |    |    |
| 8   | -0.139 | 0.347 | 0.319 | -0.114 | -0.124 | -0.207 | 0.492 | 1.337 |    |    |    |    |    |
| 9   | -0.247 | 0.298 | 0.342 | -0.081 | -0.111 | -0.174 | 0.414 | 0.733 | 1.422 |    |    |    |    |
| 10  | -0.066 | 0.178 | 0.182 | -0.031 | -0.079 | 0.039 | 0.272 | 0.605 | 0.699 | 1.476 |    |    |    |
| 11  | 0.005 | 0.269 | 0.220 | -0.011 | -0.087 | 0.047 | 0.230 | 0.552 | 0.610 | 0.980 | 1.495 |    |    |
| 12  | 0.057 | 0.209 | 0.163 | 0.053 | 0.082 | -0.018 | -0.200 | -0.447 | -0.466 | -0.731 | -0.879 | 1.587 |    |
| 13  | 0.123 | 0.193 | 0.204 | 0.086 | 0.195 | -0.054 | -0.150 | -0.393 | -0.433 | -0.634 | -0.736 | 1.182 | 1.662 |
Fig. 1. Path diagram (SEM) for patient’s satisfaction with doctor’s communication between hospitals

Fig. 2. Path diagram (SEM) for patient’s satisfaction with doctor’s communication within hospitals

Fig. 3. Path diagram (MLSEM) for patient’s satisfaction with doctor’s communication between hospitals

Fig. 4. Path diagram (MLSEM) for patient’s satisfaction with doctor’s communication within hospitals
Table 3. Estimated within hospitals covariance matrix ($\hat{\Sigma}_w$) for doctor's communication satisfaction data

|   |       |       |       |       |       |
|---|-------|-------|-------|-------|-------|
| 1 | 0.193 |       |       |       |       |
| 2 | -0.023| 0.226 |       |       |       |
| 3 | 0.002 | 0.198 | 0.188 |       |       |
| 4 | 0.123 | -0.051| -0.042| 0.116|       |
| 5 | 0.143 | -0.069| -0.042| 0.113| 0.171|
| 6 | 0.231 | -0.010| -0.002| 0.175| 0.148| 0.348|
| 7 | -0.087| -0.017| -0.030| -0.070| -0.062| -0.137| 0.102|
| 8 | 0.025 | -0.185| -0.169| 0.033| 0.084| -0.005| 0.057| 0.224|
| 9 | 0.008 | -0.147| -1.150| 0.037| 0.052| 0.017| 0.034| 0.166| 0.148|
|10 | 0.093 | -0.096| -0.083| 0.058| 0.085| 0.093| -0.006| 0.114| 0.089| 0.112|
|11 | 0.069 | -0.109| -0.089| 0.038| 0.075| 0.050| 0.006| 0.124| 0.088| 0.103| 0.103|
|12 | 0.008 | 0.092| 0.099| 0.001| -0.042| 0.034| -0.075| -0.0170| -0.129| -0.081| -0.085| 0.171|
|13 | 0.037 | 0.055| 0.077| 0.022| -0.005| 0.055| -0.098| -0.149| -0.117| -0.057| -0.058| 0.173| 0.195|

Table 4. Estimates for the fixed part of the SEM & MLSEM models

| Coefficients | SEM Estimate | SEM Std. Error | MLSEM Estimate | MLSEM Std. Error |
|--------------|--------------|----------------|----------------|------------------|
| 1            | 3.6872       | 0.1199         | 3.6928         | 0.1228           |
| 2            | 3.4150       | 0.1303         | 3.4105         | 0.1155           |
| 3            | 3.3678       | 0.1195         | 3.3725         | 0.2874           |
| 4            | 3.8557       | 0.0939         | 3.8589         | 0.0960           |
| 5            | 3.8076       | 0.1130         | 3.8040         | 0.1216           |
| 6            | 3.7127       | 0.1598         | 3.7164         | 0.1614           |
| 7            | 2.4855       | 0.0899         | 2.4711         | 0.0910           |
| 8            | 2.8050       | 0.1301         | 2.8081         | 0.1041           |
| 9            | 2.8516       | 0.1073         | 2.8447         | 0.1005           |
|10           | 2.8019       | 0.0948         | 2.7973         | 0.1202           |
|11           | 2.8246       | 0.0915         | 2.8212         | 0.1204           |
|12           | 2.9211       | 0.1152         | 2.9166         | 0.1120           |
|13           | 2.9001       | 0.1226         | 2.8952         | 0.1214           |
Table 5. Parameter estimates, standard errors and goodness of fit indices for SEM and MLSEM models of patient’s satisfaction with doctor’s communication

