Predicting Marital Stability: An Approach for More Characteristics

Frank H, NPA Rockville, United States

The Asian Conference on Psychology & the Behavioral Sciences 2024
Official Conference Proceedings

Abstract
This study aims to explore the usefulness and characteristics of data from the Divorce Predictors Scale (DPS), based on Gottman couples therapy, in predicting and understanding marital stability. The data used in this study is sourced from a previous research paper that employed the DPS questionnaire. The participants consisted of 84 (49%) divorced and 86 (51%) married couples. In addition to completing the DPS, participants also provided personal information. The current study utilizes a different approach by applying structural equation modelling (PCC-SEM) and statistical analyses with varying thresholds to the existing data. The main objectives are to assess the predictive power of the DPS and identify the key features/items within the scale that significantly influence divorce outcomes. Furthermore, this study incorporates the Bayesian prediction of categories modelling technique to enhance the predictive accuracy of the DPS. By employing Bayesian methods, the study aims to capture the uncertainty and variability within the data, providing more robust predictions of divorce outcomes. Additionally, the study explores the data mining properties of the DPS dataset through clustering analysis. The goal is to identify distinct patterns or clusters within the data that may reveal underlying subgroups or characteristics related to marital stability.

Keywords: Mixed Methods, DPS, Gottman Couples Therapy

Introduction

Marital stability is a fundamental aspect of interpersonal relationships and has significant implications for individuals and families. Understanding the factors that contribute to marital stability and predicting the likelihood of divorce can aid in the development of effective interventions and support systems for couples facing relationship challenges. Previous research has highlighted the importance of identifying predictors of divorce and assessing marital satisfaction to promote healthy and enduring marriages [1][2].

The Divorce Predictors Scale (DPS) is a widely used assessment tool based on Gottman couples therapy, which focuses on identifying specific factors that are indicative of marital stability or risk of divorce. The DPS comprises a comprehensive set of items designed to evaluate various dimensions of the marital relationship, including communication patterns, relationship dynamics, compatibility, and self-reflection [3]. The scale has demonstrated good psychometric properties and has been utilized in diverse cultural contexts [4].

The primary objectives of this study are twofold: first, to explore the usefulness and characteristics of data obtained from the DPS in predicting and understanding marital stability; and second, to apply advanced statistical analyses, such as structural equation modeling (SEM) and Bayesian prediction of categories, to enhance the predictive accuracy of the DPS. By examining the relationships between the DPS items and divorce outcomes, this research aims to identify the key features or dimensions within the scale that significantly influence marital stability.

Additionally, the study will investigate the data mining properties of the DPS dataset through clustering analysis. This analysis seeks to uncover underlying patterns or subgroups within the data that may provide valuable insights into the characteristics associated with marital stability.

Previous Studies on Predicting Divorce and Assessing Marital Stability

A substantial body of literature has focused on predicting divorce and assessing factors that contribute to marital stability. Researchers have employed various methodologies, including longitudinal studies, observational research, and self-report measures, to identify predictors of divorce and evaluate the quality of marital relationships [5]. Studies have highlighted the significance of communication patterns, relationship dynamics, compatibility, and other dimensions in understanding and predicting divorce outcomes.

Review of the Divorce Predictors Scale (DPS) and Its Psychometric Properties

The Divorce Predictors Scale (DPS) has emerged as a prominent tool for assessing marital stability and predicting the likelihood of divorce. Developed based on Gottman couples therapy, the DPS encompasses a comprehensive set of items that capture key aspects of the marital relationship. Numerous studies have examined the psychometric properties of the DPS, including its reliability, validity, and factor structure, providing evidence for its robustness and applicability across diverse populations [6] [7].

