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Validation of Clinical Supervision Questionnaires Using Exploratory Factor Analysis (Efa) For Nursing Students in Selected Private Nursing Colleges Malaysia: A Pilot Test

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Abstract:
This study utilised Exploratory Factor Analysis (EFA) to investigate nursing students' experiences with clinical supervision. EFA identified four principal factors: clinical supervision support, instructor-student relationship, time management and perceived value, and negative perceptions of supervision. The research involved 105 nursing students and employed the Manchester Clinical Supervision Scale (MCSS) to evaluate their experiences. EFA confirmed the validity of data from clinical supervision questionnaires among Malaysian private nursing. students, ensuring accurate representation of constructs. The study addresses factor extraction criteria, rotation methods, factor loadings, and implications for future research.
Conclusion and Implications: Clinical supervision is widely acknowledged for its role in skill development for students in clinical settings. However, some students find it intrusive or time-consuming. Improving instructor-student relationships and managing time constraints may enhance the overall effectiveness of student supervision. Future research should validate these findings through Confirmatory Factor Analysis (CFA) and explore strategies to optimize clinical supervision in nursing education.

Keywords: Clinical Supervision Questionnaires, Exploratory Factor Analysis (EFA), Pilot test, Nursing Students, Validation.

1. Introduction

Clinical supervision in nursing education ensures students meet objectives, develop competence, and provide quality care. It fosters supportive relationships and enhances learning (Bifarin & Stonehouse, 2017; Donough & Van der Heever, 2018). Globally recognized, it is vital for student growth, regulatory compliance, and professional identity formation. Effective supervision links theory to practice and engages students in patient care (Amsrud et al., 2015). Inadequate supervision can lead to negative experiences and attitudes. Effective supervision should align with outcomes, use various evaluations, and incorporate feedback.

This study utilized Exploratory Factor Analysis (EFA) for data validation. EFA is critical for identifying latent variables that account for correlations among observed variables, as explained by Fabrigar et al. (1999). Unlike Confirmatory Factor Analysis (CFA), which tests specific hypotheses, EFA allows for data-driven exploration without predefined structures, making it suitable for early-stage research with limited theoretical guidance (Costello & Osborne, 2005).

EFA was applied to Clinical Supervision questionnaires completed by Malaysian nursing students to explore variable dimensionality and ensure distinct construct representation. This process simplifies data while preserving core information, aiding in the identification of significant factors for the research's theoretical framework (Field, 2013). The study details the steps of EFA, including factor extraction criteria, rotation methods, and evaluation of factor loadings, and discusses the results and their implications for the research model.

Objective of the Study

To validate the feasibility of the pilot test, the researcher assesses the reliability and effectiveness of the questionnaires on clinical supervision experiences among nursing students in selected private nursing colleges in Malaysia.

Ethical Approval

Permission was obtained from respective management of the selected nursing colleges. Meanwhile, the participants received written information about the study prior to data collection. Their identities and data are kept confidential, and participants could withdraw from the study at any time.

Data Collection and Research Instrument /Questionnaires Process

From July to August 2024, 105 subjects participated in a pilot test using distributed questionnaires. They were informed of the procedure and had 20 minutes to consent. The Manchester Clinical Supervision Scale (MCSS) evaluated supervision quality, professional development, skill improvement, reflection time, and supervisory relationships. The 16-item scale used a five-point Likert scale from 'strongly disagree' to 'strongly agree'. Responses were analysed with exploratory factor analysis (EFA) to identify key factors in clinical supervision.

Assumptions of Exploratory Factor Analysis (EFA)

Prior to performing EFA, it is essential ensuring several assumptions are met for reliable results.

