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A Pilot Study Examining the Factor Structure of Pittsburgh Sleep Quality Index in Indian Context

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***Abstract*—The Pittsburgh Sleep Quality Index (PSQI) has gained widespread acceptance as a useful tool to measure subjective sleep quality. The Cantonese version of PSQI has shown the two factor model of PSQI fits all the data nicely. There is no such factor structure created for any Indian context to the best of our knowledge. In this work, we seek to estimate such a structure in the Indian context.**

We have used Confirmatory Factor Analysis (CFA) on the factors suggested in literature and endorsed in the Cantonese study. We found the two factor model fitting the data nicely for many cases (age groups) but it fails for other cases (or age groups). We attribute this to the somewhat small sample data size. Seeing this deficiency, we used the Exploratory Factor Analysis (EFA) technique to identify new factor structures. Using this new structure we found the data fitting better as is evident from a better Goodness of Fit index (CFI) in many cases. For the remaining cases the CFI is poor requiring these cases to be explored further

***Index Terms*— Exploratory and Confirmatory Factor Analysis, Pittsburg Sleep Quality Index, Goodness of Fit measure, Global Sleep Quality.**

I. INTRODUCTION

Poor sleep quality has received increasing attention in various surveys and research. This is because poor sleep quality very often brings acute lifestyle problems. Sleep problems increase with age and constitute some of the most difficult afflictions in late life. However, while sleep problems are widely studied in the West, there are very few studies in the oriental societies, like China and India. One possible reason could be due to a lack of valid and reliable measurement tools to assess sleep quality in such societies [1].

Since its introduction in 1989, the Pittsburgh Sleep Quality Index (PSQI) [2] has gained widespread acceptance. The inventory possesses good psychometric properties, including internal consistency, reliability, validity, as well as high correlations with sleep log data. Because of this PSQI has been used in a variety of populations. In many cases PSQI has formed the basis of identifying responsible factors for sleep related disorders and hence became excellent enablers in the diagnosis process. Hence it is important to identify the basic factor based structure of PSQI results so that appropriate diagnosis and remedial measures can be adopted by specialists. The interesting observation here is that this factor based structure is not uniform across cultures. This stems from the fact that sleep and its associate disorders have been shown to be quite dependent on the cultural background. Below we seek to study this in detail.

The single factor contains all the PSQI items. The 2-factor model has as the first factor the measurements of sleep efficiency which consists of the two PSQI items: sleep duration and habitual sleep efficiency. The

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second factor is sleep quality and consists of the remaining five items, viz., subjective sleep quality, sleep latency, sleep medication, sleep disturbance and daytime dysfunction. The 2-factor model is used from Magee's [4]. The 3-factor model is as it is from Cole's [3] and Magee's [4]. In this model first factor is sleep efficiency which consists of the two PSQI items sleep duration and habitual sleep efficiency as in 2-factor model. The second factor sleep quality consists of the three items: subjective sleep quality, sleep latency and sleep medication. The third factor daily disturbance is identified by the remaining two items sleep disturbance and daytime dysfunction. A notable feature of the factor analysis here is that an item is mapped to only one factor.

In [1], authors have discussed in detail about the various factor structure suggested and adopted by various researchers. The original developers of PSQI [2] recommended the use of a single factor. However most researchers have now found breaking down the PSQI into a multiple factor model can capture sleep quality better [1]. JC Cole et. el. has used Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) approaches on a sample of elderly people to recommend the 3-factor [1]. Cole's 3-factor was in a sample of PSQI study of 520 Nigerian university students. Magee et el has conducted the PSQI survey on a sample of 364 Australian adults and found both 2-factor and 3-factor models give better results. In [5] authors have studied PSQI measures on 134 community dwelling renal transplant patients and found the 3-fctor model better. Thus we see opinions differ about the most suitable factor structure drastically.

