

Which Factor Retention Method Performs Best? A Monte Carlo Simulation for Psychological and Educational Measurement

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Abstract : Determining the appropriate number of factors is the most critical decision in exploratory factor analysis (EFA), but evidence-based guidance for the context of skewed ordinal data remains limited. This study compares the performance of three factor retention methods: optimal coordinates (OC), parallel analysis (PA), and exploratory graph analysis (EGA) through Monte Carlo simulations with 1000 replications using negatively skewed 5-category Likert scale data. Controlled conditions included the number of factors (2, 3, 5), sample size (300, 500, 900, 1500), factor loadings (0.4; 0.7), and inter-factor correlations (0.0; 0.3). The results show that PA achieved the highest accuracy (94.7%), followed by EGA (92.8%), while OC lagged far behind (36.8%). PA achieved perfect accuracy on large samples with high loadings, whereas OC exhibited a tendency toward under-extraction that increased drastically as the number of factors increased. EGA outperformed PA in minimizing over-extraction but was more prone to under-extraction in complex structures. These findings recommend PA as the primary method and EGA as a complementary method in Likert-scale-based research and confirm that algorithmic scree plots are not suitable for use as the sole criterion for factor retention.

Keywords : Dimensionality Assessment, Exploratory Graph Analysis, Factor Retention, Monte Carlo Simulation, Parallel Analysis

Abstrak : Menentukan jumlah faktor yang tepat merupakan keputusan paling krusial dalam analisis faktor eksploratori (EFA), namun panduan berbasis bukti untuk konteks data ordinal yang asimetris masih terbatas. Penelitian ini membandingkan kinerja tiga metode pemilihan faktor: koordinat optimal (OC), analisis paralel (PA), dan analisis grafik eksploratori (EGA) melalui simulasi Monte Carlo dengan 1.000 replikasi menggunakan data skala Likert 5 kategori yang asimetris negatif. Kondisi yang dikendalikan meliputi jumlah faktor (2, 3, 5), ukuran sampel (300, 500, 900, 1.500), bobot faktor (0,4; 0,7), dan korelasi antar-faktor (0,0; 0,3). Hasil menunjukkan bahwa PA mencapai akurasi tertinggi (94,7%), diikuti oleh EGA (92,8%), sedangkan OC tertinggal jauh di belakang (36,8%). PA mencapai akurasi sempurna pada sampel besar dengan beban faktor tinggi, sedangkan OC menunjukkan kecenderungan under-extraction yang meningkat drastis seiring bertambahnya jumlah faktor. EGA lebih unggul daripada PA dalam meminimalkan ekstraksi berlebihan, tetapi lebih rentan terhadap ekstraksi kurang pada struktur yang kompleks. Temuan ini merekomendasikan PA sebagai metode utama

dan EGA sebagai metode pelengkap dalam penelitian berbasis skala Likert, serta menegaskan bahwa grafik scree algoritmik tidak cocok digunakan sebagai satu-satunya kriteria untuk retensi faktor.

Kata Kunci : *Penilaian Dimensi, Analisis Graf Eksploratori, Retensi Faktor, Simulasi Monte Carlo, Analisis Paralel*

INTRODUCTION

Exploratory Factor Analysis (EFA) is one of the most fundamental statistical techniques in psychology, education, and the social sciences for identifying the latent structure underlying a set of observed variables. The quality of EFA results depends on the researcher's accuracy in determining the number of factors to retain, as this will determine the entire interpretation of the resulting latent structure (Goretzko & Bühner, 2020). Retaining too few factors can lead to different psychological dimensions being erroneously grouped together, while retaining too many factors can result in spurious factors that obscure the actual structure (Goretzko, 2022). The decision regarding which factors to retain is not merely a technical procedure but a critical step that determines the construct validity of the developed instrument.

For decades, the method most used by researchers to determine the number of factors has been the visual evaluation of scree plots. This method identifies a breakpoint (elbow) on a downward-sloping curve of eigenvalues, where the factors to the left of that point are considered significant (Cattell, 1966). Although easy to understand and available in nearly all statistical software, the scree plot has long been criticized for its reliance on the researcher's subjective judgment, as it is highly likely that two researchers observing the same scree plot could reach different decisions (Howard, 2016; Sakaluk & Short, 2017). A survey of EFA practices in psychological research indicates that the scree plot remains the second most popular method after the Kaiser criterion, even though simulation evidence consistently highlights the shortcomings of both methods (Fabrigar et al., 1999; Goretzko & Bühner, 2020).

