Appendix B.

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

This appendix contains further details regarding the initial three-factor solution from the EFA of the EmpathiSEr-P 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.		.915
Bartlett's Test of Sphericity	Approx. Chi-Square	4423.587
	df	666
	Sig.	<.001

The overall **Kaiser-Meyer-Olkin (KMO)** measure of sampling adequacy was 0.915, 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, $X^2(666) = 4423.587$, $p < .001$, meaning that the items were meaningfully interrelated and thus suitable for uncovering a factor structure.

Communalities

Communalities

	Initial	Extraction
emp_p1	.406	.283
emp_p2	.515	.421
emp_p3	.700	.575
emp_p4	.671	.554
emp_p5	.263	.125
emp_p6	.621	.458
emp_p7	.597	.467
emp_p8	.546	.367
emp_p9	.299	.242
emp_p10	.512	.499
emp_p11	.730	.564
emp_p12	.723	.523
emp_p13	.501	.422
emp_p14	.416	.374
emp_p15	.359	.327
emp_p16	.643	.610
emp_p17	.634	.527
emp_p18	.624	.611
emp_p19	.482	.254
emp_p20	.614	.562
emp_p21	.401	.361
emp_p22	.627	.489
emp_p23	.615	.504
emp_p24	.497	.360
emp_p25	.351	.314
emp_p26	.334	.116
emp_p27	.490	.442
emp_p28	.387	.243
emp_p29	.643	.539
emp_p30	.678	.635
emp_p31	.522	.439
emp_p32	.742	.607
emp_p33	.682	.525
emp_p34	.297	.178
emp_p35	.511	.372
emp_p36	.405	.327
emp_p37	.680	.601

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-P scale.

Total Variance Explained

Total Variance Explained

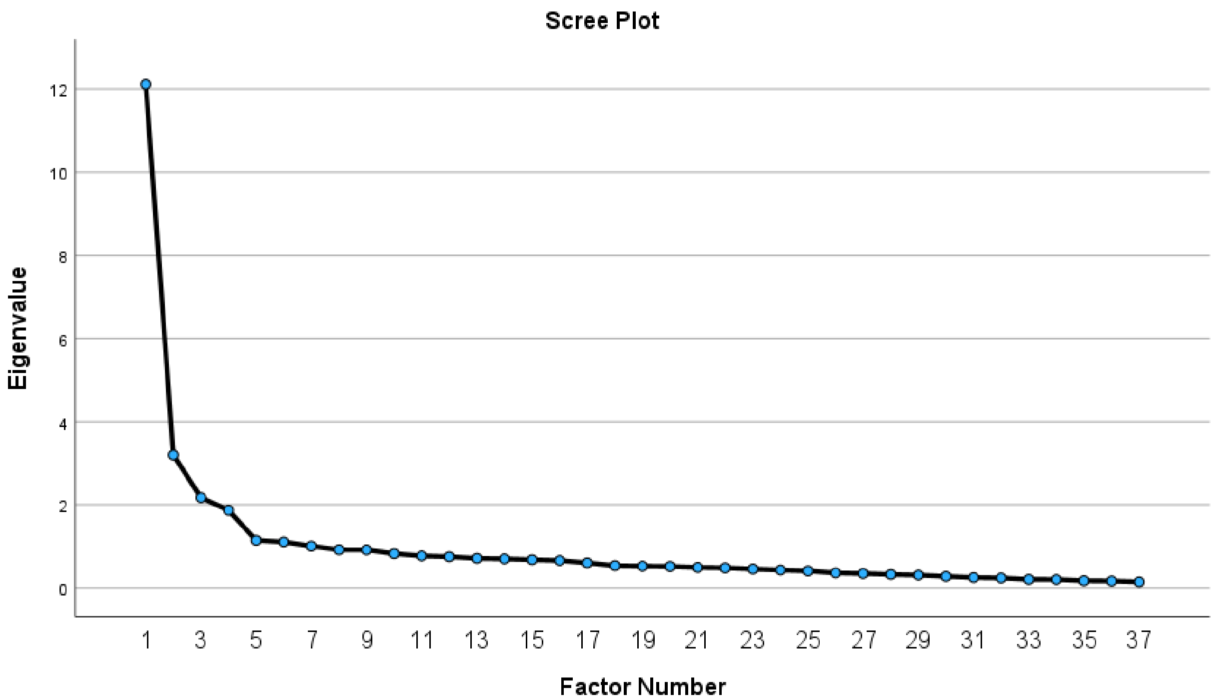
Factor	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %	Rotation Sums of Squared Loadings[a] Total
1	12.111	32.733	32.733	11.599	31.348	31.348	10.958
2	3.197	8.642	41.375	2.618	7.076	38.423	4.931
3	2.172	5.869	47.244	1.598	4.319	42.742	3.232
4	1.868	5.049	52.293				
5	1.145	3.095	55.387				
6	1.106	2.990	58.378				
7	1.006	2.718	61.096				
8	.918	2.482	63.578				
9	.916	2.475	66.054				
10	.825	2.231	68.284				
11	.771	2.084	70.369				
12	.751	2.029	72.398				
13	.712	1.925	74.323				
14	.700	1.891	76.214				
15	.679	1.834	78.048				
16	.660	1.783	79.831				
17	.602	1.627	81.459				
18	.537	1.451	82.909				
19	.524	1.416	84.325				
20	.517	1.398	85.723				
21	.493	1.332	87.055				
22	.482	1.302	88.358				
23	.456	1.232	89.589				
24	.431	1.166	90.755				
25	.409	1.107	91.862				
26	.362	.978	92.840				
27	.347	.938	93.778				
28	.325	.879	94.657				
29	.310	.837	95.494				
30	.279	.753	96.247				
31	.251	.679	96.926				
32	.240	.648	97.574				
33	.206	.558	98.132				
34	.204	.550	98.683				
35	.174	.471	99.154				
36	.167	.452	99.606				
37	.146	.394	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 47.244% of the total common variance, suggesting that the factors adequately capture the underlying structure of the EmpathiSEr-P 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 after the fifth factor, supporting the choice of the exploratory factor solutions of the EmpathiSEr-P scale.