II. Indian Context for PSQI

Unfortunately not a whole lot of focus has been given on the PSQI in Indian context so far. In [6], authors present the study in an Indian university student context, a common ground for sleep disorder related problems. They have evaluated the PSQI with the PSG test (polysomnography) and found some concurrence between them. Also they found that PSQI responses can be a useful tool to diagnose some sleep problems. Little effort has been spent to discover the influence of latent factors in the sample however.

In [7] authors survey more than 1000 healthy people in South India using PSQI and other suitable measures of sleep related disorders (SRD). They have found that PSQI responses can diagnose a few SRD types. This paper also however does not try to understand the structural components.

So we see that in PSQI front India lags a lot. First, there are only a small number of reported publications attempting to cover the Indian context. Second, most of these studies aim at clinical aspects. These try to diagnose the root cause of a sleep disorder and take action correspondingly. Unfortunately these never attempted to validate and verify the underlying latent factors that may be responsible for the disorder. Neither EFA nor CFA were ever applied in Indian scenario to the best of our knowledge. This is in sharp contrast to [1] where authors have discussed in detail about the Chinese PSQI (the Cantonese version) factors and pointed out the same across other countries. Third, most of the samples in India refer to a special group like students or patients. In fact [7] referred to only otherwise healthy population with few sleep related disorders. We wonder what is the purpose of choosing this kind of population.

In our present we seek to overcome some of these deficiencies. We rigorously evaluate via CFA the appropriate factor structure suitable in this context in the line as in [1]. Also the survey was conducted on a random population with similar representation from all age group people in between 18 to unlimited (the highest age in our survey is 89 years). The mixture has students, elderly, middle aged, women groups represented in appropriate proportion.

III. Methods

A. Conduction of the survey

PSQI is a self-rating tool designed to assess a wide variety of indicators of sleep quality during the month before testing. It consists of 19 items from which 7 component scores are calculated and summed into a global score; they are subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. The score of each component has a range of 0 to 3, yielding a global score of sleep quality ranging from 0 to 21, with a higher score indicating poorer sleep quality [1] [2]. Although it is a practice of assigning values 0 to 3 for each of the components in the questionnaire, we chose 1 to 4 as the range (to avoid problems arising out of use of 0 in certain cases). Also we inverted the interpretation of the scale, i.e., we chose a higher value to represent better sleep quality. [This is opposite to what is reported in [1] [2] etc.].

As mentioned before, we chose respondents randomly. They were all known to the authors, with various age, gender and other parameters. We deviated from [1] from the age groups as many respondents were from the students community where the authors have more access. Remaining respondents were from the neighbours, relatives and friends circle. This eliminated the necessity for any explicit permission and also reduces the cost. This however restricted the numbers a bit. In all we could collect a sample of 85 only. The grouping details are shown in Table 1. Please note that since there were a large number of students present in the sample, we made a new group (compared to [1]) for the age group 18-29. This is consistent with results in Indian context where students and young people exhibit a lot of sleep related disorder problem. Also the number of 60+ people was small, so we did not create any subgroups among them (in [1] there are two subgroups created, one for 60-74 years, and the other for 75+ years of age). One additional benefit of resorting to familiar group of people is that there was no difficulty in communicating the PSQI questions to the respondents. The translation requirement was very little. (This is in sharp contrast to [1] where there was an explicit need for translating the PSQI to Cantonese version). Also the level of education of the respondents was reasonable. So the authors themselves could conduct the interview instead of trained personal interviewers as stated in [1]. This however reduced the scope and variety of participants to some extent. The mode of the interview was different for different people. Some were asked to note down their responses on a PSQI printed sheet. Some replied via emails. Others provided responses over phone. Apart from the age and gender info, the survey remained anonymous.

B. Data analysis of the survey

In statistics, confirmatory factor analysis (CFA) is a special form of factor analysis, most commonly used in social research. It is used to test whether measures of a construct are consistent with a researcher's understanding of the nature of that construct (or factor). As such, the objective of confirmatory factor analysis is to test whether the data fit a hypothesized measurement model. This hypothesized model is based on theory and/or previous analytic research.

