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Evaluation on the Application of Factor Analysis Method in the Field of English Education in Korea

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This paper evaluates the use of Factor Analysis (FA) in English education research in Korea and suggests improvements in methodology. A detailed coding protocol was used to review 179 FA cases from 12 major English education journals (2014-2023). The review identified several key issues, including small sample sizes and lenient criteria for sample size selection, insufficient reporting on data appropriateness and normality, confusion between principal component analysis and FA, overreliance on the Eigenvalue > 1 criterion for determining the number of factors, inappropriate factor rotation methods, inconsistency between factor rotation and extraction methods, inadequate reporting on factor loadings and cross loadings criteria, and excessive reliance on SPSS as a statistical tool for FA. This study provides specific guidelines for applying FA appropriately and reporting results accurately.

Key words: factor analysis, exploratory factor analysis, common factor analysis, factor extraction method, factor rotation

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1. INTRODUCTION

The ultimate aim of English education goes beyond just enabling learners to speak English fluently; it focuses on developing their ability to communicate effectively in various global contexts (Aum, 2006). Understanding different learner characteristics and individual differences, such as cognitive, motivational, and affective factors (Kim & Kim, 2013), is therefore a key priority in English education research. Given this approach to English education, it is essential to clarify learners' psychological constructs. These constructs are unobservable traits (Mahmoudi & Mahmoudi, 2016), called latent variables, and can only be inferred indirectly through operational definitions and measurement tools. Consequently, there has been a continuous effort within the field of English education research to measure these constructs in a valid and reliable manner, with factor analysis being one of the primary methods for ensuring the validity of these measurement tools.

Factor analysis (FA) is a statistical method that identifies latent variables and assesses the structural validity of measurement instruments (Kang, Jo, & Oh, 2013). Researchers can improve the reliability and validity of their studies by confirming whether a measurement tool accurately assesses the defined constructs through factor analysis. It signifies that employing factor analysis is essential for achieving research objectives in the relevant research. In addition, it highlights the importance for researchers in this field to be proficient in performing factor analysis.

However, despite the importance of factor analysis as a methodological aspect in the social sciences including the domain of English education, various challenges have been suggested when researchers apply it. First, significant statistical and mathematical expertise is required to comprehend and utilize factor analysis effectively. For instance, a foundational understanding of concepts like variance, correlation, regression models, and eigenvalue decomposition is essential for grasping factor analysis, as these concepts pertain to parameter estimation within the factor model (C. T. Kim, 2016). Conducting factor analysis mechanically without a thorough understanding of those parameters can result in an inadequate factor structure. Second, researchers should make various decisions during the factor analysis process, such as selecting the factor extraction and rotation methods. Additionally, factor analysis is not a one-time process; it requires repeated iterations to achieve the optimal factor structure based on indicators (e.g., factor loadings) and theoretical knowledge (Park & Cho, 2022). That is, this decision-intensive and iterative nature necessitates a high level of experience from researchers to perform factor analysis correctly. Essentially, the researcher's choice of parameter fitting methods directly impacts the results, and poor decisions can produce inaccurate factor analysis outcomes, jeopardizing the study's overall reliability.

Likewise, conducting factor analysis correctly is a challenging task for researchers, but despite its complexity, factor analysis is useful, considering the attributes of studies in the English education research, and can benefit the advancement of relevant research. Hence, it is important to ensure that factor analysis is correctly used as a methodology and that its outcomes are adequately reported in the academic community. To achieve this, papers published in the field of English education research ought to be reviewed to see how factor analysis is utilized and reported, and to identify any issues in its execution and reporting processes. However, a review of previous studies reveals that such efforts have been lacking in this field. To our knowledge, there has been only one small-scale case study (Plonsky & Gonulal, 2015) examining researchers' factor analysis practices based on papers published in international second language journals, but no investigations or reviews have been conducted within the field of English education research in Korea. Unlike the research field of English education, related disciplines such as education and psychology have long recognized the importance of factor analysis as a research methodology and have made efforts to understand its application and address related issues (C. T. Kim, 2016). These efforts have reportedly reduced the misapplication of factor analysis over time (Lee, Youn, Lee, & Jung, 2016). Nevertheless, each academic community has its distinct culture, leading to different issues in the use of factor analysis (Gorsuch, 2014). This suggests that it is impractical to directly apply factor analysis issues elicited from related disciplines to the English education research. It necessitates an independent examination of factor analysis application in the field of English education to identify problems and seek solutions.

This study aims to explore the use and application of factor analysis in English education research, building on the limitations identified in previous studies. Specifically, it seeks to pinpoint the issues encountered in the application of factor analysis and to recommend improvements based on these insights. By addressing current challenges and offering suggestions for better application, the study provides specific guidelines for researchers to effectively understand and use factor analysis. Ultimately, the outcomes of this research are expected to enhance the overall quality of English education research.

The research questions of this study are outlined as follows:

1) How is factor analysis currently employed in English education research in Korea?
2) What issues are found in the application of factor analysis within this field?

2. Literature Review

2.1. Brief Overview of Factor Analysis

Factor analysis has been defined in different ways. For example, Seong and Si (2023) described factor analysis as a process that identifies factors by analyzing the relationships among highly correlated observed variables and then assigns meaning to those factors to clarify the data structure. Similarly, Noh (2014) explained factor analysis as a statistical method that condenses multiple observed variables into a few common factors to explain the data. Additionally, Loewen and Gonulal (2015) defined factor analysis as a statistical technique used to examine the underlying correlations among a group of observed variables, aiming to identify the smallest number of variables that can still account for a significant amount of variance in the data. Thus, considering these definitions, factor analysis can be summarized as a statistical method that detects the common factors causing correlations among related variables and condenses many variables into a few ones. Likewise, factor analysis performs the primary roles of data exploration and data reduction. Consequently, it is also known as ‘exploratory factor analysis’ (EFA) or ‘common factor analysis’.

The data exploration and reduction capabilities of factor analysis can provide researchers with several benefits (Field, 2018; Kang *et al*., 2013; C. T. Kim, 2016). First, factor analysis helps researchers explore and understand the structure among numerous variables, offering detailed information on their relationships and differences. Second, factor analysis allows the condensation of numerous observed variables into a few common factors, helping researchers reduce multidimensional data while preserving as much original information as possible. Third, by identifying the common factors underlying the variables, researchers can use factor analysis to develop survey tools for measuring specific target concepts.

In particular, the task of identifying common factors underlying variables through factor analysis aligns closely with various research objectives in the social sciences. Thus, factor analysis has high applicability as a research methodology in numerous social science fields, including English education. The common factors, also referred to as latent variables, are variables of interest to researchers, though they cannot be directly observed. In the social sciences, there is significant interest in defining and measuring latent variables. Latent variables can be concretized through operational definitions based on theoretical foundations, and factor analysis is one method for inferring these latent variables (C. T. Kim, 2016). Indeed, it is widely recognized that the origin of factor analysis stems from efforts to substantiate the existence of latent variables (e.g., g-factor, s-factor) (Seong & Si, 2023). More specifically, in 1904, Spearman suggested that human intelligence could be inferred through a general ability common to all intellectual activities, which he termed the g-factor. Conversely, Spearman (1904) posited that each intellectual task could be affected by unique ability factors in addition to the g-factor, which he named the s-factors. To test this hypothesis, Spearman (1904) introduced a two-factor model for explaining human intelligence and by analyzing the relationships among various intelligence subtests, confirmed the presence of a common factor influencing intelligence test scores.

Meanwhile, performing factor analysis necessitates estimating multiple parameters to fit the factor model. Therefore, factor analysis is usually an iterative process rather than a single-step procedure. Due to the complexity of this process, it is challenging to establish a deterministic procedure for factor analysis. However, several previous studies provide guidelines for researchers to follow when conducting factor analysis (Field, 2018; Kang *et al*., 2013; Park & Cho, 2022; Plonsky & Gonulal, 2015; Seo, Lee, Kim & Kim, 2018; Seong & Si, 2023). Drawing from these studies, the steps for performing factor analysis can be summarized as follows: first, confirm the appropriateness of the data; second, select the factor extraction method; third, decide the number of factors; fourth, choose a rotation method; and finally, assign meanings to the extracted factors. In fact, third to fifth steps are generally recursive. Furthermore, throughout the five-step factor analysis process, researchers need to make various decisions at each stage to determine the best parameters, taking into account the data attributes and monitoring the initially estimated parameter values. Therefore, successful execution of factor analysis requires researchers to comprehend the meanings of the parameters in the factor model and possess the ability to adjust these parameters to create the optimal factor structure. In consideration of the significance of this parameter adjustment, the next section will comprehensively discuss the specific decision-making considerations for each stage of factor analysis.

