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A Comparative Analysis of Spearman and Pearson Correlation Using SPSS

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ABSTRACT

Correlation is one of the statistical methods used to measure the relationship between two variables. Two commonly used types of correlation are Spearman Correlation and Pearson Correlation. Spearman's Correlation is used for ordinal data or data that do not meet the assumption of normality, while Pearson Correlation is applied to interval or ratio data that follow a normal distribution. This study aims to compare the results of analyses using these two correlation methods through the SPSS software. By analyzing both simulated and real-world data, tests were conducted on various data scenarios, including variations in data types, distribution patterns, and levels of variable relationships. The results indicate that Pearson Correlation is more sensitive to normally distributed data, whereas Spearman Correlation provides more stable results for non-normally distributed data or data containing outliers. This article also presents a step-by-step guide for using SPSS to perform analyses with both correlation methods, making it easier for readers, especially students and researchers, to apply the appropriate method based on their data characteristics. By understanding the differences and advantages of each method, users are expected to choose the right approach for correlation analysis.

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1. INTRODUCTION

The Statistical Package for the Social Sciences (SPSS) is widely recognized as a robust software for statistical analysis, especially among academics and professionals. Its intuitive interface and comprehensive features make it user-friendly, particularly for correlation analysis (Wulansari, 2016). With SPSS, users can easily import data, choose the desired analysis, and quickly obtain clear and interpretable outputs. Beyond correlation analysis, SPSS supports a wide range of statistical tests, including regression, t-tests, ANOVA, multivariate analysis, and both validity and reliability tests. Additionally, the software excels in handling large datasets, offering efficient data processing and generating visualizations such as graphs and tables. These capabilities make SPSS a versatile tool for quantitative data analysis, appealing to researchers across diverse disciplines, including social sciences, education, and health (Sugianto and SmitDev, 2014).

Correlation analysis, a fundamental statistical technique, is essential for examining the relationship between two variables, focusing on the strength and direction of their linear association (Yolanda et al., 2024). The correlation coefficient, which ranges from -1 to +1, provides critical insights into these relationships: a coefficient of +1 indicates a perfect positive relationship, -1 a perfect negative relationship, and 0 no linear relationship. This method enables researchers to identify data patterns, test hypotheses, and support data-driven decision-making. For example, correlation analysis can reveal the relationship between employee satisfaction and productivity or assess the impact of an educational program by comparing pre- and post-intervention outcomes (Suryono and Rejekiningsih, 2007). Across various fields, including psychology, economics, and the social sciences, correlation analysis underpins the development of evidence-based strategies and enhances the rigor of research.

Correlational research is a statistical approach used to explore relationships between two or more quantitative variables without manipulating any of them. The primary goal is to determine the degree and nature of the relationships among the variables under study. This method offers significant advantages, such as the ability to analyze multiple variables simultaneously and provide valuable insights into their associations (El Hasbi et al., 2023). By examining the strength and direction of these relationships, researchers can build a deeper understanding of the phenomena being studied and inform future research directions or policy decisions.

Two widely used methods in correlation analysis are Pearson and Spearman correlations, each tailored for specific data characteristics and research needs. Pearson correlation is designed for interval or ratio data with a normal distribution and linear relationships. It generates an “r” coefficient ranging from -1 to +1, quantifying the strength and direction of the linear association between variables (Nugroho et al., 2008). This method is ideal when data assumptions of normality and linearity are satisfied. On the other hand, Spearman correlation is more versatile, suitable for ordinal data or data that deviate from a normal distribution. It ranks the data and measures monotonic relationships, making it a robust choice for datasets with significant outliers or non-linear trends. The selection between these methods depends on the data type and its distribution. Pearson is preferable for numerical data with normality, whereas Spearman is better suited for ordinal or non-normal data. Understanding these distinctions enables researchers to select the most appropriate method, ensuring accurate and reliable analysis outcomes (Nugroho et al., 2008).