Both EFA (Exploratory Factor Analysis) and CFA are employed to understand shared variance of measured variables that is believed to be attributable to a factor or latent construct. Despite this similarity, however, EFA and CFA are conceptually and statistically distinct analyses. The goal of EFA is to identify factors based on data and to maximize the amount of variance explained. By contrast, CFA evaluates a priori hypotheses and is largely driven by theory. CFA analyses require the researcher to hypothesize, in advance, the number of factors, whether or not these factors are correlated, and which items/ measures load onto and reflect which factors. As such, in contrast to EFA, where all loadings are free to vary, CFA allows for the explicit constraint of certain loadings to be zero. EFA is often considered to be more appropriate than CFA in the early stages of scale development because CFA does not show how well your items load on the non-hypothesized factors. Another strong argument for the initial use of EFA, is that the misspecification of the number of factors at an early stage of scale development will typically not be detected by CFA. At later stages of scale development, CFA may provide more information by the explicit contrast of competing factor structures [9].

In CFA, several statistical tests are used to determine how well the model fits to the data. Kline (2010) recommends reporting the Chi-squared test, the Root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the standardized root mean square residual (SRMR) [10]. The chi-squared test indicates the difference between observed and expected covariance matrices. Values closer to zero indicate a better fit. One difficulty with the chi-squared test of model fit, however, is that researchers may fail to reject an inappropriate model in small sample sizes and reject an appropriate model in large sample sizes. The root mean square error of approximation (RMSEA) avoids issues of sample size by analyzing the discrepancy between the hypothesized model, with optimally chosen parameter estimates, and the population covariance matrix. The RMSEA ranges from 0 to 1, with smaller values indicating better model fit. Standardized root mean square residual (SRMR) is the square root of the discrepancy between the sample covariance matrix and the model covariance matrix. The goodness of fit index (GFI) is a measure of fit between the hypothesized model and the observed covariance matrix. Comparative fit indices (CFI) compare the chi-square for the hypothesized model to one from a “null”, or “baseline” model. This null model almost always contains a model in which all of the variables are uncorrelated, and as a result, has a very large chi-square (indicating poor fit) [9].

CFA was conducted in our work using the “lavaan” package [11] with “R” software. As has been mentioned before, the single factor in CFA for PSQI contains all the items. The 2-factor model has as the first factor the measurements of sleep efficiency which consists of the two PSQI items: sleep duration and habitual sleep efficiency. The second factor is sleep quality and consists of the remaining five items, viz., subjective sleep quality, sleep latency, sleep medication, sleep disturbance and daytime dysfunction as the identifying items. The 3-factor model has as its first factor sleep efficiency which consists of the two PSQI items sleep duration and habitual sleep efficiency as in 2-factor model. The second factor sleep quality consists of the three items: subjective sleep quality, sleep latency and sleep medication. The third factor daily disturbance is identified by the remaining two items sleep disturbance and daytime dysfunction. A notable feature of the factor analysis here is that an item is mapped to only one factor.

In addition to using data from all participants, CFA employed data from different age groups, one aged 18 to 29 (the young ones), another aged 30 to 59 (the young and the middle aged), and a third aged 60 or above (the old). The breakup is somewhat different from other sources for two reasons. First, we had samples with age values varying very widely (smallest 18 to maximum 89). Second, since the number of surveyed population was small, having age groups as discussed in other references ranging over smaller intervals, take [1] for example, would have yielded an insignificant number of samples per group. Unfortunately CFA would not be able to converge to a solution with such a small sample size per group. Hence our choice. One problem with our group selection is that some groups will not be able to identify the group characteristics very well. Obviously a 30 something person is grossly different from a person of 55. Same true for two persons aged 61 and 89 respectively. This is a deficiency we have identified.

Furthermore, CFA fitted multiple age group data by constraining factor loadings as equal across the groups, as well as allowing factor loadings to be different among the groups. As can be found in [12], the "R" package has a module that can simultaneously compare models with free loading as well as different levels of constrained factor loadings. We only compared the first two of these models as stated above.

