REPORT

Future-Oriented Search Behavior and Economic Development

Group-11

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Foundations of Computational Social Science

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1. Motivation

Economic development is often approached through structural indicators such as investment, education, and technological infrastructure, which are commonly used to explain cross-national differences in GDP per capita (Preis et al. 2012, pp. 1-2; Varian 2014, pp. 7-9). However, structural indicators alone may miss how collective expectations and planning horizons relate to economic outcomes.

Future orientation describes the extent to which individuals or societies direct attention and planning toward the future. From a sociological perspective, the capacity to plan ahead is unequally distributed and shaped by social and economic conditions. (Becker & Mulligan 1997, pp. 730-732; Haushofer & Fehr 2014, pp. 862-865)

Becker and Mulligan argue that future orientation is economically relevant because valuing the future increases incentives to invest in education, skills, and capital. They also stress that time preferences are shaped by social and institutional environments rather than being purely individual traits (Becker & Mulligan 1997, pp. 730-732). Conversely, Haushofer and Fehr show that poverty and economic insecurity can reduce long-term planning by increasing cognitive and emotional strain (Haushofer & Fehr 2014, pp. 862–865). This implies that future orientation can be both a correlation of structural conditions and a potential channel through which they matter.

1.1 Measuring future orientation using digital search behavior

A key challenge is measurement. Survey measures are often limited in scale and comparability across countries. Digital trace data provides an alternative behavioral signal.

Preis et al. propose the Future Orientation Index (FOI) using Google search data. FOI is defined as the ratio of searches for a future year relative to a past year and is intended to capture how strongly a country's search behavior is oriented toward the future (Preis et al. 2012, pp. 1-2). Varian argues that search data can complement traditional economic indicators because it reflects timely, behavior-based information (Varian 2014, pp. 3-5).

1.2 Research question and contribution

This project examines whether future-oriented search behavior is associated with GDP per capita across countries. Because GDP per capita is strongly linked to structural determinants, the analysis controls for investment, internet access, and tertiary education to assess whether FOI adds explanatory value beyond established predictors.

Research question: Is future-oriented search behavior associated with GDP per capita across countries after accounting for investment, internet access, and education?

The aim is not to make causal claims but to evaluate the empirical usefulness and limits of FOI as a cross-national indicator.

2. Data Retrieval

This project combines digital search data with macroeconomic indicators to examine the relationship between future-oriented behavior and economic development at the country's level. This analysis draws on Google Trends data and indicators from the World Bank Open Data platform.

2.1 Google Trends data and the Future Orientation Index

Future-oriented behavior was operationalized using the Future Orientation Index (FOI) introduced by Preis et al. The FOI is based on aggregated Google search data and captures the relative attention directed toward the future compared to the past (Preis et al. 2012, pp. 1-2).

Following Preis et al. search interest for a future year and a past year was retrieved from Google Trends. In this project, searches for the years 2025 (future) and 2023 (past) were used. These years were selected because they are close to the present and reliably available in Google Trends, allowing the index to capture future-oriented attention embedded in current social and economic contexts rather than distant or speculative futures (Preis et al. 2012, p. 2).

The FOI was calculated as the ratio of search interest for the future year relative to the past year. Because Google Trends reports normalized rather than absolute search volumes, the index reflects relative differences in future orientation within countries and allows for cross-national comparison (Preis et al. 2012, pp. 1-2).

Google Trends was chosen because search data provides large-scale, behavior-based information that is generated independently of survey instruments and is less affected by social desirability bias. As Varian argues, online search data can complement traditional economic indicators by offering timely insights into collective interests and expectations (Varian 2014, pp.3-5).
Search interest data was retrieved via the Google Trends web interface, which provides publicly accessible, country-level search interest indices.

The analysis includes 30 countries for which comparable Google Trends data was available. This sample covers countries from multiple world regions, including Europe, North America, South America, Asia, and Africa and was constrained by data availability and consistency across all variables used in the analysis.

2.2 World Bank economic indicators

Macroeconomic indicators were obtained from the World Bank Open Data platform, which provides standardized measures suitable for cross-national comparison.

The main outcome variable is GDP per capita, used as an indicator of average economic development. In addition, three structural control variables were included: gross capital formation as a measure of investment, internet users as a percentage of the population as an indicator of digital infrastructure and tertiary education enrollment as a proxy for human capital.