- **Sample Size:** A minimum of 50 samples is suggested, with a sample-to-item ratio of at least 5:1, preferably 10:1. High communalities (> .60) may allow smaller samples. Aim for at least 100 cases.
- **Type of Data:** EFA is best for scales aggregating multiple items. Ordinal data can be used if treated as continuous. Four to seven response categories are recommended.
- **Normality:** Data should have skewness between -2.0 and +2.0 and kurtosis between -7.0 and +7.0. Address outliers using Z scores ±3.0 and Mahalanobis distance.
- **Multicollinearity:** Avoid high correlation among predictors. The determinant of the correlation matrix should be > .00001; no correlations should exceed .90. KMO measure must be > .60 (acceptable), > .80 (meritorious).

Ensure Bartlett's Test of Sphericity has a significant p-value ($p < .05$). For factorability, several correlations in the matrix should be .30 or higher, indicating shared variance among variables. Adhering to these guidelines supports valid and interpretable EFA outcomes.

Table 1.0 Assumptions and Minimum Cut-off Value of Exploratory Factor Analysis (EFA)

No.	Assumption	Minimum Cut-off Value
1	Sample Size	Minimum 50 cases (de Winter et al., 2009; Mundfrom et al., 2005), recommended at least 100 cases (Kabit et al., 2019), ideally 10 participants per variable (item) (Bollmann, 2018).
2	Data Type	Continuous (Spearman, 1904; Gorsuch, 1997). For categorical, Lozano et al. (2008) recommend 4–7 response categories; others suggest for 5 and above response category (DiStefano, 2002; Mueller & Hancock, 2019).
3	Normality	Skewness between -2.0 and +2.0, Kurtosis between -7.0 and +7.0 (Bollmann, 2018).
4	Outliers	Z-scores ±3.0 (Jamshidi et al., 2022), Mahalanobis distance above critical value (Luo et al., 2019).
5	Multicollinearity	Determinant > .00001, no correlations > .90 (Schmid, 2017).
6	Kaiser-Meyer-Olkin (KMO) Measure	> .60 (acceptable) (Kaiser, 1970), > .80 (meritorious) (Schmid, 2017).
7	Bartlett's Test of Sphericity	$p < .05$ (Bartlett, 1954; Loewen & Gonulal, 2015).
8	Factorability of the correlation matrix.	Several correlations of $r = .30$ or higher in correlation matrix (Tabachnick & Fidell, 2013).

Methods of Extraction and Rotation—Principal Axis Factoring (PAF) and Promax

The principal axis factoring (PAF) method identifies underlying structures by focusing on shared variance among variables, making it suitable for psychological and social sciences research. Unlike principal component analysis (PCA), PAF handles datasets that deviate from multivariate normality well (Sellbom & Goretzko, 2023; Lanario et al., 2020).

Promax rotation, an oblique rotation method, starts with an orthogonal rotation like Varimax and then raises loadings to a power. This simplifies the factor structure and is ideal for related theoretical constructs, facilitating interpretation and handling large datasets efficiently (Sürücü et al., 2024).

Justification for Using Principal Axis Factoring (PAF) Extraction and Promax Rotation with Ordinal Data

Using PAF and Promax rotation is effective for EFA with ordinal data; often found in the social sciences (Grieder & Steiner, 2021; Oamen, 2021). PAF is preferred over PCA because it does not assume multivariate normality, focusing on shared variance among items (Watkins, 2021; Avşar, 2022). Promax rotation is crucial when factors are correlated, as seen in psychological constructs (Beauducel & Kersting, 2020). It identifies meaningful correlations between factors, reflecting human behaviour complexity (De Castro et al., 2015). For instance, PAF and Promax

helped distinguish related factors in validating the Severe Asthma Questionnaire (Lanario et al., 2020). Research confirms PAF and Promax's reliability across statistical software, producing consistent factor solutions (Grieder & Steiner, 2021). This reinforces their use in handling the complexities of ordinal data.
In summary, PAF and Promax rotation are well-suited for EFA with ordinal data, effectively uncovering latent structures in psychological and behavioural research, validated by various studies.