To have a common metric across the three age groups, the CFA used standardized scores of the seven components as inputs. Altogether, this analyses involved twelve models for different numbers of factors and different sets of data (see Table 3). A model demonstrated a good fit to the data when its standardized root-mean square residual (SRMR) was below 0.05, root-mean square error of approximation (RMSEA) below 0.07, and Comparative Goodness-of-Fit Index (CFI) above 0.95 [8].

IV. Results

A. Participant characteristics

Among the 85 candidates, we had similar representations from the three age groups 18-29, 30-59 and 60+. There were respondents from both genders. Table 1 lists the characteristics in detail.

TABLE I: PERSONAL CHARACTERISTICS OF PARTICIPANTS (N= 85)

	Age 18-29	**Age 30-59**	**Age 60+**
Male	26	18	13
Female	11	5	12
Total	37	23	25

B.Psychometricproperties of the PSQI survey

Each of the 7 component scores ranged from 1 to 4[1]. The global PSQI score ranged from 7 to 28, with a mean 22.26 (SD =4.98). The SD matches with the Chinese score [1]. The Mean if calculated from the opposite end, which is 28 for very good sleep (this is taken as 0 in [1]), the value is 5.76. This is less than [1], implying the Indian population studied has better sleep quality compared to their Chinese counterpart. We are not going to analyze the causes, but one point worth mentioning is that the Indian survey contains a large proportion of student population (aged 18-29). They might have impacted the score positively. Following [1], if the PSQI global score of 5 or above were taken as the cutoff point for sleep problems, as suggested by the developers [2] (this translated to the value 19 or less in our case), only 23% of the participants (compared to 58.50% of the Chinese population as in [1]) would be seen as having some sleep problems. The Cronbach's alpha of Indian PSQI was 0.728, reflecting good internal consistency.

From Table 2, we see the correlation between various factors C1 through C7. Mostly the correlation is strong or moderately strong. There are two cases however where the correlation is weak. In particular we see very strong correlation between Sleep Latency and Sleep Disturbance (0.54) which is easily explained by the fact

[1] In almost all works, this value is 0 to 3 as recommended by the PSQI docs. We have however shifted the scale by 1, so that "0" is not handled. Also we have taken 1 to mean bad sleep and 4 to mean good sleep. This is opposite to what is followed in literature.

that that sleep latency is more for the case when there is more disturbance and vice versa. However [1] fails to catch this relation. We see a strange strong correlation (0.57) however between sleep medication and habitual sleep efficiency. We are not sure why this emerges; [1] does not report this either. This needs further investigation.

TABLE II: CORRELATIONS AND DESCRIPTIVE STATISTICS OF INDIAN PSQI (N = 85)

	(C1)	(C2)	(C3)	(C4)	(C5)	(C6)	(C7)
Subj Sleep Quality (C1)	1						
Sleep Latency (C2)	0.37	1.00					
Sleep Duration (C3)	0.04	0.13	1.00				
Habitual Sleep Efficiency (C4)	0.25	0.32	0.10	1.00			
Sleep Disturbances (C5)	0.12	0.54	0.12	0.31	1.00		
Medication (C6)	0.25	0.38	0.21	0.57	0.30	1.00	
Daytime Dysfunction (C7)	0.30	0.20	0.35	0.02	0.20	0.15	1

On the other hand, there is very weak correlation (0.04) between sleep duration and subjective sleep quality; similarly sleep medication and daytime dysfunction has a weak correlation (0.02). None of these have ready explanations and needs further investigation.

C. Confirmatory factor analysis

From the Table 3, we note that for all data present, we see gradual improvement in the fitness values form 1-factor to 2-factor models but this diminishes with more factors (models 1, 2, 3). The CFI values increase from 0.978 to 0.986 but reduces at 0.971. The RMSEA values show similar patterns (0.05 to 0.041 to 0.065). The SRMR values however decreases monotonically. So we conclude that for all data items the 2-factor model is ideally suited.

For the 60+ age group data (corresponding models are 4,5,6), however the 2-factor model shows good fit (CFI = 0.968) whereas the 1-factor model fails (0.915). The 3-factor model is however overfitting (CFI = 1.0) and this is possibly because of not enough data in this category (Age group of 60+).

