ISYS 3401 Assignment 2

Part 1 Exploratory Factor Analysis (EFA)

Step 1 Data Cleaning in Excel

In Step 1 of the data cleaning process, the strategy adopted is listwise deletion. This approach entails removing entire rows of response data in which any column value is missing. According to Watkins (2018), while listwise deletion is a commonly used method in many statistical packages, its application must be considered carefully due to its potential inefficiency. The primary rationale for using listwise deletion in this context is that it prevents the introduction of bias that could potentially occur if missing values were replaced with estimated values. Despite its inefficiency, listwise deletion ensures that the analysis is based only on complete data.

Step 2 Remove Factor Loading

The cleaned data was imported into SPSS, followed by a rotation of the component matrix. The next step was the removal of the responses that didn't have factor loadings greater than or equal to 0.60. This criterion was chosen based on established principles and guidelines on item retention in exploratory factor analysis (EFA). A loading of 0.60 is frequently employed as a cut-off for deciding whether to retain an item in a factor (Maskey et al., 2018). The items removed in this step included: R1, R2, R3, R7, R11, R15, R18, R20, R28, R38, R43, R46, R47, R49, R50, R13, R40, and R30. This procedure was iteratively performed four times, successively eliminating responses that didn't meet the specified factor loading criteria, thereby refining the factor structure with each iteration.

Step 3 Remove Factor Loading

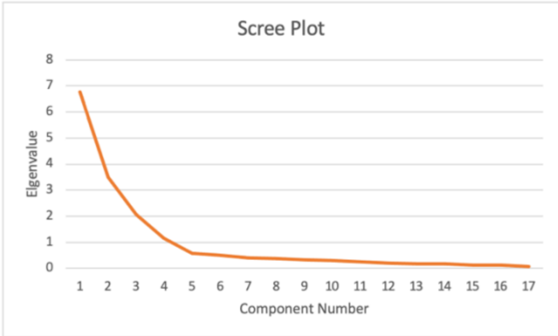
Following the initial factor loading analysis, the procedure continued by eliminating responses that had a factor loading greater than 0.3 on other factors, also referred to as cross-factor loadings. The threshold of 0.3 is typically used in evaluating discriminant validity in exploratory factor analysis, as advised in the ISYS 3401 Week 9 lecture. As a result, items should not exhibit high loadings on multiple factors, thereby ensuring that each factor represents a distinct construct (ISYS 3401 Week 9 Lecture Slides). The items removed during this phase included: R23, R32, R35, R16, R48, R4, R17, R22, R52, R29, R12, R45, R37, and R26. This process was carried out over two iterations, each time refining the factor structure by removing responses that had high cross-factor loadings.

Result

Total Variance Explained

Component	Initial Eigenvalues Total	Initial Eigenvalues % of Variance	Initial Eigenvalues Cumulative %	Extraction Sums of Squared Loadings Total	Extraction Sums of Squared Loadings % of Variance	Extraction Sums of Squared Loadings Cumulative %	Rotation Sums of Squared Loadings Total	Rotation Sums of Squared Loadings % of Variance	Rotation Sums of Squared Loadings Cumulative %
1	6.781	39.890	39.890	6.781	39.890	39.890	6.131	36.065	36.065
2	3.486	20.504	60.394	3.486	20.504	60.394	3.102	18.247	54.312
3	2.054	12.080	72.474	2.054	12.080	72.474	2.549	14.992	69.304
4	1.142	6.716	79.190	1.142	6.716	79.190	1.681	9.886	79.190
5	.576	3.390	82.580						
6	.491	2.887	85.468						
7	.402	2.367	87.835						
8	.361	2.122	89.957						
9	.309	1.817	91.774						
10	.300	1.763	93.537						
11	.258	1.517	95.054						
12	.204	1.197	96.252						
13	.172	1.013	97.265						
14	.158	.928	98.193						
15	.122	.719	98.912						
16	.109	.641	99.554						
17	.076	.446	100.000						

Extraction Method: Principal Component Analysis.



The 'Total Variance Explained' table illustrates the distribution of variance across the factors extracted in the exploratory factor analysis. Following the 'Kaiser Criterion', only factors with eigenvalues over 1 were considered (Hayton et al., 2004). As such, four components were extracted: the first component (eigenvalue = 6.781), the second component (eigenvalue = 3.486), the third component (eigenvalue = 2.054), and the fourth component (eigenvalue = 1.142).