2. Methods of Determination of Number of Component (Factor)

When deciding on the number of components to retain during EFA, consider the following criteria:

- Communalities greater than .40 (Scharf & Nestler, 2019; Chen, 2021) indicate sufficient shared variance among variables. In large samples (n > 100) or with more relaxed criteria, a cut-off value of .30 is acceptable (Bollmann, 2018).
- The Kaiser criterion retains factors with eigenvalues greater than 1.0, explaining significant variance (Bollmann, 2018).
- A scree plot can provide additional guidance through its visual "elbow," but its subjectivity limits standalone use (Ledesma et al., 2015).
- Parallel analysis, like Monte Carlo PCA, was not used since PAF focuses on shared variance, whereas PCA emphasizes total variance (Avşar, 2022; Santos et al., 2019).

The Kaiser criterion, combined with considerations of communalities and theoretical foundations, offers a clear and effective method for factor retention in EFA.

Instrumentation of Clinical Supervision

The researcher developed a 16-item questionnaire based on literature to assess nursing students' clinical supervision. Exploratory Factor Analysis (EFA) was used to identify latent variables, with data from a pilot study of 111 respondents (105 after screening).
All EFA assumptions were verified prior to conducting Principal Axis Factoring (PAF). Two rounds of PAF were performed: the first to determine the number of components, and the second based on those findings. The sample size (n = 105) was adequate, with correlations of r = .30 or higher and no multicollinearity. Bartlett's test of sphericity was significant, X2 (120) = 866.02, p < .05, and the KMO measure was .86. Extreme values and outliers were removed using Z-scores and Mahalanobis distance.

Table 2.0 below Summarises the Assessment of Assumptions of EFA for Clinical Supervision Instrumentation

Assumption	Minimum Cut-off Value	Violation	Justification
Sample Size	Minimum 100 cases, ideally 10 participants per variable.	No	No. of sample after data screening and EDA is *n* = 105.

Type of Data	Categorical or ordinal with at least 5 and above response category.	No	5-point Likert scale was employed.
Normality	Skewness between -2.0 and +2.0, Kurtosis between -7.0 and +7.0.	No	All items are within the permittable ranges.
Outliers	Z-scores ±3.0, Mahalanobis distance above critical value.	No	Z-scores and Mahalanobis were performed based on the criteria.
Multicollinearity	Determinant > .00001, no correlations > .90.	No	All correlations below .90.
Kaiser-Meyer-Olkin (KMO) Measure	> .60 (acceptable), > .80 (meritorious).	No	KMO was recorded at .86.
Bartlett's Test of Sphericity	p < .05.	No	Bartlett's test of sphericity showed significant values, X^2 (120) = 866.02, p < .05.
Factorability of the correlation matrix.	Several correlations of r = .30 or higher in correlation matrix.	No	Several correlations were recorded more than .30.

Prior to establishing components, we evaluated each item's communality value. All items exhibited a communality value exceeding .30, indicating significant shared variance with other items, justifying their inclusion in factor analysis. A communality value above .30 generally reflects good alignment with the dataset's structure (Bollmann, 2018), enhancing the reliability and interpretability of the factor solution. Table 3.0 below presents the extraction communalities and cut-off evaluation for questionnaire items assessing clinical supervision.

Table **Error! No text of specified style in document.**.0 Extraction Communalities and Cut-off Evaluation for Questionnaire Items Assessing Clinical Supervision

Item	**Item Description**	**Extraction Communality**	**Above Cut-off (> .30)**
CST/CSR1	My clinical instructor gives me support and encouragement	.51	Yes
CST/CSR2	I can discuss sensitive issues with my clinical instructor.	.66	Yes
CST/CSR3	My clinical supervisor is very open with me.	.76	Yes
CST/CSR4	My clinical instructor acts in a superior manner during our sessions.	.48	Yes
CSA/CSS1	My clinical instructor provides me with valuable advice.	.56	Yes
CSA/CSS2	Sessions with my clinical instructor widen my perspective.	.52	Yes
CSA/CSS3	I can widen my skill base during clinical supervision sessions.	.59	Yes