For the other two age groups no model is good enough (models 7 though 12). The poor values of CFI (0.739 and 0.728 respectively) reflect that. In fact in both cases the 3-factor model fails to converge to a solution. This may be because of low volume of data in these categories.

Similarly for the model representing multiple age group data with various factor loading constraints, no solution could be found (not shown here). We attribute this also to the dearth of enough sample data.

Thus we conclude that the sample data indicates towards adopting a two factor model for PSQI (Model 2, 5, 8, 11). However we have to remember this did not fit the 30-59 and 18-30 age group data (corresponding models are 8 and 11) very well.

We see from Table 4 that Models 2,5,8,11 where the two factor model is used, factor loading are quite interesting across the models. For the age group 60+ (Model 5), all the indicator variables are loaded heavily on corresponding factors. In particular the indicator variables Sleep Latency, Disturbance and the Dysfunction show a very deep impact on corresponding factors. For Model 2 (for all data), the Medication and Dysfunction indicators have somewhat poor loadings (0.575 and 0.595 respectively) – others are heavily loading corresponding factors. For Model 8 (for the age group 30-59 years), the Disturbance and Dysfunction indicators have somewhat poor loadings (0.417 and 0.276 respectively) – others are heavily loading corresponding factors, apart from somewhat the Habitual Sleep Efficiency (0.673). For Model 11 (for the age group below 30 years), again the Medication factor has poor loading (0.081). The disturbance factor is also poor loaded, in fact it shows a negative value (-0.006). This also needs further investigation.

D. Exploratory factor analysis

Since it is obvious from the discussion above that CFA using the factor structure explored in existing literature does not give very good results, it is better to resort to own Exploratory Factor Analysis (EFA). We

TABLE III: GOODNESS OF FIT OF OUR MODELS (N=85)

Model	Number of factors	Number of groups	Age	*SRMR*	*RMSEA*	*CFI*
1	1	1	All	0.055	0.050	0.978
2	2	1	All	0.053	0.041	0.986
3	3	1	All	0.051	0.065	0.971
4	1	1	60+	0.086	0.116	0.915
5	2	1	60+	0.080	0.074	0.968
6	3	1	60+	0.060	0	1.0
7	1	1	30-59	0.116	0.194	0.739
8	2	1	30-59	0.118	0.201	0.739
9	3	1	30-59	No solution		
10	1	1	<30	0.109	0.137	0.738
11	2	1	<30	0.106	0.144	0.728
12	3	1	<30	No solution		

used the "factanal" method available inside "R" to find out the latent factor structure available inside our data. It is no wonder that we found the factor structure grossly different from that proposed in literature. This structure is shown in Table 5 below. In order to complete the factorization process, we had used two most popular types of rotation tactics: "varimax" (the default one) and "promax". After deciding upon the various factors, we ram CFA on the various datasets mentioned above. We have tabulated the results in Table 6 below. We have intentionally omitted 1-factor models because of poor goodness of fit values.

We note that for models 2 and 3 our CFA gives overfitted results but original CFA (Table 3) gives results with good fitness measures. So we will accept the original model here.

For model 5, we see the original result is better (CFI = 0.968) than ours (varimax = 0.906 and promax = 0.937). So we accept the original model here also.

For model 6, the original solution is overfitted but we get good CFI for varimax (0.941). Even the promax model gets a CFI (0.898) albeit somewhat on the poorer side.

For model 8, the original solution was poor. However our model failed to find a solution in both cases. For model 9, the original approach failed to converge to a solution. Our structure however found solutions in both cases. Especially the varimax model gave a reasonably good fitness (0.926) (the promax gave a value 0.914).