The parallel analysis (PA) method offers a more objective approach by comparing empirical eigenvalues with those of random data. On this basis, only factors that exceed the random values are retained (Horn, 1965). This method accounts for sampling fluctuations that can affect empirical eigenvalues (Lim & Jahng, 2019). Various studies position PA as the best method, but its performance may decline under conditions of small sample sizes, low loadings, and high inter-factor correlations (Auerswald & Moshagen, 2019; Garrido et al., 2016; Lee & Cham, 2024; Markos & Tsigilis, 2024).

Recent developments in psychometrics have introduced exploratory graph analysis (EGA) as a network-theory-based approach that is fundamentally different from eigenvalue-based methods. The EGA retention method works by representing data as a partial correlation network using Graphical LASSO, then identifying the number of dimensions through the Walktrap community detection algorithm, which employs a random walk on that graph (H. F. Golino & Epskamp, 2017). Unlike PA, which analyzes the distribution of eigenvalues, EGA directly models the patterns of interaction among variables as an interconnected system (H. Golino et al., 2019). Various simulation studies show that EGA can rival and even outperform PA, particularly for highly correlated factors (Cosemans et al., 2022; Markos & Tsigilis, 2024). However, its accuracy may decrease when there is substantial cross-loading because the assumption of non-overlapping communities is not always met (Brandenburg & Papenberg, 2022).

Although the literature comparing factor retention methods continues to grow, there are gaps that have not yet been fully addressed. First, most previous simulation studies have used continuous or binary data, while ordinal Likert-scale data the most common format in psychological and educational surveys remains underrepresented (Lee & Cham, 2024; Markos & Tsigilis, 2024). Second, the skewed distributions commonly found in Likert-scale responses within psychology or educational populations with specific characteristics are rarely the primary focus, even though these distributions are known to systematically influence eigenvalues (Cosemans et al., 2022). An additional consideration is the variable-to-factor ratio, or the number of observed variables available to represent each latent factor, which can affect the stability and accuracy of

dimensionality estimation. Recent simulation evidence indicates that factor-retention accuracy generally improves as the number of variables per factor increases, while this condition may interact with distributional characteristics such as skewness and non-normality, making the variable-to-factor ratio particularly relevant when evaluating ordinal data under non-normal conditions (Goretzko & Bühner, 2022; Lee & Cham, 2024). Third, direct comparisons between algorithmic scree plots such as optimal coordinates (OC), PA, and EGA simultaneously within a single controlled simulation design using skewed ordinal data remain limited, so evidence-based guidance for such contexts is not yet sufficiently available.

Based on this gap, this study aims to: (1) compare the overall accuracy of optimal coordinates, parallel analysis, and exploratory graph analysis in identifying the correct number of factors in simulated data using a 5 point Likert scale with a negatively skewed distribution; (2) analyze the influence of the number of factors, sample size, factor loadings, and inter-factor correlations on the accuracy of each method; (3) examine patterns of over-extraction and under-extraction as forms of error characterization for each method; and (4) formulate evidence-based recommendations regarding the selection of factor retention methods that can be operationalized by researchers in the fields of psychology, education, and the social sciences. The results of this study are expected to provide an empirical contribution to the selection of factor retention methods, while also guiding more accurate research practices in the context of ordinal data, which clearly dominates behavioral research.

RESEARCH METHODS

This study employed a Monte Carlo simulation approach to evaluate the performance of three factor retention methods under various factor analytic conditions. The simulation design combined multiple parameters, resulting in 96 experimental conditions with a total of 96,000 replications. The simulated data were generated as five-category ordinal Likert-scale responses with a negatively skewed distribution to represent the tendency of respondents in educational and psychological measurement contexts to select higher response categories. Data generation was conducted by constructing a population loading matrix based on a simple structure, where each item loaded only on its designated factor while cross-loadings were fixed at zero. The inter-factor correlation matrix was then established based on predetermined correlation conditions, with diagonal values representing unit variance and non-diagonal values representing relationships among factors. These matrices were subsequently used to generate an inter-item correlation matrix that represented the population structure among indicators. The resulting correlation matrix served as the basis for generating continuous multivariate normal data, which were then transformed into five-category ordinal responses using predetermined cutoff points to produce a distribution concentrated in the upper response categories.