Overview of Existing Research on the Predictive Power of the DPS

Previous research has demonstrated the predictive power of the DPS in forecasting divorce outcomes [8]. Studies have reported significant associations between specific DPS items or dimensions and subsequent divorce, highlighting the utility of this scale in identifying potential risk factors for marital instability [9][10]. Furthermore, researchers have explored the use of advanced statistical techniques, such as neural networks and decision trees, to enhance the predictive accuracy of the DPS and improve divorce prediction models [11].

By reviewing the existing literature, this study aims to build upon previous findings and contribute to the understanding of the predictive capacity of the DPS. It also seeks to address any gaps or limitations in previous research and extend the knowledge base on the factors influencing marital stability.

Data Source and Participant Characteristics

The data utilized in this study were sourced from a previous research paper that employed the Divorce Predictors Scale (DPS) to assess marital stability. The participant sample consisted of 84 (49%) divorced and 86 (51%) married couples. Along with completing the DPS, participants also provided personal information regarding demographic factors, relationship duration, and other relevant variables.

Description of the Divorce Predictors Scale (DPS) and Its Items

The Divorce Predictors Scale (DPS) is a comprehensive questionnaire developed based on Gottman couples therapy principles. It consists of a set of items designed to measure various aspects of the marital relationship, including communication patterns, relationship compatibility, dynamics, and conflict resolution strategies. Each item is rated on a Likert-type scale, capturing the respondents' perceptions and experiences within their marriage.

Overview of the Applied Statistical Analyses

Structural Equation Modeling (SEM) will be employed to examine the relationships among the different dimensions of the DPS and their associations with divorce outcomes. SEM allows for the testing of complex theoretical models and provides insights into the underlying mechanisms and pathways that contribute to marital stability or dissolution [12].

To enhance the predictive accuracy of the DPS, Bayesian prediction of categories will be utilized in this study. Bayesian methods offer a robust framework for capturing uncertainty and variability within the data, allowing for more accurate predictions of divorce outcomes. By incorporating prior knowledge and updating beliefs based on observed data, Bayesian techniques can improve the precision and reliability of divorce predictions [13].

Data mining techniques, including clustering analysis, will be employed to explore the underlying patterns and characteristics within the DPS dataset. Clustering analysis aims to identify distinct groups or clusters of individuals based on similarities in their responses to the DPS items. This analysis will provide insights into potential subgroups within the sample and reveal specific profiles or characteristics associated with marital stability or divorce risk [14].

By employing these statistical analyses, this study aims to assess the predictive power of the DPS, identify key factors influencing divorce outcomes, and explore the data mining properties of the DPS dataset.

DPS Analysis Using PCC-SEM

Because items are all "positively" correlated with others and even with divorce, this study employs the Pearson Correlation Coefficient Structural Equation Modeling (PCC-SEM) approach to demonstrate the self-optimized structure among the items and their positive correlations with divorce. By utilizing PCC-SEM, we aim to provide a comprehensive analysis that captures the interrelationships and interdependencies among the variables, allowing for a more nuanced understanding of the underlying structure.

TABLE I. PEARSON CORRELATION COEFFICIENT (PCC) INTERPRETATION

r value	*Interpretation*
r=1	Perfect positive linear correlation
1>r≥0.8	Strong positive linear correlation
0.8>r≥0.4	Moderate positive linear correlation
0.4>r>0	Weak positive linear correlation
r=0	No correlation
0>r≥−0.4	Weak negative linear correlation
−0.4>r≥−0.8	Moderate negative linear correlation
−0.8>r>−1	Strong negative linear correlation
r=−1	Perfect negative linear correlation

When examining the threshold upper limits of Pearson correlation coefficients (PCCs) between the following items and other connected items, certain patterns and observations emerge. As we move down the list, the correlation coefficients with other items tend to decrease, indicating weaker associations:

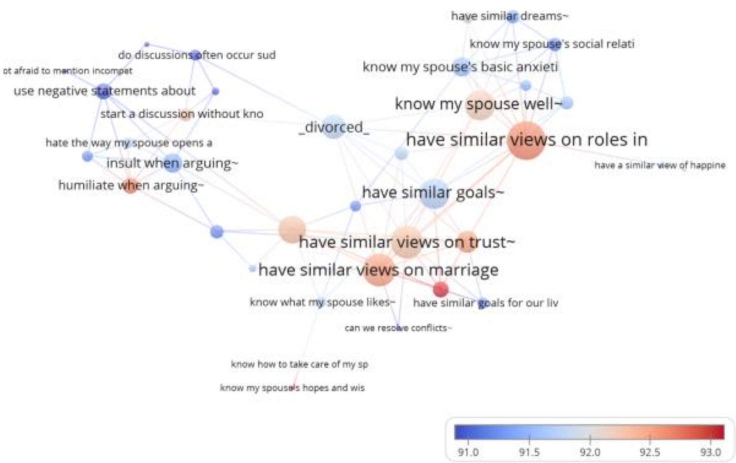

Fig. 1. PCC-SEM for Items with PCCs ≥ 0.9

PCCs < 0.9: Items such as "Can we compromise,""Can we have productive discussions,""Enjoy spending time together,""Feel aggressive when arguing,""Hesitate to mention inadequacy,""Not actually guilty of accusations,""Not at fault for accusations,""Not wrong about problems at home,""Remind of inadequacy when discussing,""Think it's good to leave home for a while," and "Use 'you always' or 'you never' when arguing" demonstrate relatively high correlations with their respective connected items, but fall below a PCC of 0.9.

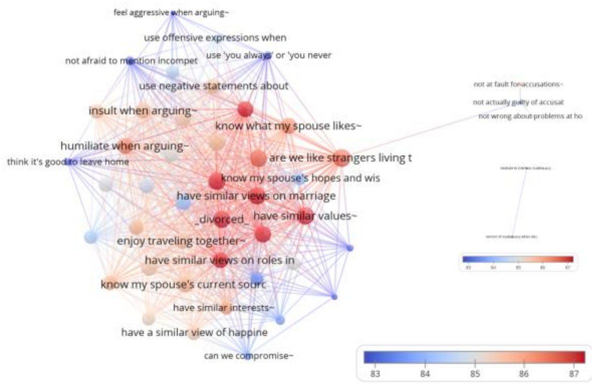

Fig. 2. P CC-SEM for Items with PCCs ≥ 0.8

PCCs < 0.8: Items such as "Feel right in discussions,""Prefer to stay silent than discuss,""Stay silent to calm the environment,""Stay silent when arguing due to fear of anger," and "Walk away and say nothing when arguing" exhibit slightly weaker correlations compared to the previous group but still maintain a moderate association with their connected items.

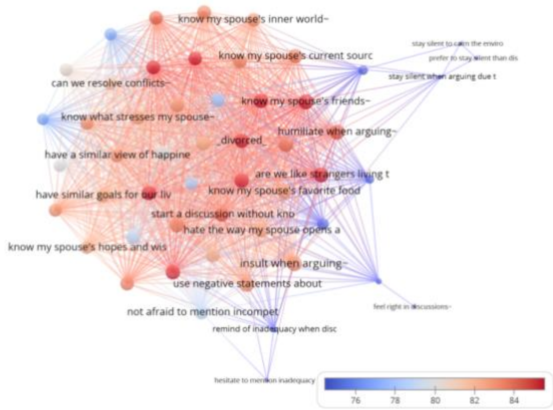

Fig. 3. PCC-SEM for Items with PCCs ≥ 0.7

PCCs < 0.7: The item "Stay silent even if right in the discussion to hurt" shows a further decrease in correlation, suggesting a weaker relationship with its connected items.