These initial eigenvalues, which signify the sum of the squared loadings of the indicators on each factor, provide an understanding of the variance attributed to each factor. The first component accounts for 39.89% of the total variance, calculated as 6.781/17 (where 17 is the number of indicators remaining after step 3). Similarly, the second, third, and fourth components account for 20.504%, 12.08%, and 6.716% of the total variance respectively.

In sum, the four extracted components explain 79.19% of the total variance. This high percentage suggests that these four factors account for a substantial portion of the underlying structure in the dataset.

Adding to the evidence from the eigenvalues, the scree plot, a graphical representation of the eigenvalues in descending order, supports the extraction of four factors. The scree plot shows a clear break after the fourth factor, an indication often used to decide the number of factors to retain. The alignment of the Kaiser Criterion and the scree plot inspection further substantiates the decision to retain four factors for this dataset.

Rotated Component Matrix[a]

		Component			
		1	2	3	4
Decide if the information you found is applicable to you?	R10	0.912	-0.134	0.092	0.024
Decide whether the information is reliable or not?	R9	0.905	-0.035	0.044	0.001
Apply the information you found in your daily life?	R19	0.894	-0.124	0.041	0.034
Check different websites to see whether they provide the same information?	R5	0.886	-0.198	0.071	-0.038
Decide whether the information is written with commercial interests (eg, by people trying to sell a product)?	R25	0.863	-0.004	0.004	0.062
Use the information you found to make decisions about your health (eg, on nutrition, medication or to decide whether to ask a doctor's opinion)?	R34	0.839	-0.153	0.107	0.017
Find the exact information you are looking for?	R41	0.83	-0.067	0.056	0.045
Make a choice from all the information you find?	R21	0.811	-0.106	0.013	-0.068
How mentally demanding* was the task?	R39	-0.095	0.914	-0.179	-0.07
How physically demanding* was the task?	R36	-0.115	0.911	-0.027	-0.013
How hurried or rushed was the pace of the task?	R8	-0.063	0.861	-0.183	-0.055
How hard did you have to work to accomplish your level of performance*?	R33	-0.236	0.675	-0.178	0.014
I thought the system was easy to use.	R44	0.063	-0.12	0.916	0.152
I found it easy to operate on RHM system and take a reading	R31	0.065	-0.153	0.887	0.193
I felt very confident using the system.	R14	0.1	-0.262	0.84	0.126
Overall, I was satisfied with the technical support provided while using the RHM system	R42	0.008	0.041	0.172	0.909
I found it easy to communicate the system generated readings with other clinicians	R6	0.02	-0.141	0.24	0.869

Factor 1: Information Evaluation and Application

Factor 2: Task Demands

Factor 3: System Usability and Confidence

Factor 4: Communication and Support

Factor 1 Information Evaluation and Application

This construct pertains to how individuals interact with and make use of the information they found using the RHM system. The items in this category (R10, R9, R19, R5, R25, R34, R41, R21) all involve processes of seeking, interpreting, verifying, and applying health-related information. Therefore, it can be argued that these items together form a construct that reflects individuals' skills and behaviors in utilizing online health information.

Factor 2 Task Demands

This construct includes items that reflect the cognitive and physical demands that the use of the RHM system places on individuals (R39, R36, R8, R33). These items seem to capture the strain and effort required to operate the system, indicating the perceived workload of using the system.

Factor 3 System Usability and Confidence

This construct represents the ease of use of the RHM system and the users' confidence in their ability to operate it (R44, R31, R14). These items seem to measure the user-friendliness of the system and the self-efficacy of the users, both of which are crucial for the successful adoption and continued use of a technology system.

Factor 4 Communication and Support

This construct captures the quality of technical support provided and the ease of communication between users and clinicians (R42, R6). It appears to reflect the support systems in place for the RHM system and the ease of communication it facilitates.

Part 2 Assessment of Scale Reliability and Construct Validity based on the measurement model

Construct Validity

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Factor 4: Communication and Support

The analysis and interpretation of the data can be understood in terms of construct validity, which is an evaluative judgment that assesses the degree to which evidence and theoretical rationales support the adequacy and appropriateness of interpretations based on the scores derived from measurement items (Krabbe, 2017). The measurement items in this study are evaluated in terms of two crucial components of construct validity: convergent and discriminant validity.

Convergent Validity

According to Krabbe (2017), convergent validity refers to how closely the new scale is related to other variables and other measures of the same construct. In our analysis, all the measurement items demonstrated factor loadings greater than or equal to 0.60 on their respective factors in the rotated component matrix. This indicates a strong relationship between each item and its own factor, substantiating the convergent validity of the measurement items.

