Appendix D.

Exploratory Factor Analysis (EFA) of the EmpathiSEr-U Scale: Initial Three-Factor Solution

This appendix contains further details regarding the initial three-factor solution from the EFA of the EmpathiSEr-U scale which includes all the 37 items of the scale. EFA was conducted using **Principal Axis Factoring (PAF)** and an **oblique rotation method (Direct Oblimin).**

PAF was chosen over Principal Component Analysis (PCA) because the goal was to identify underlying latent constructs (i.e., psychological dimensions of empathy) rather than merely reduce data into uncorrelated components. While PCA treats all variance (common, unique, and error) as meaningful, PAF focuses only on shared variance among items, which is more appropriate for construct identification.

Direct Oblimin rotation was used instead of an orthogonal method like Varimax because the dimensions of empathy such as cognitive, emotional, and behavioural aspects, are theoretically expected to be correlated rather than independent. Oblique rotation allows for these correlations to emerge in the factor solution, enabling a more accurate and psychologically meaningful representation of the underlying factor structure.

SPSS 29 was used for conducting this analysis.

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Kaiser-Meyer-Olkin (KMO) measure and Bartlett Test of Sphericity

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.946
Bartlett's Test of Sphericity	Approx. Chi-Square	5268.113
	df	666
	Sig.	<.001

The overall **Kaiser-Meyer-Olkin (KMO)** measure of sampling adequacy was 0.946, which is classified as *"marvellous"* according to Kaiser's criterion. The KMO statistic evaluates the proportion of variance among variables that might be common variance, i.e., variance that could be explained by underlying factors. Values above 0.80 are considered excellent, indicating that the data are highly suitable for factor analysis and that patterns of correlations are compact enough to yield reliable factors.

Bartlett's Test of Sphericity assesses whether the observed correlations between items are significantly different from zero (i.e., whether the correlation matrix significantly differs from an identity matrix). An identity matrix is one in which variables are completely uncorrelated, which would make factor analysis inappropriate. In simpler terms, Bartlett's test checks whether there is enough shared variance among items to justify reducing the dataset into underlying latent factors. A statistically significant result (typically $p < .05$) indicates that the correlations between variables are sufficiently large for factor analysis to proceed. In this study, Bartlett's Test of Sphericity was statistically significant, $X^2(666) = 5268.113$ $p < .001$, meaning that the items were meaningfully interrelated and thus suitable for uncovering a factor structure.

Communalities

Communalities

	Initial	Extraction
emp_user_1	.545	.394
emp_user_2	.620	.576
emp_user_3	.645	.581
emp_user_4	.593	.506
emp_user_5	.304	.210
emp_user_6	.448	.346
emp_user_7	.615	.584
emp_user_8	.234	.096
emp_user_9	.670	.592
emp_user_10	.488	.425
emp_user_11	.607	.512
emp_user_12	.465	.409
emp_user_13	.655	.616
emp_user_14	.718	.682
emp_user_15	.440	.378
emp_user_16	.647	.559
emp_user_17	.646	.593
emp_user_18	.641	.595
emp_user_19	.727	.645
emp_user_20	.684	.588
emp_user_21	.625	.515
emp_user_22	.412	.222
emp_user_23	.648	.614
emp_user_24	.660	.626
emp_user_25	.190	.151
emp_user_26	.699	.680
emp_user_27	.332	.276
emp_user_28	.706	.637
emp_user_29	.674	.557
emp_user_30	.459	.340
emp_user_31	.487	.456
emp_user_32	.595	.512
emp_user_33	.556	.424
emp_user_34	.693	.609
emp_user_35	.711	.651
emp_user_36	.677	.599
emp_user_37	.768	.644

Extraction Method: Principal Axis Factoring.

Communalities in PAF represent the proportion of an item's variance that is explained by the common factors, i.e., the shared variance among items, excluding unique variance and measurement error. PAF focuses specifically on the variance that is common across items, making it more appropriate for identifying underlying latent constructs such as empathy dimensions. In this analysis, the initial communalities reflect the estimated shared variance, while the extracted communalities show how much of that shared variance is accounted for by the final three-factor solution. Higher extracted communalities (e.g. > .40) suggest that the items are well-represented by the factors identified in the EmpathiSEr-U scale.