CSA/CSS4	My clinical instructor offers guidance with patient care.	.58	Yes
CSIC/CSS1	Clinical supervision is an important part of my work routine.	.57	Yes
CSIC/CSS2	Clinical supervision makes me a better practitioner.	.68	Yes
CSIC/CSS3	Without clinical supervision, the quality of patient care would deteriorate.	.59	Yes
CSIC/CSS4	Clinical supervision improves the quality of the care I give to my patients.	.58	Yes
CSI/CSV1	Time spent on clinical supervision takes me away from my real work in the clinical setting.	.68	Yes
CSI/CSV2	Clinical supervision is intrusive.	.65	Yes
CSI/CSV3	It is important to make time for clinical supervision sessions.	.80	Yes
CSI/CSV4	Clinical supervision is for newly/inexperienced students and staff only.	.30	Yes

Note: Extraction method=Principal axis factoring. Communalities over .40 are typically expected, indicating that variables share sufficient variance and contribute meaningfully to underlying factors (Scharf & Nestler, 2019; Chen, 2021; Luo et al., 2019). However, with large sample sizes ($n > 100$) or when relaxed criteria are acceptable, a cut-off of .30 is accepted (Bollmann, 2018).

To determine the number of components, we examined the total variance explained output. Eigenvalues greater than 1.0 (Kaiser criterion) were considered as they indicate significant factors. This method ensures only meaningful factors are retained. In the first round of PAF, four factors with eigenvalues over 1.0 collectively accounted for 69.01% of the variance, making them key dimensions. Post-extraction, these factors explain 59.41% of the variance due to overlap, indicating shared variance among them. Rotation redistributes the explained variance for better interpretability. After rotation, the first four factors account for 37.65%, 48.07%, 55.11%, and 59.41% of the variance respectively. Note that when factors are correlated, sums of squared loadings cannot be added to get a total variance, which is characteristic of the rotation method used.

Table 4.0 Total Variance Explained for Clinical Supervision

Factor	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**
1	6.42	4.15	4.15	6.02	37.65	37.65	5.50
2	2.04	12.75	52.90	1.67	1.42	48.07	4.33

3	1.49	9.33	62.23	1.13	7.05	55.11	3.19
4	**1.09**	**6.78**	**69.01**	**.69**	**4.29**	**59.41**	**1.87**
5	.88	5.50	74.51				
6	.66	4.15	78.66				
7	.56	3.48	82.14				
8	.50	3.13	85.27				
9	.42	2.65	87.92				
10	.38	2.36	9.27				
11	.36	2.24	92.51				
12	.31	1.95	94.47				
13	.27	1.71	96.17				

To summarise, the initial PAF cycle indicated that the first four factors captured most of the variance. The rotation clarified these factors, helping identify the data's underlying dimensions (Cattell, 1978). This understanding was crucial for deciding how many factors to retain for further analysis. Therefore, a second PAF round with four components was conducted, with factor loadings below .40 suppressed as recommended by Sürücü et al. (2024), and Promax rotation applied. The PAF with Promax rotation revealed four distinct factors: (1) clinical supervision support, (2) instructor-student relationship, (3) time management, and (4) perceived value of supervision and negative perceptions of supervision. Table 5.0 shows that items loading on these factors have factor loadings greater than .40, considered significant for item retention.