TABLE IV: FACTOR LOADINGS STANDARDIZED FOR THE WHOLE SAMPLE (N = 85)

Indicator	Model 2	Model 5	Model 8	Model 11
Sleep efficiency				
Sleep duration	1.0	1.0	1.0	1.0
Habitual sleep efficiency	0.971	1.034	0.673	2.301
Sleep quality				
Subjective sleep quality	1.0	1.0	1.0	1.0
Sleep latency	1.294	2.865	1.700	1.355
Sleep medication	0.575	1.242	1.343	0.081
Sleep disturbances	0.978	2.349	0.417	-0.006
Daytime dysfunction	0.593	2.147	0.276	0.843

TABLE V: FACTORS AFTER EXPLORATORY FACTOR ANALYSIS

"varimax" rotation		"promax" rotation	
2-factor model	3-factor model	2-factor model	3-factor model
F1=C2 + C3 + C4 + C7 F2 = C1 + C2 + C5 + C6	F1 = C1 + C2 + C5 + C6 F2 = C2 + C4 + C7 F3 = C3	F1 = C1 + C2 + C3 + C5 + C6 F2 = C2 + C4 + C7	F1 = C1 + C2 + C5 + C6 F2 = C4 + C7 F3 = C3

For model 11, the original model gave a poor solution (0.728). But our models failed to converge to any solution in both cases. For model 12, the original model fails to find a solution. Our varimax model also fails to find a solution. But the promax method finds a poor solution (0.794).

TABLE VI: GOODNESS OF FIT OF OUR MODELS (N=85) (OUR EFA)

Model	Number of factors	Number of groups	Age	*SRMR*	*RMSEA*	*CFI*
2	2 (varimax)	1	All	0.041	0.0	1.0
2	2 (promax)	1	All	0.048	0.0	1.0
3	3 (varimax)	1	All	0.041	0.0	1.0
3	3 (promax)	1	All	0.043	0.0	1.0
5	2 (varimax)	1	60+	0.126	0.138	0.906
5	2 (promax)	1	60+	0.125	0.078	0.937
6	3 (varimax)	1	60+	0.080	0.125	0.941
6	3 (promax)	1	60+	0.082	0.138	0.898
8	2 (varimax)	1	30-60	No solution		
8	2 (promax)	1	30-60	No solution		
9	3 (varimax)	1	30-60	0.113	0.116	0.926
9	3 (promax)	1	30-60	0.10	0.120	0.914
11	2 (varimax)	1	<30	No solution		
11	2 (promax)	1	<30	No solution		
12	3 (varimax)	1	<30	No solution		
12	3 (promax)	1	<30	0.086	0.131	0.794

V. DISCUSSION

In this work we conducted a pilot study of 85 Indian males and females belonging to various age groups to find out the sleep quality prevailing among them. We used the popular PSQI questionnaires to identify various sleep quality measures and associated factors. Our aim was to find out the factor structure hidden in the Indian version of the sleep quality measure. We employed the CFA methods. We used initially the 1-, 2- and 3-factor structures proposed in existing literature. One key characteristics of this breakup was that one indicator variable only loaded one factor. We found that the two factor and the three factor models better fit in some cases whereas the 1-factor model did not fit as well. This is in line what is reported in the Cantonese version of the report [1].

Our work however differs from existing reports like [1] in many aspects. First of all we see far less sleep problem reported by Indians (23%) compared to Westerners (40%-50%) and Cantonese people (58%). Second, we see there is no particular fit of factors for some cases. In fact some models failed to converge to a solution. Third, we see a strong correlation between various factors related to sleep quality that was not reported in other places. One of them is Sleep Medication. For the first case we attribute the difference related to cultural reasons. It is generally accepted that sleep related problems can be attributed to cultural heritage. In [1], Cantonese old people are shown to be more prone to sleep related disorders as they had undergone terrible socio political unrest in their lifetime. In Indian context such legacy may be absent.

In order to address the second issue we deviated from the existing factor structure. We created a new factor structure based on our survey data using EFA. We found the new structure substantially different as is evident from the fact that some single indicator variables loaded more than one factor. Using these models we ran CFA, and we found the CFI measures improving in many cases. In some cases however we still did not find good fits or failed to find a convergence. This may be because of a small dataset.

We are not sure however why the third factor is different.

