**Bulletin of Electrical Engineering and Informatics**
Vol. 14, No. 5, October 2025, pp. 3622~3631
ISSN: 2302-9285, DOI: 10.11591/eei.v14i5.9055 

# Cross-cultural prediction of marital satisfaction using machine learning algorithms and generic needs

**Khye Sponge[1], Kok-Why Ng[2], Choo-Yee Ting[2], Ian Chai[2]**
[1]Centre for Big Data and Blockchain Technologies, COE for Advanced Cloud, Multimedia University, Cyberjaya, Malaysia
[2]Faculty of Computing and Informatics, Multimedia University, Cyberjaya, Malaysia

**Article Info**

***Article history:***

Received Jul 24, 2024
Revised Jul 14, 2025
Accepted Jul 29, 2025

***Keywords:***

Cross-cultural predictors
Generic needs
Marital satisfaction prediction
Maslow needs
Sustainable development goals

**ABSTRACT**

Marital satisfaction is crucial for individual well-being and family stability. Prior research has predominantly focused on Western contexts using traditional statistical models, limiting the generalizability of findings across cultures. This study addresses a significant gap by employing machine learning algorithms Naive Bayes, support vector machine (SVM), random forest (RF), and extreme gradient boosting (XGBoost) on a diverse dataset comprising responses from 7,178 participants across 33 countries. Our methodology includes a robust data preprocessing pipeline, feature selection, and algorithm evaluation, emphasizing their practical application in relationship interventions. Using predictors derived from Maslow's generic needs, including love, respect, and pride in one's spouse, we demonstrate that these factors are significant cross-cultural predictors of marital satisfaction. Our results show that pride in spouse, love, and respect for spouse are the most significant predictors of marital satisfaction across cultures. This demonstrates the effectiveness of machine learning in capturing complex relationships, offering more accurate predictions than traditional methods. These findings suggest that fostering love, respect, and sacrifice in early relationships can significantly enhance marital satisfaction across diverse cultural contexts.



***Corresponding Author:***

Khye Sponge
Faculty of Computing and Informatics, Multimedia University
Cyberjaya, Malaysia
Email: khyesponge@yahoo.com

## 1. INTRODUCTION

Marriage takes many forms in different societies, but most societies have identifiable patterns and functions of marriage. It is a public commitment that legitimizes the sexual union of a husband and wife and is essential for both public and private functions. Matrimony exists because couples have to make a public commitment as a social contract to take on the responsibilities of the entire family, including raising children. Marriage, the desires of partners and the expectations of society, is the foundation upon which a family is formed. Family is responsible for raising dependent children into independent mature adults, which is crucial to the functioning and sustainable development of a society. From a macro perspective, it is the most important basic institution for the sustainable development of mankind.

Marital satisfaction plays a crucial role in determining the happiness and well-being of individuals and families. A satisfying marriage contributes not only to the psychological and physical health of spouses but also serves as a key factor in the stability of families and societies. Healthy marriages form the foundation of stable families, which are central to sustainable development and the well-being of future generations.

At the micro level, marriage is the most important institution that influences the maturity of an individual's personality. In addition, marriage helps to meet the generic needs of individuals and improve their happiness and life satisfaction. From the perspective of physiological needs, marriage provides support in terms of physical health [1] and mental health [2]. It provides a certain form of emotional security [3] in the form of spousal exclusivity, making the process of changing spouses more difficult and expensive, insurance, and achieves better financial conditions through the pooling of resources and joint family investment by couples [4]. From the perspective of love needs [5], marriage enables intimate unity into oneness through sexual and emotional intimacy, and marriage can also meet a person's esteem needs [6] for belonging, appreciation, and affirmation of their partner. Marriage enables a person to realize the need for self-actualization, that is, to be proud of their partner's achievements after making sacrifices for the partner [7].

Marital satisfaction, a measurement for evaluating a couple's relationship, is not only of great importance for couple's relationship self-evaluation and intervention, but also could be a comprehensive indicator to measure the health and sustainable development of society. Healthy families enable societies and nations to achieve SDGs 4 [8], 5 [9], 8 [10], 11 [11], 12 [12], 17 [13], 1 [4], 2 [4], 3 [1], [2], 10 [4], and 16 [9]. A happy marriage not only allows couples to meet the needs of their spouse and prevent loneliness, it is also highly resistant to divorce.

Marriage and family life are essential preconditions for all other social, economic, and national goods. Unfortunately, issues such as family fragmentation, divorce, and cohabitation [14], [15] have seen sustained growth in both Western [16] and Eastern [17] societies, including Malaysia. This highlights the need to find universal solutions applicable across different cultural contexts. Divorce trends have changed from unreasonable behaviors (e.g., addiction, abuse, and violence) [18] or women appearing to suffer injustices to no-fault divorces (e.g., psychological and relational problems) [13]. Collectively, high divorce rate poses a serious risk for the sustainable development of society.

