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Family Quality of Life in the GCC Countries: A ML Forecasting Approach

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ABSTRACT

Objective: This study examines the medium-term sustainability of quality of life, with a specific focus on Family Quality of Life (FQoL), in the member states of the Gulf Cooperation Council (GCC). Drawing on the literature on rentier economies and distributive inequality, the study investigates whether oil-exporting GCC countries are likely to achieve structurally meaningful improvements in family-level welfare over the medium term or whether the existing development trajectories have reached a welfare saturation point under oil-based growth models.

Method: The study adopts a data-driven forecasting framework that employs the Human Development Index (HDI) as a structural proxy for Family Quality of Life. First, an Edit Distance on Real Sequences (EDR) approach is applied to identify the World Bank indicators whose temporal dynamics closely track HDI. Based on the selected features, country-specific HDI trajectories for the period 2023-2027 are forecast using Extreme Gradient Boosting (XGBoost) models. This approach allows for capturing non-linear dynamics and cross-country heterogeneity in development patterns.

Results: The results reveal diverging medium-term development trajectories across the GCC countries. Kuwait, Bahrain, and the United Arab Emirates exhibit stable to mildly improving HDI paths, while Saudi Arabia, Qatar, and Oman display stagnation or slight deterioration in projected HDI levels. Overall, the findings indicate that, although the GCC countries maintain relatively high initial levels of human development, gains in family-level welfare remain limited and incremental, reflecting the structural constraints of rentier development models.

Conclusions: The study shows that high aggregate development levels in oil-based economies do not necessarily lead to sustained improvements in family quality of life. By linking forward-looking development forecasts to the FQoL framework, the analysis supports the use of HDI as a structural proxy for key family-relevant dimensions such as health and economic security. However, the findings caution against equating stable HDI trends with welfare sustainability under fiscal pressures and global energy transition. Policy implications point to the need for targeted interventions beyond oil-financed welfare, while future research should incorporate micro-level and gender-disaggregated data to better capture family well-being dynamics.

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Introduction

Quality of life (QoL) is a complex, contextually driven construct which has a universal definition (Berenger & Verdier-Chouchane, 2007). It aggregates individual perceptions and experiences of life in given cultural, social, and economic contexts, thus reflecting the longstanding preponderance of economic and healthcare-oriented paradigms in QoL studies. The series of global shocks in recent years, especially the COVID-19 pandemic, have in turn highlighted the complexity of well-being experiences and the inadequacy of the methods restricting the QoL definition to the tangible facts of objective well-being or to the broad indicators of collective economic performance (Nicola et al., 2020). Empirical evidence shows, in any case, QoL being a function of a combination of PHYS, MENT, SOCl, and ECsc factors, hence again sustaining an integrated approach in wellbeing studies (Afiani, 2024; Yusof et al., 2020; Szkultecka-Dębek, 2023). In this general perspective, a family is definitely one of the most important but understudied contexts influencing individual QoL. Family wellbeing is a critical mediator of access to affective support, financial security, social integration, and cognitive resilience over the whole life span. As empirical research suggests, families with a vulnerable economy, insufficient access to healthcare delivery, or weak social support ties in everyday life consistently show lower QoL levels, with consequences not limited to individual but impacting the whole corresponding community or society (Roxana, 2013). Therefore, improving individual and total family wellbeing is not a social problem but a relevant objective in social policies. This is because a family is primarily a social context where inequality, healthcare disparities, and intergenerational outcomes are reproduced.

The significance of family QoL can be especially observed in rentier economies and oil-exporting countries, where it is inextricably linked to state revenue structures and mechanisms of redistribution. In oil-dependent countries such as those in the Gulf Cooperation Council (GCC) countries, family QoL basically remains a function of government assistance in terms of income, jobs, subsidies, and social services, and not as a function of market opportunities. While oil wealth has paved the way for enhanced living standards and educational and health opportunities, in a rentier welfare state, families face a heightened level of vulnerability in terms of oil price fluctuation, budgetary readjustments, and sustainability. Hence, a way in which these countries can become less dependent on oil exports can have serious implications in terms of a precarious sense of family income security, social protection and, consequently, overall QoL. The significance of understanding family QoL in oil-exporting countries can, thus, not only gauge the social outcomes resulting from rentier economies but also try to quantify their sustainability capacity in a rapidly changing global order and in terms of energy transitions.

A growing body of literature has examined the socioeconomic implications of oil rents by emphasizing their interaction with institutional structures in resource-rich economies. Studies on oil-exporting countries show that heavy reliance on oil rents tends to weaken institutional quality by fostering rent-seeking behavior, corruption, and patrimonial forms of governance, thereby constraining accountability and effective redistribution mechanisms (Chekouri et al., 2017; Hachemaoui, 2012; Resico & Solari, 2019). Empirical evidence further indicates that the distributive consequences of oil rents are highly conditional on institutional quality, such that weak institutions amplify income inequality, whereas stronger institutional frameworks may partially offset these effects (Mehidi & Oukaci, 2025; Farzanegan & Thum, 2020). This institutional channel has direct implications for income distribution and household-level welfare outcomes. Research on rentier states demonstrates that unequal access to state-distributed benefits and public employment generates pronounced income disparities, even in high-income oil-exporting countries, undermining perceptions of economic fairness and satisfaction (Mitchell & Gengler, 2018; Pourghadiri, 2012). Beyond aggregate inequality, micro-level studies show that income inequality significantly affects household welfare by increasing economic insecurity, consumption volatility, and vulnerability, particularly among rural and marginalized households (Rashidi Chegini et al., 2021; Nugroho & Wulandhari, 2023). Evidence from household-based welfare analyses further reveals that disparities in household welfare translate into broader quality-of-life outcomes. Studies focusing on food security demonstrate that household welfare is a key determinant of sustainable well-being and that income inequality weakens the capacity of households to convert resources into stable living conditions (Rashidi Chegini et al., 2021). At the theoretical level, collective household welfare models emphasize that both inter-household and intra-household inequalities shape how income and resources are transformed into overall family welfare, reinforcing the central role of distributional mechanisms in assessing quality of life (Chavas et al., 2018). Despite these contributions, the existing literature remains largely retrospective and fragmented, offering limited forward-looking analyses that integrate oil-rent-driven institutional dynamics, inequality, and household welfare into predictive frameworks for quality-of-life outcomes in oil-exporting economies.