2.2. Essential Considerations for Factor Analysis

2.2.1. Assessing data and its appropriateness

Before initiating factor analysis, researchers are required to collect relevant data. An essential aspect to consider at this stage is determining the appropriate sample size for the factor analysis. This task is intricate and has been a long-standing subject of debate among researchers. Reviewing the sample size recommendations, Boomsma (1985) and Gorsuch (1983) indicated that a minimum of 50 participants is sufficient for factor analysis. Kline (1994) recommended at least 100 participants, while Zygmont and Smith (2014) proposed a minimum of 200 participants. Conversely, some scholars advocate for larger sample sizes. For example, Tabachnick and Fidell (2001) suggested at least 300 participants, while Comrey and Lee (1992) considered 100 participants as poor, 300 as good, and over 1000 as excellent. Meanwhile, some researchers have proposed relative standards for sample size based on the ratio of the number of observed variables to the number of samples. For instance, Costello and Osborne (2005) and Hinkin (1995) recommended a variable to sample size ratio of 1:5 to 1:10, while Pett, Lackey, and Sullivan (1999) proposed a stricter ratio of 1:10 to 1:15. Considering all these recommendations, it is advisable to secure a sample size of at least 200 participants or a sample size at least ten times the number of variables for factor analysis.

After collecting the data, researchers need to check for normality. In factor analysis, the correlation matrix between variables is used in decomposing eigenvalues and eigenvectors. Normality is a fundamental assumption for estimating appropriate correlations between factors, though it has been reported that the Pearson correlation is robust even when this normality assumption is violated (Havlicek & Peterson, 1976). Furthermore, normality is crucial for determining the factor extraction method (C. T. Kim, 2016). Specifically, the maximum likelihood method assumes normality (Seo *at el*., 2018), making it essential for researchers considering this method to verify normality.

Lastly, researchers should assess the appropriateness of the collected data for factor analysis. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity are commonly used for this assessment (Harlow, 2002). The KMO measure, which ranges from 0 to 1, indicates the degree of correlation between variables (Kaiser, 1974). KMO values above 0.9 are considered marvelous, above 0.8 meritorious, between 0.6 and 0.7 mediocre, and below 0.5 unacceptable for factor analysis (Kaiser, 1974). Researchers can evaluate the suitability of the sample size using KMO measures (Loewen & Gonulal, 2015). Bartlett's test of sphericity evaluates whether the correlation matrix is an identity matrix (Bartlett, 1954). A p-value less than the standard significance level of 0.05 indicates that the correlation matrix is not an identity matrix, allowing factor analysis to proceed (Bartlett, 1954).

2.2.2. Determining the factor extraction method

Once researchers have confirmed the appropriateness of the data for factor analysis, they need to determine the factor extraction method to decompose the sample correlation matrix or sample covariance matrix. The principal factor extraction methods in factor analysis include Ordinary Least Squares (OLS), Principal Axis Factoring (PAF), Maximum Likelihood Estimation (MLE), and Generalized Least Squares (GLS) (C. T. Kim, 2016; Lee *et al*., 2016).

Among these methods, when data achieve multivariate normality, the MLE is considered the most suitable for factor extraction (C. T. Kim, 2016; Lee *et al*., 2016; Park & Cho, 2022). This method improves the accuracy of estimates and provides test statistics for evaluating the precision of the estimates and the model's goodness of fit (C. T. Kim, 2016; Lee *et al.*, 2016). However, because data rarely follow a multivariate normal distribution in practice, the GLS has been suggested as an alternative. This method does not assume any distribution, but with larger sample sizes, it yields results close to those of the MLE (C. T. Kim, 2016; Lee *et al*., 2016). Additionally, the GLS allows for the calculation of test statistics to evaluate the model's goodness of fit. Similarly, OLS and PAF do not assume a specific data distribution. However, they do not provide test statistics to evaluate the precision of estimates and the model's goodness of fit, which may reduce the efficiency of the estimates. Furthermore, PAF is considered appropriate for population-based data (C. T. Kim, 2016; Park & Cho, 2022), which can restrict the utilization of the method.

Principal component analysis (PCA), on the other hand, focuses on reducing the dimensions of variables by extracting a few principal components that best explain the total variance of the observed variables (Field, 2018; Kang *et al*., 2013; C. T. Kim, 2016; Noh, 2014). Unlike common factor analysis, it does not separate the variance of observed variables into common variance and unique variance. Therefore, the principal components obtained from PCA include common components and unique variance (or error variance). This means that interpreting principal components as latent variables is considerably inappropriate because only the common components among the principal parts are the latent variables of interest to researchers. Nevertheless, the widespread misuse of PCA for latent variable extraction has been applied in numerous studies. Although PCA and factor analysis can yield comparable results when unique variance is minimal, this scenario is highly unlikely in practical situations (C. T. Kim, 2016).

In summary, researchers can have various extraction options when performing factor analysis. If the data exhibit normality, MLE is recommended as the first priority as the method provides the information on the factor model fit. If the normality assumption is not met, GLS can be considered as a viable alternative to MLE. In addition, researchers must differentiate clearly between PCA and factor analysis, using each method as appropriate for their specific purposes.

2.2.3. Deciding the number of factors

After selecting the factor extraction method, researchers perform an initial factor analysis using the chosen method. They then review the parameter values from the initially estimated factor model and begin refining the model to improve its fit. At this stage, researchers need to determine the optimal number of factors and evaluate the adequacy of the commonality values.

To begin with, researchers can refer to several methods to determine the number of factors, such as eigenvalue > 1, total accumulated variance, scree plot, interpretability, and parallel analysis (Kang *et al.*, 2013; Lee *et al*., 2016; Park & Cho, 2022; Seo *et al.*, 2018). According to previous studies, the eigenvalue > 1, total accumulated variance, and scree plot methods have been the most commonly used (Park & Cho, 2022; Seo *et al*., 2018), all of which are based on eigenvalues for factor number determination. Eigenvalues contain the variance information of the data, and the proportion of each factor's eigenvalue to the total eigenvalue indicates its contribution to explaining the total variance. Therefore, the criterion of eigenvalue > 1 can be advantageously interpreted alongside the cumulative variance ratio.

Additionally, the scree plot provides a visual representation of the number of factors where eigenvalues decrease sharply, offering intuitive guidance to researchers in determining the number of factors. However, there are several issues when determining the number of factors based on eigenvalues. First, an eigenvalue of 1 has different implications depending on the number of measured variables. Specifically, an eigenvalue of 1 represents 10% of the information when there are 10 variables, but only 1% when there are 100 variables (Seo *et al*., 2018). Second, the principle that factors are meaningful when the eigenvalue is greater than 1 was known as Kaiser criterion (C. T. Kim, 2016), which assumed that the data represented a population rather than a sample (Seo *et al*., 2018). Consequently, applying Kaiser's rule to determine the number of factors in a sample, which includes sampling error, can lead to the extraction of significantly different factors depending on the sample attributes, such as size. This indicates that the consistency of factor number selection may be compromised when applying Kaiser's rule, especially to small samples. Lastly, this criterion has been shown to overestimate the number of factors, leading to potential complexity and overfitting (Preacher, Zhang, Kim, & Mels, 2013). To resolve these issues, parallel analysis has been suggested. Parallel analysis helps determine the number of factors by comparing the eigenvalues from actual data with those from randomly generated data sets of the same size, repeated multiple times (Crawford *et al.*, 2010). If an eigenvalue for a specific factor in the actual data is greater than the eigenvalue for the same factor in the random data, that factor is considered significant. Finally, when choosing the number of factors, researchers can consider the interpretability of the factor structure. This involves assessing whether common factors are shared among variables that are expected to be highly related and whether the characteristics of the extracted factors can be interpreted within the theoretical framework. Since interpretability can be heavily influenced by the researcher's subjectivity, it is advisable to use it in combination with other methods.

Meanwhile, when conducting initial factor analysis, commonality values are estimated. These values indicate how much of the variance in the observed variables is explained by the extracted factors. Therefore, low commonality values indicate a weak association between observed variables and the extracted factors, and items with low commonality values are candidates for deletion. Typically, the standard for acceptable commonality in factor analysis is greater than 0.4, while it is 0.5 or higher when applied strictly (Park & Cho, 2022). Since items with low commonality values are recommended to be deleted sequentially, these values can indirectly influence the determination of the number of factors by transforming the factor structure and affecting the interpretation of factors.

2.2.4. Choosing the factor rotation method

After conducting the initial factor analysis, researchers generally perform factor rotation to better interpret the factor structure. Without rotation, the first factor typically has a high eigenvalue, acting as a general factor, while the other factors may be hard to interpret (Kang *et al*., 2013). However, factor rotation usually distributes the eigenvalues more evenly among the factors. Therefore, researchers strive for a simpler factor structure and select a rotation method that enhances interpretability. The choice of rotation method depends on the relationships among the extracted factors (Kang *et al*., 2013; C. T. Kim, 2016; Seo *et al*., 2018). The correlation between factors can be determined by examining the theoretical background, previous study findings, and observed variable correlations (Seo *et al.*, 2018). If the factors are assumed to be correlated, an oblique rotation method like Direct Oblimin or Promax is suitable. If the factors are assumed to be uncorrelated, an orthogonal rotation method such as Varimax or Quartimax can be used.