The study compared three factor retention methods, namely Optimal Coordinates (OC), Parallel Analysis (PA), and Exploratory Graph Analysis (EGA). The Optimal Coordinates method was applied as an algorithm-based extension of the scree plot approach, in which the elbow point was identified through an objective regression-based procedure rather than visual inspection. Parallel Analysis was conducted by comparing empirical eigenvalues with eigenvalues generated from random datasets with equivalent characteristics. To accommodate the ordinal nature of the simulated data, PA was implemented using a polychoric correlation matrix, while random eigenvalues were generated through repeated simulation procedures. Exploratory Graph Analysis was applied based on network theory principles by estimating the partial correlation structure among indicators through the Graphical LASSO algorithm. The resulting network structure was analysed using community detection procedures to identify groups of strongly connected items, with the number of detected communities interpreted as the estimated number of latent factors.

The performance of each factor retention method was evaluated using three indicators: accuracy rate, over-extraction rate, and under-extraction rate. The accuracy rate represented the proportion of replications in which the method correctly identified the predetermined number of factors. The over-extraction rate indicated the proportion of cases where the method retained more factors than the actual population structure, reflecting the tendency to identify unnecessary factors. Meanwhile, the under-extraction rate represented the proportion of cases where the method

identified fewer factors than the true number of factors, indicating failure to recover existing dimensions within the simulated data structure. These evaluation criteria were used to compare the consistency and effectiveness of each factor retention method across different simulation conditions.

RESULTS AND DISCUSSION

These differences were clearly observed in the Monte Carlo simulation study, which involved 1,000 replications. Overall, the PA retention method achieved an accuracy rate of 94.7%, the EGA retention method 92.8%, and the OC method 36.8%. Gaps in accuracy rates were observed across the various conditions in this study.

Table 1. Overall Accuracy of Three Factor Retention Methods

Methods	Accuracy
PA	0.947
EG	0.928
OC	0.368

Source: Monte Carlo simulation results (1,000 replications).

Table 2. Accuracy of Methods Based on the Number of Simulated Factors

Number of Factors	OC	PA	EGA
2	0.564	0.980	0.956
3	0.341	0.959	0.938
5	0.199	0.902	0.891

Source: Monte Carlo simulation results (1,000 replications).

The number of factors served as an important condition distinguishing the performance of the retention methods. In general, increasing the complexity of the factor structure was associated with a decrease in accuracy in identifying the correct number of factors. However, PA and EGA maintained relatively high accuracy across the simulated factor structures. For PA, accuracy decreased from 98.0% for two factors to 95.9% for three factors and 90.2% for five factors. EGA showed a similar pattern, decreasing from 95.6% to 93.8% and 89.1%, respectively. In contrast, OC exhibited a much sharper decline, from 56.4% for two factors to 34.1% for three factors and only 19.9% for five factors. These findings indicate that PA and EGA are considerably more robust than OC as the complexity of the latent structure increases.

The decline in accuracy across methods suggests that identifying the correct dimensionality becomes increasingly difficult as the number of latent factors increases. Nevertheless, the relatively small decline observed for PA and EGA indicates that both methods retain substantial capacity to recover more complex factor structures. In contrast, the pronounced deterioration of OC suggests that algorithmically identifying a clear point of transition in the eigenvalue sequence becomes increasingly difficult as the number of factors increases.

Another condition was observed in the sample-size-based simulations. In general, PA and EGA showed increased accuracy as the sample size increased. In fact, even with very large sample sizes common in psychology and education research both methods demonstrated near-perfect accuracy. This indicates that an increase in sample size provides additional information that is optimally utilized by the PA and EGA retention methods. However, the OC retention method exhibits the opposite trend. As the sample size increases, the accuracy of the OC retention method decreases. This suggests that the OC retention method is less capable of utilizing the additional information provided by an increased sample size.

Table 3. Method Accuracy Based on Sample Size

N	OC	PA	EGA
300	0.428	0.850	0.761
500	0.379	0.944	0.955
900	0.343	0.994	0.997

1500	0.321	1.000	1.000
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Source: Monte Carlo simulation results (1,000 replications).