The role of statistics in research, especially in quantitative studies, is indispensable as it provides a foundation for analyzing data numerically and drawing meaningful conclusions. Quantitative research inherently relies on statistical tools to explore, interpret, and validate findings, underscoring the critical importance of statistical methods in supporting rigorous investigations (Siagian, 2021). This study specifically highlights the use of Pearson and Spearman correlations as key statistical methods in data analysis, demonstrating their relevance in various research contexts. By understanding and applying these methods appropriately, researchers can ensure that their findings are both credible and impactful, contributing to advancements in their respective fields.

2. METHODS

In this study, the research method employed is a literature review, which focuses on analyzing and comparing the Spearman and Pearson correlation methods. The literature review involves systematically collecting, evaluating, and synthesizing information from relevant sources, such as scientific articles, books, and other publications. These sources provide insights into the characteristics, advantages, disadvantages, and applications of both correlation methods, particularly in their implementation using SPSS statistical software. The primary aim of this study is to comprehensively identify the strengths and weaknesses of each method based on findings from previous research, thereby offering a deeper understanding of their appropriate usage in various contexts (Hart, 1998).

According to Hart (1998), the process of conducting a literature review can be structured into five essential stages. The first stage involves the identification of research topics and questions, ensuring clarity and focus in addressing the objectives of the study. The second stage is the literature search, where researchers systematically locate and gather relevant resources from credible databases, libraries, or archives. Next is the evaluation and selection of literature, which entails critically assessing the quality, relevance, and credibility of the collected materials. The fourth stage, analysis and synthesis, focuses on examining the selected literature to extract key findings, compare results, and identify patterns or discrepancies. Finally, the last stage is reporting the results of the literature review, where the researcher presents a coherent narrative that integrates the findings and highlights their implications.

By adhering to these stages, the study ensures a systematic and rigorous approach to understanding the distinctions between Spearman and Pearson correlations. This process not only strengthens the reliability of the findings but also provides a solid foundation for further research and practical applications of statistical methods.

3. FINDINGS AND DISCUSSIONS

3.1. Findings

The data comparison in this study draws from the research instrument titled "The Relationship between Fear of Missing Out and Emotional Intelligence among Adolescents in Bandung City." Data analysis was conducted using SPSS version 25.0, employing a series of systematic testing models to ensure comprehensive insights into the dataset. The analysis began with data categorization, where scores for fear of missing out (FoMO) and emotional intelligence were transformed into specific categories based on predetermined thresholds. This transformation helped in identifying patterns and distributions within the dataset.

Following the categorization, a crosstabulation test was performed to examine the respondents' placement within the respective categories of FoMO and emotional intelligence.

This test provided a clear overview of how individuals were distributed across different levels of both variables, enabling a better understanding of the potential relationships between them. Finally, case summaries testing was applied to pinpoint individual respondents within the established categories, further detailing their specific positions concerning the two variables (Ratner, 2009).

This step-by-step approach aims to uncover meaningful data patterns while establishing the relational dynamics between FoMO and emotional intelligence. By combining categorization, crosstabulation, and case summaries, the study ensures a nuanced analysis that facilitates a deeper understanding of the interaction between the two variables. This process lays a solid foundation for conducting subsequent correlation tests and interpreting the findings effectively (Dancey and Reidy, 2017).

3.1.1. Pearson Correlation

To conduct a Pearson correlation test using SPSS, the following steps are carried out systematically: First, the dataset containing the variables "FoMO Score" and "EI Score" is imported into the SPSS application. Once the data is loaded, navigate to the SPSS main menu and select **Analyze**, then click on **Correlate**, and choose the **Bivariate** option. In the **Bivariate Correlations** dialog box, the two variables to be analyzed are entered into the **Variables** column. The Pearson correlation method is selected, ensuring that the **Two-tailed** option is checked for a two-tailed significance test.