As previously noted, the choice of rotation method should be based on correlations between factors, but previous studies have shown that researchers tend to prefer orthogonal rotation over oblique rotation (Kang *et al*., 2013; C. T. Kim, 2016; Park & Cho, 2022). This is another instance where researchers misuse factor analysis, as it is improbable to assume that the correlations between variables of interest to social science researchers are zero.

Meanwhile, after factor rotation, researchers need to review the factor loadings of each observed variable to enhance the interpretability of the factor structure. Factor loadings show the strength of the relationship between observed variables and factors. Low factor loadings mean that a particular factor has a minimal effect on observed variables, making these variables candidates for deletion. The acceptable standard for factor loadings in factor analysis is typically set at 0.4 (Stevens, 1992), but higher loadings are preferable. Additionally, to improve the interpretability of the factor structure, researchers should consider observed variables with cross-loadings (Park & Cho, 2022). Cross-loading variables show high loadings on two or more factors. An observed variable can be considered to have cross-loadings if the difference between its loadings on different factors is less than 0.2-0.3 (Matsunaga, 2010). Without a theoretical basis for the complex nature of cross-loading variables, it is better to delete them to ensure the clarity of the factor structure.

2.2.5. Interpreting the factors

Upon confirming the final factor structure through the steps of factor analysis, researchers interpret the factors by examining the relationship between the extracted factors and the observed variables loaded onto them. This relationship can be summarized in two major aspects: the consistency of the variables loaded onto a particular factor and the level of factor loadings of the variables on that factor. Researchers should take into account the common characteristics of the loaded variables when interpreting factors. Moreover, greater emphasis should be placed on observed variables with higher factor loadings. This is particularly crucial when observed variables of different natures are loaded onto the same factor.

3. METHODOLOGY

3.1. Article Inclusion and Exclusion Criteria

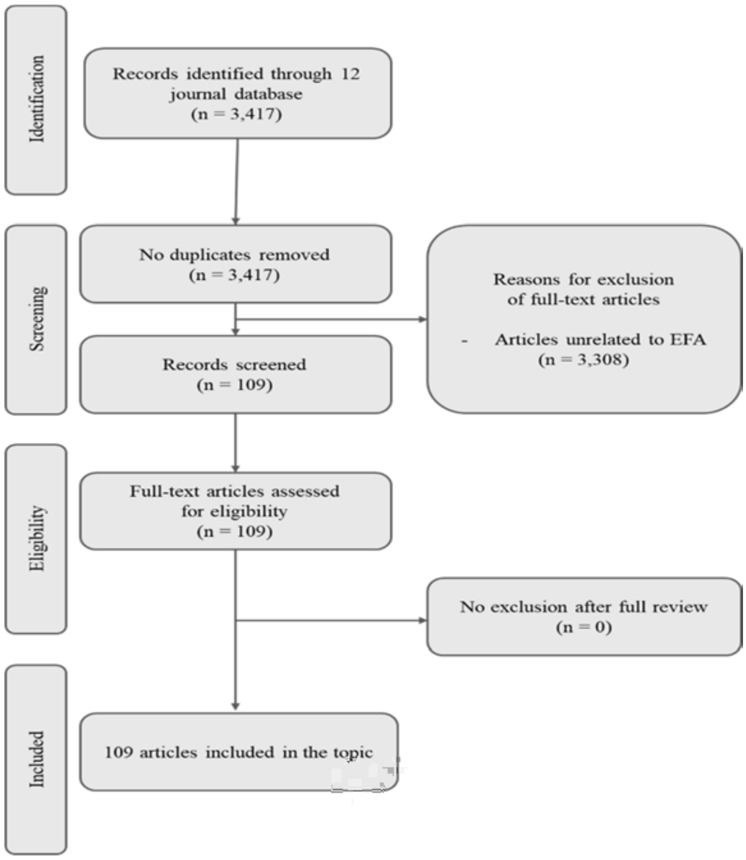
This research aimed to identify the current application and challenges of factor analysis in English education research in Korea and suggest improvements for the identified issues. To accomplish these objectives, articles for data analysis were chosen based on the following strict criteria. First, only articles from journals in the field of English education in Korea were considered, excluding those from other fields. Second, only articles conducting factor analysis, including PCA, were included, while those using confirmatory factor analysis (CFA) were excluded because CFA operates under a completely different theoretical assumption. Simply put, factor analysis assumes that researchers have no particular expectations about the number and nature of the underlying factors, whereas CFA assumes that researchers have specific expectations about the data's underlying structure (Loewen & Gonulal, 2015). Third, only articles with downloadable full texts were considered. Lastly, only articles published over the decade from 2014 to 2023 were included.

3.2. Article Collection Procedure

Following the aforementioned criteria for selecting articles, articles were collected through the following steps. First, twelve reputable journals in the field of English education in Korea were selected (see Appendix A). Second, once the journals were chosen for article collection, three journals were assigned to each of the four researchers in this study, who then gathered a total of 3,417 articles published between 2014 and 2023 from these twelve journals. Third, to filter out articles that use factor analysis from the 3,417 articles, the researchers employed a skimming method rather than a keyword-based approach. To elaborate, since 12 target journals were pre-selected for data collection, the researchers in this study reviewed the research methods and results of individual articles to identify candidates for analysis, instead of using keywords to conduct a search for articles on the web. Lastly, to verify that no target articles were missed, the participating researchers carried out two rounds of cross-verification by reviewing each other's list of collected articles from specific journals. Through this process, a total of 109 target articles were identified from 3,417 papers. The data search, collection, and cross-verification process took about one month. A summary of the data collection procedure is shown in Figure 1 and brief statistics on the collected data are presented in Appendix A.

FIGURE 1

PRISMA Flowchart for Article Selection



3.3. Data Coding and Analysis Procedure

After completing the article selection process, data coding was undertaken. The data coding process proceeded as follows. First, a data coding protocol was developed to evaluate the application of factor analysis. This protocol was partially adapted from those presented in previous studies by Jang (2015), Kang *et al.* (2013), C. T. Kim (2016), Mirabelli, Jensen, Vohra, and Johnson (2022), and Seo *et al*. (2018). The protocol included 14 coding categories, such as 'Sample Size,' 'Initial Item Count,' 'Data Appropriateness Check,' 'Normality Test,' 'Factor Extraction Method,' 'Purpose of Using Factor Analysis,' 'Methods for Presenting Factor Correlations,' 'Criteria for Determining Number of Factors,' 'Accumulated Variance Reported or Not,' 'Communality Criteria,' 'Rotation Method,' 'Factor Loading Criteria,' 'Cross Loading Criteria,' and 'Statistical Packages Employed.' A summary of the data coding protocol used in this study is presented in Appendix B.

Next, four researchers participated in the coding process following the coding protocol. Specifically, the 109 selected articles were divided by journal, and each researcher coded the articles from three different journals, with each researcher handling approximately 25 to 30 papers. The coding process was completed over one month, during which weekly meetings were held to discuss ambiguous coding values and ensure consistency in the coding outcomes. Additionally, cross-verification was performed twice, with two other researchers reviewing the coding results of one researcher at weekly intervals. Finally, just before finalizing the data coding process, two researchers conducted a final review of the coding results. To assess inter-rater reliability, 22 articles (20%) out of the 109 were randomly selected, and the consistency across the 14 coding items was found to be perfect.

Meanwhile, during the data coding process, it was identified that some articles reported multiple factor analysis results. These articles generally used the factor analysis on individual sub-components that fall under a larger construct (e.g., intrinsic motivation and extrinsic motivation under the umbrella of language learning motivation). Upon in-depth investigation, it was found that the number of items (i.e., observed variables) varied with each factor analysis, and occasionally the criteria for factor loadings and communalities differed. Given that this study includes variable-to-sample ratio, factor loading criteria, and communality criteria in its analysis, multiple factor analysis reports from the same study were coded individually as separate cases if factor analysis was applied to each sub-component or if different criteria were applied. However, repeated factor analyses to identify the optimal factor structure with the same subject were considered a single factor analysis. Consequently, while the initial number of coded articles was 109, the total number of cases for statistical analysis increased to 179 after coding.

Finally, to analyze the coding results in this study, frequency analysis was performed using Jamovi version 2.5.3. In addition, Python packages such as pandas and matplotlib were utilized to visualize the time series analysis of the number of articles and cases by publication year.