Table 4. Method Accuracy Based on Factor Loadings

Factor Loadings	OC	PA	EGA
0.4	0.281	0.894	0.857
0.7	0.455	1.000	1.000

Source: Monte Carlo simulation results (1,000 replications).

A significant effect was observed under simulated high factor loading conditions. The PA and EGA retention methods demonstrated excellent accuracy, with accuracy improving to near-perfect levels. The OC retention method also showed improved performance under high loading conditions. However, the accuracy of OC remained lower than that of PA and EGA. These findings indicate that the OC retention method is highly dependent on the strength of factor loadings, but an increase in factor loadings is not sufficient to achieve accuracy comparable to the PA and EGA methods. In fact, under conditions of high factor loadings, the OC method still fails to accurately identify the number of factors in most replications.

An interesting dynamic was observed under conditions simulating variations in inter-factor correlation. The PA and EGA retention methods maintained good accuracy levels under both orthogonal and correlated factor conditions, although they experienced a decline in accuracy as inter-factor correlation increased. In contrast to PA and EGA, the OC retention method actually showed improved accuracy as inter-factor correlations increased. The OC retention method demonstrated a significant improvement in accuracy when factors were correlated compared to orthogonal conditions. However, the accuracy performance of the OC method remained lower than that of PA and EGA.

Table 5. Accuracy of PA and EGA According to the Number of Indicators per Factor

Number of indicators per factor	PA	EGA
4	93.88%	92.65%
6	95.51%	93.02%

Source: Monte Carlo simulation results (1,000 replications).

The number of indicators per factor provides an additional perspective on the performance of factor-retention methods. In this study, each latent factor was represented by either four or six observed indicators. Both PA and EGA maintained high accuracy under the two conditions; however, the magnitude of improvement associated with additional indicators differed between the methods. PA accuracy increased from 93.88% with four indicators per factor to 95.51% with six indicators, representing an improvement of 1.63 percentage points. EGA showed a smaller increase, from 92.65% to 93.02%, corresponding to an improvement of only 0.37 percentage points. Thus, increasing the number of indicators per factor was associated with a greater improvement in PA accuracy than in EGA accuracy.

The effect of the number of indicators became more apparent as the factor structure increased in complexity. For PA, accuracy increased from 97.79% to 98.20% under the two-factor condition, from 95.12% to 96.68% under the three-factor condition, and from 88.73% to 91.66% under the five-factor condition when the number of indicators increased from four to six. EGA showed a weaker but generally similar pattern, with accuracy changing from 95.91% to 95.34%, 93.71% to 93.97%, and 88.34% to 89.77%, respectively. The largest improvement therefore occurred for PA under the five-factor condition, where increasing the number of indicators produced a 2.93-percentage-point increase in accuracy.

These findings suggest that the availability of more indicators may provide additional information for recovering the underlying latent structure, particularly when the factor structure is relatively complex. The finding is consistent with recent simulation evidence indicating that the number of variables available to represent each factor is an important determinant of factor-retention accuracy. However, the relatively small overall change in EGA accuracy suggests that the

effect of additional indicators is not uniform across retention methods. Therefore, the variable-to-factor ratio should be considered together with other characteristics of the factor structure, rather than interpreted as an independent guarantee of accurate factor recovery.

Table 6. Accuracy of the Method Based on Inter-Factor Correlation

Inter-factor Correlation	OC	PA	EGA
0.0	0.215	0.952	0.942
0.3	0.521	0.942	0.915

Source: Monte Carlo simulation results (1,000 replications).

Table 8. Overall Rates of Over-extraction and Under-extraction

Methods	Over-extraction	Under-extraction
OC	0.175	0.457
PA	0.039	0.014
EGA	0.024	0.047

Source: Monte Carlo simulation results (1,000 replications).

Based on the direction of estimation errors, clear differences in characteristics among the retention methods were observed. The OC retention method was dominated by under-extraction errors, indicating that the OC method tends to estimate a smaller number of factors than the actual number. In contrast, the PA and EGA retention methods exhibited lower error rates and relatively balanced error directions. The PA retention method tends to produce over-extraction more frequently, while EGA is more moderate, with a slightly higher proportion of under-extraction than PA. These findings demonstrate that the PA and EGA retention methods not only have high accuracy but also produce lower errors compared to the OC retention method.