Factor Matrix

Factor Matrix[a]

	Factor		
	1	2	3
emp_p1	-.481		
emp_p2	.614		
emp_p3	.700		
emp_p4	.696		
emp_p5		.315	
emp_p6	-.662		
emp_p7	.664		
emp_p8	.570		
emp_p9	-.328	.367	
emp_p10	-.451	.344	.422
emp_p11	.737		
emp_p12	.701		
emp_p13	.323	.487	
emp_p14	-.333	.391	.332
emp_p15			-.489
emp_p16	.570	.316	-.430
emp_p17	.681		
emp_p18	.555	.447	-.320
emp_p19	-.496		
emp_p20	.728		
emp_p21	-.341	.412	
emp_p22	.682		
emp_p23	.704		
emp_p24	.542		
emp_p25		.471	
emp_p26			
emp_p27	-.494	.435	
emp_p28	-.432		
emp_p29	.597	.405	
emp_p30	.664	.425	
emp_p31	-.579		
emp_p32	.730		
emp_p33	.686		
emp_p34			
emp_p35	.604		
emp_p36	-.497		
emp_p37	.770		

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_p1	-.458		
emp_p2	.650		
emp_p3	.790		
emp_p4	.759		
emp_p5			
emp_p6	-.529		
emp_p7	.662		
emp_p8	.628		
emp_p9		.365	
emp_p10		.663	
emp_p11	.658		
emp_p12	.637		
emp_p13			-.582
emp_p14		.614	
emp_p15			-.563
emp_p16			-.638
emp_p17	.563		-.343
emp_p18	.361		-.629
emp_p19	-.461		
emp_p20	.703		
emp_p21		.592	
emp_p22	.666		
emp_p23	.656		
emp_p24	.470		
emp_p25		.494	
emp_p26		.330	
emp_p27		.520	
emp_p28		.319	
emp_p29	.511		-.462
emp_p30	.584		-.472
emp_p31	-.306	.465	
emp_p32	.790		
emp_p33	.747		
emp_p34		.398	
emp_p35	.460		
emp_p36	-.538		
emp_p37	.714		

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

a. Rotation converged in 14 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	Factor 2	Factor 3
emp_p1	-.490	.329	
emp_p2	.643		
emp_p3	.743		
emp_p4	.729		
emp_p5		.320	
emp_p6	-.632	.455	
emp_p7	.674		
emp_p8	.603		
emp_p9	-.301	.439	
emp_p10	-.315	.674	
emp_p11	.728	-.438	
emp_p12	.698	-.427	
emp_p13			-.621
emp_p14		.606	
emp_p15			-.541
emp_p16	.459		-.692
emp_p17	.644		-.454
emp_p18	.478		-.700
emp_p19	-.496		
emp_p20	.729		-.314
emp_p21		.600	
emp_p22	.694	-.333	
emp_p23	.703	-.343	
emp_p24	.536	-.420	
emp_p25		.529	
emp_p26			
emp_p27	-.435	.617	
emp_p28	-.392	.422	
emp_p29	.563		-.563
emp_p30	.633		-.587
emp_p31	-.498	.578	
emp_p32	.762		
emp_p33	.722		
emp_p34		.418	
emp_p35	.565	-.378	
emp_p36	-.530		
emp_p37	.767	-.370	

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	-.368	-.197
2	-.368	1.000	4.477e-5
3	-.197	4.477e-5	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.