4. Results

4.1. Trend Analysis in the Application of Factor Analysis Over Time

Before examining the specific application of factor analysis in research papers published in the field of English education, the frequency of its reporting over time was reviewed. This evaluation separately analyzed 109 selected articles and 179 cases. The findings are presented in Figure 2 and Table 1.

FIGURE 2

Number of Articles and Cases Reporting Factor Analysis from 2014 to 2023

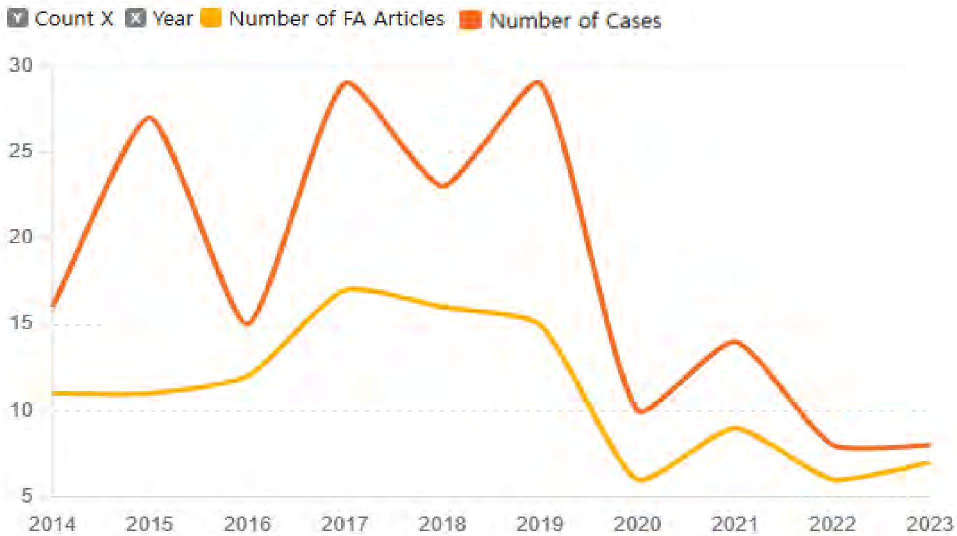


TABLE 1

Frequency of Reporting Factor Analysis Over Time in English Education Research

Year	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Articles	11	11	12	17	16	15	6	8	6	7
Cases	16	27	15	29	23	29	10	14	8	8

Initially, the trend indicates a consistent application of factor analysis in English education research. More specifically, the number of articles reporting factor analysis steadily increased until 2019, and this trend is also observed in the cases, with each journal reporting an average of 1 to 2 cases, despite some fluctuations. However, after 2019, there was a sharp decline, with fewer than one case reported per journal on average. Although there has been a noticeable decrease in the use of factor analysis in English education research since 2019, it is premature to consider this a decline in its popularity among researchers in this field. The years 2020 to 2022 were during the COVID-19 period, and this global threat may have caused a reduction in the use of factor analysis because it deterred researchers from gathering data (Shoukat *et al*., 2021). In summary, the trend analysis shows that factor analysis has been consistently reported in English education journals in Korea throughout the entire period under review, suggesting that researchers in this field still recognize its practical value.

4.2. Trend Analysis in Data Evaluation for Factor Analysis

4.2.1. Analysis of sample size

Table 2 presents the sample sizes used by researchers in English education research for factor analysis. A detailed look at the sample size indicates that about 60 cases utilized small samples of fewer than 100, making up roughly one-third of all cases. When the threshold is increased to 200, the number of cases with small sample size grows to 111, comprising about 63% of the total. In contrast, only 37 cases used a sufficient sample size of 300 or more, accounting for approximately 21% of the total. Furthermore, only 31 cases employed a large sample size of 400 or more, representing just 17.3% of the total cases.

TABLE 2

Results of the Sample Size Analysis

Sample Size	Frequency	%
Not Reported	2	1.1
≤50	15	8.4
51-100	45	25.1
101-150	35	19.6
151-200	16	8.9
201-250	10	5.6
251-300	19	10.6
301-350	5	2.8
351-400	1	0.6
≥ 401	31	17.3
Total	179	100.0

Next, to estimate the appropriateness in sample size from the different perspective (i.e., lenient or strict), the ratio of the number of observed variables to the number of samples was calculated. The results are presented in Table 3.

More specifically, the results illustrates that a ratio of less than 1:5 included 64 cases, approximately 35.7%. Expanding the ratio to less than 1:7.5 increased the number of cases to about 86, indicating that approximately 48% of the total cases determined the sample size using relatively lenient criteria. Conversely, cases with a sample size ratio exceeding 1:15 included 45 cases, about 25.2%. Overall, these results reveal that researchers in English education research generally tend to use smaller sample sizes and apply somewhat lenient criteria when determining sample sizes for factor analysis.

TABLE 3

Results of Analysis of Variable-to-Sample Ratio

Sample Size Ratio	Frequency	%
Not Reported	4	2.2
Less than 1: 2.5	24	13.4
1:2.5 ~ 1: 5	40	22.3
1:5 ~ 1: 7.5	22	12.3
1:7.5 ~ 1: 10	17	9.5
1: 10 ~ 1: 12.5	21	11.7
1:12.5 ~ 1: 15	6	3.4
1:15 ~ 1: 17.5	6	3.4
1: 17.5 ~ 1: 20	3	1.7
More than 1: 20	36	20.1
Total	179	100.0

4.2.2. Analysis of data appropriateness

Table 4 illustrates how English education studies using factor analysis report the data's appropriateness. A detailed analysis shows that 80 cases, or about 44.7% of the total, reported both the KMO value and Bartlett's test of sphericity results. In contrast, 93 cases, representing 52% of the total, did not report either indicator. Furthermore, only 6 cases reported either the KMO value or the results of Bartlett's test of sphericity. These findings indicate that approximately 55% of the cases do not adequately report on the appropriateness of the data used in factor analysis.

TABLE 4

Results of Analysis of Data Appropriateness

Data Appropriateness Check	Frequency	%
Not Reported	93	52.0
KMO Measure of Sample Adequacy	5	2.8
Bartlett's Test of Sphericity	1	0.6
KMO Measure of Sample Adequacy and Bartlett's Test of Sphericity	80	44.7
Total	179	100.0

4.2.3. Analysis of normality test

The review of reporting data normality in 179 cases showed that 169 cases, or 94.4% of the total, failed to report on it. Only 9 cases did report on it, with 6 cases (3.3%) mentioning skewness and kurtosis, and 3 cases (1.7%) reporting the Shapiro-Wilk test results. The results are presented in Table 5.

Moreover, data normality affects the choice of factor extraction method. Notably, when using the maximum likelihood method, confirming normality is required. Thus, we examined how data normality is reported based on the factor extraction method. The results, shown in Table 6, indicate that PCA is the method most frequently associated with normality reporting. In contrast, no cases using the maximum likelihood method reported on normality checks.

TABLE 5

Results of Analysis on Assessment of Normality Test

Normality Test	Frequency	%
Not Reported	169	94.4
Shapiro-Wilk	3	1.7
Skewness and kurtosis	6	3.3
Others	1	0.6
Total	179	100.0

TABLE 6

Results of Analysis on Factor Extraction Methods by Normality Testing

Factor Extraction Method	Normality Test				
	Not Reported	Shapiro-Wilk	Skewness and kurtosis	Others	Total
Not Reported	69	0	3	0	72
PCA	82	3	2	1	88
MLE	4	0	0	0	4
PAF	14	0	1	0	15
Total	169	3	6	1	179

These findings indicate that in English education research, there is a significant lack of proper assessment of data appropriateness for factor analysis.

4.3. Trend Analysis in Factor Extraction Methods

4.3.1. Analysis of factor extraction methods by purpose of using factor analysis

We examined the trends in factor extraction methods in English education research using factor analysis. As shown in Table 7, out of 179 cases, PCA was used in 88 cases, accounting for about 49.2% of the total, making it the most frequently reported method. In contrast, common factor extraction techniques were reported in only 19 cases, or 10.6% of the total. Additionally, 72 cases did not report the factor extraction method.

Notably, among the 92 cases that reported both the factor extraction method and the purpose of using factor analysis, 74 cases (80.4%) reported that the purpose was to extract common factors. Nevertheless, PCA was used in 57 of these 74 cases, representing approximately 77.0% of the total. In contrast, common factor extraction techniques were used in only 17 cases, accounting for about 23.0% with principal axis factoring used in 14 cases, and the maximum likelihood method in 3 cases.

TABLE 7
Results of Analysis of Factor Extraction Methods by Purpose of Using Factor Analysis

Factor Extraction Method	Purpose of Using Factor Analysis						
	Not Reported	Finding Common Factors	Reduction in Dimensions	Others	Finding Common Factors + Reduction in Dimensions	Exploring Relations between Variables	Total
Not Reported	15	53	0	2	1	1	72
PCA	13	57	7	8	2	1	88
MLE	1	3	0	0	0	0	4
PAF	1	14	0	0	0	0	15
Total	30	127	7	10	3	2	179

4.3.2. Analysis of factor extraction methods by statistical packages

The results of reviewing the factor extraction methods based on the statistical package are shown in Table 8 below.