Divorce and family breakdown, which contribute to poverty and social class inequalities, remain widespread in Malaysia and show no signs of improving. Infidelity and incompatibility have replaced unreasonable behaviors in the divorce trend. The negative economic and social consequences of divorce on women and especially children have been well-documented. Many of the social problems are a result of the youth grow up without the benefits of two caring parents [9]. Family breakdown costs U.S. citizens at least $112 billion a year, or more than $1 trillion each decade. These costs come from expanded taxpayer spending for antipoverty, education programs, and criminal justice, as well as from reduced taxes paid by individuals who are more likely to grow up in poverty as adults, resulting in fewer opportunities and lower incomes.

There were many studies that tried to explore the causes of divorce and propose various solutions. Findings were inconsistent and varying satisfactory result [19], [20] from these solutions has been shown. For all that, divorce is continuing to deteriorate, especially with the burgeoning of 'divorce industry' [21]. Early diagnosis improves cancer outcomes, but it is difficult to cure cancer in the advanced stage. Likewise, a marriage can be difficult to save when both partners have lost hope in the other and are on the verge of divorce, but there is hope if it is detected early on. Therefore, rather than just understanding the reasons why divorcees divorce, this study aims to examine what are the factors that can predict or explain marital satisfaction for improving relationship quality to make a successful marriage.

While the importance of marital satisfaction is well-established in personal well-being and societal stability, it is crucial to understand how these factors manifest across different cultural contexts, which is often underexplored in current research. Most studies on marital satisfaction have been conducted in Western countries, focusing on cultural norms specific to these regions. These studies primarily use traditional statistical methods, which may not capture the complex dynamics of marital relationships across diverse cultures. For example, many Western studies, focus primarily on predictors like communication patterns and sexual satisfaction [22], which may not fully capture marital dynamics in non-Western societies. The findings of these studies may not apply to non-Western contexts, creating a need for research that identifies universal predictors of marital satisfaction that are relevant in diverse cultural settings.

Understanding variables that are applicable cross-culturally for marital satisfaction is arduous as research on marital satisfaction and its related factors has been conducted mostly in Western countries [23]. Many proposed solutions are trying to solve the phenomenal symptoms or issues pertaining to a certain culture that are not applicable across diverse cultures or regions [24]. While many Western dataset predictors are applicable to other cultures, some predictors (e.g. "had anal sex") for predicting infidelity [25] and for predicting sexual desire [26] are taboo in many traditional cultures and religions, including Malaysia. As such, datasets available only in the West have limitations in generalizing results across different cultures.

While traditional statistical methods have been used extensively to study marital satisfaction, they often fail to capture the complexities of relationships and the diversity of cultural contexts. Machine learning presents a powerful alternative. By processing large, diverse datasets, machine learning models can uncover patterns and predictors of marital satisfaction that may be overlooked by traditional approaches. However, the application of machine learning in cross-cultural marital satisfaction studies remains limited, highlighting the need for further exploration.

With the increasing availability of digital data due to digitization, machine learning seems to be a good match and an emerging tool to improve prediction performance. As such, a few machine learning works have been employed [22], but if the input features are not relevant, the results will not be significant, especially using personality traits to predict relationship quality [27], [28].

Given these limitations and to answer the question of whether satisfying marriages are both culturally unique and universally applicable, we look for more universally accepted predictors like generic needs [29]. Despite there has been debate regarding the validity of Maslow's needs due to their "hierarchical" nature, the widespread prevalence and adoption of generic needs was evidenced by gallup world poll (GWP) [30]. Rather than relying on traditional statistics [31], which are widely used in most marital satisfaction studies, we respond to the royal society’s call to apply the potential of machine learning to new areas and fill gaps in existing research [32]; we propose to use machine learning algorithms to investigate the generic needs predictors on marital satisfaction.

This study aims to fill these gaps by applying four machine learning algorithms Naive Bayes, support vector machine (SVM), random forest (RF), and extreme gradient boosting (XGBoost) to predict marital satisfaction across 33 countries. The focus is on using generic needs, such as love, respect, and pride in one’s spouse, as predictors of marital satisfaction. By identifying these universal predictors, the study seeks to contribute to a deeper understanding of marital satisfaction that can be applied across diverse cultural contexts.

This study contributes not only to the academic understanding of marital satisfaction across cultures but also provides practical insights that could inform marital counseling and relationship interventions, particularly in non-Western societies. These findings could also serve as a foundation for developing tools for couples to assess and improve their relationships by focusing on key predictors such as respect, pride, and spouse self-actualization.

The remainder of this paper is organized as follows: section 2 outlines the research methodology, including data collection and preprocessing. Section 3 presents the results of applying machine learning algorithms to the marital satisfaction dataset and discussing implications for future research. Finally, section 4 concludes the study by summarizing key findings.

## 2. METHOD

This study aims to develop a machine learning model that predicts marital satisfaction based on generic needs across diverse cultures. The methodology involves four major stages: data collection, preprocessing, model selection, and evaluation. By using machine learning algorithms on a dataset spanning 33 countries, this study seeks to identify universal predictors of marital satisfaction that apply across different cultural contexts.

Existing research on marital satisfaction is predominantly based on Western-centric datasets, limiting the generalizability of findings. This study seeks to overcome this limitation by utilizing a diverse dataset containing responses from 7,178 participants across 33 countries. The goal is to build a machine learning model that predicts marital satisfaction using generic needs (physiological, love, esteem, self-actualization, and safety needs) as the primary features.