After setting these parameters, click the **OK** button to run the analysis. The results are then displayed in the SPSS **Output** window, which includes the Pearson Correlation coefficient (r) and the significance value (Sig. (2-tailed)). The **r** value provides insight into the strength and direction of the relationship between the two variables, where positive or negative values indicate the nature of the relationship. Meanwhile, the Sig. (2-tailed) value indicates whether the relationship is statistically significant.

The analysis using these steps produces results that facilitate the interpretation of how the Fear of Missing Out (FoMO) score correlates with Emotional Intelligence (EI) score, offering valuable insights for further research or practical applications.

Correlations

		Score FOMO	Score EI
Score FOMO	Pearson Correlation	1	.063
	Sig. (2-tailed)		.275
	N	306	306
Score EI	Pearson Correlation	.063	1
	Sig. (2-tailed)	.275	
	N	306	306

Figure 1. Fear of Missing Out (FoMO) score correlates with Emotional Intelligence (EI).

The results of the Pearson correlation analysis as shown in **Figure 1** indicate that the relationship between the FoMO Score and EI Score is characterized by a correlation coefficient of 0.063, suggesting a very weak positive relationship between the two variables. However, the significance value (Sig. 2-tailed) is 0.275, which exceeds the commonly accepted significance threshold of 0.05. This indicates that the observed correlation is not statistically significant.

With a sample size of 306 respondents, these findings imply insufficient evidence to assert a meaningful or reliable relationship between fear of missing out (FoMO) and emotional intelligence (EI). While a weak correlation is present, it lacks practical or statistical relevance due to its insignificance. As a result, the analysis concludes that there is no significant relationship between FoMO and EI in the context of this study.

These findings highlight the need for further research to examine additional factors or variables that might influence the interplay between FoMO and EI. Future studies could explore alternative frameworks, mediating variables, or broader population samples to gain deeper insights into the dynamics of these constructs.

3.1.2. Spearman Correlation

To conduct a Spearman correlation analysis in SPSS, several systematic steps are followed to ensure accurate results. First, the dataset containing the variables of interest, namely the **FoMO Score** and **EI Score**, is imported into the SPSS application. Once the dataset is successfully loaded and organized, the analysis process begins by navigating to the main menu in SPSS. Here, the user selects the **Analyze** option, followed by **Correlate**, and then chooses the **Bivariate** option. This opens the Bivariate Correlations window, where the two variables to be analyzed are specified by entering them into the **Variables** field. To ensure the analysis aligns with the characteristics of the data, the **Spearman** correlation method is selected under the **Correlation Coefficients** section. Spearman's method is particularly suitable for ordinal data or datasets that do not meet the assumption of normal distribution. Additionally, the user selects the **Two-tailed** option to conduct a two-tailed test of significance, which assesses whether there is a statistically significant relationship in either direction between the variables. After these selections are made, the user clicks the OK button to execute the analysis. The results of the analysis are displayed in the SPSS Output window, where the key metrics include the **Correlation Coefficient** (Spearman's rho) and the **Sig. (2-tailed)** value.

The Correlation Coefficient indicates the strength and direction of the relationship between the variables, with values ranging from -1 (a perfect negative correlation) to +1 (a perfect positive correlation). Meanwhile, the Sig. (2-tailed) value is used to determine the statistical significance of the relationship, where a value less than 0.05 generally indicates a significant relationship. This step-by-step approach ensures that researchers can effectively assess the association between the FoMO Score and EI Score, particularly when the data does not conform to parametric assumptions. Through the systematic application of Spearman correlation in SPSS, insights can be drawn about the non-linear or ordinal relationships between the variables as shown in **Figure 2**.

Correlations

			Score FOMO	Score EI
Spearman's rho	Score FOMO	Correlation Coefficient	1.000	.008
		Sig. (2-tailed)	.	.883
		N	306	306
	Score EI	Correlation Coefficient	.008	1.000
		Sig. (2-tailed)	.883	.
		N	306	306

Figure 2. The Spearman correlation analysis of FoMO and EI.