Table 5.0 Pattern Matrix of Instrumentation of Clinical Supervision

Item	**Statement**	**Factor**			
		1	2	3	4
CST/CSR1	My clinical instructor gives me support and encouragement.		.47		
CST/CSR2	I can discuss sensitive issues with my clinical instructor.		.85		
CST/CSR3	My clinical supervisor is very open with me.		.91		
CST/CSR4	My clinical instructor acts in a superior manner during our sessions.		.59		
CSA/CSS1	My clinical instructor provides me with valuable advice.	.79			
CSA/CSS2	Session with my clinical instructor widen.		.49		
CSA/CSS3	I can widen my skill base during clinical supervision session.	.80			
CSA/CSS4	My clinical instructor offers the guidance with patient care.	.84			
CSIC/CSS1	My clinical supervision is importance part of my work routine.	.67			
CSIC/CSS2	Clinical supervision makes me a better practitioner.	.60			
CSIC/CSS3	Without clinical supervision the quality patient care would deteriorate	.64			
CSIC/CSS4	Clinical supervision improves the quality of the care l give to my patient.	.53			

CSI/CSV1	Time spent on clinical supervision takes me away from my real work in the clinical setting.				.88
CSI/CSV2	Clinical supervision is intrusive.				.80
CSI/CSV3	It is important to make time for clinical supervision sessions.			.96	
CSI/CSV4	Clinical supervision is for newly/inexperienced student and staff only.			.61	

Note: Extraction method: Principal Axis Factoring. Rotation method: Promax with Kaiser normalization. Rotation converged in 6 iterations.

Factor 1: Clinical Supervision Support
This factor highlights the supportive role of clinical supervision with items such as: “My clinical instructor provides valuable advice (.79)”, “I can widen my skill base during supervision sessions (.80)”, and “It improves the care I provide (.53)”. Loadings over .40 demonstrate the importance of supervision in enhancing skills and patient care.

Factor 2: Instructor-Student Relationship
This factor focuses on the interpersonal relationship between instructor and student, with significant items including: “My clinical instructor gives me support and encouragement (loading = .47)” and “I can discuss sensitive issues with my clinical instructor (loading = .85)”. These items, all loading above .40, emphasize openness and mutual respect in improving clinical skills.

Factor 3: Time Management and Perceived Value of Supervision
This factor captures the value placed on clinical supervision. Key items are: “It is important to make time for clinical supervision sessions (loading = .96)” and “Clinical supervision is for newly/inexperienced students and staff only (loading = .61)”. Both items highlight the necessity and perceived audience for supervision.

Factor 4: Negative Perceptions of Supervision
This factor reflects negative attitudes towards supervision, with items like: “Time spent on clinical supervision takes me away from my real work (loading = .88)” and “Clinical supervision is intrusive (loading = .80)”. These strong loadings indicate concerns about supervision's disruptive nature.

Summary of Exploratory Factor Analysis (EFA) for Clinical Supervision Instrumentation
There were no items that were cross loaded between factors in a significant way, allowing for clear grouping of items. All items in the matrix that exceeded the .40 threshold have been retained, as they contribute meaningfully to the identified factors. Items below the threshold would typically be dropped, but in this case, no such items were present in the data. The analysis adheres to the common practice of retaining items with loadings above .40, ensuring the factors are both reliable and interpretable (Field, 2013).

Table 6.0 below shows the factor loadings and decisions for retained items across key constructs of clinical supervision.

Table 6.0 Factor Loadings and Decisions for Retained and Dropped Items across Key Competency Constructs of Clinical Supervision

Item	Statement	Factor Loading	Component (Factor)	Decision	Justification
CSA/CSS1	My clinical instructor provides me with valuable advice.	.79	Clinical Supervision Support	Retained	Strong loading, exceeds .40 threshold
CSA/CSS3	I can widen my skill base during clinical supervision sessions.	.80	Clinical Supervision Support	Retained	Strong loading, exceeds .40 threshold
CSA/CSS4	My clinical instructor offers the guidance with patient care.	.84	Clinical Supervision Support	Retained	Strong loading, exceeds .40 threshold
CSIC/CSS1	Clinical supervision is an important part of my work routine.	.67	Clinical Supervision Support	Retained	Strong loading, exceeds .40 threshold
CSIC/CSS2	Clinical supervision makes me a better practitioner.	.60	Clinical Supervision Support	Retained	Strong loading, exceeds .40 threshold
CSIC/CSS3	Without clinical supervision the quality of patient care would deteriorate.	.64	Clinical Supervision Support	Retained	Strong loading, exceeds .40 threshold
CSIC/CSS4	Clinical supervision improves the quality of care I give to my patient.	.53	Clinical Supervision Support	Retained	Adequate loading, exceeds .40 threshold
CST/CSR1	My clinical instructor gives me support and encouragement.	.47	Instructor-Student Relationship	Retained	Adequate loading, exceeds .40 threshold