TABLE 8
Results of Analysis of Factor Extraction Methods by Statistical Packages

Factor Extraction Methods	Statistical Packages						
	Not Reported	SPSS	SAS	R	Mplus	Others	Total
Not Reported	12	60	0	0	0	0	72
PCA	30	55	0	0	0	3	88
MLE	0	3	0	0	0	1	4
PAF	1	11	3	0	0	0	15
Total	43	129	3	0	0	4	179

To begin with, the analysis indicated that SPSS was the most frequently used statistical package, with 129 cases, representing approximately 72% of the total. On the other hand, statistical packages such as SAS, R, or Mplus, which require programming languages or scripting, were never or marginally reported with only SAS confirmed in 3 cases.

Next, an examination of the statistical packages employed with different factor extraction methods revealed that out of 76 cases where both the extraction method and the statistical package were reported, 55 cases used SPSS for PCA, accounting for about 72.4% of the total. Additionally, 11 cases, or 14.5%, employed SPSS for principal axis factoring. On the other hand, SAS was used in only 3 cases, all of which applied the principal axis factoring method.

4.4. Trend Analysis in Factor Number Determination

4.4.1. Analysis of factor number determination methods

Table 9 presents the frequency of methods used to determine the number of factors in 179 cases.

TABLE 9

Results of Analysis of Factor Number Determination Methods

Criteria for Determining Number of Factors	Frequency	%
Not Reported	108	60.3
Eigenvalue > 1	58	32.4
Scree Plot	2	1.1
Accumulated Variance	2	1.1
Model Fit	1	0.6
Mixed	8	4.5
Parallel Analysis	0	0.0
Total	179	100.0

To be specific, approximately 60% of the cases did not disclose the method for deciding the number of factors, and the most frequent method involved checking if the eigenvalues were greater than 1. However, cases where multiple methods were combined to determine the number of factors comprised 4.5% of the total, significantly lower than the method of eigenvalue > 1.

Additionally, the use of Scree Plot, Accumulated Variance, and Model Fit as standalone methods appeared in about 1% of cases, suggesting these methods are seldom used in English education research using factor analysis.

4.4.2. Analysis of reporting cumulative variance

In general, it is advisable to report the metrics of cumulative variance along with the extracted factors. Nevertheless, as shown in Table 10 below, only about 60% of the 179 cases included information on cumulative variance, detailing how much the extracted factors explained the total variance.

TABLE 10

Results of Analysis of Reporting of Cumulative Variance

Accumulated Variance	Frequency	%
Not Reported	71	39.7
Reported	108	60.3
Total	179	100.0

4.4.3. Criteria analysis for communality values by factor extraction methods

Table 11 below shows the reporting standards for communality levels displayed in English education research cases. More specifically, 155 cases, or about 86% of the total, did not report the communality criterion.

In contrast, 22 cases, or 12.3% of the total, reported a criterion of 0.4. These findings reveal that studies within the English education field employing factor analysis frequently fail to include reports on commonality.

TABLE 11

Results of Analysis of Communality Criteria

Commonality Criteria	Frequency	%
Not Reported	154	86.0
0.3	0	0
0.4	22	12.3
0.5	2	1.1
0.6	1	0.6
Total	179	100.0

4.4.4. Analysis of factor number determination methods by statistical packages

Table 12 below shows the results of reviewing the criteria for determining the number of factors based on the statistical package.

Specifically, the analysis indicated that among the 54 cases that reported both the factor number determination method and the statistical package employed, most used SPSS with the criterion of Eigenvalue > 1. Similarly, SPSS was also the most frequently reported statistical package in 7 cases using the Mixed method.

TABLE 12

Results of Analysis of Criteria for Determining Number of Factors by Statistical Packages

Criteria for Determining Number of Factors	Statistical Packages						
	Not Reported	SPSS	SAS	R	Mplus	Others	Total
Not Reported	26	79	3	0	0	0	108
Eigenvalue > 1	13	45	0	0	0	0	58
Scree Plot	1	1	0	0	0	0	2
Accumulated Variance	2	0	0	0	0	0	2
Model Fit	0	0	0	0	0	1	1
Mixed	1	4	0	0	0	3	8
Parallel Analysis	0	0	0	0	0	0	0
Total	43	129	3	0	0	4	179

4.5. Trend Analysis in Factor Rotation Method Selection

4.5.1. Analysis of criteria for factor rotation method by factor extraction method

Table 13 shows the preferred factor rotation methods in English education research. Specifically, Varimax was confirmed to be the most frequently used method, appearing in 87 out of 179 cases (48.6%). This is followed by Direct Oblimin in 16 cases (8.9%) and Promax in only 2 cases (1.1%). Notably, in 69 cases (38.5%), the factor rotation method was not specified.

TABLE 13

Results of Analysis of Criteria for Factor Rotation Methods by Factor Extraction Method

Rotation Method	Factor Extraction Method				
	Not Reported	PCA	ML	PAF	Total
Not Reported	54	14	0	1	69
Varimax	18	62	0	7	87
Oblique	0	0	0	2	2
Promax	0	1	0	1	2
Direct Oblimin	0	11	4	1	16
Others	0	0	0	3	3
Total	72	88	4	15	179

An additional analysis of the use of factor rotation methods based on factor extraction methods revealed that Varimax was chosen in 62 cases when PCA was employed, highlighting its high frequency. Conversely, Direct Oblimin was selected in 11 PCA cases. When principal axis factoring was used, Varimax was chosen in 7 cases, while Promax and Direct Oblimin were each chosen in 1 case, showing their low frequency.

4.5.2. Analysis of factor rotation method by method for presenting factor correlation

Table 14 below shows the analysis results of factor rotation methods based on whether inter-factor correlations were considered prior to factor analysis. The analysis indicates that out of 179 cases, 170 cases (95%) did not mention any assumptions about inter-factor correlations. Only 9 cases assumed an inter-factor correlation before performing factor analysis. Of these 9 cases, 5 provided both theoretical justification and correlation analysis results to support the assumption. Conversely, 2 cases only presented correlation analysis results as evidence of inter-factor correlation, and another 2 assumed inter-factor correlation without any references.

TABLE 14

Results of Analysis of Factor Rotation Methods by Methods for Presenting Factor Correlations

Rotation Method	Method for Presenting Factor Correlations				
	Not Reported	Priori Correlation	Priori Correlation + Literature Review	Assumption without Reference	Total
Not Reported	69	0	0	0	69
Varimax	86	0	0	1	87
Oblique	0	0	2	0	2
Promax	2	0	0	0	2
Direct Oblimin	10	2	3	1	16
Others	3	0	0	0	3
Total	170	2	5	2	179

Meanwhile, among the cases that assumed inter-factor correlation, only 1 used Varimax as the factor rotation method, while most others used Direct Oblimin.

4.6. Trend Analysis for Clarifying Factor Structures

4.6.1. Analysis of factor loading criteria

Table 15 below displays the analysis results concerning the criteria for factor loadings in English education studies using factor analysis. Out of 70 cases reporting factor loading criteria, 29 cases, or about 41.4%, suggested 0.4 as the suitable standard. This was followed by 16 cases, or 22.9%, recommending 0.5, and 11 cases, or 15.7%, proposing 0.3 as the standard. It is remarkable that many cases suggest 0.4 or higher as the appropriate level for factor loadings. However, in more than half of the 179 cases, 109 cases (60.9%), the criteria for factor loadings were not reported.

TABLE 15

Results of Analysis of Factor Loading Criteria

Factor Loading Criteria	Frequency	%
Not Reported	109	60.9
0.2	0	0.0
0.3	11	6.1
0.32	2	1.1
0.35	6	3.4
0.4	29	16.2
0.5	16	8.9
0.6	6	3.4
Total	179	100.0

4.6.2. Analysis of cross loading criteria

An analysis of 179 cases revealed, as displayed in Table 16 below, that 161 cases (89.9%) did not address the criteria for or occurrence of double loadings. Only 17 studies, or 9.5% of the total, reported suspected double-loaded variables.

TABLE 16

Results of Analysis of Cross Loading Criteria

Cross Loading Criteria	Frequency	%
Not Reported	161	89.9
0.2	0	0.0
0.3	0	0.0
More than 0.3	1	0.6
Not Specific but Reported	17	9.5
Total	179	100.0

5. Discussion

Based on examination of the 179 cases of factor analysis presented in 109 articles selected from a total of 3,418, the following 8 issues were identified. This section addresses each issue and its implications for appropriate application of factor analysis for future researchers.