The simulation results in this study confirm that parallel analysis (PA) is the factor retention method with the highest accuracy for ordinal data on a negatively skewed Likert scale. These findings align with the consensus in the literature that positions PA as the gold standard in factor retention (Goretzko & Bühner, 2022; Lee & Cham, 2024). PA's status as a reliable method was first established by Horn (1965), who proposed a parallel simulation approach to correct for sampling bias in eigenvalues, and was subsequently supported by various comparative studies demonstrating PA's superiority over classical methods such as scree plots and the Kaiser criterion (Fabrigar et al., 1999; Zwick & Velicer, 1986). The PA retention method also maintains good and consistent performance under various conditions (Lee & Cham, 2024). The PA retention method is also sensitive to sample size and factor loadings (Garrido et al., 2016). These results were also observed in this study.

The increase in PA accuracy as the sample size increases reflects the nature of the PA method as a simulation-based procedure that depends on the stability of the correlation matrix. The PA method has been shown to be sensitive to sample size and prone to under-factoring at small sample sizes (Garrido et al., 2016; Markos & Tsigilis, 2024). The findings of this study can serve as a practical guideline: for sample sizes $N \geq 900$, the PA method can be fully trusted to identify the correct factor structure in 5-point Likert-scale data.

The EGA retention method in this study proved to be a competitive retention method when compared to the PA retention method. The EGA method, as a network psychometric approach that uses GLASSO and the Walktrap community detection algorithm, demonstrated performance comparable to PA in identifying factor structures (Cosemans et al., 2022; H. F. Golino & Epskamp, 2017). The EGA retention method is capable of competing with the PA retention method, particularly under conditions of highly correlated factors (H. Golino et al., 2019). A distinctive advantage of EGA that emerged in this study is its stability under conditions of correlated factors. While PA experienced a drop in accuracy from 95.2% to 94.2% as correlation increased from 0 to 0.3, EGA's accuracy dropped from 94.2% to 91.5%; although this decline was larger, it still demonstrated EGA's massive superiority over OC.

One interesting finding is that EGA has a lower over-extraction rate than PA, but a higher under-extraction rate. The EGA retention method is more sensitive to cross-loading and more prone

to estimating an incorrect number of factors in complex factor conditions (Brandenburg & Papenberg, 2022; Markos & Tsigilis, 2024). From a psychometric perspective, the consequences of under-extraction are generally more impactful because they can obscure the true latent structure (Goretzko & Bühner, 2020, 2022). Practically, this difference in error profiles means that under-extraction by EGA implies that several meaningful psychological dimensions may be erroneously combined into a single factor, whereas PA over-extraction implies the potential emergence of spurious factors. Under conditions of low loadings, EGA's performance declines. This is because the choice of detection algorithm affects EGA's accuracy, and performance degradation occurs in polytomous data with 5 categories (Christensen et al., 2023). Nevertheless, EGA's overall profile remains excellent, making it a valid alternative to PA.

This study revealed a striking finding: the OC retention method demonstrated very low accuracy. As the number of factors increased from two to five, the accuracy of the OC method dropped from 56.4% to just 19.9%, a decline that reflects the method's difficulty in identifying a single, clear breakpoint as the factor structure becomes more complex. Several previous studies have cautioned that the scree test and its variants are not recommended for exclusive use (Fabrigar et al., 1999; Goretzko et al., 2024), yet its popularity among applied researchers remains high (Howard, 2016; Sakaluk & Short, 2017), so these findings have important practical implications.

The pattern of OC under-extraction increases as the number of factors rises, from 28.2% with two factors to 62.7% with five factors. This confirms that the primary shortcoming of OC is not over-estimation, but rather a systematic tendency to underestimate the number of factors. This finding is consistent with the criticism that scree plots tend to yield too few factors because algorithmically detected elbows often occur earlier than their actual positions when the factor structure is complex (Goretzko & Bühner, 2020). A striking finding in this study was that OC accuracy was higher under correlated factor conditions (52.1%) compared to orthogonal conditions (21.5%), which may indicate that correlations between factors alter the shape of the eigenvalue curve in such a way that its breakpoint is easier to identify algorithmically. However, even under the best conditions namely, high loadings and correlated factors OC never exceeded 50% accuracy.