| Factor Loadings | SEM | | | Multilevel SEM | |
|-----------------|-----|------|------|----------------|------|
|                 | Estimate | Standard Error | $R^2$ | Estimate | Standard Error | $R^2$ |
| 1               | 1.000 | - | - | 1.000 | - | - |
| 2               | 2.209 | 0.381 | -0.039 | 0.026 |
| 3               | 2.076 | 0.363 | 0.330 | 0.035 |
| 4               | 0.681 | 0.184 | 0.737 | 0.011 |
| 5               | 0.940 | 0.205 | 0.783 | 0.016 |
| 6               | 0.563 | 0.186 | 1.288 | 0.017 |
| 7               | -2.284 | 0.391 | -0.534 | 0.014 |
| 8               | -4.224 | 0.664 | 0.063 | 0.026 |
| 9               | -4.516 | 0.708 | 0.071 | 0.022 |
| 10              | -5.506 | 0.853 | 0.455 | 0.016 |
| 11              | -5.737 | 0.887 | 0.325 | 0.017 |
| 12              | 5.508 | 0.855 | 0.032 | 0.023 |
| 13              | 5.120 | 0.800 | 0.182 | 0.025 |
| Factor Variance | $\psi$ | 0.026 | 0.008 | 0.271 | 0.015 |
| Error Variances (Between) | | | | | |
| 1 | 0.198 | 0.078 | 0.021 | 0.017 | 0.001 | 0.910 |
| 2 | 0.153 | 0.063 | 0.120 | 0.223 | 0.008 | 0.001 |
| 3 | 1.126 | 0.040 | 0.016 | 0.692 | 0.017 | 0.027 |
| 4 | 0.119 | 0.048 | 0.016 | 0.021 | 0.001 | 0.818 |
| 5 | 0.195 | 0.077 | 0.019 | 0.062 | 0.002 | 0.635 |
| 6 | 0.354 | 0.137 | 0.004 | 0.052 | 0.002 | 0.849 |
| 7 | 0.081 | 0.035 | 0.216 | 0.055 | 0.002 | 0.477 |
| 8 | 0.062 | 0.029 | 0.553 | 0.221 | 0.008 | 0.003 |
| 9 | 0.040 | 0.021 | 0.687 | 0.146 | 0.005 | 0.006 |
| 10 | 0.058 | 0.029 | 0.693 | 0.071 | 0.003 | 0.338 |
| 11 | 0.047 | 0.025 | 0.750 | 0.083 | 0.003 | 0.183 |
| 12 | 0.030 | 0.019 | 0.813 | 0.171 | 0.006 | 0.001 |
| 13 | 0.077 | 0.036 | 0.592 | 0.188 | 0.007 | 0.030 |
|          | SEM | Multilevel SEM |
|----------|-----|----------------|
|          | Estimate | Standard Error | R² | Estimate | Standard Error | R² |
| **Error Variances (Within)** | | | | | |
| 1 | 0.839 | 0.030 | 0.030 | 0.581 | 0.024 | 0.318 |
| 2 | 1.135 | 0.040 | 0.100 | 1.270 | 0.044 | 0.000 |
| 3 | 1.126 | 0.040 | 0.090 | 0.692 | 0.017 | 0.041 |
| 4 | 0.834 | 0.767 | 0.014 | 0.664 | 0.025 | 0.181 |
| 5 | 0.767 | 0.027 | 0.029 | 0.639 | 0.025 | 0.206 |
| 6 | 0.981 | 0.034 | 0.008 | 0.583 | 0.029 | 0.436 |
| 7 | 1.118 | 0.040 | 0.107 | 1.104 | 0.039 | 0.065 |
| 8 | 0.886 | 0.034 | 0.342 | 1.350 | 0.047 | 0.001 |
| 9 | 0.899 | 0.035 | 0.369 | 1.436 | 0.050 | 0.001 |
| 10 | 0.688 | 0.030 | 0.532 | 1.510 | 0.053 | 0.036 |
| 11 | 0.637 | 0.029 | 0.571 | 1.501 | 0.053 | 0.019 |
| 12 | 0.807 | 0.034 | 0.492 | 1.587 | 0.055 | 0.000 |
| 13 | 0.986 | 0.039 | 0.407 | 1.657 | 0.058 | 0.005 |
| **Chi-Square** | 3285.142 | 41079.797 |
| **Degrees of freedom** | 143 | 143 |
| **RMSEA** | 0.115 | 0.105 |
| **95% CI for RMSEA** | 0.112 – 0.119 | 0.097 – 0.113 |
The two level structural equation model carries few restrictions on level-1 and level-2 components of variance.