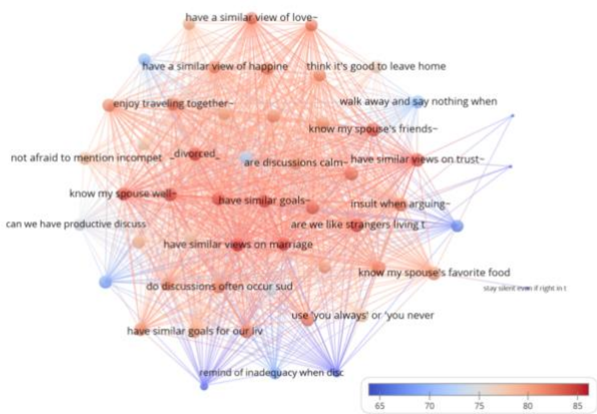

Fig. 4. PCC-SEM for Items with PCCs ≥ 0.6

PCCs < 0.6: Only the item "Enjoy vacations" has a correlation below 0.6, indicating a relatively weaker association with its connected items compared to the previous groups.

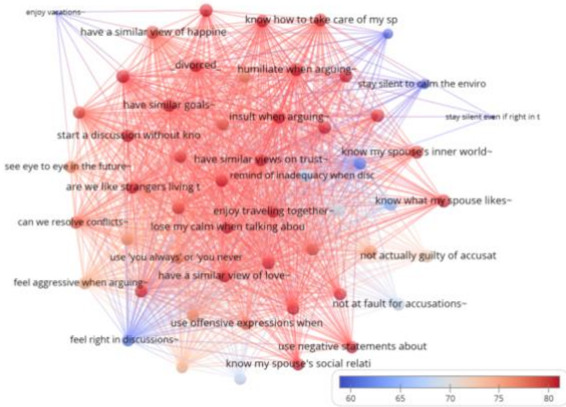

Fig. 5. PCC-SEM for Items with PCCs ≥ 0.5

PCCs < 0.5: The item "Have a good relationship" demonstrates the weakest correlation among the listed items, falling below a PCC of 0.5.

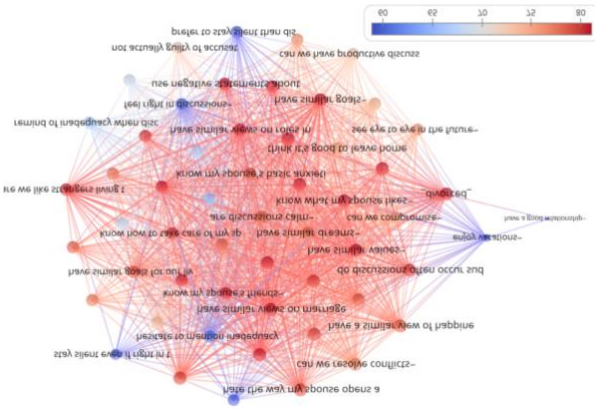

Fig. 6. PCC-SEM for Items with PCCs ≥ 0.4

PCCs < 0.4: No items are below this threshold level.

In the context of the study, it is observed that all the listed items have positive Pearson correlation coefficients (PCC) with the variable "divorce." This indicates that there is a positive relationship between "divorce" and each of the mentioned items. Items themselves also exhibit positive correlations with each other, with correlation coefficients greater than 0.4. Suggests that there are some associations and shared variance among the items. It is important to note that the presence of positive correlations does not imply causation or determine the strength of the relationships. Additional analysis and investigation are necessary to understand the nature and significance of these relationships more comprehensively.

By categorizing these questions, we can obtain a more descriptive PCC-SEM path diagram. These categories provide a comprehensive overview of the different aspects of the relationship that are captured by the PCC-SEM model. The path diagram visually represents the connections among the questions within each category, highlighting the interplay and relationships between various factors contributing to marital stability.