Based on previous research, this paper aims to present a forward-looking perspective on household welfare/quality-of-life outcomes in oil-exporting rentier economies. Its originality lies in the use of a combination of distributive rent structures and medium-term welfare forecasts through the Human Development Index (HDI) framework, which incorporates all the essential elements of household living standards in a composite format, focusing on income, education, and health. Although previous literature has largely focused on a retrospective analysis of inequality and welfare outcomes, this paper attempts to make a new contribution to this literature by critically assessing a forecast of welfare output improvements based on a continuous structure of rentier distribution. Owing to the unequal and state-tied nature of oil rent distribution in the Gulf Cooperation Countries, a major hypothesis asserts that household welfare and total living standards are less likely to see major transformative improvements over a medium-term forecast horizon. Hence, this study assesses whether or not the present levels of development in the Gulf economies can facilitate any major improvements in household welfare despite a continuous structure of rentier distribution.

The rest of this article is organized as follows. The second section reviews the theoretical and empirical literature on oil rents, institutional quality, income inequality, and household welfare, with a particular emphasis on rentier-state dynamics. The third section describes the data sources, variables, and methodological framework employed to forecast the Human Development Index for the GCC countries over a five-year horizon. The fourth section presents and discusses the empirical results, focusing on projected welfare trends and cross-country differences. Finally, the fifth section concludes by summarizing the main findings, discussing their implications for household welfare sustainability in oil-exporting economies, and outlining a few directions for future research.

Method

Proxy Construction for Family Quality of Life

Family Quality of Life (FQoL) is widely recognized as a multidimensional construct encompassing both objective and subjective aspects of family well-being. It extends beyond material conditions to include emotional, relational, and social dimensions. Drawing on established frameworks (Felce & Perry, 1995; Cummins, 2000; Diener, 2009; Brown & Brown, 2003; Schalock & Verdugo, 2002), FQoL is commonly conceptualized across interrelated domains such as health and well-being, economic stability, education and personal development, family cohesion, social participation, physical environment, and leisure, with subjective well-being often serving as an overarching evaluative dimension. Despite this conceptual richness, measuring FQoL remains methodologically challenging, as many of its core elements, particularly cohesion, emotional well-being, and satisfaction, are context-dependent and difficult to quantify. Consequently, empirical research often relies on proxy indicators that capture the structural foundations of family well-being. In this study, the Human Development Index (HDI), integrating health, education and income dimensions, is employed as a proxy for FQoL, as these components closely align with core family well-being domains and have been shown to correlate with life satisfaction, social participation, and intergenerational opportunity. This provides a robust and internationally comparable framework for cross-country and longitudinal analyses.

Table 1. Conceptual mapping of family quality of life (FQoL) domains to HDI dimensions

FQoL domain	Conceptual definition	Corresponding HDI dimension	Reason for inclusion / Proxy justification
Health and Well-being	Physical and mental health of family members; Access to medical care and healthy living conditions	Life expectancy (Health index)	Life expectancy reflects healthcare access, nutrition, and overall family health status.
Education and personal development	Opportunities for learning, literacy, and educational attainment of parents and children	Mean & expected years of schooling (Education index)	Education increases family resilience, empowerment, and intergenerational opportunity.
Economic stability / Material well-being	Household income, employment, and economic security	GNI per capita (Income index)	Financial stability enables access to housing, healthcare, and education.
Housing and physical environment	Quality, safety, and adequacy of living spaces	Indirect via income and health	Higher income and better health conditions improve housing and neighborhood quality.
Family relationships and cohesion	Emotional support, communication, and family functioning	Indirect via education and health	Education enhances communication and parenting skills. Health sustains family stability.
Social inclusion and participation	Integration in community, civic engagement, and social capital	Indirect via education and income	Education and economic means foster social participation and belonging.
Leisure and life satisfaction	Balance between work and family life; Perceived happiness	Aggregate effect of all HDI dimensions	HDI dimensions together predict life satisfaction and perceived QoL (Diener, 2009).

The human development index (HDI), which averages within-country inequalities, is insensitive to gender gaps and cannot observe relational/cultural dynamics inside families; improvements in its quantitative indicators may not always reflect true gains in health or education quality, and ecological or newer inequality dimensions may be omitted (Tan, 2021). Therefore, one should a) add gender-sensitive controls (e.g., GII/GDI), b) run robustness checks with microdata or validated FQoL scales where available (e.g., DHS/MICS), and c) estimate subnational models to reduce aggregation bias, following the best-practice guidance (UNDP, 2022).

Based on the correlation-mapping results and the correlation analysis conducted across the six GCC countries, a consistent structural pattern emerges in the types of the variables that exhibit the strongest associations with the HDI. Although the magnitude and ordering of the correlations vary across the countries, the dominant groups of high-correlation variables follow a remarkably similar logic. In Bahrain and Saudi Arabia, demographic structure and dependency-load indicators, such as the proportion of children and older adults, show the highest similarity and correlation with the HDI, underscoring the central role of family life-cycle dynamics and demographic pressures in shaping family quality of life. In contrast, the United Arab Emirates and Qatar display a different but internally cohesive pattern, where child and infant health indicators (including infant mortality, under-five mortality, and neonatal survival measures) consistently rank as the strongest correlates, highlighting early-childhood health as a foundational driver of family well-being in these contexts. Meanwhile, Kuwait and Oman are characterized by high correlations between the HDI and the economic-and-employment indicators, such as imports, exports, broad money supply, and sectoral employment. This suggests that macroeconomic stability and labor-market conditions are the primary structural determinants of family well-being in these countries. Taken together, the similarity-mapping analysis demonstrates that the HDI meaningfully captures the three core pillars of family quality of life, namely family health, demographic dynamics, and economic stability, across the GCC region. This provides both theoretical and empirical justification for using the HDI as a structural proxy for FQoL in contexts where harmonized family-level data are unavailable.

Dataset

In this study, the Human Development Index (HDI) is used as the dependent variable to represent household welfare and overall living standards. Developed by the United Nations Development Programme (UNDP), the HDI is a composite indicator that reflects three core dimensions of human development, including health, captured by life expectancy at birth, education, measured through the mean years of schooling and expected years of schooling, and material well-being, proxied by gross national income (GNI) per capita adjusted for purchasing power parity. Through a process of normalization and geometric aggregation, these dimensions are combined to produce a multidimensional welfare measure that goes beyond conventional economic metrics and enables robust comparisons across countries over time.

In supervised learning frameworks, the existence of relevant explanatory variables is essential for accurately capturing the behavior and dynamics of the dependent variable (Cox, 2001). The selection of independent variables is typically conducted using two alternative approaches. The first is based on prior empirical literature to identify theoretically important predictors, while the second employs data-driven feature selection techniques to extract relevant variables from a large pool of candidates. Although theory-based selection is widely done, it may overlook the variables that exhibit hidden, nonlinear, or time-dependent relationships with the dependent variable (Hastie et al., 2009). To mitigate this risk and to fully exploit the multidimensional nature of human development, the present study adopts a data-driven approach.