### 2.1. Data collection

The dataset used in this study was obtained from an open-access marital satisfaction dataset comprising 7,178 participants from 33 countries [33]. This dataset was selected based on the following criteria:

- A large sample size to ensure statistical robustness in machine learning models.
- Diversity in terms of cultural and regional representation to capture cross-cultural predictors of marital satisfaction.
- Inclusion of key variables related to both generic needs (physiological, love, esteem, self-actualization, and safety) and marital satisfaction, providing a comprehensive basis for prediction models.

### 2.2. Pre-processing dataset

Before applying machine learning models, the dataset was subjected to a thorough preprocessing pipeline to ensure data integrity and consistency. The step includes processes of cleaning, organizing, and transforming the dataset. It addresses issues like anomalies and noisy data, missing and null values, outliers, duplicate values, and improves the integrity, reliability, and quality of the data. This involved the following steps:

- Handling missing values: missing values for non-key variables (such as ‘religious affiliation’) were replaced with a placeholder value "10" to represent “Other-very specific” without removing the data.
- Outlier treatment: out-of-range values in variables like 'physio' (physiological needs) were identified and replaced with the maximum permissible value in the dataset (e.g., replacing values of '6' with '5'). Similarly, the replacement for all out-of-range values for: love1, love2, love4: 6 replaced with 4 and love1, love2, sact: 7 replaced with 5.
- Reversing scales: for variables with ordinal scales (e.g., 'physio', 'love4', and 'esteem'), the scales were standardized so that higher values represented greater satisfaction or agreement. For example, scales were reversed in some columns so that 1 indicated Strong Disagreement and 5/7 indicated Strong Agreement. To ensure all categorical variables are properly encoded (factorized), the scaled ordinal data values in the dataset were rearranged so that all columns agree in the same order to avoid inconsistency and confusion, with "Very Disagreeing" being the lowest and "Strongly Agree" being the highest ordinal value. Smaller numbers (1) indicate strong disagreement or lower satisfaction, while higher numbers (5/7) indicate strong agreement or higher satisfaction. Thus, these columns of 'physio', 'love4', 'happy', 'esteem2', 'love5', 'love3', 'esteem1', 'sact', 'love2', 'love1' have been reversed (in order of Very Dissatisfied (1) to Very Satisfied (5)) to match the above, as well as 'safety', 'scoll1', 'scoll2', 'scoll3', 'scoll4', 'icoll1', 'icoll2', 'icoll3', and 'icoll4' have been reversed (in order of Strongly Disagree (1) to Strongly Agree (7)). The variables 'raf', 'rel', 'ms1', 'ms2', and 'ms3' remain the same.
- Binary classification setup: the outcome variable marital satisfaction of ms1, ms2, and ms3 were 7 classes labels ranging from "Yes" (7) to "No" (1). To simplify the analysis, the outcome variable ('ms1', 'ms2', and 'ms3') representing marital satisfaction was transformed into binary classes: 1 (low satisfaction) and 0 (high satisfaction). This transformation helps in focusing the machine learning models on predicting dissatisfaction in marriage, which is often more critical. Traditionally, in binary classification problems, the positive class (1) is usually the class of interest (e.g., unsatisfactory marital satisfaction), while the negative class (0) represents satisfactory marital satisfaction. This convention helps focus the analysis on the minority class, which is often of greater interest in imbalanced datasets. Binary classes (ms1r, ms2r, and ms3r) were created by merging 7 to 5 into 0 and 4 to 1 into 1.
- Features or attributes names were shortened to acronyms or five-generic-need-based name.

### 2.3. Machine learning models

This study applied four machine learning algorithms Naive Bayes, XGBoost, SVM, and RF to predict marital satisfaction. Each algorithm was selected based on its ability to handle classification problems and identify patterns in complex datasets:

- Naive Bayes: chosen for its simplicity and efficiency. As Naive Bayes assumes that all features are independent, which is useful when there is minimal interaction between input features, the simplicity and efficiency of Naive Bayes makes it ideal for a quick initial analysis of marital satisfaction. Its probabilistic nature can help assess the likelihood of different levels of satisfaction based on the input features.
- XGBoost: due to its gradient boosting framework that links multiple decision trees to produce an effective learner, XGBoost’s high performance and feature importance insights are valuable for understanding the complex factors that influence marital satisfaction. While it can be extensively tuned via hyperparameters, we chose not to use hyperparameter tuning as it has been shown to perform well with default settings [34].
- SVM: was selected for its ability to maximize the margin between distinct classes, thus generalizing better on unseen data. As SVM employs regularization parameters to handle overfitting, particularly in high-dimensional feature spaces, it is well suited to capture intricate relationships in high-dimensional feature spaces related to marital satisfaction. Since SVM performed well, its default parameters were used.
- RF: is a type of ensemble learning that combines multiple decision trees to reduce overfitting and improve generalization. As an ensemble method, RF was used to handle non-linear relationships between features while providing insights into feature importance. This was crucial for identifying which generic needs had the most influence on marital satisfaction. Because RF performs well, its default settings can be used without tuning hyperparameters [35].