The Spearman correlation analysis reveals that the relationship between the **FoMO Score** and **EI Score** is characterized by a correlation coefficient value of 0.008, which indicates a very weak or negligible relationship between the two variables. Additionally, the significance value (Sig. 2-tailed) is reported at 0.883, which is substantially higher than the conventional significance threshold of 0.05. This result demonstrates that the relationship between **FoMO** and **EI** is not statistically significant. With a sample size of 306 respondents, these findings suggest that there is insufficient evidence to support the existence of a meaningful relationship between **fear of missing out** (FoMO) and **emotional intelligence** (EI) within this study's context. Consequently, it can be concluded that there is no significant relationship between the **FoMO Score** and **EI Score**. The very weak and statistically insignificant correlation underscores the lack of a relevant connection between these two variables. These results highlight the need for further research to investigate alternative factors or conditions that might influence the potential association between **fear of missing out** and **emotional intelligence**. Future studies may consider exploring other variables, contexts, or methodological approaches to gain a more comprehensive understanding of this phenomenon.

3.2. Discussions

Correlation analysis plays a crucial role in research as it helps to uncover the relationship between two or more variables. By analyzing the degree of association between these variables, researchers can better understand underlying patterns or trends that might exist in their data. Two of the most frequently utilized correlation techniques are Pearson's correlation and Spearman's correlation. While both methods serve the purpose of quantifying the strength and direction of a relationship between variables, they are distinct in terms of their assumptions, applications, and the type of data they are best suited to analyse (Hinkle et al., 2003).

Pearson's correlation, also known as the Pearson Product-Moment Correlation, assumes that the relationship between the variables is linear and that both variables are measured on an interval or ratio scale. This technique measures the strength and direction of the linear relationship between two continuous variables and provides a correlation coefficient that ranges from -1 to 1. A value close to 1 indicates a strong positive linear relationship, while a value close to -1 indicates a strong negative linear relationship. A coefficient of 0 suggests no linear relationship between the variables. However, Pearson's correlation may not be appropriate if the data does not meet the assumption of linearity or if the variables are not continuous (Gauthier, 2001).

On the other hand, Spearman's correlation, or Spearman's rank correlation, is a non-parametric measure that does not require the assumption of linearity or interval-level data. This method is based on the ranks of the data rather than the actual values and is more flexible in handling ordinal data, as well as data that may not follow a normal distribution. Spearman's correlation is often used when the relationship between the variables is monotonic but not necessarily linear. In cases where the relationship is not linear, Spearman's correlation can still provide valuable insights by assessing the strength and direction of the monotonic relationship (Field, 2018).

While both Pearson and Spearman correlations are useful tools, they come with certain limitations. Pearson's correlation is sensitive to outliers, which can distort the results if the data contains extreme values. In contrast, Spearman's correlation is more robust to outliers, but it may not capture subtle linear relationships as effectively as Pearson's method. Additionally, Spearman's correlation is not ideal for measuring relationships in datasets with a small number of distinct values or when the variables are not well ranked (Schober, 2018).

In conclusion, the choice between Pearson and Spearman correlation depends on the nature of the data and the relationship between the variables being studied. Researchers must carefully consider the assumptions of each method and select the one that best aligns with their data type and research objectives (Mukaka, 2012).

3.2.1. Concept of Using Correlation Analysis in SPSS in the Context of Statistical Learning

Correlation refers to the relationship between two or more variables within a sample, and this relationship is often generalized to the entire population from which the sample is drawn. In correlation analysis, the primary goal is to assess whether the sample data provides sufficient evidence to suggest a relationship between the variables in question and the population from which the sample originates. Moreover, once the relationship is identified, it is essential to determine the strength of this relationship. One key step in correlation analysis involves calculating the correlation coefficient, a numerical measure that quantifies the degree of association between the variables (Khotimah, 2017).