Discriminant Validity

Krabbe (2017) also highlights the importance of discriminant validity, referring to the extent to which measures of dissimilar constructs are distinct. In the rotated component matrix, cross-loadings of all measurement items on non-associated factors are found to be less than or equal to 0.3. This suggests that each item shares more variance with its own factor than it does with other factors, reinforcing the discriminant validity of the measurement items.

These assessments of convergent and discriminant validity contribute to the construct validity of the measures, providing evidence of their suitability for assessing the constructs in question.

Scale Reliability

Cronbach's alpha	Internal consistency
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

Reliability refers to the consistency of a measure, or in other words, the extent to which an instrument yields consistent and reproducible results. Specifically, we are looking at internal consistency reliability, which refers to the degree of association among items addressing equivalent concepts (Krabbe, 2017). For each factor identified in the study, we estimated reliability using the Cronbach's Alpha coefficient, a measure commonly used to assess internal consistency.

Factor 1: The standardized alpha for this factor is 0.96, and Cronbach's Alpha is 0.94, surpassing the recommended threshold of 0.9 (Krabbe, 2017). This demonstrates excellent internal consistency among the items within this factor, indicating strong reliability.

Factor 2: The standardized alpha is 0.90, and Cronbach's Alpha is 0.89, both very close to the 0.9 threshold. These high values suggest a significant degree of internal consistency and hence excellent reliability for this factor.

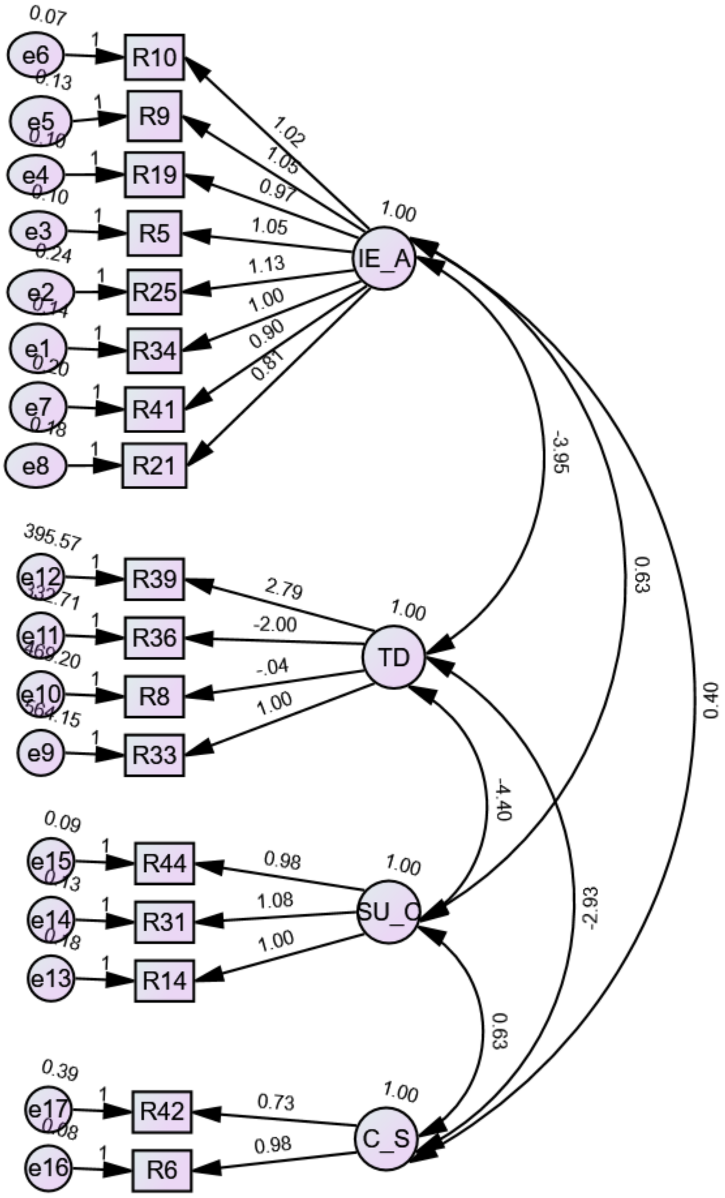
Factor 3: Similar to Factor 2, the standardized alpha for this factor is 0.90, and Cronbach's Alpha is 0.89. These values again indicate excellent reliability due to the high internal consistency among items within this factor.