In two level SEM carry some restrictions on between (level-2) and within (level-1) variance components. By differentiating (5) w.r.t \( \gamma \), estimates of unknown restricted parameters was obtained.

2.1 Model Assessment and Goodness of Fit Statistics for MLSEM

In two-level structural equation model \( M(\gamma) \) the covariance structure \( \Sigma_{xy}(\gamma) \), \( \Sigma_{xx}(\gamma) \) and mean structure \( \mu(\gamma) \) for observed random variables is used, where \( \gamma \) is a \( k \times 1 \) vector of parameters. Steiger proposed an approximated root mean square error (RMSEA)

\[
RMSEA = \sqrt{\frac{\hat{F}_0}{d}}
\]

Where \( \hat{F}_0 \) is a function of sample size, degrees of freedom and the fit function

\[
\hat{F}_0 = \max \left( \frac{c-d}{n}, 0 \right)
\]

A value of RMSEA close to 0.05 indicate a better fit of the model and value up to 0.08 shows satisfactory goodness of fit of the model.

The path diagrams and the results of the components of the model-1 generated through LISREL 8.84 are presented.

Table 2 &3 showed the estimated between hospitals covariance matrix and estimated within hospitals covariance matrix under patient’s satisfaction with the doctor’s communication data. Clearly we observe the differences between the two covariance matrices and comparatively the values of covariance matrix under between the hospitals model is higher than the values of within covariance matrix. Table 4 represented the results of regression coefficients, standard errors, z-statistics and p-values for the observed variables under SEM and MLSEM models respectively. Comparatively estimates under MLSEM are higher than the estimates under SEM models. Table 5 depicted the estimates regarding the factor loadings, latent variable error variance, error variances concerning the between and within error variances, squared multiple correlations, and goodness of fit indices under SEM and MLSEM models. Differences have been observed in the results of two models. Factor loadings under MLSEM model are comparatively smaller with low standard errors than the SEM model. Estimated error variance of latent variable is well diagnosed under MLSEM model. Similarly error variances for observed variables between and within hospital are estimated well under MLSEM model. The goodness of fit statistic \( \chi^2 \) under MLSEM model showed comparatively a higher significance than the SEM model and indicating a better fit of the model. Another meaningful measure of goodness of fit of a model is RMSEA and the value of RMSEA under MLSEM model showed comparatively a less discrepancy between true and estimated model. So we can say that the factor loadings between hospitals and within hospitals under MLSEM model are reasonable. The structural relations between latent variables and the observed variables under SEM and MLSEM models also have been shown in Figs. 1-4.

3. CONCLUSION

Multilevel structural equation models must be in use while studying causal relations between observed and latent variables from a clustered population even the variables of second level or higher levels are not considered in the analysis.

CONSENT

It is not applicable.

ETHICAL APPROVAL

It is not applicable.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Stapleton LM. Variance estimation using replication methods in structural equation modeling with complex sample data. Structural Equation Modeling. 2008;15(2):183-210.
2. Stapleton LM. Using multilevel structural equation modeling techniques with
complex sample data. Structural equation modeling: A second course. 2006;345-383.