Accordingly, the World Bank's World Development Indicators (WDI) database is used as the initial dataset from which the explanatory variables are extracted. This dataset encompasses a wide range of economic, social, demographic, institutional, and environmental indicators, providing a rich and multidimensional information base that is well suited for modeling the complex determinants of human development and household welfare.

Data preprocessing

The data preprocessing stage consists of the three main steps of handling missing data, data standardization, and feature selection prior to constructing a machine learning model.

Missing data

One of the main challenges in working with real-world macroeconomic and development datasets is the issue of missing observations, which can adversely affect model accuracy and inference reliability. In this study, the variables with more than 70% missing observations over the sample period were excluded from the analysis to ensure data quality and temporal consistency. Retaining variables with excessive missingness may introduce bias, lead to unstable parameter estimates, and reduce the predictive performance of machine learning models.

For the variables with partially missing observations, the Random Forest Imputation method was applied to estimate and replace the missing values. The core idea of this approach is to model each variable with missing data as a function of the remaining variables using a Random Forest algorithm. The general form of the imputation process is expressed as:

$$\hat{x}_{i,j} = f_j(X_{i,-j}) \quad (1)$$

Where $\hat{x}_{i,j}$ denotes the imputed value of variable *j* for observation *i*, *X_*(*i*,-*j*) represents the set of all other variables for the same observation, and *f_j* (·) is the Random Forest model trained to predict variable *j*.

In practice, the imputation procedure is implemented iteratively. Initially, the missing values are replaced with simple statistics such as the mean or median. Subsequently, for each variable containing missing values, a Random Forest model is trained using the remaining variables as predictors, and the missing entries are updated with the predicted values. This process continues until the maximum absolute difference between the successive iterations falls below the predefined convergence threshold ε:

$$\max_j \mid \hat{x}_{i,j}^{(t)} - \hat{x}_{i,j}^{(t-1)} \mid < \varepsilon \quad (2)$$

This method dynamically reconstructs the missing observations by exploiting nonlinear and interaction effects among the variables, while preserving the original data distribution and demonstrating robustness to the outliers (Tang & Ishwaran, 2017). These properties make Random Forest Imputation particularly suitable for highly dimensional development datasets such as the WDI.

Feature selection

The selection of explanatory variables is conducted using the Edit Distance on Real Sequences (EDR) technique. This technique identifies variables whose temporal behavior closely resembles that of the dependent variable over the study period, allowing for pattern-based rather than purely correlation-based feature selection.

For each development indicator extracted from the World Bank database, a corresponding time series was constructed for each GCC country and aligned with the HDI time series for the same country and period. For each pair of sequences (X_iⓜ,Y), where X_irepresents the time trajectory of the i[th] candidate explanatory variable and Ydenotes the HDI trajectory, the EDR distance was computed as follows:

$$DR(X_i, Y) = \frac{\text{Number of edits required to align } X_i \text{ and } Y}{\max(|X_i|,|Y|)} \tag{3}$$

An "edit" operation is defined as an instance in which the absolute difference between the corresponding elements of the two sequences exceeds the predefined tolerance threshold ε. Smaller EDR values indicate greater similarity between the temporal patterns of the explanatory variable and the HDI.

Based on this criterion, the variables exhibiting the lowest EDR distances were identified as those most closely aligned with the evolution of human development. They were selected as input features for the XGBoost forecasting model. This approach enables the identification of the variables that share similar dynamic and behavioral patterns with the HDI, even in the presence of nonlinear relationships and temporal shifts, thereby enhancing the robustness and interpretability of the predictive framework (Goldani, 2024).

Model

Machine learning (ML) is one of the most effective means of generating precise and reliable predictions and is considered a subcategory of computational intelligence methods mainly applied to obtain definitive knowledge from large datasets for pattern recognition, classification, function approximations, and more. With the emergence of Big Data and the availability of large datasets, making reliable and robust predictions is of great significance (Campisi et al, 2024). In this study, XGBoost is considered as an algorithm based on ensemble learning methods, in which multiple models are combined to generate one model that has better performance than the other individual models (Chen & Fan, 2021). It is considered one of the better algorithms in generating effective and robust predictions and has outperformed other algorithms in dealing with large datasets and missing data as well as avoiding overfitting and tuning options. It has emerged as a very effective algorithm in making robust and effective predictions in both research and industrial applications.

Extreme gradient boosting (XGBoost)

Chen and Guestrin (2016) introduced the XGBoost concept which stands for extreme gradient boosting. The term "Gradient Boosting" originates from the paper titled 'Greedy Function Approximation: A Gradient Boosting Machine' by Friedman (2001). XGBoost is based on the gradient boosting algorithm, a key method in ensemble learning. It combines weak classifiers to create a stronger model, enhancing efficiency and flexibility compared to a single model. XGBoost improves classification performance by iteratively building decision trees.

A salient characteristic of objective functions is that they consist of two parts: a training loss and a regularization term (Eq. 4).

$$obj^{(t)} = l(f_t) + \Omega(f_t) \tag{4}$$

In Eq. (4), f_t represents the t[th] tree model, $l(f_t)$ is the loss function in the risk prediction, $\Omega(f_t)$ is the regular term used to reduce overfitting, which can be expressed as Eq.(5)

$$\Omega(f_t) = \gamma T + \frac{1}{2}\lambda\|\omega\|^2 \tag{5}$$

In Eq. (2), T denotes the number of leaf nodes in the t^{th} decision tree, while $\gamma$and λ jointly determine the strength of the regularization penalty. The term ω represents the weight assigned to each leaf node. The training loss quantifies the predictive performance of the model with respect to the training data. The commonly used specification for the loss function L is the mean squared error, as defined in Eq. (6).

$$l(f_t) = \sum_i (y_i^t - \hat{y}_i^t) \tag{6}$$

The prediction results of the model are the weighted sum of all the decision trees, when the t[th] iteration is performed, the prediction result can be expressed by Eq. (7).

$$\hat{y}_i^{(t)} = \sum_{k=1}^{K} f_{(x_i)=}\, \hat{y}_i^{(t-1)} + f_t(x_i),\ f_t \epsilon F \tag{7}$$

In Eq. (7), $f_t(x_i)$ represents the t[th] tree model, F is the decision tree space, is also the set of all sample risk prediction decision trees. Here, $\hat{y}_i^{(t)}$represents the prediction results of the sample I after the t[th] iteration, and$\hat{y}_i^{(t-1)}$ represents the prediction results of the previous *t-1* trees. Therefore, the objective function can be expressed as Eq. (8):

$$obj^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t)}\right) + \Omega(f_t) + costant \tag{8}$$

Overfitting is a well-known and undesirable issue in machine learning models, occurring when a model becomes excessively tailored to a specific training dataset and fails to be generalized to new observations. One effective strategy to mitigate overfitting is hyperparameter tuning, which aims to optimize model performance while controlling model complexity. Various approaches can be employed for this purpose. Given the limited size of the available dataset, a grid search strategy is adopted as an appropriate and systematic method for hyperparameter optimization.