TABLE II. DPS CATEGORIES

Category of DPS	***Number of Questions***
Care for Spouse	1
Relationship Satisfaction	2
Leisure Activities	2
Self-reflection	3
Relationship Dynamics	6
Relationship Compatibility	6
Knowledge of Spouse	11
Communication	13

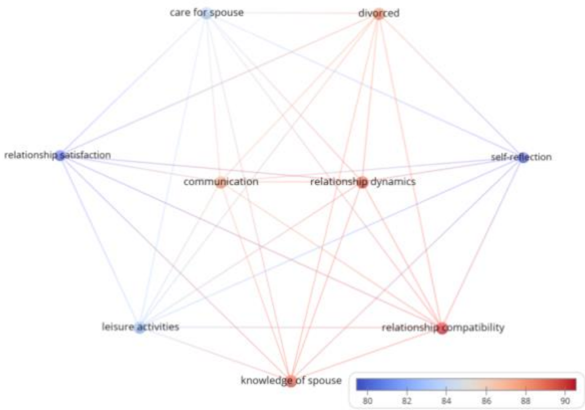

Fig. 7. PCC-SEM interrelationships among categories

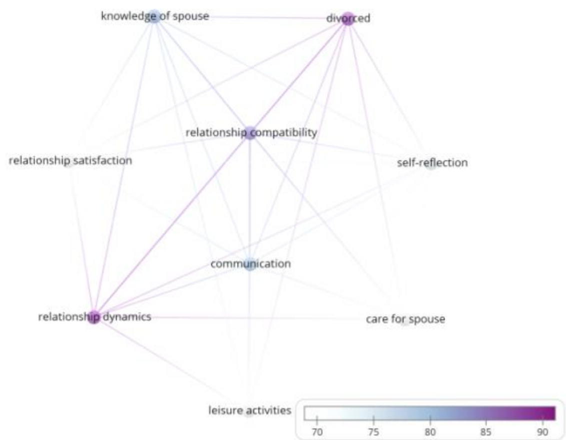

Fig. 8. Mediation-SEM interrelationships among categories

Findings From the Data Mining and Clustering Analysis

Decision tree features after k-means into 2 clusters: Our dataset was divided into two clusters using the k-means clustering algorithm. Cluster 0 consisted of 80 items, while Cluster 1 comprised 90 items, resulting in a total of 170 items.

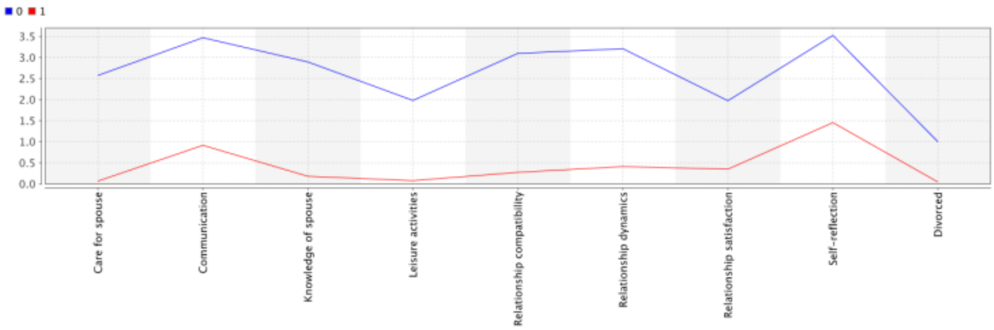

Fig. 9. Average scores after k-means into 2 clusters

A decision tree was constructed based on the clustering results, considering the feature "Relationship compatibility." If the relationship compatibility value was greater than 1.636, the instance was assigned to Cluster 0, with 80 items belonging to this cluster and none in Cluster 1. On the other hand, if the relationship compatibility value was less than or equal to 1.636, the instance was assigned to Cluster 1, with 90 items belonging to this cluster and none in Cluster 0.