These variables capture key structural characteristics commonly associated with economic development and time-related behavior, as emphasized by Becker and Mulligan's discussion of investment and future-oriented behavior and by Haushofer and Fehr's analysis of economic insecurity and planning horizons (Becker & Mulligan 1997, pp. 730-732; Haushofer & Fehr 2014, pp. 862-865).

For each indicator, annual data was retrieved from the World Bank database and averaged over a five-year period to reduce short-term fluctuations and measurement noise, resulting in a more stable representation of underlying structural conditions.
World Bank indicators were accessed through the World Bank Open Data platform and downloaded into tabular format for further analysis.

3. Data Processing

Data processing was conducted to ensure comparability across countries and variables and to prepare the dataset for statistical analysis.

3.1 Processing of World Bank indicators

World Bank indicators were processed in a standardized manner. Annual data for the years 2019 to 2023 was extracted for each variable where available. For each country, values were converted to numeric format and averaged across years, resulting in one mean value per indicator.

To enable merging across datasets, country names were harmonized. The differences in naming conventions between Google Trends and World Bank data were manually corrected. Countries with missing values for any of the variables were excluded, resulting in a final sample of 30 countries.

3.2 Computation of the Future Orientation Index

The Future Orientation Index was computed separately for each country using Google Trends data. Search interest values for the years 2023 and 2025 were extracted, converted to numeric format, and averaged within each year.

The FOI was calculated as the ratio of average search interest for 2025 relative to 2023. Countries with missing or invalid search data were excluded from further analysis. This procedure follows the approach proposed by Preis et al. and focuses on relative future-oriented attention rather than absolute search volume (Preis et al. 2012, pp. 1-2).

3.3 Merging and normalization

After processing all variables, the FOI and World Bank indicators were merged using country names as a common identifier. Only countries with complete data across all variables were retained.

Prior to regression analysis, all variables were standardized using z-scores. This normalization step ensures that variables measured on different scales are directly comparable and allows regression coefficients to be interpreted in terms of relative associations.

4. Analysis

This section presents the statistical analyses and visualizations used to assess whether future-oriented search behavior, measured by the Future Orientation Index (FOI), is associated with GDP per capita.