Model evaluation

Due to the small sample size, the cross-validation method is chosen to gain reliable insights from the available data set. This method is more appropriate when dealing with small datasets because it makes the most out of the available data by splitting it into training sets and validation sets.

The mean absolute percentage error method is used to evaluate the accuracy of the predictions made on the training set as well as the test set. This method is defined as follows:

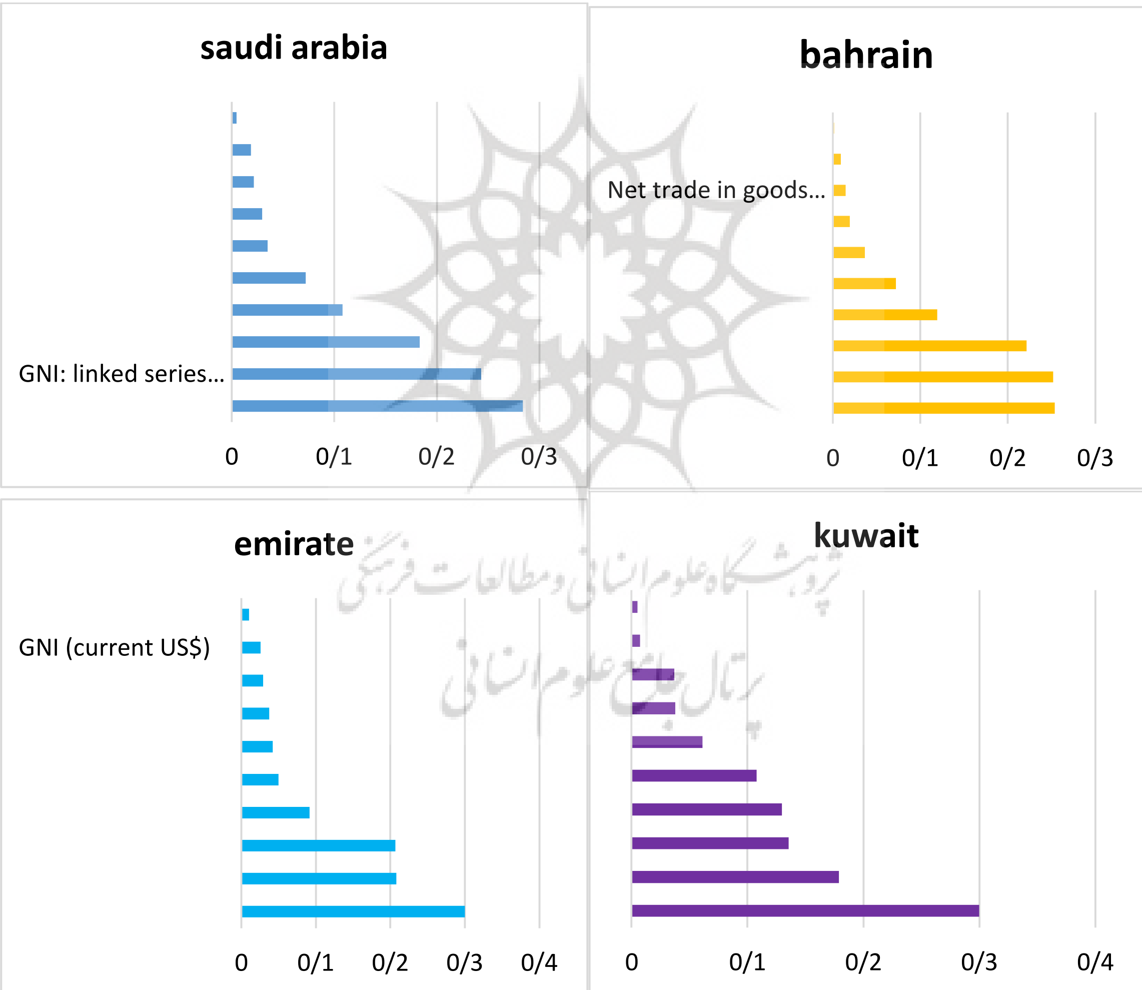
$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right| \times 100 \tag{9}$$

whereA_i is the actual value and F_i is the forecasted value. This metric provides a straightforward and interpretable measure of forecast accuracy (Hyndman, 2006).

Results

Feature importance

The predictors in any machine learning prediction model certainly serve crucially to increase the accuracy of the model. The more properly the predictors can explain the behavior of the target variable, the more accurate the forecast is. Instead of drawing on the research literature, this study has used the large dataset of the World Bank to select the most effective predictor. Since it is less sensitive to sample size and computation is simpler, according to Goldani and Asadi (2024), feature selection was performed using the Edit Distance on Real sequence (EDR) method. Figure1 shows the importance of each predictor for each dataset.