### 2.4. Feature selection

The challenge of building a good model from data using machine learning lies in the complex balance between feature selection and model performance to reveal the unseen truth behind the dataset. By diagnosing and understanding the underlying causal relationships between relevant features and labels, the best model with the most relevant feature combination generally can be found. Not only can model performance and accuracy be improved by adding key relevant features, but removing irrelevant features can also improve accuracy, reduce noise to prevent overfitting, and reduce the computational cost of modeling.

Feature selection was performed to ensure that only the most relevant variables were included in the model. The following steps were taken:

– Correlation threshold: variables with a Spearman correlation coefficient (ρ) between -0.3 and 0.3 were excluded from the analysis due to their weak correlation with marital satisfaction. However, 'physio' and 'safety' were retained for further analysis as they represent core components of generic needs.
– Feature engineering: additional features were created to test their interaction effects. After careful evaluation, the dataset was reduced to five key predictors: physiological needs, safety, love, esteem, and pride in spouse, with the same number of records in the dataset are shown in Table 1.

Table 1. Selection of variables or features in the dataset (rearranged)

| Variables | Description |
|---|---|
| physio | Respondent's material situation. Ranging from much better than average in my country (5) to much worse than average in my country (1). |
| safety | Respondent's belief about their ability to rely on pension and social benefits in old age, with options ranging from 'Strongly Agree' (7) to 'Strongly Disagree' (1). |
| love1 | How much the respondent loves their spouse, with options ranging from "Yes" (5) to "No" (1). |
| esteem1 | Respondent's level of respect for their spouse, with options ranging from "Yes" (5) to "No" (1). |
| sact | Respondent's level of pride in their spouse, with options ranging from "Yes" (5) to "No" (1). |
| ms2 | Respondent's satisfaction with their husband or wife as a spouse, with options ranging from "Yes" (7) to "No" (1). |

## 3. RESULTS AND DISCUSSION

The performance of the four machine learning algorithms Naive Bayes, XGBoost, SVM, and RF was evaluated using the marital satisfaction dataset. Each model was assessed based on its accuracy, precision, recall, F1 score, receiver operator characteristic area under the curve (ROC AUC) in Table 2 and receiver operating characteristic (ROC) curve in Figure 1. The goal was to identify the model that best generalized across different cultural contexts while maintaining low overfitting.

Table 2. Performance metrics of all models on marital satisfaction

| Algorithm | Test data | | | | | Train data | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ROC AUC | F1 score | Recall | Precision | Accuracy | ROC AUC | F1 score | Recall | Precision | Accuracy |
| Naive Bayes | 0.8306 | 0.8552 | 0.8607 | 0.8525 | 0.8607 | 0.8312 | 0.8558 | 0.8615 | 0.8532 | 0.8620 |
| XGBoost | 0.8265 | 0.8332 | 0.8545 | 0.8405 | 0.8545 | 0.8270 | 0.8340 | 0.8555 | 0.8412 | 0.8555 |
| SVM | 0.7443 | 0.8313 | 0.8565 | 0.8467 | 0.8565 | 0.7450 | 0.8320 | 0.8578 | 0.8472 | 0.8578 |
| RF | 0.7959 | 0.8375 | 0.8565 | 0.8428 | 0.8565 | 0.7965 | 0.8380 | 0.8572 | 0.8435 | 0.8572 |

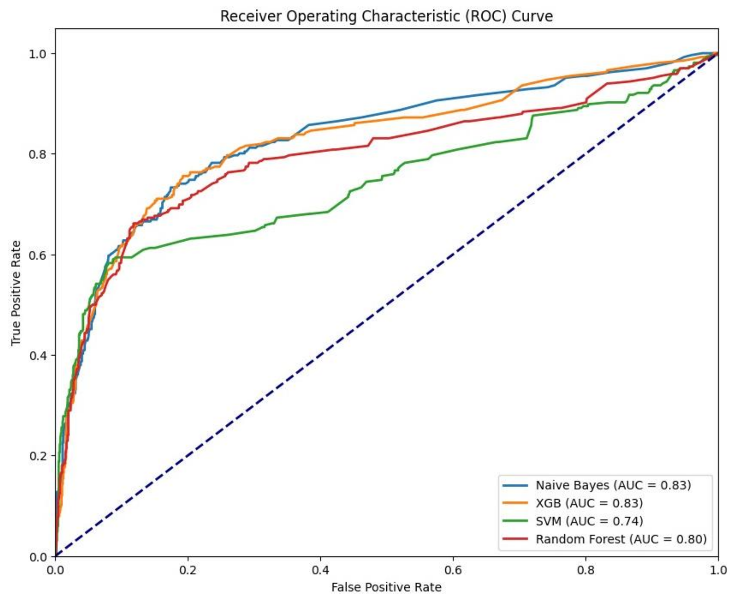


Figure 1. ROC curve

To select an algorithm with good model generalization and low overfitting, the algorithm with the smallest difference in accuracy between the training set and the test set should be preferred. When the performance indicators on the training set and the test set are analyzed, the difference between the test set accuracy and the training set accuracy of the four algorithms is almost the same, with none of the difference exceeds two decimal places, indicating that the four machine learning algorithms have a small degree of overfitting and good generalization ability. However, when there are more than two decimal places, the difference between the test set accuracy and the training set accuracy of the RF algorithm is the smallest among the four algorithms.