3. Hu LT, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural equation modeling: A multidisciplinary journal. 1999;6(1):1-55.

4. Muthen B. Latent Variable Modeling in Heterogeneous Populations. Psychometrika. 1989;54(4): 557-585.

5. Muthen BO, Satorra A. Complex sample data in structural equation modeling. Sociological Methodology. 1995; 267-316.

6. Hofmann DA. An overview of the logic and rationale of hierarchical linear models. Journal of Management. 1997;23 (6):723-744.

7. Du Toit S. Analysis of structural equation models based on a mixture of continuous and ordinal random variables in the case of complex survey data. Current Topics in the Theory and Application of Latent Variable Modeling. New York, NY: Routledge Academic; 2012.

8. Triandis HC, Bontempo R, Betancourt H, Bond M, Leung K, Brenes A, de Montmollin G. The measurement of the etic aspects of individualism and collectivism across cultures. Australian journal of Psychology. 1986;38(3):257-267.

9. Raudenbush SW, Bryk AS. Hierarchical linear models: Applications and data analysis methods. sage. 2002;1.

10. Ahmad I, Nawaz A, Din S. Dynamics of patient satisfaction from health care services. Gomal Journal of Medical Sciences. 2011;9(1):37-41.

11. Charalambous A. Variations in patient satisfaction with care for breast, lung, head and neck and prostate cancers in different cancer care settings. European Journal of Oncology Nursing. 2013;17(5):588-595.

12. Farin E. Patient-provider communication in chronic illness: current state of research in selected areas. Die Rehabilitation. 2010;49(5):277-291.

13. Davenport DL, Henderson WG, Mosca CL, Khuri SF, Mentzer Jr RM. Risk-adjusted morbidity in teaching hospitals correlates with reported levels of communication and collaboration on surgical teams but not with scale measures of teamwork climate, safety climate, or working conditions. Journal of the American College of Surgeons. 2007;205(6):778-784.

14. Cavrini G, Galimberti G, Soffritti G. Evaluating patient satisfaction through latent class factor analysis. Health and place. 2009;15(1): 210-218.

15. Herman JS, Peter MMS, Marja AAP. Patient satisfaction with the general practitioner: A two-level analysis. Medical Care.1998;36(2):212-229.

16. Mallidou AA, Cummings GG, Estabrooks CA, Giovannetti PB. Nurse specialty subcultures and patient outcomes in acute care hospitals: A multiple-group structural equation modeling. International journal of nursing studies. 2011;48(1):81-93.

17. Naseer M, Zahidie A, Shaikh BT. Determinants of patient's satisfaction with health care system in Pakistan: a critical review. Pakistan Journal of Public Health. 2012;2(2):52-61.

18. Quaschning K, Körner M, Wirtz M. Analyzing the effects of shared decision-making, empathy and team interaction on patient satisfaction and treatment acceptance in medical rehabilitation using a structural equation modeling approach. Patient education and counseling. 2013;91(2):167-175.

19. Qureshi MO, Shafqat F, Ahmed S, Niazi TK, Khokhar N. Factors affecting patient satisfaction during endoscopic procedures. Journal of the College of Physicians and Surgeons Pakistan. 2013;23(11):775-779.

20. Thompson L, McCabe R. The effect of clinician-patient alliance and communication on treatment adherence in mental health care: a systematic review. BMC psychiatry. 2012;12(1):1-12.

21. Ancarani A, Mauro CD, Giammanco MD. How are organizational climate models and patient satisfaction related? A competing value framework approach. Social Science & Medicine. 2009;69(12):1813–1818.

22. Kim SS, Kaplowitz S, Johnston MV. The effects of physician empathy on patient satisfaction and compliance. Evaluation & the health professions. 2004;27(3):237-251.
23. Roter DL, Stewart M, Putnam S, Lipkin MJ, Stiles W, Inui T. Communication patterns of primary care physicians. J Amer MedAssoc. 1997;277: 350-356.

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