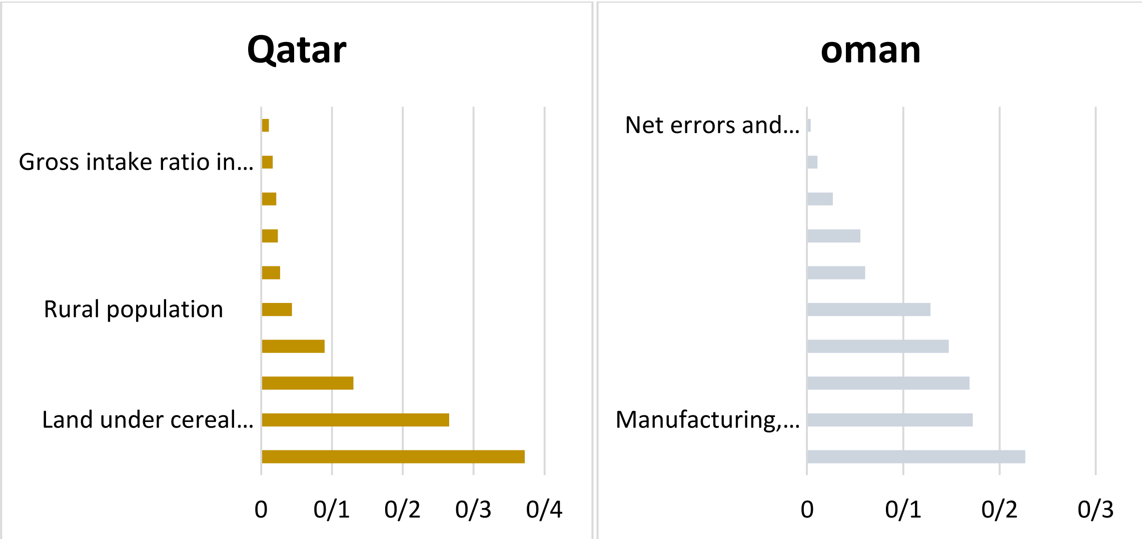
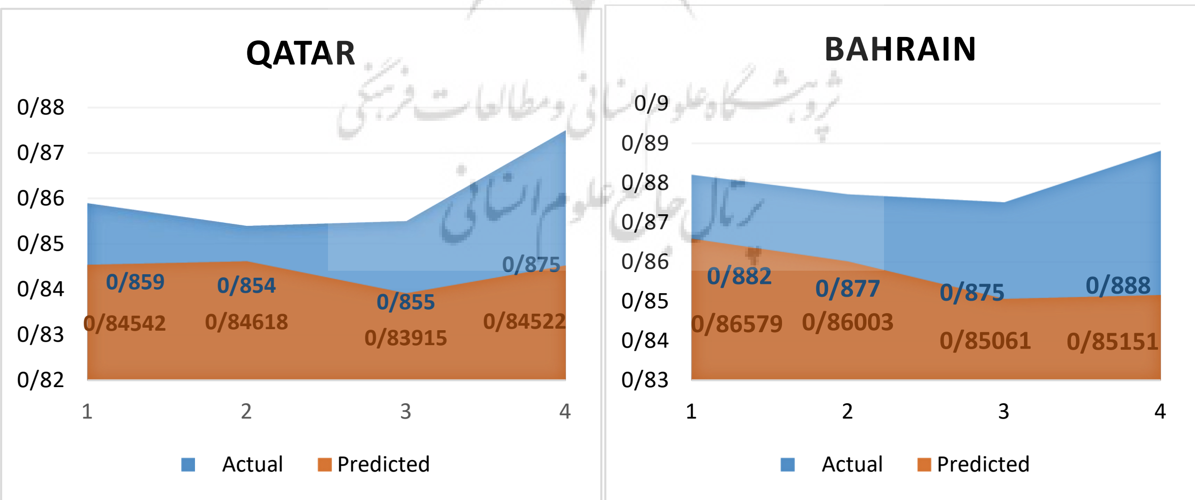


Figure 1. Top 10 predictors identified by the Edit Distance on Real Sequence (EDR) feature selection method

Train-Test Split

The predictors and target variable were divided into training and testing sets to evaluate the model performance for each country-specific dataset. To assess the within-sample forecasting accuracy, the model was estimated using the data from 1996 to 2018. The fitted model was then used to generate out-of-sample forecasts for the period 2018-2022, which were compared with the observed values. As the comparison indicated, the predicted trends closely track the actual data for Qatar, Kuwait, and the United Arab Emirates, demonstrating relatively stronger predictive performance for these countries compared to the remaining datasets (Figure 2).