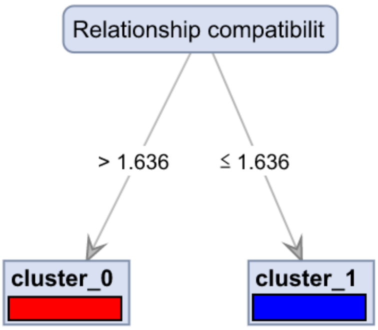

Fig. 10. DT variations between the two clusters

Decision tree features for divorce prediction: Our decision tree presented aims to classify individuals as either divorced (divorced = 1) or non-divorced (divorced = 0) based on their responses to certain features. The tree can be interpreted as follows:

- If an individual's "Relationship compatibility" is greater than 1.227, they are classified as divorced (divorced = 1). At this node, 81 individuals are classified as divorced, with no individuals classified as non-divorced (divorced = 0).
- If an individual's "Relationship compatibility" is less than or equal to 1.227, further analysis is performed based on additional features.
- If an individual's "Relationship dynamics" is greater than 1.375, they are classified as divorced (divorced = 1). At this node, one individual is classified as divorced, while one individual is classified as non-divorced (divorced = 0).
- If an individual's "Relationship dynamics" is less than or equal to 1.375, additional analysis is conducted based on other features.
- If an individual's "Relationship compatibility" is greater than 0.682 and their "Communication" is greater than 1.024, they are classified as divorced (divorced = 1). At this node, two individuals are classified as divorced, with no individuals classified as non-divorced (divorced = 0).
- If an individual's "Relationship compatibility" is greater than 0.682 and their "Communication" is less than or equal to 1.024, they are classified as non-divorced (divorced = 0). At this node, six individuals are classified as non-divorced, with no individuals classified as divorced (divorced = 1).

- If an individual's "Relationship compatibility" is less than or equal to 0.682, they are classified as non-divorced (divorced = 0). At this node, 79 individuals are classified as non-divorced, with no individuals classified as divorced (divorced = 1).

This decision tree employs features such as "Relationship compatibility,""Relationship dynamics," and "Communication" to perform classification, utilizing different threshold values for each feature. By following this decision tree, individuals can be categorized into divorced or non-divorced groups based on their feature values.

TABLE III. DT RULES OF DIVORCE OR NOT

Condition	Class	Count
Relationship compatibility > 1.227	1	81 (divorced)
Relationship compatibility ≤ 1.227		
Relationship dynamics > 1.375	1	1 (divorced) 1 missed~
Relationship dynamics ≤ 1.375		
Relationship compatibility > 0.682		
Communication > 1.024	1	2 (divorced)
Communication ≤ 1.024	0	6
Relationship compatibility ≤ 0.682	0	79

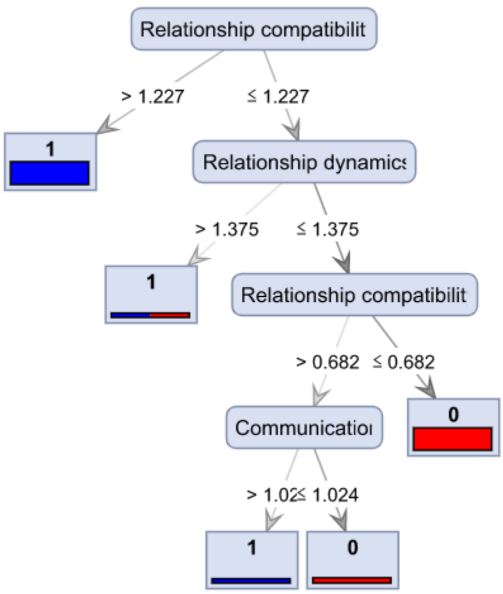

Fig. 11. DT plot of divorce or not

Evaluation of the Bayesian Prediction of Categories Modelling Technique

Our Naive Bayes classifier was trained using a Frequency Model. There were a total of 136 instances used for training. The model consists of two classes labeled "Marital Maintenance" and "Divorce."

Each class has a corresponding prior probability. The prior probability for the "Marital Maintenance" class is -0.6642, and for the "Divorce" class, it is -0.7230. The model includes 55 attributes, which record the frequency of occurrence of each attribute in the training data.