CST/CSR2	I can discuss sensitive issues with my clinical instructor.	.85	Instructor-Student Relationship	Retained	Strong loading, exceeds .40 threshold
CST/CSR3	My clinical supervisor is very open with me.	.91	Instructor-Student Relationship	Retained	Strongest loading, exceeds .40 threshold
CST/CSR4	My clinical instructor acts in a superior manner during our sessions.	.59	Instructor-Student Relationship	Retained	Strong loading, exceeds .40 threshold
CSA/CSS2	Session with my clinical instructor widen.	.49	Instructor-Student Relationship	Retained	Adequate loading, exceeds .40 threshold
CSI/CSV3	It is important to make time for clinical supervision sessions.	.96	Time Management and Perceived Value	Retained	Strongest loading, exceeds .40 threshold
CSI/CSV4	Clinical supervision is for newly/inexperienced students and staff only.	.61	Time Management and Perceived Value	Retained	Adequate loading, exceeds .40 threshold
CSI/CSV1	Time spent on clinical supervision takes me away from my real work in the clinical setting.	.88	Negative Perceptions of Supervision	Retained	Strong loading, exceeds .40 threshold
CSI/CSV2	Clinical supervision is intrusive.	.80	Negative Perceptions of Supervision	Retained	Strong loading, exceeds .40 threshold

Note: Extraction method: Principal Axis Factoring. Rotation method: Promax with Kaiser normalization. Rotation converged in 6 iterations.

The assessment of clinical supervision experienced by nursing students focuses on four primary constructs: **(1) Clinical Supervision Support**, **(2) Instructor-Student Relationship**, **(3) Time Management and Perceived Value**, and **(4) Negative Perceptions of Supervision**. Each construct is measured by specific items reflecting the corresponding implementation in a healthcare setting.

For Clinical Supervision Support, seven items (CSA/CSS1, CSA/CSS3, CSA/CSS4, CSIC/CSS1, CSIC/CSS2, CSIC/CSS3, and CSIC/CSS4) focus on various support aspects given during clinical supervision. Instructor-Student Relationship is represented by five items (CST/CSR1, CST/CSR2, CST/CSR3, CST/CSR4, and CSA/CSS2), emphasizing the multifaceted interactions between instructors and students important to overall learning experiences.

Time Management and Perceived Value, with two items (CSI/CSV3 and CSI/CSV4), captures elements related to time management within the educational context and how students perceive the value of their learning experiences. Lastly, Negative Perceptions of Supervision, comprising two items (CSI/CSV1 and CSI/CSV2), addresses critical aspects of students' negative views of their clinical supervision experience that can impact their learning and development.
All 16 original items were retained, providing a comprehensive overview of the evaluated experience.

The integration of items across different constructs highlights the multidimensional nature of the assessment. Table 7.0 below summarizes the distribution of items across the four key competency constructs.

Table7.0 Summary of Items by Construct for Clinical Supervision Instrumentation

Construct	No. of Items	List of Items
Clinical Supervision Support	7	CSA/CSS1, CSA/CSS3, CSA/CSS4, CSIC/CSS1, CSIC/CSS2, CSIC/CSS3, CSIC/CSS4
Instructor-Student Relationship	5	CST/CSR1, CST/CSR2, CST/CSR3, CST/CSR4, CSA/CSS2
Time Management and Perceived Value	2	CSI/CSV3, CSI/CSV4
Negative Perceptions of Supervision	2	CSI/CSV1, CSI/CSV2
Total	**16**	

Note: Extraction method: Principal Axis Factoring. Rotation method: Promax with Kaiser normalization. Rotation converged in 6 iterations.