Total Variance Explained

Total Variance Explained

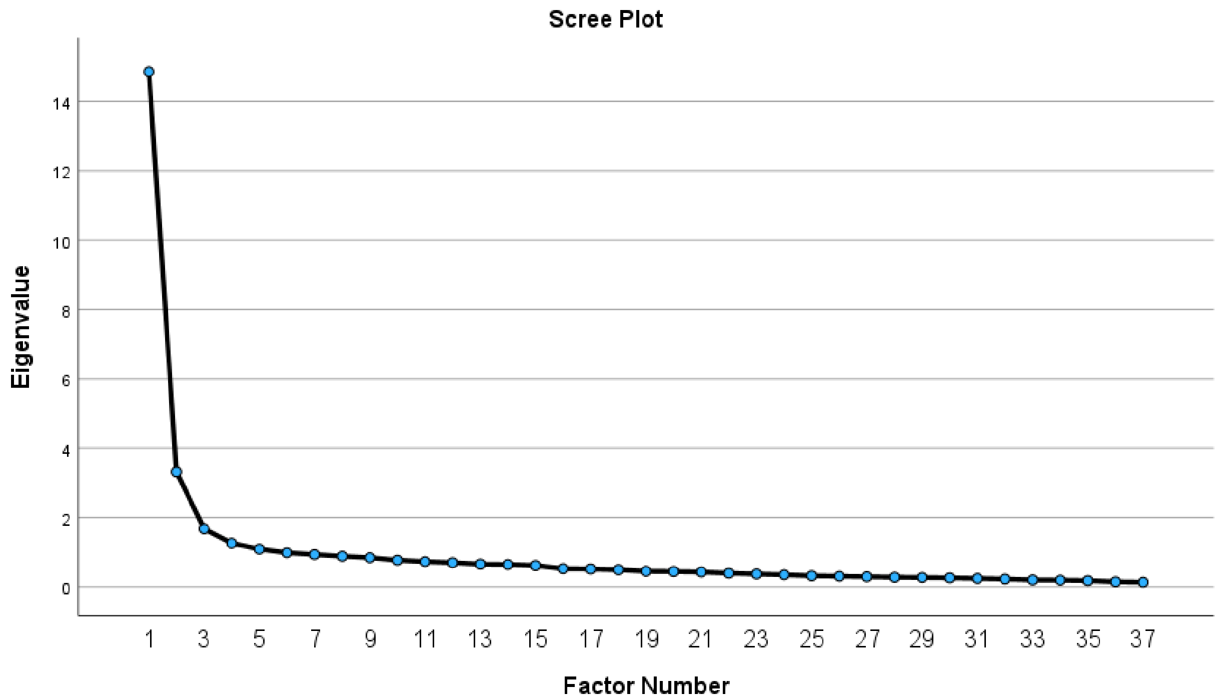
Factor	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %	Rotation Sums of Squared Loadings[a] Total
1	14.858	40.156	40.156	14.405	38.932	38.932	12.045
2	3.314	8.958	49.114	2.855	7.716	46.649	7.712
3	1.675	4.526	53.640	1.137	3.073	49.721	7.532
4	1.259	3.402	57.042				
5	1.089	2.943	59.985				
6	.984	2.658	62.643				
7	.932	2.518	65.162				
8	.882	2.385	67.547				
9	.841	2.272	69.819				
10	.768	2.076	71.894				
11	.727	1.964	73.858				
12	.696	1.882	75.740				
13	.655	1.770	77.511				
14	.644	1.739	79.250				
15	.616	1.664	80.914				
16	.525	1.420	82.333				
17	.516	1.396	83.729				
18	.494	1.336	85.065				
19	.452	1.221	86.286				
20	.444	1.200	87.487				
21	.430	1.163	88.650				
22	.396	1.070	89.720				
23	.373	1.009	90.729				
24	.351	.949	91.678				
25	.322	.869	92.548				
26	.308	.832	93.380				
27	.295	.797	94.177				
28	.280	.756	94.933				
29	.273	.737	95.670				
30	.262	.709	96.379				
31	.245	.663	97.041				
32	.228	.617	97.658				
33	.203	.549	98.207				
34	.196	.530	98.737				
35	.183	.494	99.231				
36	.149	.403	99.633				
37	.136	.367	100.000				