The present study however suffers from a number of limitations. First of all, as repeatedly mentioned, the number of participant was too small to carry out CFA so that its results can be deemed very convincing (literature says at least a count of 300 is required). We did not include the attribute Marital status in the sample. This is included in [1] and we suspect has some relevance to sleep disorder. Also a more wide group of participants with lesser level of education should be included. In [1] it is stated that the level of education especially among the elderly play an important role in determining sleep quality. This may be attributed to the more socio economic pressure this group of people have to undergo. Also as we have stated earlier we have group structures having very broad range of values. Hence some groups may not be representing their population in a best possible manner. But we had to resort to this so that each group gets some significant number of samples. Of course as more and more samples are added we can leverage the wide range of values in our samples into multiple groups, possibly more in number than the ones reported in other sources. That would have made our analysis more comprehensive than other works (see [1] for example) performing a more purposive sample in this regards.

VI. CONCLUSION

We have conducted a pilot study on 85 Indian males and females belonging to different age groups regarding their sleep quality. The popular and powerful PSQI questionnaires were used to identify indicator variables necessary for producing good sleep quality. We found that Indians in general have less sleep disturbance compared to Westerners and Cantonese people. Since identifying latent factors responsible sleep quality can help diagnose sleep problems for medical usage, we employed CFA to identify responsible factors. A similar study was done on Cantonese people and reported in [1]. Using existing literature, 1-, 2- and 3-factor models were used. We found that 1-factor model gives a poor fit measure. The 2-factor and 3-factor models give good measures in some cases (across various age group data) but fail to either give a good fit or converge to a solution in other cases.

Hence we employed EFA to identify responsible factors on our own. We discovered very different latent factor structure. Using two different popular rotation methods (varimax and promax) we came up with new CFA measures. We have seen in certain cases where the original CFA failed to find a good or even a solution at all, our model fitted better. However in other cases either it failed to find a solution or in some cases overfitted. We suspect this anomaly owing to small dataset size. This however needs further investigation.

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REFERENCES

[1] Alice M.L. Chong and Chau-kiu Cheung. Factor Structure of a Cantonese-version Pittsburgh Sleep Qualilty Index. Sleep and Biological Rhythms.

[2] Buysse DJ, Reynolds CF, Monk TH, Berman SR, Kupfer DJ. The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research. Psychiatry Res. 1989; 28: 193–213.

[3] Cole JC, Motivala SJ, Buysse DJ, Oxman MN, Levin MJ, Irwin MR. Validation of a 3-factor scoring model for the Pittsburgh Sleep Quality Index in older adults. Sleep 2006; 29 (1): 112–16.

[4] Magee CA, Caputi P, Iverson DC, Huang XF. An investigation of the dimensionality of the Pittsburgh Sleep Quality Index in Australia adults. Sleep Biol. Rhythms 2008; 6: 222–7.

[5] Burkhalter H, Sereika SM, Engberg S, Wirz-Justice A, Steiger J, De Geest S. Structure validity of the Pittsburgh Sleep Quality Index in renal transplant recipients: a confirmatory factor analysis. Sleep Biol. Rhythms 2010; 8: 274–81.

[6] Md. Dilshad Manzar et el. Validity of the Pittsburgh Sleep Quality Index in Indian University Students. Oman Medical Journal [2015], Vol. 30, No. 3: 193– 202.

[7] S. Panda et el: Sleep-related disorders among a healthy population in South India. eurology India [2012], Vol. 60, Issue: 1, pp 68-74.

[8] Hu LT, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct. Equation Model. 1999; 6 (1): 1–55.

[9] https://en.m.wikipedia.org/wiki/Confirmatory_factor_analysis

[10] Kline, R. B. (2010). Principles and practice of structural equation modeling (3rd ed.). New York, New York: Guilford Press.

[11] http://www.understandingdata.net/2017/03/22/cfa-in-lavaan/

[12] Gerrit Hirschfeld and Ruth von Brachel, “Group confirmatory factor analysis in R”, Practical Assessment, Research & Evaluation, Volume 19, Number 7, July 2014.