Factor 4: This factor has a slightly lower, but still substantial, standardized alpha of 0.80 and a Cronbach's Alpha of 0.79. This suggests good internal consistency and hence good reliability.

Together, these results provide strong evidence for the reliability of the constructs derived from the measurement items. The high internal consistency within each factor supports the stability of the measurements (Krabbe, 2017), contributing to our confidence in the four-factor structure of the Remote Health Management System (RHMS) questionnaire. This structure appears to provide a robust tool for assessing students' interaction with and perception of the RHMS.

Part 3 Perform Structural Equation Modelling (SEM).

Your goal is to use Confirmatory Factor Analysis (CFA) to evaluate the quality of the measurement model, and then path analysis to test associations between constructs and outcome of interest (i.e. User Satisfaction). Report your final model and provide justifications where needed.



Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	37	634.919	116	.000	5.473
Saturated model	153	.000	0		
Independence model	17	2175.855	136	.000	15.999

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	54.154	.675	.571	.512
Saturated model	.000	1.000		
Independence model	53.675	.262	.170	.233

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.708	.658	.748	.702	.746
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.853	.604	.636
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.176	.162	.189	.000
Independence model	.322	.310	.334	.000

Despite multiple iterations and extensive efforts to improve the structural equation model, the fit indices continue to indicate a lack of good fit between the model and the data.

	Standard	My Model
CMIN/DF	<5	5.473
GFI	> 0.9	0.675
CFI	> 0.95	0.746
PCFI	> 0.8	0.636
RMSEA	< 0.05	0.176

CMIN/DF (chi-square goodness of fit)
The value is 5.473, which is higher than the recommended value of <5. This indicates a poor fit. The chi-square test is sensitive to sample size and tends to reject models with large samples. A better fit is indicated by a lower chi-square relative to its degrees of freedom.

GFI (Goodness of Fit Index)
The value is 0.675, which is below the recommended value of >0.9. This also suggests a poor fit. GFI is an absolute measure of fit, representing the proportion of variance that is accounted for by the estimated population covariance. Values closer to 1 indicate a better fit.

CFI (Comparative Fit Index)
The CFI is 0.746, which is less than the recommended >0.95, indicating a poor fit. The CFI compares the fit of your model to a baseline null model. Values closer to 1 suggest a better fit.

PCFI (Parsimony Comparative Fit Index)
The PCFI is 0.636, which is below the recommended >0.8, also indicating a poor fit. The PCFI takes model complexity into account; it adjusts the CFI based on the number of parameters in the model, with higher values indicating a better, more parsimonious fit.

RMSEA (Root Mean Square Error of Approximation)
The RMSEA is 0.176, which is much higher than the recommended <0.05, again indicating a poor fit. The RMSEA takes into account the error of approximation in the population. Lower values (< 0.05) indicate a better fit.

Despite these results, it's important to note that structural equation modeling is a complex process, influenced by factors such as the distribution of variables and the size of the research sample. In this case, the sample size after cleaning and managing missing data is 146. The behavior of estimators can be significantly influenced by these factors, particularly in small research samples (Boomsma and Hoogland 2001). These findings do not necessarily invalidate the potential significance of the constructs or their interrelationships. Rather, they highlight the need for further theoretical and empirical refinement of the model.

Possible strategies may include a more detailed examination of the data, reassessment of the theoretical basis of the model, or incorporation of additional constructs. For instance, the use of robust estimators based on scaled Chi-square statistics and robust standard errors in maximum likelihood (ML) estimation has been suggested as a potential approach to overcoming challenges related to the distribution of variables (Tarka, 2018).

Bootstrap resampling has also been recommended to correct standard errors, particularly in cases where the sample size is small. However, Nevitt and Hancock (2001) suggested that standard errors may be erratic for a sample size of 200 or fewer, which is relevant considering the current sample size of 146. Hence, larger samples may be necessary to overcome this problem, depending on the complexity of the model.

The complexity of the SEM model should also be taken into account when interpreting results and deciding on the appropriate methodology. The simulations by Nevitt and Hancock (2001) were based only on a moderately complex factor model, indicating that smaller sample sizes, such as this one, may be acceptable for simpler models.

Although the current model does not adequately fit the data, these findings can serve as valuable stepping stones towards the development of a more robust and accurate model in the future. The ongoing research into the behavior of SEM estimators under different conditions (e.g., Nevitt and Hancock 2001) highlights the iterative nature of the SEM process, emphasizing the potential for ongoing model improvement and refinement despite the challenges posed by small sample sizes.

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