The use of correlation analysis within the SPSS software in statistical learning serves multiple important purposes that not only enhance the understanding of statistical concepts but also contribute to their practical application in real-life scenarios. As outlined by Siagian (2021), the following points highlight the urgent need to master correlation analysis through SPSS:

a. **Facilitating Understanding of Correlation Concepts.**
SPSS simplifies the process of performing correlation analysis by offering various intuitive options, making it more accessible and easier to grasp. In addition, SPSS provides clear visualization features, allowing users to observe the relationships between variables visually. This can significantly aid in understanding how changes in one variable may influence another, offering a more concrete comprehension of the concepts being studied.

b. **Efficiency in Data Analysis.**
SPSS streamlines the process of correlation analysis, enabling researchers to perform it quickly and with minimal risk of errors. Unlike manual calculations, which can be time-consuming and prone to mistakes, SPSS automates the calculation of correlation coefficients, such as Pearson and Spearman, and presents the results in an easily interpretable format. This efficiency is crucial for handling large datasets and performing analyses with a higher degree of accuracy.

c. **Development of Analytical Skills.**
Engaging with correlation analysis through SPSS promotes the development of critical analytical skills. Users are encouraged to formulate hypotheses, collect relevant data, and assess the relationships between variables. This process fosters critical thinking and helps individuals make informed, evidence-based decisions. Moreover, it strengthens the ability to evaluate data from various perspectives, which is an invaluable skill in both academic and professional settings.

d. **Facilitating Research**
In the realm of research, correlation analysis is an essential tool that aids in examining the relationships between variables. SPSS facilitates more complex analyses, such as regression analysis, which involves multiple variables and can provide a deeper understanding of the relationships within the data. The software's user-friendly interface

enables researchers to design and execute more thorough and comprehensive research projects with ease, enhancing the overall quality of their studies.

e. Better Interpretation of Results

Beyond simply calculating the correlation coefficient, SPSS also provides a significance value, or p-value, which is crucial for evaluating the strength and statistical significance of the relationship between variables. This feature is particularly important for researchers and students, as it helps them understand how to interpret the results accurately and draw valid conclusions based on the data. Proper interpretation ensures that findings are meaningful and can be used to support further investigation or decision-making.

In summary, the integration of SPSS in conducting correlation analysis significantly enhances the learning and application of statistical concepts. It not only facilitates a deeper understanding of the relationship between variables but also supports more efficient, accurate, and meaningful research. By mastering correlation analysis in SPSS, individuals can hone their analytical skills, conduct more robust research, and interpret data with greater precision (Joost et al, 2016).

3.2.2. Use Of Pearson and Spearman Correlations in SPSS

a. Pearson Correlation

Pearson Correlation, also known as Product-Moment Correlation, is a statistical method employed to measure the linear relationship between two quantitative variables, specifically those measured on an interval or ratio scale. This method is widely used when the objective is to examine how changes in one variable are associated with changes in another variable, assuming that both variables exhibit a linear relationship. The assumptions underlying Pearson correlation are essential for its proper application and include that the data should follow a linear relationship, be normally distributed, and be free from extreme outliers that could distort the relationship. These assumptions must be carefully checked before applying the Pearson correlation to ensure the results are valid and reliable (Benesty et al., 2008).

Correlation, as a statistical measure, quantifies the degree of association between two variables. It can reveal two key aspects of the relationship:

1) Direction of the Relationship.

Pearson correlation helps to determine the direction of the relationship between the variables. A **positive** correlation means that as one variable increases, the other also increases (or as one decreases, the other decreases), reflecting a direct relationship. In contrast, a **negative** correlation indicates that as one variable increases, the other decreases, or vice versa, signifying an inverse relationship.

2) Strength of the Relationship.

The strength of the correlation is expressed through the correlation coefficient, denoted as **r**, which ranges from **-1 to +1**. A value of **+1** represents a perfect positive relationship, where the variables move in exact harmony. Conversely, **-1** signifies a perfect negative relationship, where the variables move in exactly opposite directions. A value of **0** indicates no relationship between the variables, meaning that changes in one variable do not predict any changes in the other.