5.1. Small Sample Size and Lenient Criteria for Sample Selection

An analysis of the use of factor analysis in English education research revealed a significant number of cases where factor analysis was conducted with small sample sizes, aligning with the results from previous studies (Plonsky & Gonulal, 2015). Specifically, the results indicate that approximately 63% of the cases used sample sizes of 200 or fewer, and about 33.5% used sample sizes of 100 or fewer. Even some extreme instances displayed sample sizes of fewer than 30, as noted by Joo and Kim (2015) and Zhang, Ahn, and Park (2023). Additionally, considering the ratio of the number of observed variables to sample size, 35.7% of the cases had a ratio of 1:5 or less, and 57.5% had a ratio of 1:10 or less, with some extreme cases showing ratio of less than 1:1, namely, 1:0.76 and 1:0.78, as noted by Joo and Kim (2015) and Won and Park (2014).

Comparing the practice of sample sizes applied in the field of English education to that in related disciplines reveals a tendency for English education researchers to use smaller samples and more lenient criteria. For example, Kang *et al*. (2013), who analyzed trends in factor analysis in the field of education, found that approximately 15.8% of studies conducted factor analysis with sample sizes of 200 or fewer, and only 3.1% used sample sizes of 100 or fewer. Similar trends were observed in psychology. According to Seo *et al*. (2018), 14% of factor analysis studies in psychology had sample sizes of 200 or fewer, and only 2.3% had sample sizes of 100 or fewer.

When performing factor analysis with a small sample size, the most significant problem is the increased sampling error in constructing the sample correlation matrix. Additionally, factor structures derived from small samples lack generalizability, meaning the established factor structure is less likely to be reproducible in other samples. Consequently, the reliability of factor analysis results obtained from insufficient samples may be compromised.

5.2. Insufficient Reporting on Data Normality and Appropriateness

The results from this study revealed that a high number of cases did not report the review of data appropriateness. Specifically, more than half of the cases did not report the KMO measure or Bartlett's test of sphericity. These outcomes are consistent with previous research findings. For example, in the study conducted by Plonsky and Gonulal (2015), approximately 76.5% of the total 51 cases did not include the KMO report, and about 78% omitted the results of Bartlett's test of sphericity. In addition, most cases in this study did not address the verification of normality. Particularly, in the few cases, such as Kim (2018) and Kang (2017), that used the maximum likelihood method, there was no reporting on the normality assumption, which is a must-check item for the factor extraction method.

This trend in the field of English education was confirmed to be similar to the practices reported in the fields of education and psychology. For instance, Kang *et al*. (2013) found that approximately 58.3% of studies in the field of education did not report a review of data appropriateness. Seo *et al*. (2018) also reported that more than 50% of psychology papers did not adequately report the KMO measure or Bartlett's test of sphericity results for factor analysis though about 10% of papers did report the review of normality, contrasting with the findings of this study. More critically, a study on the trends in factor analysis use in the marketing field found that over 95% of papers did not report data appropriateness (Cho, 2007).

These findings suggest that the importance of reporting data appropriateness and normality checks has often been overlooked among researchers in the field of English education, including the social sciences. Not reporting these results can seriously undermine the overall validity of the analysis procedures and results, given that the results of Bartlett's test of sphericity, the KMO measure, and data normality are fundamental assumptions for factor analysis. As stated earlier, factor analysis relies significantly on the correlations between variables, with KMO and Bartlett's test of sphericity providing crucial information about the feasibility of factor analysis based on these correlations. Failing to report those results thus can impede researchers and their colleagues from properly assessing the feasibility of the analysis. Similarly, omitting data normality reporting can cast doubt on the validity of factor analysis results through the maximum likelihood method.

Meanwhile, it is unclear why these assumptions are often omitted when reporting factor analysis results. However, we can infer several reasons from Hoekstra, Kiers, and Johnson's (2012) research, which examined how frequently researchers check for statistical assumption violations and the reasons behind their practices. According to their findings, researchers were unaware of the importance of these assumptions, believed the statistical results were robust despite assumption violations, and considered assumption checks to be complex and time-consuming. Additionally, they tended to focus more on hypothesis testing and reporting primary statistical results. Based on those findings, we can postulate that researchers' lack of knowledge, perceived robustness despite unchecked assumptions, perceived complexity and difficulty in checking assumptions, and publication bias might have caused them to omit assumption checks.

5.3. Limited Awareness of the Distinctions between PCA and FA

Another critical issue identified in this study is the over-dependence on PCA as a factor extraction method. More critically, there was a noticeable tendency to use factor extraction methods that do not align with the objectives of factor analysis. Specifically, the analysis results indicate that about 78% of the cases in the English education field that reported their factor extraction method used PCA. Moreover, approximately 77% of those cases stated that their purpose for using PCA was to extract common factors for scale validation or scale development. Considering that PCA is a completely distinct analytical method developed on a different philosophical foundation from factor analysis, many cases reported in this field reflect the use of inappropriate factor extraction methods. Citing specific examples from our analyzed articles, H. D. Kim (2016) applied PCA to determine if his survey items assessed English teachers' perceived practicality of performance assessment using a picture-based narrative task in computer-based testing. In a similar manner, Kim and Lee (2018) employed PCA, with their main goal being the validation of the English learning style scale.

At this point, it is important to note that Korean researchers tend to rely more on PCA for factor analysis compared to foreign researchers. More specifically, when examining trends in the use of factor analysis in papers published in international journals within the second language field, it was observed that, as in Korea, PCA was the most relied upon, but the frequency of common factor analysis was also comparable to that of PCA (Plonsky & Gonulal, 2015).

In fact, the misuse and overuse of PCA are not confined to the field of English education. Previous studies suggest that similar misuse of PCA is frequently observed in the fields of education and psychology as well. However, PCA overuse appears less prevalent in those fields compared to English education. Kang *et al*. (2013) found that around 46% of studies in education used PCA, and Seo *et al*. (2018) reported that only about 20.13% of psychology papers used PCA. Moreover, the rates of non-reporting of factor extraction methods were only 16% and 4%, respectively, in these fields. In contrast, an analysis of factor analysis in English education showed that about 60% of cases did not report their factor extraction method.

Such a heavy preference for PCA in English education factor analysis is likely tied to SPSS's default PCA setting, as noted in previous studies (Park & Cho, 2022; Seo *et al.*, 2018). However, the misuse of PCA cannot be solely attributed to the use of SPSS, as SPSS also offers solutions for common factor analysis. We propose further interpretations for the misuse of PCA as follows. First, the misuse of PCA, as noted in earlier studies (Kang *et al*., 2013; C. T. Kim, 2016; Seo *et al*., 2018), might stem from researchers' lack of statistical literacy, making it difficult for them to understand the differences between PCA and common factor analysis. In other words, researchers may be conducting factor analysis without fully understanding the principles of PCA and common factor analysis. Second, reference books on factor analysis might present incorrect information regarding PCA. Third, the results of PCA and common factor analysis are often similar (Loewen & Gonulal, 2015). Therefore, researchers might perform factor analysis with a focus on the research results rather than the analytical process. Fourth, researchers may uncritically reference the factor analysis methods from previous studies when performing factor analysis. In particular, this emphasizes the need for proper use of factor analysis, as similar studies can influence each other as references, leading to the possibility that incorrect use of factor analysis becomes a sort of practice as it is passed on to subsequent studies and repeated.

5.4. Excessive Reliance on the Criterion of Eigenvalue > 1

A review of factor analysis cases from this study shows that the majority of studies used the Eigenvalue > 1 criterion to determine the number of factors. However, only 4.5% of cases used more than one criterion, either using Eigenvalue > 1 and the scree plot (Hahn, 2016) or incorporating interpretability along with Eigenvalue > 1 and the scree plot (Chon & Kim, 2019). In addition, about 60% did not report the method for determining the number of factors at all, constituting the majority. This contrasts with the findings of Plonsky and Gonulal (2015), where 25.5% used multiple criteria and 37.3% did not report the method. Additionally, criteria related to communality were mostly unreported, with a similarly low rate of reporting found in Plonsky and Gonulal (2015)'s study.

While the reliance on the Eigenvalue > 1 criterion and the lack of reporting on factor determination criteria are not unique to the field of English education, the degree of dependence is more pronounced compared to other related fields. For instance, in psychology, the Eigenvalue > 1 criterion was the most frequently used method for determining the number of factors, but its dependence was relatively low, with other methods such as scree plots, explained variance, interpretability, and even parallel analysis also being employed. In the field of education, about 82% of papers reported the criteria for determining the number of factors, while in psychology, 100% of the analyzed papers reported their factor selection criteria.