### 3.1. Performance comparison of algorithms

The four algorithms performed similarly in terms of best test accuracy, with the difference not exceeding two decimal places. However, in terms of best test recall, the best test recall among the four results was Naive Bayes. Naive Bayes stood out, with the highest test accuracy (0.8607), test precision (0.8525), test recall (0.8525), test F1 score (0.8552), and test ROC AUC (0.8306). Although the Naive Bayes algorithm is simple, it is effective in the context of the marital satisfaction dataset, indicating that it performed well in predicting marital satisfaction across diverse cultures. This result suggests that the features in the marital satisfaction dataset such as love, pride, and respect exhibit relatively independent relationships, making Naive Bayes an effective model. Naive Bayes is superior to algorithms that can handle complex relationships, indicating that its probabilistic nature allows people to clearly understand the impact of each feature on the prediction.

RF also showed strong performance, with an accuracy of 85.65%, while XGBoost and SVM achieved slightly lower accuracy rates of 85.45% and 85.65%, respectively. The differences between the training and test accuracies for all models were minimal, indicating low overfitting in Table 2. Although the SVM exhibits consistent performance metrics for both the training and testing datasets, the ROC AUC score is relatively low among the four algorithms, which indicates that the model may not be able to distinguish the classes effectively.

### 3.2. Key predictors of marital satisfaction

The key predictors identified by the models were pride in one's spouse, love, and respect for one's spouse. These predictors were consistent across all four algorithms, emphasizing the significance of these variables in determining marital satisfaction. Specifically, the feature importance analysis from the RF algorithm highlighted that love and pride in one's spouse had the highest contribution to marital satisfaction. This finding aligns with Maslow's hierarchy of needs, where love and esteem are central to fulfilling relational satisfaction. Interestingly, physiological needs and safety, though part of the model, contributed less significantly to the overall prediction. This may suggest that in the context of marital satisfaction, emotional and psychological needs outweigh basic material needs.

### 3.3. Implications of the results

The findings suggest that machine learning can be a powerful tool in predicting marital satisfaction across different cultural contexts. By identifying universal predictors such as love, pride, and respect, this study offers insights into how marital satisfaction can be improved globally. Interventions aimed at fostering mutual respect and pride in one's partner may prove to be effective strategies for improving marital outcomes across diverse populations.

The implications of these findings extend beyond the academic field. In practical terms, these results suggest that fostering love, mutual respect, and pride in one’s partner can significantly improve marital satisfaction. This provides a potential framework for interventions aimed at strengthening marital relationships, particularly in regions where traditional counseling methods may not resonate. Additionally, the cross-cultural nature of this study shows that the predictors of marital satisfaction are not confined to Western norms, but are applicable globally, thus contributing to the broader understanding of marital dynamics across cultures.

### 3.4. Limitations and future research

Although this study provides valuable insights into predictors of marital satisfaction, it must be acknowledged that it has several limitations. The dataset used in this analysis is cross-sectional and limited to 33 countries, which limits the ability to make causal inferences about the relationship between generic needs and marital satisfaction worldwide. Future research should expand to more countries to validate the predictors of love, pride, and esteem in marital satisfaction in a global context and explore the possibility of incorporating additional features (more about spouse’s self-actualization) to further refine the prediction model. Specifically, more attention should be given to the role of respect and pride in one's spouse as critical factors in long-term marital satisfaction. Current literature has extensively explored predictors such as communication patterns, conflict resolution, appreciation, and sexual satisfaction, but respect, pride and self-actualization remain underrepresented despite their potential impact on relationship dynamics.

Future studies should investigate how feeling proud of one's partner and respecting their achievements contributes to relational well-being across different cultures. Additionally, research should examine the role of spouse self-actualization—the process by which one partner helps the other achieve personal goals or ambitions—and its impact on marital satisfaction. Supporting a spouse's self-actualization may deepen emotional bonds and strengthen the relationship, especially in contexts where mutual growth is valued. By exploring these less-studied dimensions of marital satisfaction, future research can offer a more comprehensive understanding of the factors that promote long-lasting and fulfilling marriages across diverse cultures.

## 4. CONCLUSION

This study successfully applied machine learning algorithms to predict marital satisfaction across 33 countries, providing robust evidence that generic needs—particularly love, respect, and pride in one's spouse—are universal predictors of marital satisfaction. Among the algorithms tested, Naive Bayes exhibited the best performance, highlighting the independence of the predictors within the dataset. These findings emphasize that love, pride, and respect are central to marital satisfaction, regardless of cultural context. Moreover, the results suggest that respecting one's spouse at every stage of the relationship can serve as a critical intervention to enhance marital satisfaction, particularly when challenges arise. Similarly, the study underscores the importance of fostering pride in one's spouse by supporting their goals and making sacrifices to meet their needs, thereby strengthening the relationship.