Interestingly, the accuracy of OC decreases rather than increases as the sample size grows a pattern not observed in PA and EGA. Consistent with this, eigenvalue-based methods without comparison to random data are highly sensitive to sample size and are strongly recommended not to be used as the standard method for determining the number of factors (Cosermans et al., 2022; Goretzko & Bühner, 2020). The findings of this study also provide strong empirical evidence to support this recommendation in the context of skewed ordinal Likert data.

The decline in accuracy across all methods as the number of factors increases indicates that the complexity of the latent structure is a major challenge in factor retention, as reported in various simulation studies (Goretzko & Bühner, 2020; Ruscio & Roche, 2012). Nevertheless, the PA and EGA retention methods continue to maintain high performance even in higher-dimensional structures, whereas OC shows a decline. Finch's (2023) finding that an increase in the number of factors tends to reduce the accuracy of all retention methods, so structural complexity must be considered when selecting the method to use (Finch, 2023).

The improved accuracy of the PA and EGA retention methods was found to be influenced by sample size and factor loadings. Consistent with this, research by Lee and Cham (2024) confirms that the performance of both methods becomes increasingly optimal with larger samples and indicators that have strong relationships with the factors. These findings also support recommendations regarding the importance of an adequate sample size in EFA (Howard & Henderson, 2023; Lorenzo-Seva & Ferrando, 2024; Sürücü et al., 2024). Furthermore, the findings of this study also confirm that factor loadings are one of the primary predictors of successful factor retention (Garrido et al., 2016).

The correlations among factors provide insight into the characteristics of each method. The PA retention method continues to demonstrate slightly better performance than EGA, whereas the improvement in OC accuracy under correlated factor conditions is likely due more to changes in the eigenvalue patterns than to an improvement in the method's capabilities. The EGA retention method remains an alternative retention method for correlated factors (H. Golino et al., 2019; H. F.

Golino & Epskamp, 2017). However, the EGA retention method is prone to factor merging when the correlation between factors is high, and the risk of under-extraction increases (Brandenburg & Papenberg, 2022; Cosemans *et al.*, 2022).

The findings of this study have implications for researchers who use EFA on Likert-scale data. The results demonstrate that the PA and EGA retention methods are consistently more accurate than the OC retention method. This recommendation aligns with findings supporting the use of PA on ordinal data, as well as the view of Goretzko and Bühner (2022) that the scree test is no longer sufficient as a sole standard in psychometric research. Although the accuracy of PA and EGA decreases in small samples, both remain more reliable than OC. In practice, the PA and EGA retention methods have distinct advantages and thus cannot fully replace one another. The PA retention method tends to be better at avoiding under-extraction, whereas EGA is slightly better at mitigating over-extraction. Therefore, PA is more appropriate when the risk of losing latent dimensions is considered critical, while EGA can be a suitable choice in exploratory studies aiming to minimize the emergence of spurious factors.

CONCLUSION AND SUGGESTIONS

This study shows that parallel analysis and exploratory graph analysis outperform optimal coordinates in determining the number of factors in Likert-scaled ordinal data with a negatively skewed distribution. PA provides the highest and most consistent accuracy across the simulated conditions, while EGA demonstrates competitive performance with a lower tendency toward over-extraction. In contrast, OC shows substantially lower accuracy and is more prone to under-extraction, particularly in complex factor structures. These findings suggest that PA and EGA are more appropriate factor-retention methods for exploratory factor analysis of ordinal data, whereas the use of OC alone is not recommended. However, the selection of EGA should be made with caution when the survey instrument contains multidimensional indicators with substantial cross-loadings. Under such conditions, the community-detection process underlying EGA may be affected by overlapping associations among indicators, potentially leading to shifts in the detected community structure and, consequently, the estimated number of dimensions. Therefore, EGA results should be interpreted alongside the substantive factor structure and, where possible, corroborated using complementary factor-retention evidence. These findings are limited to the simulation conditions examined in this study. Future research should therefore investigate a wider range of data distributions, more complex factor structures, varying degrees of cross-loading, and additional factor-retention methods to provide more comprehensive recommendations for dimensionality assessment.

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