It is essential to carefully decide the method for determining the number of factors, as the factor structure can vary greatly with different methods, which can significantly influence the results of a factor analysis. Considering the significant impact of the factor determination process on the overall analysis, it is crucial to explore the reasons behind the study's findings. One reason could be the complexity of determining the number of factors. This process is intricate because researchers must look at more than just eigenvalues; they need to consider the size of explained variance, communality values, factor loadings, and interpretability. When multiple elements are assessed, the results might not align with the expected factor structure, complicating the interpretation and potentially causing confusion among researchers. Consequently, researchers may prefer the Eigenvalue >1 criterion as it offers a straightforward single standard for interpretation. Additionally, it is noteworthy that the Eigenvalue >1 criterion is widely favored not only in the field of English education but also in the social sciences, indicating its conventional status. This implies that specific guidelines for determining the number of factors were lacking in the field of English education. Therefore, to enhance transparency, rigor, validity, and even ease in English education research, it is urgent to establish standard criteria for factor analysis.

5.5. Incorrect Application of Factor Rotation Method

The most frequently reported method of factor rotation in factor analysis cases in the field of English education was Varimax, used in about 48.6% of all reported cases. This is higher than 37.3% reported in Plonsky and Gonulal (2015)'s study. In fact, this high frequency of using Varimax as a factor rotation method is also evident in other social science research fields (Cho, 2007; Kang *et al*., 2013; Park & Cho, 2022). However, it is noteworthy that oblique rotation methods are frequently seen not only in sister disciplines such as education but also in studies published in international second language journals. In addition, studies in the field of psychology have reported much more use of oblique rotations than that of orthogonal methods (Seo *et al*., 2018). These findings demonstrate that the use of Varimax is declining in the social sciences; nonetheless, researchers in the English education sector in Korea have not yet followed this trend.

Korean researchers' heavy reliance on Varimax among rotation methods may be, though speculated, attributed to the insufficient reporting of assumptions about factor correlations, as demonstrated in this research. According to the study's findings, about 95% of the 179 cases did not mention any prior assumptions regarding factor correlations. Ironically, numerous studies reviewed in the research, nevertheless, reported correlations between extracted factors. For instance, J. W. Lim (2021) and Jong and Shin (2018) both chose Varimax as their rotation method but reported correlations between extracted factors, illustrating a contradiction where researchers initially assume no correlations but later report them. Ultimately, this inconsistency can undermine the validity of the study analysis procedures. The overuse of Varimax may also be linked to PCA. Researchers often assume that the principal components produced by PCA are uncorrelated and should therefore be rotated while preserving their independence. However, this assumption is not valid. Fundamentally, factor rotation is not allowed in principal component analysis (Kang *et al*., 2013; C. T. Kim, 2016), as it results in equalizing the eigenvalues among the factors, which contradicts the goals of PCA (Kang *et al*., 2013). Further details on cases where factor rotation methods diverged from factor extraction methods are discussed below.

5.6. Incompatibility Between Factor Rotation and Extraction Methods

In addition to the high dependence on Varimax for factor rotation, this study also revealed a significant problem where factor rotation methods did not match factor extraction methods in many cases. While factor rotation needs to be compatible with factor extraction methods that extract common factors, such as MLE or PAF, this study found that many cases applied factor rotation even when using PCA, as briefly mentioned above. For example, Kang (2016) applied Varimax with PCA to develop items for creativity tests, whereas Choi and Jang (2017) employed Promax with PCA to discern differences in test takers' strategies. Similarly, Lee and Kim (2019) utilized Direct Oblimin with PCA to develop and validate a scale for self-regulated learning abilities.

In fact, whatever rotation methods, whether orthogonal or oblique, are applied with PCA, this practice is incorrect because PCA does not allow for factor rotation. Numerous previous studies have repeatedly pointed out that PCA and FA are different analytical methods, and that performing factor rotation with PCA is incorrect. However, this mistake persists in various social science research fields, including English education. The exact reasons for this error are unclear, but Kang *et al*. (2013) and C. T. Kim (2016) mentioned several causes, such as researchers' dependence on SPSS default functions for factor analysis, errors in factor analysis manuals, and a lack of understanding of PCA and FA. Another possible hypothesis regarding the inconsistency is that researchers, like in the misuse of PCA, may rely on previous studies that used factor analysis rather than consulting experts or appropriate references. Indeed, when tracing the rationale for using PCA and Varimax while conducting this study, it was often found that previous studies' results were uncritically accepted. Once more, this underscores the role of proper factor analysis practices in advancing research in English education.

5.7. Deficient Reporting on Factor and Cross-Loadings Criteria

Although it is essential to clearly present criteria for appropriate factor loadings and cross-loadings for proper interpretation of factor structures, the results from this study found that many cases did not report these criteria. Specifically, about 61% of the cases did not report criteria for appropriate factor loadings, and about 90% did not report criteria for cross-loadings. Notably, the non-reporting rate for appropriate factor loading levels in this study was markedly higher compared to previous studies in education, psychology and even similar fields, which reported rates of 4.6% (Kang *et al*., 2013), 43.2% (Seo *et al*., 2018), and 49% (Plonsky & Gonulal, 2015), respectively. However, it is somewhat reassuring that this study found a mention of cross-loadings in about 9.5% of the cases, as noted in Maeng (2014)'s report where one item simultaneously loaded on multiple factors with a factor loading of 0.4. Additionally, 26% of the cases reported an appropriate factor loading criterion in the range of 0.3 to 0.6, as indicated in H. W. Cho (2016) and Kim and Kang (2014), respectively.

To summarize, these results suggest that Korean researchers in the field of English education, when using factor analysis, are somewhat aware of the importance of considering issues related to cross-loadings and factor loadings, but that they still prioritize the interpretability of the final factor structure over the specific components that make up the structure. Indeed, the criteria for factor loadings and cross-loadings are crucial not only for the clarity of the factor structure but also as evidence of the convergent and discriminant validity of the extracted factors. Therefore, researchers should consider and clearly disclose the criteria for factor loadings and cross-loadings.

5.8. Overreliance on SPSS for Factor Analysis

Finally, a notable issue identified in this study is the significant reliance on SPSS as a statistical tool. This study found that 72% of the factor analysis cases in English education research used SPSS. Instead, only a small number of cases employed other statistical tools, such as STATA (Hong & Hyun, 2015) and SAS (Yim & Lim, 2019). As its full name, 'Statistical Package for the Social Sciences,' suggests, SPSS was developed for social science research and has been widely used in various social science fields, including English education, as the basic statistical software for conducting factor analysis. However, statistical programs have their distinct capabilities and can produce different results for factor analysis, with varying types of outcomes. For example, SPSS does not include a built-in feature for Parallel Analysis for determining the number of factors (Loewen & Gonulal, 2015), whereas Mplus and R do. Likewise, given that the expected outcomes of factor analysis can vary depending on the statistical software used, excessive reliance on SPSS can limit researchers' decision-making, such as factor extraction and determining the number of factors, thus hindering the successful execution of factor analysis.

6. Conclusion and Suggestions

Before finalizing this paper, the following specific strategies are proposed to improve the practice of factor analysis in English education research based on the issues identified in this study. Additionally, we provide a model reporting description for researchers to use in their future studies. Finally, we discuss research limitations and suggest topics for further research.

6.1. Effective Strategies to Enhance Factor Analysis

First, researchers planning to conduct factor analysis need to secure as many samples as they can. Additionally, it is important to provide a solid rationale for the sample size. While there is no universally accepted standard for determining sample size, this study recommends gathering at least 200 samples or more for researchers in English education research. This recommendation is informed by prior studies' strict guidance (Pett *et al*., 1999; Zygmont & Smith, 2014) and the empirical estimates identified in this study. Specifically, when the average number of observed variables was calculated using surveys from the 179 cases in this study, it resulted in approximately 20 items. This led to a sample size of about 200 or more, assuming a somewhat strict 1:10 variable-to-sample ratio was applied. Of course, we acknowledge that this recommendation may be too strict to apply to every research context. In cases where the survey has a small number of items, we suggest applying a strict 1:10

ratio and calculating the suitable sample size for each study. Furthermore, if conducting factor analysis with a smaller sample, it is also recommended to provide additional information that demonstrates the stability of the factor structure. This includes reporting factor loadings, communalities, cross-loadings, and ensuring that there are at least three observed variables loaded per factor. Such efforts will enable peer researchers to adequately evaluate the stability of the factor structure.

Second, researchers need to enhance their understanding of the principles and philosophy of factor analysis when performing it. The key components of factor analysis are factor extraction, factor rotation, and factor interpretation. Researchers should fully comprehend the principles of each stage and endeavor to adhere to the fundamental principles of factor analysis. This effort will help correct improper factor analysis practices.

Third, it is essential for researchers to seek assistance from multiple sources when performing factor analysis. As noted earlier, some studies tended to uncritically follow the factor analysis procedures of prior research. Given that researchers must make numerous decisions across different aspects of factor analysis, they should obtain advice from various sources, including factor analysis experts and reference books on factor analysis.