4.1 Bivariate relationships

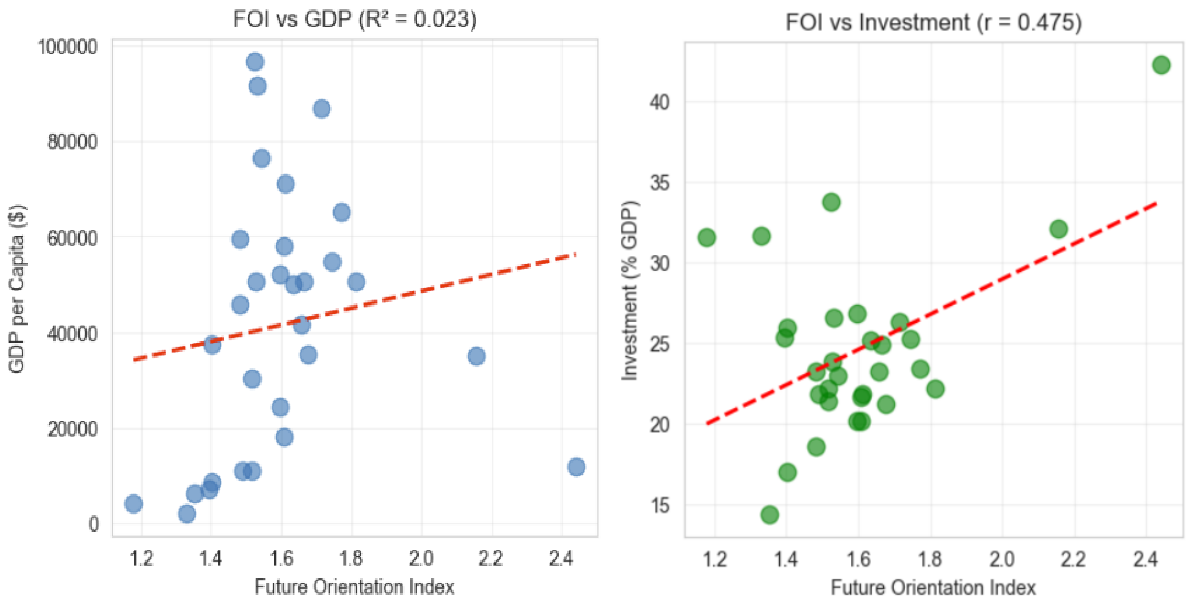

Figure 1. Bivariate relationships between the Future Orientation Index (FOI) and key economic variables.
(a) Relationship between FOI and GDP per capita.
(b) Relationship between FOI and investment, measured as gross capital formation as a percentage of GDP.

Figure 1a displays the relationship between FOI and GDP per capita. The scatterplot shows a wide dispersion of countries and no clear linear pattern. Countries with similar FOI values differ substantially in their GDP per capita. The very low R^2 value ($R^2 = 0.023$) indicates that FOI alone explains only a negligible share of cross-national variation in GDP per capita.

Figure 1b shows the relationship between FOI and investment, measured as gross capital formation as a percentage of GDP. In contrast to GDP per capita, FOI exhibits a moderate positive association with investment ($r = 0.475$), suggesting that future-oriented search behavior is more closely related to investment activity than to income levels.

4.2 Multivariate regression results

Figure 2. Multivariate regression results explaining GDP per capita.
(a) Comparison of regression models using R^2 values.
(b) Standardized regression coefficients from the full regression model.

Figure 2 summarizes the multivariate regression results. Models including only FOI explain almost none of the variation in GDP per capita (Figure 2a). Structural control variables substantially increase explanatory power, with the largest improvement occurring when education is included. The standardized coefficients show that internet access, investment, and education are positively associated with GDP per capita, while FOI has a smaller and negative coefficient once structural factors are taken into account (Figure 2b).

4.3 Model diagnostics and correlation structure

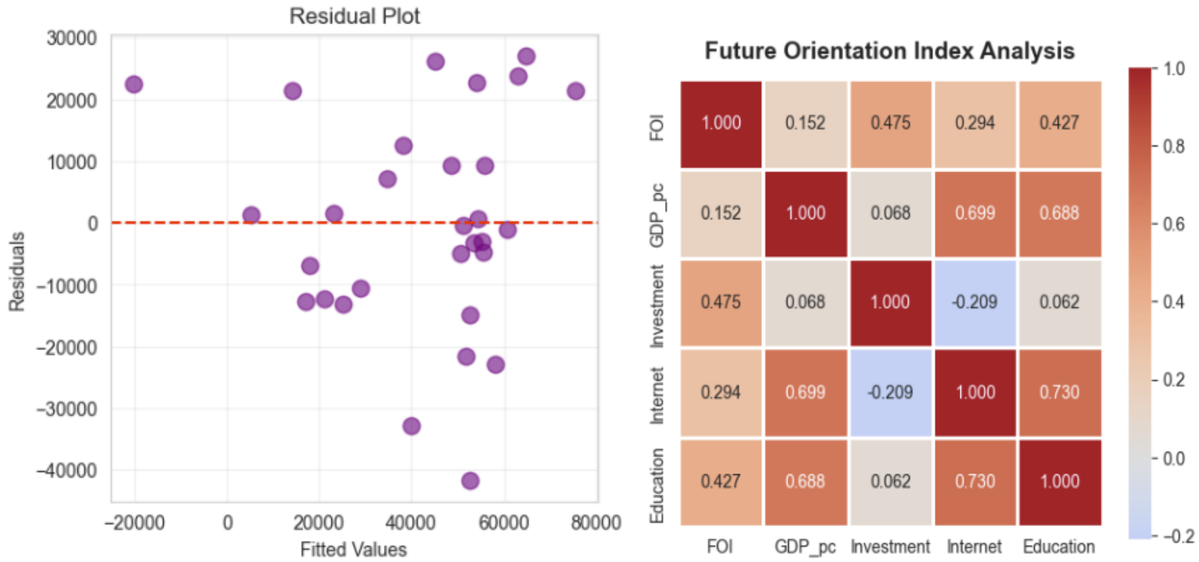

Figure 3. Model diagnostics and correlation structure.
(a) Residuals plotted against fitted values from the full regression model.
(b) Correlation heatmap showing pairwise Pearson correlations between all variables used in the analysis.