Pearson Correlation is a powerful tool for assessing the linear relationship between two quantitative variables. However, its validity relies heavily on meeting the assumptions of linearity, normality, and the absence of extreme outliers. By evaluating the direction and strength of the relationship between variables, Pearson correlation provides valuable insights into the nature of the association, making it an indispensable method in both research and data analysis (Sedgwick, 2012).

Here is the pearson correlation formula:

$$r = \sum (Xi - \bar{X})(Yi - \hat{Y})$$

Use in Learning

a) Pearson correlation is commonly used in educational contexts to understand the linear relationship between two variables. For instance, it can be applied to examine the relationship between study time (in hours) and exam scores. This allows students to see how an increase in one factor (study time) might correspond with improvements or changes in another (exam performance). This practical example helps students grasp the concept of correlation and its application in real-life scenarios, fostering a deeper understanding of statistical relationships (Armstrong, 2019).

b) In teaching Pearson correlation, it is crucial to explain the underlying assumptions, particularly the normal distribution of data and the need for a linear relationship. Students should be made aware that these assumptions are fundamental for the validity of the analysis. Understanding these concepts helps students to not only conduct the analysis correctly but also interpret the results accurately, ensuring that they apply Pearson correlation in appropriate contexts.

Limitations

a) One significant limitation of Pearson correlation is that it is not suitable when the relationship between the variables is non-linear. Pearson correlation is designed to measure linear relationships, and if the data does not follow a straight-line trend, the results may be misleading or inaccurate. In such cases, other methods, such as Spearman's rank correlation, should be considered.

b) Pearson correlation is also highly sensitive to outliers. Extreme values can disproportionately affect the correlation coefficient, leading to skewed or distorted interpretations of the data. This limitation highlights the importance of performing data cleaning and outlier detection before conducting correlation analysis. If outliers are present, alternative approaches or robust correlation measures may be necessary to ensure more reliable results.

In conclusion, while Pearson correlation is a useful tool for analyzing linear relationships between variables, it is important to be mindful of its assumptions and limitations. Educators should emphasize the significance of normal distribution and linearity, as well as caution students about the impact of outliers on the results.

b. Spearman Correlation

Spearman Correlation, also known as Spearman’s Rank Correlation Coefficient, is a statistical technique used to assess the relationship between two variables based on their ranks rather than their actual values. Unlike Pearson correlation, which assumes a linear relationship and requires interval or ratio-scaled data, Spearman correlation is more flexible and can handle a broader range of data types, including ordinal data or data that does not follow the assumption of normality. This flexibility makes Spearman correlation particularly useful for analyzing monotonic relationships, where one variable consistently increases or decreases in relation to the other, even if the relationship does not follow a straight-line pattern (Hauke and Kossowski, 2011).

To calculate the Spearman correlation, the data values are first transformed into ranks. Then, the Spearman coefficient (rs) is computed based on the differences in ranks between paired data points. The formula for Spearman’s rank correlation is given by:

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Where:
d_I: is the rank difference for each data pair,
n: is the total number of observations.
The Spearman correlation coefficient (rs) ranges from -1 to +1, where:
+1 indicates a perfect positive monotonic relationship,
-1 indicates a perfect negative monotonic relationship,
0 indicates no monotonic relationship.

One of the primary advantages of Spearman correlation is its ability to handle non-parametric data, including ordinal data and data with outliers. Since the calculation is based on ranks, extreme values have a reduced impact on the results, unlike in Pearson correlation, where outliers can significantly distort the relationship. Spearman correlation is also capable of detecting non-linear but still monotonic relationships, making it a valuable tool in diverse research fields such as social science, business, and psychology. This versatility allows it to be applied in situations where the relationship between variables is not strictly linear but still maintains a consistent directional pattern (Marie et al, 2015).