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

Total Variance Explained refers to the proportion of common variance in the data accounted for by each factor extracted during the EFA. This table displays the eigenvalues and the percentage of variance explained by each factor after extraction, i.e., the amount of shared variance among items that each factor captures. It also presents the cumulative variance, showing how much of the total common variance is explained by the solution as a whole. A higher cumulative variance indicates a more comprehensive and effective factor structure. In this study, the initial three-factor solution explains 53.64% of the total common variance, suggesting that the factors adequately capture the underlying structure of the EmpathiSEr-U scale.

Scree Plot



Scree Plot is a visual tool used in EFA to help determine the optimal number of factors to retain. It displays the eigenvalues associated with each factor on the y-axis, plotted against the factor number on the x-axis. The key point of interest in the scree plot is the “elbow” or inflection point, the point at which the slope of the curve noticeably levels off. Factors above this elbow typically have higher eigenvalues and are considered meaningful, while those below represent smaller amounts of variance and are often interpreted as noise or less substantive factors. In this study, the scree plot suggested two to four factor solutions, as the curve began to flatten at the fifth factor, supporting the choice of the exploratory factor solutions of the EmpathiSEr-U scale.

Factor Matrix

Factor Matrix[a]

	Factor 1	Factor 2	Factor 3
emp_user_1	-.569		
emp_user_2	.643	-.359	
emp_user_3	.681		
emp_user_4	.670		
emp_user_5	-.383		
emp_user_6	-.428	.400	
emp_user_7	.687		
emp_user_8			
emp_user_9	.399	.603	
emp_user_10	-.600		
emp_user_11	.489	.506	
emp_user_12	-.601		
emp_user_13	-.693		.322
emp_user_14	.595	.549	
emp_user_15	-.540		
emp_user_16	.685		
emp_user_17	-.750		
emp_user_18	-.654	-.306	
emp_user_19	.685	.419	
emp_user_20	-.711		
emp_user_21	.706		
emp_user_22	-.403		
emp_user_23	.730		
emp_user_24	.717		
emp_user_25			
emp_user_26	.623	.519	
emp_user_27	-.429		.301
emp_user_28	.794		
emp_user_29	.745		
emp_user_30	-.535		
emp_user_31	-.604		
emp_user_32	.604		
emp_user_33	-.560	.319	
emp_user_34	.733		
emp_user_35	.793		
emp_user_36	.760		
emp_user_37	.794		

Extraction Method: Principal Axis Factoring.

a. 3 factors extracted. 5 iterations required.

Factor Matrix shows the factor loadings, which represent the correlations between each item and the extracted factors before rotation. These loadings indicate the extent to which each item is associated with each underlying factor. Higher absolute values (typically above 0.4) suggest a stronger relationship between the item and the factor. However, because this matrix reflects unrotated loadings, the interpretation may be less clear if multiple factors are present and items load on more than one factor. For this reason, rotated solutions (e.g., pattern matrix) is generally used for final interpretation. This unrotated factor matrix is included for completeness and to illustrate how items initially aligned with the emerging factor structure prior to rotation.