Figure 3 provides additional information on model diagnostics and the relationship between variables. The residual plot shows no clear systematic pattern, indicating no major violations of linear regression assumptions (Figure 3a). The correlation heatmap highlights strong correlations between GDP per capita, internet access, and education, while FOI shows only weak correlations with GDP per capita and moderate correlations with investment and education (Figure 3b).

5. Conclusion

This study examined whether future-oriented search behavior, measured by the Future Orientation Index (FOI), is associated with GDP per capita across countries, and how this relationship changes once structural factors are taken into account.

Across both descriptive and multivariate analyses, FOI shows only a very weak direct association with GDP per capita. The bivariate relationship between FOI and GDP per capita is small ($R^2 \approx 0.02$) and statistically insignificant, indicating that future-oriented search behavior alone does not meaningfully explain cross-national income differences. This finding is consistent with previous research suggesting that search-based indicators primarily reflect patterns of attention rather than direct economic outcomes (Preis et al. 2012, pp. 2-3; Choi & Varian 2012, p. 5).

In contrast, the structural control variables explain a substantial share of the variation in GDP per capita. Investment intensity, internet access, and tertiary education are strongly interrelated and show robust positive associations with GDP per capita, as reflected in both the correlation structure and the controls-only regression model ($R^2 \approx 0.54$). These results align with established growth literature emphasizing capital accumulation, human capital, and technological infrastructure as central components of economic development (Varian 2014, pp. 7-9).

Including FOI in the full regression model leads to only a marginal improvement in model fit. This suggests that FOI does not add substantial explanatory power beyond conventional structural determinants. Rather than acting as an independent driver of economic development, FOI appears to capture a complementary behavioral dimension related to societal orientation toward the future. Similar interpretations have been proposed in prior work using Google search data, which emphasizes the contextual and interpretive nature of such indicators (Preis et al. 2012, p. 4; Varian 2014, p. 10).

Overall, the findings support a cautious interpretation of future-oriented search behavior. While FOI shows moderate correlations with investment and education, its direct relationship with GDP per capita remains weak and sensitive to model specification. The reliability of the results is further limited by the small sample size and the cross-sectional design. Nevertheless, the analysis demonstrates that FOI can be meaningfully integrated into quantitative models as a behavioral complement to structural indicators, rather than as a substitute for them.

6. Critique

This project relies on digital trace data and cross-national indicators, which provides valuable analytical opportunities but also entails several important limitations.

A central limitation concerns the measurement of future orientation. The Future Orientation Index is derived from Google search behavior and captures relative attention to future versus past years. While this approach follows Preis et al., it remains an indirect proxy for societal time orientation. Search behavior may be influenced by short-term events, media dynamics, or institutional calendars rather than stable future-oriented attitudes (Preis et al. 2012, pp. 3-4). In addition, Google Trends reports normalized rather than absolute search volumes, which limits interpretability and comparability across countries.

A second limitation relates to digital inequality. Search-based indicators depend on internet access and digital infrastructure. As emphasized by Varian, such data is informative only where internet usage is widespread and relatively comparable (Varian 2014, pp. 7-10). In this analysis, internet access is strongly correlated with GDP per capita and education, raising the possibility that FOI partly reflects differences in digital access rather than future orientation itself. The unstable and negative FOI coefficient in the full regression model supports this concern.

Third, the cross-sectional design restricts causal inference. The analysis cannot determine whether future-oriented behavior influences economic outcomes or whether economic and institutional conditions shape future-oriented search behavior. Prior research suggests that economic insecurity can reduce long-term planning capacities, indicating potential reverse or bidirectional causality (Haushofer & Fehr 2014, pp. 862-865).

Finally, the relatively small sample size and country selection limit the generalizability of the findings. The analysis includes 30 countries and excludes contexts with low internet penetration, which may bias results toward more developed settings.

Overall, these limitations suggest that FOI should be interpreted cautiously. Rather than serving as an independent explanatory factor, future-oriented search behavior appears to function as a complementary indicator that reflects broader structural and institutional conditions (Preis et al. 2012, p. 4).

GitHub

https://github.com/TrinishRocky/Group-11

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