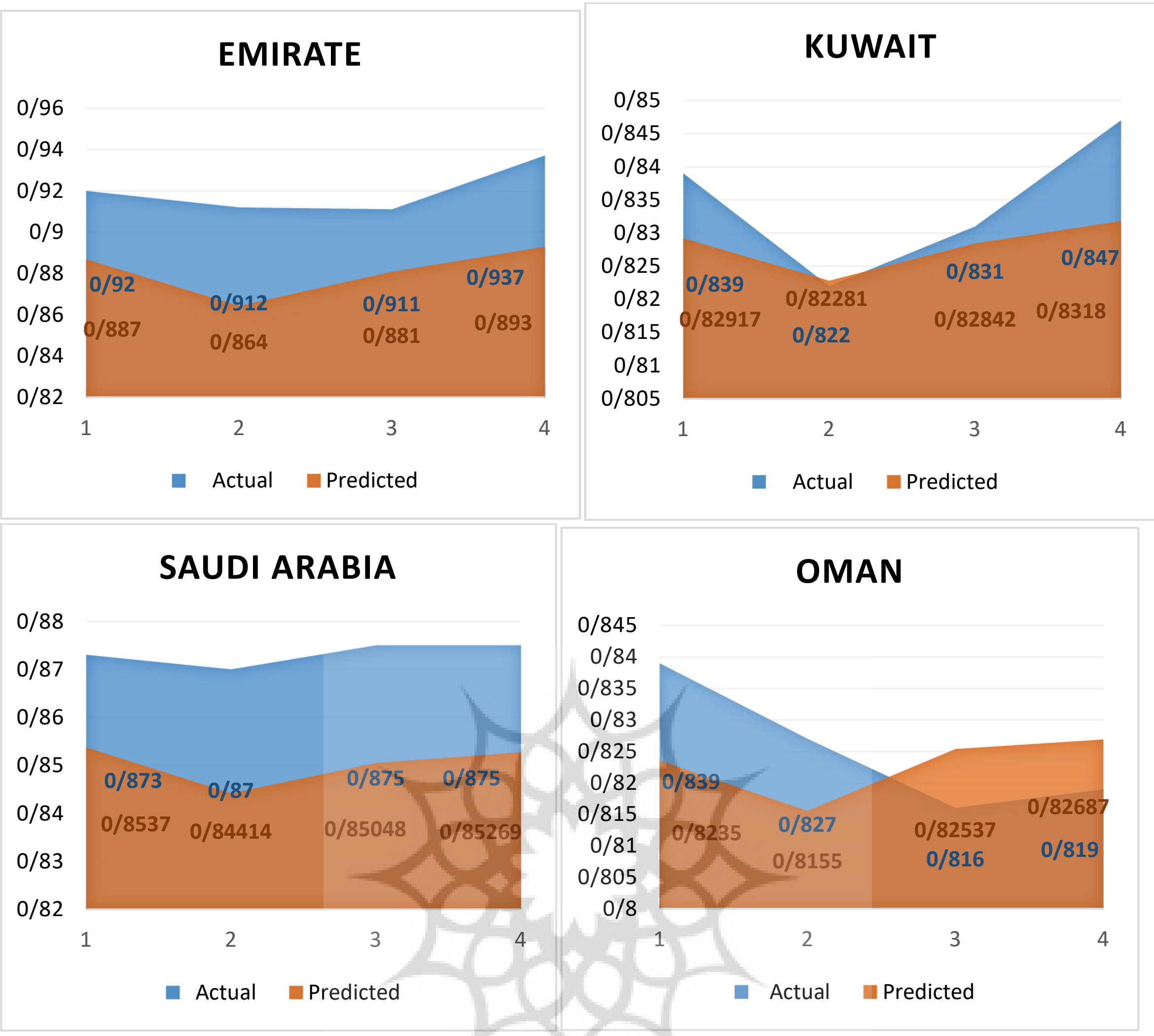


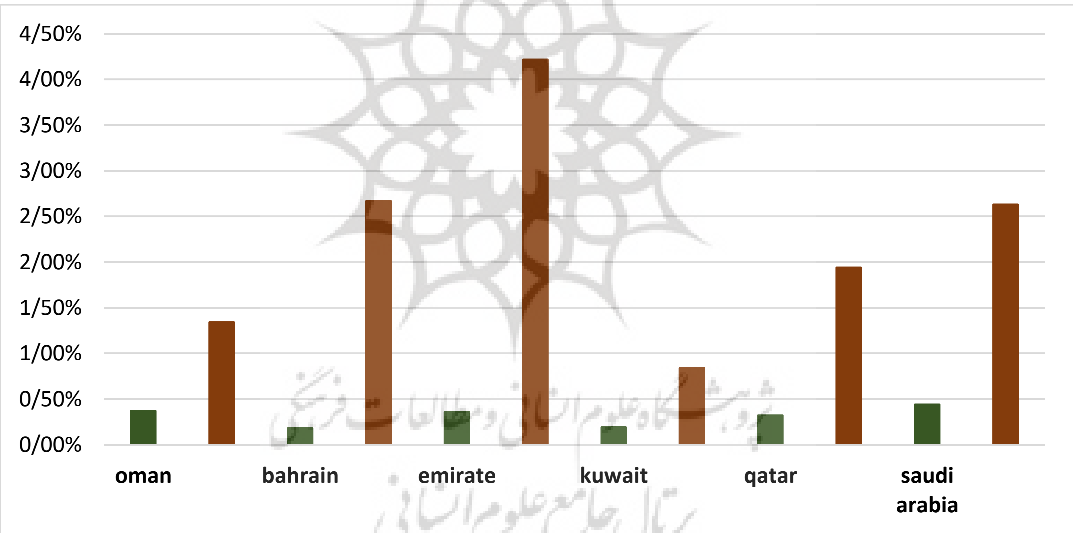
Figure 2. Model fit and forecast results for the training dataset

From this finding, one can comprehend very well that, while the model fits quite well for in-sample data, the MAPE shows a sharp increase for out-of-sample data. This is a hint to potential overfitting issues. Hence, in this study, reasons for overfitting had to be identified, and another approach could be considered for better improvement in generalizing the model performance. Kuwait has the best performance among the available datasets. The United Arab Emirates has the worst performance (Table 2).

Although the out-of-sample forecast error is larger than the in-sample error across all countries, this pattern should not be interpreted as evidence of severe overfitting. First, the target variable (HDI) exhibits a narrow dynamic range in high-development contexts such as the GCC countries. As a result, even small absolute deviations in prediction can translate into relatively higher percentage-based error measures such as MAPE. Second, the differences observed between in-sample and out-of-sample errors remain moderate and systematic, rather than erratic or explosive, indicating limited generalization loss rather than noise memorization. Therefore, an increase in the out-of-sample MAPE reflects the intrinsic forecasting difficulty of low-variance development indicators rather than structural model misspecification.

Table 2. In-sample and out-of-sample forecast accuracy (MAPE) for HDI-based FQoL models in Persian Gulf States

countries		MAPE
oman	In-sample MAPE	0.37%
	Out-of-sample MAPE	1.34%
bahrain	In-sample MAPE	0.18%
	Out-of-sample MAPE	2.67%
emirate	In-sample MAPE	0.36%
	Out-of-sample MAPE	4.22%
kuwait	In-sample MAPE	0.19%
	Out-of-sample MAPE	0.84%
qatar	In-sample MAPE	0.32%
	Out-of-sample MAPE	1.94%
saudi arabia	In-sample MAPE	0.44%
	Out-of-sample MAPE	2.63%



Figur 3. In-sample and out-of-sample forecast accuracy (MAPE) for HDI-based FQoL models in Persian Gulf States

Simulation of the predictors

The next step is to forecast the future trend of the political stability index for the six countries under investigation over a five-year period. To achieve this objective, a projection is made for the predictor variables over a similar period. An ARIMA model is used to simulate a five-year forecast for the predictor variables based on their historical patterns.

Forecast of HDI

The Human Development Index, or HDI, is a composite measure for assessing the key dimensions of human development, namely life expectancy, education, and per capita income. For most of the studied countries, HDI assumes stable or rather slightly increased values, meaning further improvement in life expectancy, education, and income levels in the next five years.

According to Figure 4, Saudi Arabia, Qatar, and Oman experience slight decreases or standstill in their HDIs, while Kuwait, Bahrain, and the UAE display stability or a slight increase. The table above indicates that human development in the Gulf countries remains at a high level, with just insignificant fluctuations from year to year within the forecasted period. More specifically, the leading HDI scores are for the United Arab Emirates, whereas Oman demonstrates the lowest indicators in this group.

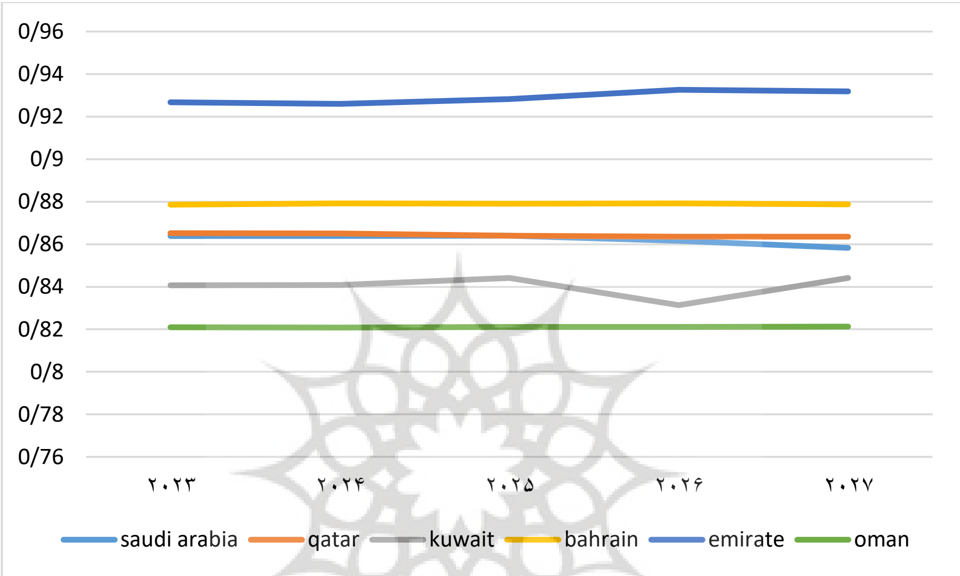


Figure 4. Forecast of the trends in Family Quality of Life (FQoL) using HDI as a proxy, 2023-2027

Discussion

The primary purpose of this research was to assess and forecast the Family Quality of Life (FQoL) in the Gulf Cooperation Council (GCC) countries. The Human Development Index (HDI) served as a sectional proxy for the welfare and quality of life of households. Proceeding with the assumption that a rentier and/or asymmetric distribution system could potentially limit further improvements in welfare, the research was conducted to assess whether a forecasted level of development in petroleum-based export-oriented economics leads to a beneficial increase in family life quality. The findings show that Kuwait, Bahrain, and UAE are expected to make stable or mildly improving changes to a higher welfare status through the forecast period of 2023-2027, but Saudi Arabia, Qatar, and Oman will stagnate or mildly decline in this regard. It was also shown that, overall, a consistently high level of human development is not necessary for a corresponding trend of improvements to FQoL.