These findings provide a comprehensive, cohesive, and cross-cultural framework for conceptualizing love, respect, and pride as foundational components of a potential grand generic theory of marital satisfaction. As the top three layers of Maslow's generic needs—love, esteem, and self-actualization—require interpersonal relationships for fulfillment, high marital satisfaction emerges as a vital path for attaining these needs. Maturity of the heart, shaped through responsibility and relational growth, can be nurtured more effectively within the context of marriage, fostering deeper emotional and relational development.

While the body inevitably matures and declines, the human mind—especially in terms of intellect, emotions, and will—often fails to reach its full potential. This lack of maturity and willpower frequently leads individuals to prioritize short-term pleasures over long-term happiness, resulting in internal conflicts that can cascade into interpersonal discord and societal challenges. Addressing this immaturity can have far-reaching implications, extending beyond the personal domain to resolve broader social and relational difficulties, from family dynamics to organizational and governmental interactions. By promoting personal growth and maturity, this framework can serve as a foundation for addressing real-world problems rooted in interpersonal conflicts and immaturity.

Future research on cross-cultural marital satisfaction should further investigate the role of generic needs—especially love, respect, and pride—as universal predictors of marital satisfaction. Such research could explore additional dimensions, such as the interplay between generic and specific needs, and how their ratios vary across cultures. For instance, understanding how combinations of generic and specific needs influence marital satisfaction could provide deeper insights into commonalities in human nature and conditions across diverse cultural settings. These findings lay a foundation for empirical research aimed at uncovering shared human experiences and fostering a unified understanding of relational dynamics.

This study also holds significant implications for improving marital quality and family well-being through a focus on generic needs. The insights gained could guide policymakers in formulating evidence-based strategies and future educational programs aimed at enhancing couple relationships. By prioritizing healthy families, nations can advance strategic agendas aligned with the sustainable development goals (SDGs), fostering societal stability and sustainable growth.

## ACKNOWLEDGMENTS

This work was supported by Faculty of Computing and Informatics at Multimedia University. We would like to express our gratitude to Faculty of Computing and Informatics. No specific grant from a public, private, or nonprofit funding organization was given for this research.

## FUNDING INFORMATION

Authors state no funding involved.

## AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Khye Sponge | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | | ✓ | |
| Kok-Why Ng | | | | | | ✓ | ✓ | | | ✓ | | ✓ | ✓ | |
| Choo-Yee Ting | | | | | | ✓ | | | | ✓ | | ✓ | | |
| Ian Chai | | | | | | ✓ | | | | ✓ | | | | |

| | | |
|---|---|---|
| C : **C**onceptualization | I : **I**nvestigation | Vi : **Vi**sualization |
| M : **M**ethodology | R : **R**esources | Su : **Su**pervision |
| So : **So**ftware | D : **D**ata Curation | P : **P**roject administration |
| Va : **Va**lidation | O : Writing - **O**riginal Draft | Fu : **Fu**nding acquisition |
| Fo : **Fo**rmal analysis | E : Writing - Review & **E**diting | |

## CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## DATA AVAILABILITY

The data that support the findings of this study are openly available at http://doi.org/10.3389/fpsyg.2017.01728, reference number [33].

## REFERENCES


[1] E. M. Lawrence, R. G. Rogers, A. Zajacova, and T. Wadsworth, “Marital Happiness, Marital Status, Health, and Longevity,” *Journal of Happiness Studies*, vol. 20, no. 5, pp. 1539–1561, Jun. 2019, doi: 10.1007/s10902-018-0009-9.

[2] J. Grundström, H. Konttinen, N. Berg, and O. Kiviruusu, “Associations between relationship status and mental well-being in different life phases from young to middle adulthood,” *SSM - Population Health*, vol. 14, pp. 1-11, Jun. 2021, doi: 10.1016/j.ssmph.2021.100774.

[3] S. M. Stanley, G. K. Rhoades, and H. J. Markman, “Sliding Versus Deciding: Inertia and the Premarital Cohabitation Effect*,” *Family Relations*, vol. 55, no. 4, pp. 499–509, Oct. 2006, doi: 10.1111/j.1741-3729.2006.00418.x.

[4] J. L. Zagorsky, “Marriage and divorce’s impact on wealth,” *Journal of Sociology*, vol. 41, no. 4, pp. 406–424, Dec. 2005, doi: 10.1177/1440783305058478.

[5] M. K. Ambrož, J. Suklan, and D. Jelovac, “Values and Virtues as Correlates of Quality and Stability of Romantic Relationships and Marriage in a Post-Socialist Transitional Society,” *Social Sciences*, vol. 10, no. 8, pp. 1-14, 2021, doi: 10.3390/socsci10080289.

[6] A. A. Udofia, E. E. Bonsi, G. F. Agbakpe, and E. A. Udofia, “The Impact of Pre-Marital Counseling and Psychological Variables on Marital Satisfaction Among Married Couples in Laterbiokoshie, Accra, Ghana,” *Journal of Psychological Research*, vol. 3, no. 1, pp. 7–15, Feb. 2021, doi: 10.30564/jpr.v3i1.2544.