Fourth, to conduct factor analysis more appropriately, it is recommended for researchers to utilize statistical software that more effectively supports factor analysis. As mentioned earlier, SPSS was the most preferred statistical software for factor analysis in English education research. Although SPSS is user-friendly, it has several functional limitations in determining the number of factors, providing model fit information, and comparing and selecting factor models. Notably, parallel analysis has recently been recommended as an alternative method for determining the number of factors instead of the eigenvalue > 1 criterion. Therefore, researchers need to consider using other statistical software, such as Mplus or R, which offer more advanced support for factor analysis.

Fifth, it is recommended to promote the use of the maximum likelihood method in future research employing factor analysis. This study found that the use of the maximum likelihood method was minimal when factor analysis was performed in the field of English education. The maximum likelihood method is known to provide the most stable parameter estimates when the assumption of normality is met. Furthermore, it offers model fit indices, which provide additional useful information for determining factor structures.

Sixth, researchers conducting factor analysis need to thoroughly report their decisions and results throughout the process to enhance the reliability of their research findings. The results of this study revealed that a significant number of cases had missing information in their factor analysis results. Such omissions can diminish the validity and reliability of the research findings. Moreover, if this practice is repeated by researchers, it could establish undesirable reporting practices. The following guidelines outline what should be reported after conducting factor analysis:

· Sample size
· Assumption of data normality
· Appropriateness of the data for factor analysis
· Factor extraction method and its rationale
· Factor rotation method and its rationale
· Criteria for factor loadings, cross loadings and communalities
· Cumulative variance
· Method for determining the number of factors and its rationale
· Final factor matrix
· Statistical software used for analysis

With the suggested guidelines above, it is expected that this study will provide assistance for the proper use of factor analysis in future research within the field of English education.

6.2. Exemplary Reporting of Factor Analysis Methods

This is the model reporting guide that researchers can use when documenting their factor analysis. The description below was created under a fictional scenario that investigates the underlying structure of data evaluating English writing strategies for college EFL learners. We also recommend referring to Loewen and Gonulal (2015) for further examples of FA report samples.

· Research Question
What underlying constructs can be identified in EFL college learners' responses to a questionnaire about their perceived English writing strategies?

· Instrument
The study employed a questionnaire with 40 Likert-scale questions covering different English writing strategies. This questionnaire was created based on prior relevant studies and a theoretical framework for L2 writing strategies. Expected potential underlying sub-constructs are metacognitive strategies, cognitive strategies, L1 use strategies, compensatory strategies, and social strategies.

· Data Analysis
In this study, factor analysis was used to identify the sub-elements of English writing strategies among university students. The analysis followed several procedures. First, the suitability of the collected data for factor analysis was assessed using the KMO measure and Bartlett's test of sphericity. The KMO measure evaluated the adequacy of the sample size,

while Bartlett's test assessed the appropriateness of the correlations among variables for factor analysis. Second, the factor structure was extracted using the maximum likelihood method, which assumes data normality. Therefore, a normality test was conducted to ensure the validity of the factor extraction results. Third, the appropriate number of factors was determined based on multiple criteria, including the Eigenvalue > 1, the total explained variance (≥ 60 %), the interpretability, the significant reduction in chi-square values, and the AIC values. Parallel analysis was also performed to confirm the number of factors. Fourth, to improve the interpretability of the factor structure, factor rotation was performed. Based on prior research indicating potential correlations among various learner strategies, English writing strategies are also predicted to be correlational. Thus, Promax rotation, an oblique rotation method, was used. Fifth, the criteria for retaining items in this factor analysis included a communality value and a factor loading value of 0.4. Items that did not show at least a 0.2 difference in factor loadings among factors were considered double-loaded and were deleted. Sixth, the characteristics of each factor were described based on the factor loadings and item content, and appropriate names were assigned to each factor. This study's factor analysis was executed with the help of the psych, GPArotation, and lavaan packages in R version 4.4.1.

6.3. Limitations and Suggestions for Future Studies

The study has several limitations. First, it centers on research published within the domain of English education in Korea, which makes it challenging to generalize the results to the global field of English education. This limitation underscores the necessity for future studies to compare the application and reporting of factor analysis across various research contexts, such as different countries. Second, this study examined trends in factor analysis and its reporting using a quantitative approach. While this method offers insights into general trends, it does not provide specific examples of how factor analysis is applied. Consequently, future research should adopt a qualitative approach to analyze and compile instances of factor analysis misuse. Lastly, the study does not sufficiently address co-occurring mistakes in factor analysis. Identifying patterns in the misuse of factor analysis could be essential for reducing potential errors. Therefore, future research should delve deeper into the relationships between different types of misuse, particularly through the use of network analysis. Network analysis can help researchers explore the dynamic relationships and characteristics between variables in a detailed and efficient manner.

Applicable levels: Early childhood, elementary, secondary, tertiary

Evaluation on the Application of Factor Analysis Method in the Field of English Education in Korea

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References marked with asterisk (*) were utilized for data analysis in this study.

APPENDIX A

Brief Statistics on the Collected Data from 12 Journals

Selected Journals	Articles (10 Years)	Articles using EFA	EFA Cases
The Korea Association of Teachers of English(KATE)	314	11	13
Global English Teachers Association(GETA)	249	13	24
The Society for Teaching English through Media(STEM)	311	8	9
The Korea Association of Foreign Language Education(KAFLE)	408	20	42
Korea Association of Multimedia-Assisted Language Learning(KAMALL)	284	7	15
Journal by the Research Institute of Curriculum & Instruction at Ewha Womans University (JRCI)	76	1	1
Pan-Korea English Teachers Association(PKETA)	298	17	26
The Korea Association of Secondary English Education(KASEE)	256	7	12
The English Teachers Association in Korea(ETAK)	336	7	7
The Applied Linguistics Association of Korea(ALAK)	232	5	7
The Korea Association of Primary English Education(KAPEE)	335	6	9
Modern English Education Society(MEESO)	318	7	14
Total	3,417	109	179

APPENDIX B

Data Coding Criteria for Factor Analysis

Coding Category	Coding Objective	Coding Scheme
1) Sample Size	To confirm the number of samples used to construct the correlation matrix	Numeric (as stated in the paper)

2) Observed variable Count	To confirm the number of observed variables used in factor analysis	Numeric (as stated in the paper)
3) Data Appropriateness Check	To confirm the adequacy of the data used for factor analysis	Not Reported: 0, KMO Measure of Sample Adequacy: 1, Bartlett's Test of Sphericity: 2, KMO Measure of Sample Adequacy and Bartlett's Test of Sphericity: 3,
4) Normality Test	To confirm the normality distribution of the observed variables	Not Reported: 0, Shapiro-Wilk: 1, Skewness and Kurtosis: 2, Others: 3
5) Factor Extraction Method	To confirm the factor extraction method used	Not Reported: 0, PCA: 1, ML: 2, PAF: 3
6) Purpose of Using Factor Analysis	To confirm the purpose of applying factor analysis	Not Reported: 0, Finding Common Factors: 1, Reduction in Dimensions: 2, Others: 3, Finding Common Factors + Reduction in Dimensions: 4, Exploring Relations between variables: 5
7) Method for Presenting Factor Correlations	To confirm the methods used for assuming inter-factor correlations before factor analysis	Not Reported: 0, Priori Correlation: 1, Priori Correlation + Literature Review (LR): 2, Assumptions without Reference: 3
8) Criteria for Determining Number of Factors	To confirm the criteria for deciding the number of factors	Not Reported: 0, Eigenvalue > 1: 1, Scree Plot: 2, Accumulated Variance: 3, Model Fit: 4, Mixed: 5, Parallel Analysis: 6,
9) Accumulated Variance Reported or Not	To confirm whether cumulative variance is reported	Not Reported: 0, Reported: 1
10) Communality Criteria	To confirm the criteria for commonality	Not Reported: 0, 0.3: 1, 0.4: 2, 0.5: 3, 0.6: 4
11) Rotation Method	To confirm the method of factor rotation used	Not Reported: 0, Varimax: 1, Oblique: 2, Promax: 3, Direct Oblimin: 4, Others: 5
12) Factor Loading Criteria	To confirm the criteria for factor loadings	Not Reported: 0, 0.2: 1, 0.3: 2, 0.32: 3, 0.35: 4, 0.4: 5, 0.5: 6, 0.6: 7
13) Cross Loading Criteria	To confirm the criteria for cross loadings	Not Reported: 0, 0.1~Less than 0.2: 1, 0.2~Less than 0.3: 2, More than 0.3: 3, Not Specific but Reported: 4
14) Statistical Packages Employed	To confirm the statistical package used for factor analysis	Not Reported: 0, SPSS: 1, SAS: 2, R: 3, Mplus: 4, Others: 5