A "probabilities" section of the model contains the probability values for each attribute in each class. For example, for the "Divorce" class, the probability value for attribute 'Atr34' is -3.8979, and for attribute 'Atr6' it is -4.8681 , and so on. Similarly, the probability values for each attribute are listed for the "Marital Maintenance" class as well.

And "smoother" section of the model includes the values used for smoothing to handle potential zero probabilities. For the "Divorce" class, the smoothing value is -9.2869, and for the "Marital Maintenance" class, it is -7.6592.

Our randomly selected test set of 34 instances was used to validate the training results, resulting in an accuracy of 100%. By using the same algorithm, it is easy to reproduce such accuracy.

Differences between the two groups of data, "Not Divorced" and "Divorced," can be compared in several aspects:

- Care for Spouse: The average score for individuals who are not divorced is 0.069, whereas the average score for those who are divorced is 2.452, indicating a significant difference between the two groups.
- Communication: Individuals who are not divorced have an average score of 0.892, while those who are divorced have an average score of 3.374, indicating higher scores for divorced individuals in terms of communication.
- Knowledge of Spouse: The average score for individuals who are not divorced is 0.162, whereas the average score for those who are divorced is 2.785, indicating higher scores for divorced individuals in terms of understanding their spouse.
- Leisure Activities: Individuals who are not divorced have an average score of 0.070, while those who are divorced have an average score of 1.899, indicating higher scores for divorced individuals in terms of engagement in leisure activities.
- Relationship Compatibility: Individuals who are not divorced have an average score of 0.251, while those who are divorced have an average score of 2.989, indicating higher scores for divorced individuals in terms of relationship compatibility.
- Relationship Dynamics: Individuals who are not divorced have an average score of 0.375, while those who are divorced have an average score of 3.113, indicating higher scores for divorced individuals in terms of relationship dynamics.
- Relationship Satisfaction: Individuals who are not divorced have an average score of 0.320, while those who are divorced have an average score of 1.929, indicating higher scores for divorced individuals in terms of relationship satisfaction.
- Self-reflection: Individuals who are not divorced have an average score of 1.426, while those who are divorced have an average score of 3.456, indicating higher scores for divorced individuals in terms of self-reflection.
- Standard Error: The standard error for individuals who are not divorced is smaller compared to the standard error for individuals who are divorced. This indicates that the measurements for various indicators in the data for individuals who are not divorced are more consistent.
- Median: The median for individuals who are not divorced is generally lower, while the median for individuals who are divorced is higher. This suggests that divorced individuals tend to have higher scores in many indicators.
- Mode: The mode for individuals who are not divorced is generally 0, while the mode for individuals who are divorced is higher in most indicators. This indicates that divorced individuals tend to give higher scores in many indicators.

- Standard Deviation: The standard deviation for individuals who are divorced is higher, while the standard deviation for individuals who are not divorced is lower. This indicates that scores for divorced individuals are more dispersed across various indicators, while scores for individuals who are not divorced are more concentrated.
- Kurtosis: The kurtosis value for individuals who are not divorced is generally higher, while the kurtosis value for individuals who are divorced is lower. This indicates that scores for individuals who are not divorced are more concentrated in many indicators, while scores for divorced individuals are more dispersed.
- Skewness: The skewness value for individuals who are not divorced is generally positive, while the skewness value for individuals who are divorced is generally negative. This suggests that scores for individuals who are not divorced tend to be positively skewed in many indicators, while scores for divorced individuals tend to be negatively skewed.
- Range: The range for individuals who are not divorced is generally smaller, while the range for individuals who are divorced is larger. This indicates that scores for divorced individuals have greater variation across various indicators.