However, Spearman correlation has certain limitations. While it is effective for monotonic relationships, it cannot detect complex non-monotonic relationships, where the relationship pattern between variables fluctuates or changes direction in a non-consistent manner. In such cases, Spearman would fail to produce accurate results. Additionally, when dealing with normal and linear interval or ratio data, Pearson's correlation method is generally more appropriate. This is because Pearson correlation considers the actual values of the data, rather than just the ranks, making it more suitable for data that follows a linear trend (Schmid and Schmidt, 2007).

In summary, while Spearman correlation is a highly adaptable method for measuring relationships between variables, its use should be carefully considered based on the type of data and the specific goals of the analysis. For data that meets the assumptions of normality and linearity, Pearson correlation remains the more appropriate choice, whereas Spearman offers a robust alternative for non-parametric or non-linear data (Gilpin, 1993).

3.2.3. The Relationship Between Fear Of Missing Out (Fomo) And Emotional Intelligence (EI)

To gain a more comprehensive understanding of the relationship between Fear of Missing Out (FoMO) and Emotional Intelligence (EI), this study references various relevant literatures. Based on the analysis conducted, the following review and discussion of the findings are provided:

a. The Concept of Fear of Missing Out (FoMO).

FoMO is defined as the anxiety that arises when an individual perceives they are missing out on significant information, experiences, or social opportunities (Przybylski et al., 2013). This phenomenon is commonly associated with the use of social media platforms, where individuals are continuously exposed to the activities of others, which they often view as more exciting or fulfilling (Alt, 2015). FoMO can evoke feelings of inadequacy and anxiety, particularly when individuals compare their own lives to the curated representations of others online. However, the effects of FoMO on psychological aspects, such as emotional intelligence, remain an area that requires further exploration and empirical investigation.

b. Emotional Intelligence and Its Impact on Social Life.

Emotional Intelligence (EI), as defined by Mayer and Salovey (1997), refers to the ability to recognize, understand, and regulate one's own emotions, as well as the ability to recognize and influence the emotions of others. In the context of adolescence, EI plays a critical role in an individual's ability to build healthy interpersonal relationships, manage emotional challenges, and navigate social interactions. Goleman (1995) emphasized that individuals with high emotional intelligence are better equipped to handle stress, conflict, and social situations, making EI a key determinant in fostering social well-being and emotional resilience. Consequently, emotional intelligence is crucial for young people as they undergo emotional development and seek to establish meaningful connections with others.

c. Previous Research Context

Several previous studies have explored the potential relationship between FoMO and EI. For example, a study by Blackwell et al. (2017) suggested that individuals with high levels of FoMO often experience difficulties with emotional regulation, which can negatively impact their social relationships and overall psychological well-being. However, the results of this research diverge from those of the present study. The Pearson and Spearman correlation analyses conducted here reveal that the relationship between FoMO and EI is extremely weak and not statistically significant. This disparity in findings may suggest that the impact of FoMO on emotional intelligence could be more nuanced than initially anticipated or that the connection between the two variables is less pronounced in certain contexts.

d. Interpretation of Research Findings.

The notably weak correlation observed between FoMO and EI in this study may be attributed to several factors, which include:

1) Sample Variability.

The characteristics of the respondents—such as their age, social background, and level of engagement with social media—may have influenced the outcomes of the analysis. For instance, younger individuals or those with high social media usage may experience more pronounced FoMO, potentially leading to stronger correlations with emotional intelligence. However, differences in social background and life experiences may affect how FoMO is perceived and experienced, leading to variability in the data.

2) Measurement Instruments

The scales used to assess both FoMO and EI may have inherent limitations in capturing the full complexity of the relationship between these two variables. It is possible that the tools did not fully account for the multi-dimensional nature of both FoMO and EI, which could have led to an underestimation of their potential relationship.

3) Cultural Context.

The research was conducted in Bandung, a city that has its own distinct cultural and social dynamics. The local cultural context could have influenced how individuals process FoMO experiences and how they develop and utilize emotional intelligence. Cultural differences in social interaction, emotional expression, and the significance of social media could have played a role in shaping the study's findings.