Pattern Matrix

Pattern Matrix[a]

	Factor		
	1	2	3
emp_user_1	-.551		
emp_user_2	.807		
emp_user_3	.745		
emp_user_4	.406	.472	
emp_user_5	-.442		
emp_user_6	-.587		
emp_user_7	.771		
emp_user_8			
emp_user_9		.813	
emp_user_10			.443
emp_user_11		.691	
emp_user_12	-.358		.365
emp_user_13			.575
emp_user_14		.784	
emp_user_15			.436
emp_user_16		.516	
emp_user_17	-.598		
emp_user_18		-.362	.538
emp_user_19		.619	
emp_user_20			.494
emp_user_21	.355	.353	
emp_user_22	-.469		
emp_user_23	.741		
emp_user_24	.789		
emp_user_25			.393
emp_user_26		.759	
emp_user_27			.439
emp_user_28	.461	.366	
emp_user_29	.471	.316	
emp_user_30	-.490		
emp_user_31	-.429		.384
emp_user_32	.748		
emp_user_33	-.586		
emp_user_34	.712		
emp_user_35	.637	.303	
emp_user_36	.633		
emp_user_37	.483	.404	

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.[a]

a. Rotation converged in 10 iterations.

Pattern Matrix presents the rotated factor loadings from the EFA, showing the unique contribution of each item to each factor after rotation (in this case, direct oblimin). These loadings represent the partial regression coefficients of each item on the factors, indicating the strength and direction of the relationship while controlling for other factors. Higher absolute values (commonly above 0.3) suggest that an item strongly loads on that factor, meaning it is a good indicator of the underlying construct represented by that factor. Because direct oblimin rotation allows factors to correlate, the pattern matrix provides a clearer and more interpretable structure by separating overlapping variance between factors. The pattern matrix is typically used to decide which items belong to which factors, aiding in interpreting and naming the factors.

Structure Matrix

Structure Matrix

	Factor		
	1	2	3
emp_user_1	-.611		.407
emp_user_2	.752		
emp_user_3	.727	.389	
emp_user_4	.554	.599	-.355
emp_user_5	-.447		
emp_user_6	-.551		
emp_user_7	.757	.307	-.307
emp_user_8			
emp_user_9		.758	
emp_user_10	-.491	-.347	.599
emp_user_11		.712	-.315
emp_user_12	-.545		.550
emp_user_13	-.503	-.490	.733
emp_user_14	.312	.821	-.370
emp_user_15	-.377	-.415	.563
emp_user_16	.483	.663	-.507
emp_user_17	-.734	-.363	.539
emp_user_18	-.419	-.566	.688
emp_user_19	.431	.745	-.528
emp_user_20	-.549	-.486	.691
emp_user_21	.575	.545	-.520
emp_user_22	-.467		
emp_user_23	.780	.311	-.413
emp_user_24	.785	.318	-.338
emp_user_25			.359
emp_user_26	.349	.814	-.398
emp_user_27	-.362		.505
emp_user_28	.674	.584	-.552
emp_user_29	.651	.524	-.502
emp_user_30	-.562		.399
emp_user_31	-.590		.564
emp_user_32	.687		
emp_user_33	-.628		.408
emp_user_34	.774	.300	-.455
emp_user_35	.750	.518	-.446
emp_user_36	.733	.465	-.433
emp_user_37	.678	.607	-.512

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

Structure Matrix displays the correlations between each item and the extracted factors in the EFA. While the pattern matrix provides a clear simple structure with items loading distinctly on single factors, the structure matrix often shows cross-loadings because it represents the total correlations between items and factors, including shared variance from factor inter-correlations. In other words, even if an item loads primarily on one factor in the pattern matrix, it can still correlate moderately with other factors in the structure matrix due to factor correlations allowed by the oblique rotation method. This difference highlights why the pattern matrix is generally preferred for determining factor membership, whereas the structure matrix offers insight into the broader relationships among items and factors.

Factor Correlation Matrix

Factor Correlation Matrix

Factor	1	2	3
1	1.000	.317	-.475
2	.317	1.000	-.352
3	-.475	-.352	1.000

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

The Factor Correlation Matrix shows the degree of correlation between the extracted factors in the final solution. Since an oblique rotation method (Direct Oblimin) was used in the analysis, it allows the factors to be correlated rather than assuming they are completely independent (as in orthogonal rotations). The values in this matrix indicate how much the factors relate to each other. For example, a moderate to high correlation suggests that the constructs measured by the factors may share some underlying conceptual overlap, which is expected in psychological constructs like empathy.