The findings of this study broadly support the central hypothesis derived from the rentier state literature; that is, in economies characterized by heavy dependence on oil rents and uneven, state-mediated distribution mechanisms, improvements in family well-being are unlikely to be profound or transformative over the medium term. The stagnation or slight decline observed in Saudi Arabia, Qatar, and Oman is consistent with earlier empirical evidence highlighting how oil rents, when filtered through weak or segmented institutional structures, fail to translate macro-level development achievements into sustained household welfare gains (Chekouri et al., 2017; Hachemaoui, 2012; Mitchell & Gengler, 2018). Structural factors such as demographic pressures, segmented labor markets, and limited diversification appear to weaken the transmission channels between aggregate development indicators and family-level living conditions in these contexts.

By contrast, the relatively stable trajectories observed in Kuwait, Bahrain, and the United Arab Emirates suggest that more diversified economic structures and comparatively stronger institutional arrangements may partially insulate family welfare from the volatility and distributive distortions associated with rentier systems. This pattern aligns with the studies arguing that institutional quality conditions the distributive effects of resource rents and may mitigate, though not fully eliminate, inequality-driven welfare losses (Farzanegan & Thum, 2020; Mehidi & Oukaci, 2025). Importantly, however, the observed stability remains incremental rather than transformative, reinforcing the argument that, even in higher-performing rentier states, structural dependence on oil revenues constrains long-term welfare advancement at the household level. These results are also consistent with micro-level welfare studies, emphasizing the role of income inequality in shaping household insecurity, consumption volatility, and vulnerability (Rashidi Chegini et al., 2021; Nugroho & Wulandhari, 2023). By linking HDI forecasts to a Family Quality of Life framework, this study has extended the existing literature, which has largely remained retrospective and cross-sectional, toward a forward-looking and predictive assessment of welfare dynamics in oil-exporting economies. To do so, it has provided complementary evidence that structural resource dependence imposes measurable limits on future family welfare outcomes, even when aggregate development indicators remain stable.

There exist certain limitations to mention. First, although the HDI has strong theoretical foundations and facilitates global comparison, it tends to measure essentially structural and objective aspects of welfare related to families, ignoring subjective, emotional, or relationally defined elements that form an essential part of FQoL. Secondly, HDI tallies the intercountry disparities of welfare while ignoring the disparities based on gender or within-family variations that can be more nuanced. Thirdly, the use of simulated explanatory variables in multi-year forecasting functions is inherently associated with certain degrees of uncertainty, despite employing conservative modeling strategies. Finally, accuracy assessments expressed in terms of percentages can overstate certain relative errors when welfare indicators belong to the higher HDI ranks affected by limited temporal variation.

The implications of this research are diverse. In terms of policy-making, the results of the research show that the policies aimed at improving and sustaining family quality of life in the

GCC should adopt a focus and target approach beyond simple measures to achieve development in general. What seems to make more positive impacts within the GCC is policies targeting work and job opportunities for the young generation, policies focused on improving the health and well-being of mothers and children, policies emphasizing support and services for caregivers and their dependents, housing and job/work and family balance, and policies within a comprehensive approach to development and growth targeting living conditions beyond money and public expenditures. In terms of insights and contributions to knowledge and practice, this research underscores the critical value of considering family and psychological aspects within development forecasting models and theories in rentier and high-income economies.

Conclusion

This research seeks to analyze and forecast the Family Quality of Life (FQoL) in the Gulf Cooperation Council (GCC) countries using the Human Development Index (HDI) as a structural indicator for the welfare of households. Based on the existing literature on rentier economies and distributive inequalities, the primary research question is ‘Are oil-exporting countries in the GCC likely to see any substantial progress in family-level welfare in the medium-term future within the existing structures of rent-led development trajectories?’ This research has adopted data-driven methods including feature selection and machine learning simulation to forecast the individual country-specific paths of HDI from 2023 to 2027.

The empirical evidence suggests that there is divergence in welfare trends across the GCC states. The states of Kuwait, Bahrain, and the UAE have relatively stable to slightly improving HDI indexes, while those of Saudi Arabia, Qatar, and Oman have shown stagnation and slight decline, respectively. These findings support the central hypothesis of the study, namely ‘in rentier economies where the mechanisms of distribution are unbalanced and conducted through the state, starting development points remain high and do not easily translate to structurally significant advancements of FQoL’. A key implication of the issues projected in this study is that, even for states that have considerable development measurements, progress in FQoL is likely to remain incrementally positive at best.

In terms of methodology, the research highlights the benefits of data-informed variable selection to forecast the welfare state. Here, using the Edit Distance on Real Sequences (EDR) approach to screen an abundance of World Bank variables helps the researcher select predictors whose time paths have been observed to track those of the HDI score, as opposed to variables based solely on the theoretical frameworks of variable selection. The XGBoost models produced have strong in-sample fits and adequately decent out-of-sample forecast performance for different nations. Though the MAPE values for the prediction performance of the models increase compared to their in-sample values, this development should not cause undue concern for several reasons related to the forecasting outcomes in similar environments with higher values of HDI, as seen in the GCC nations.

Conceptually, this research refines the literature on oil rent, institutions, and inequality by arguing a connection between development predictions and the Family Quality of Life model and model domain. Although most studies have remained focused on posterior evaluations and comparisons in petro-states on welfare states in a post-hoc manner, this article essentially retains a prospective indicator, formulating a connection between institutions and welfare at a familial sphere. The correlational mapping also increases the conceptual appropriateness of the HDI as a trait carrier in FQoL measurement, filling in related domains such as health and infant statistics, dependency ratios, and economic security.

There have been some limitations in this study. Firstly, the HDI mainly measures the objective and structural aspects of well-being, but it fails to measure the subjective and relational elements of FQoL. Secondly, the HDI measures within-country inequalities and ignores the gaps between genders and among households, thereby likely to mask important variations in family experiences. Thirdly, the prediction of the variables by ARIMA models carries certain uncertainties of forecasting, although these are made clear and conservative.