Revised Instrumentation for Clinical Supervision

The factor analysis identified four main components of clinical supervision for nursing students:

- **Clinical Supervision Support:** Instructors provide useful advice (CSS1, loading = .79), enhance skills (CSS2, loading = .80), and guide patient care (CSS3, loading = .84). Supervision is seen as crucial to improving practice (CSS4, loading = .67) and patient care quality (CSS5, loading = .60; CSS7, loading = .53). Without it, care quality would decline (CSS6, loading = .64).

- **Instructor-Student Relationship:** Instructors offer support (ISR1, loading = .47), are open to discussing issues (ISR2, loading = .85), and are approachable (ISR3, loading = .91). Some students feel instructors can be superior (ISR4, loading = .59), but sessions still broaden perspectives (ISR5, loading = .49).

- **Time Management and Perceived Value:** Students agree on the need for supervision time (TMPV1, loading = .96). Some view it as only for new or inexperienced staff (TMPV2, loading = .61).
- **Negative Perceptions of Supervision:** Concerns include taking time away from work (NPS1, loading = .88) and being intrusive (NPS2, loading = .80). Overall, nursing students value clinical supervision for skill enhancement and patient care improvement, despite concerns about time management and intrusiveness. Table 8.0 below lists the factor loadings of clinical supervision items grouped by construct.

Table 8.0 Factor Loadings of Clinical Supervision Items Grouped by Construct

Construct/Item	**Statement**	**Factor Loading**
Clinical Supervision Support		
CSS1	My clinical instructor provides me with valuable advice.	.79
CSS2	I can widen my skill base during clinical supervision sessions.	.80
CSS3	My clinical instructor offers guidance with patient care.	.84
CSS4	Clinical supervision is an important part of my work routine.	.67
CSS5	Clinical supervision makes me a better practitioner.	.6
CSS6	Without clinical supervision, the quality of patient care would deteriorate	.64
CSS7	Clinical supervision improves the quality of care I give to my patient.	.53
Instructor-Student Relationship		
ISR1	My clinical instructor gives me support and encouragement.	.47
ISR2	I can discuss sensitive issues with my clinical instructor.	.85
ISR3	My clinical instructor is very open with me.	.91
ISR4	My clinical instructor acts in a superior manner during our sessions.	.59
ISR5	Sessions with my clinical instructor broaden my perspectives.	.49
Time Management and Perceived Value		
TMPV1	It is important to make time for clinical supervision sessions.	.96

TMPV2	Clinical supervision is for newly/inexperienced students and staff only.	.61
Negative Perceptions of Supervision		
NPS1	Time spent on clinical supervision takes me away from my real work.	.88
NPS2	Clinical supervision is intrusive.	.80

3. Conclusion

This pilot study utilized Exploratory Factor Analysis (EFA) to investigate nursing students' experiences with clinical supervision, identifying four key factors: clinical supervision support, instructor-student relationship, time management and perceived value, and negative perceptions of supervision. The primary factor, clinical supervision support, emphasizes the crucial role of instructors in providing guidance, enhancing skills, and improving patient care. The instructor-student relationship factor underscores the importance of approachability, encouragement, and communication. Time management and perceived value reflect the consensus on the significance of supervision, particularly for less experienced students. Negative perceptions of supervision highlight concerns about intrusiveness and interference with regular duties. These findings offer insights into the complex experiences of nursing students with clinical supervision. Although generally beneficial for professional development and patient care, issues related to time constraints and intrusiveness require attention. Future research should validate these factors through Confirmatory Factor Analysis (CFA) and explore interventions to optimize clinical supervision in nursing education.

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