Previous research suggests a potential connection between FoMO and EI, the findings of this study highlight the need for further exploration of this relationship. Factors such as sample variability, the choice of measurement tools, and cultural context should be considered when interpreting the results. Future research could aim to refine the measurement of these variables and explore the relationship in different populations or cultural settings to provide a more comprehensive understanding of how FoMO impacts Emotional Intelligence.

3.2.4. Implications of the Research

The results of the Pearson and Spearman correlation analyses carry profound implications in the context of data processing, particularly when considering the type of data being utilized. Pearson correlation is commonly employed to assess the linear relationship between two variables that are numeric and measured on an interval or ratio scale. One of the key prerequisites for this method is that the data must adhere to a normal distribution and demonstrate a linear relationship. Consequently, the implication of using Pearson correlation in research is particularly relevant for studies that involve quantitative data meeting these specific characteristics. For instance, in the case of a study involving the FoMO Score and EI Score, if both are continuous variables that meet the assumption of normality, Pearson correlation becomes the most suitable technique for examining the strength and direction of their linear relationship. However, if the relationship between the variables deviates from linearity, Pearson may not provide reliable results. In such cases, a linearity test should be conducted prior to the correlation analysis. Pearson's method is highly appropriate in fields like psychology or education research, where variables such as test scores, measurements, or survey data are typically continuous (Rebekic et al, 2015).

Conversely, Spearman correlation is utilized to measure the monotonic relationship between two variables, regardless of whether they are ordinal, interval, or ratio. Unlike Pearson correlation, Spearman does not require the assumption of normality, making it more adaptable, especially for data that does not follow a normal distribution or is ordinal in nature. The implication of employing Spearman correlation in research arises in situations where the relationship between variables is not linear but still exhibits a monotonic pattern, such as one variable consistently increasing or decreasing in tandem with the other. Furthermore, Spearman is especially useful when dealing with ordinal data, where variables are ranked or classified into ordered categories, such as preferences, satisfaction levels, or other qualitative measures. As a result, Spearman correlation proves to be highly relevant in social or psychological research, where the data may be either qualitative or quantitative, and often does not meet the requirements for normality (Chok, 2010).

Overall, the primary implication of both correlation methods is that researchers must possess a clear understanding of the data's characteristics before selecting the appropriate analysis technique. Using the wrong method—for example, applying Pearson correlation to non-normal or ordinal data—can lead to misleading or invalid conclusions. As such, conducting assumption tests, including normality and linearity tests, is essential to ensure that the selected method is appropriate for the data at hand. Additionally, the flexibility of Spearman correlation makes it a valuable tool in a variety of research contexts, particularly when the data does not satisfy the criteria for parametric analysis. The findings derived from these correlation analyses not only inform the research at hand but also pave the way for future inquiries, such as exploring deeper relationships through more complex methods like regression analysis or structural equation modeling. By carefully selecting the appropriate analysis method, researchers can ensure their findings are valid, relevant, and contribute meaningfully to the advancement of knowledge in their respective fields (Thirumalai et al., 2017).

4. CONCLUSION AND RECOMMENDATION

This study compares the Pearson and Spearman correlation analysis methods using SPSS software to evaluate the relationship between Fear of Missing Out (FoMO) and Emotional Intelligence (EI). The analysis results indicate that both methods produce very weak correlation values, 0.063 for Pearson and 0.008 for Spearman, with significance values far above the standard threshold (0.275 and 0.883, respectively). This suggests that there is no significant relationship between FoMO and EI in the sample studied.

Pearson correlation is more sensitive to normality and linearity assumptions, while Spearman is more flexible and can be used for data that do not meet these assumptions. Although both methods show no meaningful relationship, selecting the appropriate analysis method is crucial for obtaining valid results. This study reinforces the importance of understanding the characteristics of data before conducting correlation analysis and highlights the need for further research to explore other factors that may influence the relationship between these two variables. Thus, the findings of this study serve as a reference for researchers and academics in selecting suitable analysis methods in broader research contexts.

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