In this context, future research should consider complementing HDI forecasts with micro-data and subjective well-being data, as well as gender and inequality-disaggregated data where possible. In this respect, a subnational analysis and a combination of family datasets (such as DHS and MICS) could also contribute to lessening aggregation bias and increasing interpretability. From a policy perspective, one can infer that those aggregated developments should not be associated with improvements in the quality of family life despite stable HDI performance. In a rentier economy that is in a phase of economic transition, improvements related to youth employment, support for caregiving, health, housing, and work and family life could be more fruitful than improvements due to aggregated developments. In terms of overall contribution to the existing bodies of literature, the research has implications for methodological research related to the integration of machine learning forcasting techniques and analysis of welfare and quality of life for families within an oil-based economy, as well as for the broader substantive area related to theories of sustainable welfare, particularly in high-income societies with a rentier state-run economy.

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CRediT authorship contribution statement

All authors have participated in the design, implementation and writing of all sections of the present study**.**

Declaration of Generative AI and AI-assisted technologies in the writing process

All the substantive intellectual contributions, analyses, and conclusions were produced exclusively by the author, with absolutely no aid taken from AI tools.

Conflict of interest

The author declares no conflict of interests regarding this research.

Ethical considerations

The author confirms that this research was conducted in accordance with academic integrity standards. The study avoided data fabrication, falsification, plagiarism, and any form of research misconduct. As the study was based exclusively on secondary data sources, no ethical approval was required.

Data availability statement

The data used in this study were obtained from publicly available secondary sources. Any processed data supporting the findings of this study are available from the author upon a reasonable request.

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References

Afiani, N. (2024). The key to a quality life. *Jurnal Research of Service Administration Health and Sains Healthys, 5*(1).

Brown, I., & Brown, R. I. (2003). *Quality of life and disability: An approach for community practitioners*. Jessica Kingsley Publishers.

Campisi, G., Muzzioli, S., & De Baets, B. (2024). A comparison of machine learning methods for predicting the direction of the US stock market on the basis of volatility indices. *International Journal of Forecasting, 40*(3), 869–880. https://doi.org/10.1016/j.ijforecast.2023.04.005

Chavas, J.-P., Menon, M., Pagani, E., & Perali, F. (2018). Collective household welfare and intra-household inequality. *Theoretical Economics, 13*(2), 667–696. https://doi.org/10.3982/TE2459

Chekouri, S. M., Benbouziane, M., & Chibi, A. (2017). Oil rents and institutional quality: Empirical evidence from Algeria. *Topics in Middle Eastern and North African Economies*, *19*(2), 1–32.

Chen, Z., & Fan, W. (2021). A freeway travel time prediction method based on an XGBoost model. *Sustainability, 13*(15), 8577. https://doi.org/10.3390/su13158577

Cummins, R. A. (2000). Objective and subjective quality of life: An interactive model. *Social Indicators Research*, *52*(1), 55–72. https://doi.org/10.1023/A:1007027822521

Diener, E. (2009). *Assessing well-being: The collected works of Ed Diener*. Springer. https://doi.org/10.1007/978-90-481-2354-4

Farzanegan, M. R., & Thum, M. (2020). Does oil rents dependency reduce the quality of education? *Empirical Economics, 58*(4), 1863–1911. https://doi.org/10.1007/s00181-018-1548-y

Felce, D., & Perry, J. (1995). Quality of life: Its definition and measurement. *Research in Developmental Disabilities*, *16*(1), 51–74. https://doi.org/10.1016/0891-4222(94)00028-8

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics, 29*(5), 1189–1232. https://doi.org/10.1214/aos/1013203451

Goldani, M., & Asadi Tirvan, S. (2024). Sensitivity assessing to data volume for forecasting: Introducing similarity methods as a suitable approach in feature selection methods. *arXiv e-prints*. https://doi.org/10.1007/s11205-024-03377-8

Hachemaoui, M. (2012). Does rent really hinder democracy? A critical review of the "rentier state" and "resource curse" theories. *Revue française de science politique, 62*(2), 207–230. https://doi.org/10.3917/rfsp.622.0207

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting, 22*(4), 679–688. https://doi.org/10.1016/j.ijforecast.2006.03.001

Mehidi, K., & Oukaci, K. (2025). Oil rents and income inequality: The moderating role of institutional quality in oil-rich developing countries. *Central European Journal of Economic Modelling and Econometrics, 17*(1), 111–130. https://doi.org/10.24425/cejeme.2025.152864

Mitchell, J. S., & Gengler, J. J. (2019). What money can't buy: Wealth, inequality, and economic satisfaction in the rentier state. *Political Research Quarterly, 72*(1), 75–89. https://doi.org/10.1177/1065912918776128

Nugroho, A., & Wulandhari, O. (2023). The effect of household income and consumption on family welfare with lifestyle as a moderating variable. *International Journal of Applied Finance and Business Studies, 12*(2), 81–92.

Pourghadiri, B. E. (2012). *Inequality and the rentier state: Vertical and horizontal inequality patterns in Iran* [Unpublished doctoral dissertation]. SOAS, University of London. http://eprints.soas.ac.uk/17359/

Rashidi Chegini, K., Pakravan-Charvadeh, M. R., Rahimian, M., & Gholamrezaie, S. (2021). Is there a linkage between household welfare and income inequality and food security to achieve sustainable development goals? *Journal of Cleaner Production, 326*, 129390. https://doi.org/10.1016/j.jclepro.2021.129390

Resico, M., & Solari, S. (2019). Rentier capitalism as structural corruption and its impact on development and inequality: An ordoliberal approach. In *Proceedings of the WINIR Conference* (Lund, Sweden).

Roxana, P. (2013). Family life: Component of quality of life. *Procedia – Social and Behavioral Sciences, 82*, 266–270. https://doi.org/10.1016/j.sbspro.2013.06.256

Schalock, R. L., & Verdugo, M. A. (2002). *Handbook on quality of life for human service practitioners*. American Association on Mental Retardation.

Tan, A. H. T. (2021). Is the Human Development Index still appropriate for the assessment of quality of life? In *Quality of Life* (pp. 1–17). CRC Press. https://doi.org/10.1201/9781003183501-1

Yusof, Z., Ayob, M., Amran, A., & Norizan, F. (2020). Factors that influence the quality of life among undergraduate School of Quantitative Sciences (SQS) students in Universiti Utara Malaysia (UUM). *Malaysian Journal of Social Sciences and Humanities (MJSSH), 5*(9), 39–48. https://doi.org/10.47405/mjssh.v5i9.475