[7] C. E. Rusbult, E. J. Finkel, and M. Kumashiro, “The Michelangelo Phenomenon,” *Current Directions in Psychological Science*, vol. 18, no. 6, pp. 305–309, Dec. 2009, doi: 10.1111/j.1467-8721.2009.01657.x.

[8] M. Joyce, “For the Sake of the Child: Quality of Spousal Relationship Impact on the Early Education of Their Child,” *Randwick International of Social Science Journal*, vol. 1, no. 3, pp. 451–463, Oct. 2020, doi: 10.47175/rissj.v1i3.99.

[9] J. Wallerstein, J. Lewis, and S. P. Rosenthal, “Mothers and their children after divorce: Report from a 25-year longitudinal study.,” *Psychoanalytic Psychology*, vol. 30, no. 2, pp. 167–184, Apr. 2013, doi: 10.1037/a0032511.

[10] S. Curtin, T.-V. Betzaida, and R. Anderson, “Death Rates by Marital Status for Leading Causes of Death: United States, 2010-2019,” Atlanta, Georgia, Aug. 2021, doi: 10.15620/cdc:109161.

[11] L. Nevelichko and I. Vorotilkina, “Problems of transformation of the institution of family and marriage at the present stage,” *World of Science. Series: Sociology, Philology, Cultural Studies*, vol. 14, no. 2, Jun. 2023, doi: 10.15862/43SCSK223.

[12] G. J. Duncan, B. Wilkerson, and P. England, “Cleaning up their act: The effects of marriage and cohabitation on licit and illicit drug use,” *Demography*, vol. 43, no. 4, pp. 691–710, Nov. 2006, doi: 10.1353/dem.2006.0032.

[13] K. Gravningen *et al.*, “Reported reasons for breakdown of marriage and cohabitation in Britain: Findings from the third National Survey of Sexual Attitudes and Lifestyles (Natsal-3),” *PLOS ONE*, vol. 12, no. 3, pp. 1-13, Mar. 2017, doi: 10.1371/journal.pone.0174129.

[14] B. Perelli-Harris, A. Berrington, N. S. Gassen, P. Galezewska, and J. A. Holland, “The Rise in Divorce and Cohabitation: Is There a Link?,” *Population and Development Review*, vol. 43, no. 2, pp. 303–329, Jun. 2017, doi: 10.1111/padr.12063.

[15] J. Horowitz, N. Graf, and G. Livingston, “Marriage and Cohabitation in the U.S.,” *Population Research and Policy Review*, pp. 1–53, Nov. 2019.

[16] A. Solaz, “MORTELMANS Dimitri (ed.), 2020, Divorce in Europe, New insights in trends, causes and consequences of relation break-ups, European Studies of Population 21, Springer Open, 370 pages,” *Population*, vol. 77, no. 3, pp. 504–506, Dec. 2022, doi: 10.3917/popu.2203.0504.

[17] M. Chen and P. S. F. Yip, “Decomposing the crude divorce rate in five countries: Singapore, Taiwan, South Korea, the UK, and Australia,” *Asian Population Studies*, vol. 14, no. 2, pp. 137–152, May. 2018, doi: 10.1080/17441730.2018.1452380.

[18] P. Cardinali, L. Migliorini, F. Giribone, F. Bizzi, and D. Cavanna, “Domestic Violence in Separated Couples in Italian Context:

Communalities and Singularities of Women and Men Experiences," *Frontiers in Psychology*, vol. 9, Sep. 2018, doi: 10.3389/fpsyg.2018.01602.
[19] S. B. Scott, G. K. Rhoades, S. M. Stanley, E. S. Allen, and H. J. Markman, "Reasons for divorce and recollections of premarital intervention: Implications for improving relationship education.," *Couple and Family Psychology: Research and Practice*, vol. 2, no. 2, pp. 131–145, 2013, doi: 10.1037/a0032025.
[20] J. Engl, F. Thurmaier, and K. Hahlweg, "Prevention of Divorce: Results of a 25-Year Follow-Up Study," *Verhaltenstherapie*, vol. 32, no. Suppl. 1, pp. 96–106, 2022, doi: 10.1159/000502393.
[21] D. Medved, *Don't Divorce: Powerful Arguments for Saving and Revitalizing Your Marriage*. Washington: DC: Regnery Publishing, a division of Salem Media Group, 2017.
[22] S. Joel *et al.*, "Machine learning uncovers the most robust self-report predictors of relationship quality across 43 longitudinal couples studies," *Proceedings of the National Academy of Sciences*, vol. 117, no. 32, pp. 19061–19071, Aug. 2020, doi: 10.1073/pnas.1917036117.
[23] K. Zhao, "Sample representation in the social sciences," *Synthese*, vol. 198, no. 10, pp. 9097–9115, Oct. 2021, doi: 10.1007/s11229-020-02621-3.
[24] M. S. Satu, K. Howlader, M. P. Hosen, N. Chowdhury, and M. A. Moni, "Identifying the Stability of Couple Relationship Applying Different Machine Learning Techniques," in *2020 11th International Conference on Electrical and Computer Engineering (ICECE)*, Dec. 2020, pp. 246–249, doi: 10.1109/ICECE51571.2020.9393131.
[25] L. M. Vowels, M. J. Vowels, and K. P. Mark, "Is Infidelity Predictable? Using Explainable Machine Learning to Identify the Most Important Predictors of Infidelity," *The Journal of Sex Research*, vol. 59, no. 2, pp. 224–237, Feb. 2022, doi: 10.1080/00224499.2021.1967846.
[26] L. M. Vowels, M. J. Vowels, and K. P. Mark, "Uncovering the Most Important Factors for Predicting Sexual Desire Using Explainable Machine Learning," *The Journal of Sexual Medicine*, vol. 18, no. 7, pp. 1198–1216, Jul. 2021, doi: 10.1016/j.jsxm.2021.04.010.
[27] S. Joel, P. W. Eastwick, and E. J. Finkel, "Is Romantic Desire Predictable? Machine Learning Applied to Initial Romantic Attraction," *Psychological Science*, vol. 28, no. 10, pp. 1478–1489, Oct. 2017, doi: 10.1177/0956797617714580.
[28] I. Großmann, A. Hottung, and A. Krohn-Grimberghe, "Machine learning meets partner matching: Predicting the future relationship quality based on personality traits," *PLOS ONE*, vol. 14, no. 3, pp. 1-16, 2019, doi: 10.1371/journal.pone.0213569.
[29] S. Khye, K. W. Ng, C. Y. Ting, I. Chai, and S. Gopinathan, "Generic Happiness: The Link Of Common Happiness, Motivation And Maturity Of Heart," *Journal of Positive School Psychology*, vol. 6, no. 8, pp. 4292–4310, 2022.
[30] L. Tay and E. Diener, "Needs and subjective well-being around the world.," *Journal of Personality and Social Psychology*, vol. 101, no. 2, pp. 354–365, 2011, doi: 10.1037/a0023779.
[31] D. B. Dwyer, P. Falkai, and N. Koutsouleris, "Machine Learning Approaches for Clinical Psychology and Psychiatry," *Annual Review of Clinical Psychology*, vol. 14, no. 1, pp. 91–118, May 2018, doi: 10.1146/annurev-clinpsy-032816-045037.
[32] The Royal Society, "Machine learning: the power and promise of computers that learn by example. Graduate Research Papers," 2017.
[33] P. Sorokowski *et al.*, "Marital Satisfaction, Sex, Age, Marriage Duration, Religion, Number of Children, Economic Status, Education, and Collectivistic Values: Data from 33 Countries," *Frontiers in Psychology*, vol. 8, pp. 1-7, Jul. 2017, doi: 10.3389/fpsyg.2017.01199.
[34] T. Kavzoglu and A. Teke, "Advanced hyperparameter optimization for improved spatial prediction of shallow landslides using extreme gradient boosting (XGBoost)," *Bulletin of Engineering Geology and the Environment*, vol. 81, no. 5, pp. 1-22, May 2022, doi: 10.1007/s10064-022-02708-w.
[35] P. Probst, M. N. Wright, and A. Boulesteix, "Hyperparameters and tuning strategies for random forest," *WIREs Data Mining and Knowledge Discovery*, vol. 9, no. 3, pp. 1–15, May. 2019, doi: 10.1002/widm.1301.

## BIOGRAPHIES OF AUTHORS

**Khye Sponge or Hoo-Thye Neoh** is a lecturer at MMU FCI. He is passionate about applying MAD (machine learning/artificial intelligence/data analytics) to social sciences to facilitate data-driven decision-making for organizations and individuals. He can be contacted at email: khyesponge@yahoo.com or htneoh@mmu.edu.my.

**Kok-Why Ng** is an Associate Professor in the Faculty of Computing and Informatics (FCI) in Multimedia University (MMU), Malaysia. His research interests are in family management, recommender system, artificial intelligence, deep learning, 3D modeling and segmentation. He leads several projects grants, collaborates with some universities and companies. He can be contacted at email: kwng@mmu.edu.my.

**Choo-Yee Ting** is a Professor at the Faculty of Computing and Informatics (FCI) in Multimedia University (MMU), Cyberjaya, Malaysia. He was the Deputy Dean of the Institute for Postgraduate Studies in 2020-2022. Prof. Ting received the Fellow of Microsoft Research by Microsoft Research Asia, Beijing, China. He had been active in research projects related to predictive analytics and Big Data. He received a few funded projects from MOE, MOSTI, Telekom Malaysia, MDeC, and industries. His team won two national level big data analytics competitions. Prof. Ting has been the trainer for MDeC and INTAN for courses related to big data and data science. He is also the consultant, mentor and assessor for projects under MDeC funding. He can be contacted at email: cyting@mmu.edu.my.

**Ian Chai** received his bachelor's degree from the University of Kansas. After that, he worked in Ulm, Germany for a research institute. Later, he worked as a technical consultant for the computer division of the Hartford Insurance Company in Connecticut, before finishing a Ph.D. at the University of Illinois (Urbana-Champaign). He is now teaching at Multimedia University. He can be contacted at email: ianchai@mmu.edu.my.