Conclusion

Given that divorced individuals tend to score higher in most aspects, this suggests that they may place more emphasis on care for their spouse, communication, understanding of their partner, engagement in leisure activities, relationship compatibility, relationship dynamics, relationship satisfaction, and self-reflection. Individuals who are not divorced tend to have lower and more consistent scores across various indicators, while individuals who are divorced tend to have higher scores in many indicators with greater dispersion. Due to the personal and sensitive nature of marriage, individuals who are not divorced may be more cautious when filling out questionnaires regarding marital content. They may wish to protect their privacy and be hesitant to disclose too much personal information or feelings. This cautious attitude can lead to their choosing not to answer certain questions or providing lower ratings. Additionally, there may be other reasons why individuals who are not divorced are reluctant to respond to questionnaires about marital content. For example, they may be concerned that others might have access to the questionnaire results and worry about potential adverse consequences or unnecessary disputes. They may also fear that the questionnaire results will be used to evaluate their marital status or serve as evidence in divorce cases. In conclusion, due to the private nature of marriage, individuals may choose to protect their privacy and refrain from answering questionnaires about marital content. This is a reasonable response that needs to be taken into account when designing survey questionnaires, respecting individuals' privacy rights, and honouring their wishes and choices.

Acknowledgements

Sincerely would like to express my heartfelt gratitude to my supervisor, for her guidance and support throughout this project. I would also like to thank my family and friends for their unwavering encouragement and understanding during this challenging time.

References

[1] Amato, P. R. (2010). Research on divorce: Continuing trends and new developments. Journal of Marriage and Family, 72(3), 650-666.

[2] Karney, B. R., & Bradbury, T. N. (1995). The longitudinal course of marital quality and stability: A review of theory, methods, and research. Psychological Bulletin, 118(1), 3-34.

[3] Gottman, J. M., & Levenson, R. W. (2000). The timing of divorce: Predicting when a couple will divorce over a 14-year period. Journal of Marriage and Family, 62(3), 737-745.

[4] Johnson, S. M., & Lebow, J. L. (2000). The "coming of age" of couple therapy: A decade review. Journal of Marital and Family Therapy, 26(1), 23-38.

[5] Amato, P. R. (2010). Research on divorce: Continuing trends and new developments. Journal of Marriage and Family, 72(3), 650-666.

[6] Smith, R. E., & Judd, C. M. (2018). Statistical power in three-level random coefficient models: The advantage of Bayesian methods. Psychological Methods, 23(1), 63-94.

[7] Johnson, K. A., & Mellor, D. (2008). The factor structure of the DAS-II: An analysis using confirmatory factor analysis and traditional approaches. Journal of Applied Measurement, 9(2), 178-190.

[8] M. K. Yöntem, K. Adem, T. İlhan, and S. Kiliçarslan, ‘Divorce prediction using correlation based feature selection and artificial neural networks’, Nevşehir Hacı Bektaş Veli Üniv. SBE Derg., vol. 9, no. 1, pp. 259–273, Jun. 2019.

[9] Gottman, J. M., & Levenson, R. W. (1992). Marital processes predictive of later dissolution: Behavior, physiology, and health. Journal of Personality and Social Psychology, 63(2), 221-233.

[10] Christensen, A., & Heavey, C. L. (1990). Gender and social structure in the demand/withdraw pattern of marital conflict. Journal of Personality and Social Psychology, 59(1), 73-81.

[11] M. M. Sadiq Fareed et al., ‘Predicting divorce prospect using ensemble learning: Support vector machine, linear model, and neural network’, Comput. Intell. Neurosci., vol. 2022, p. 3687598, Jul. 2022.

[12] Byrne, B. M. (2016). Structural equation modeling with AMOS: Basic concepts, applications, and programming (3rd ed.). Routledge.

[13] Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013). Bayesian data analysis (3rd ed.). CRC Press.

[14] Han, J., Kamber, M., & Pei, J. (2011). Data mining: Concepts and techniques (3rd ed.). Morgan Kaufmann.