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Seeking Forward, Looking Forward: A Replication and Generalization of the Future Orientation Index Utilizing Baidu Index

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Search interest in the upcoming year compared with the past has been proposed as the Future Orientation Index (FOI) to assess forward-looking tendencies. Our study aimed to replicate and extend correlations between the FOI and key development indicators, such as GDP and Human Development Index (HDI), across countries with different dominant search engines (from Google to Baidu), time periods (from 2012 to 2021), and measurement levels (inter-country, intra-country, and individual). Our results successfully replicated the correlation between the Baidu-based FOI and province-level GDP (r = .719–.860, ps < .001) and HDI (r = .635–.867, ps < .001) from 2012 to 2021 in China. However, the FOI could not predict patience (β = −.038, p = .402) measured at an individual level. Our findings provide an easily accessible index to investigate intra-cultural differences in future orientation and underscored two prerequisites for the FOI: 1) the selection of a locally dominant search engine and unambiguous keywords and 2) the application of the FOI within a group-level context.

1. Introduction

As a fundamental concept in decision-making, future orientation is a predominant focus on the future (Nuttin & Lens, 1985) that emphasizes the extent to which thinking and behavior are directed toward the future (Gjesme, 1979). Future orientation may encompass not only people's motivations and thoughts (e.g., expectations of future goals) but also their future-oriented behaviors (e.g., exploration of the future through information gathering) based on the three-component model (Seginer, 2000). Higher future orientation can benefit individuals by increasing self-regulation and long-term planning, as well as delaying gratification (Johnson et al., 2014; Strathman et al., 1994).

Future orientation has been a widely used variable for over 50 years, and it shares similarities with several psychological constructs although it remains distinct from them. For instance, as a broader concept, the future time perspective is closely related to future orientation. Previous reviews have even defined future orientation as a sub-dimension of this overarching concept (Kooij et al., 2018). Additionally, both future orientation and prospection involve future-oriented thinking. However, future orientation focuses more on the degree to which an individual's thoughts and behaviors are directed toward the future (Gjesme, 1979), whereas prospection refers to the cognitive ability to represent possible future events mentally (Szpunar et al., 2014).

Considering its importance and benefits, a growing body of research has focused on developing diverse measurements or indices for future orientation grounded in various theories and concepts. A key distinction among these measurements is the level of analysis: individual-level measurements may aim to capture individual differences in future orientation, while group-level measurements are designed to measure variations among different groups or countries. Most *individual-level* measurements are based on self-reported scales. For example, the Future Time Orientation Scale (Gjesme, 1979) assesses the general capacity to anticipate the future at an individual level, while the Future Time Perspective Scale (Hershey & Mowen, 2000) measures individual-level future orientation based on the extent to which individuals plan for or enjoy thinking about the future (for a review, see Kooij et al., 2018, Table 1). However, some researchers have conceptualized future orientation as a cultural value (Hofstede & Minkov, 2010) and used *group-level* measures to assess it at the country level. For instance, the score on the long-term orientation subscale of the Val-

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ues Survey Module may be aggregated as an average to represent the future orientation of a country or religion (Hofstede et al., 2011). It is crucial to note that measurements at different levels should not be conflated: the aggregate-level measure is not suitable for individual-level research, such as comparing individual differences or measuring individual-level traits (Bond et al., 2002; Hofstede et al., 2011).

Unlike the self-report measurements mentioned before, Preis et al. (2012) innovatively developed the Future Orientation Index (FOI), which utilizes online search data of countries extracted from Google Trends (https://trends.google.com). Practically, the FOI assesses country-level future orientation by quantifying the extent to which Internet users seek information about the future rather than the past, i.e., the ratio of searches made for the coming year (e.g., 2025) to searches made for the previous year (e.g., 2023). In line with the definition of future orientation—especially its behavioral component (Seginer, 2000)—this index assesses future orientation by quantifying people's interest in searching about the future (i.e., future-oriented information seeking). Comparing the FOI of 45 countries and corresponding per capita GDP, the results showed that countries with higher FOI (i.e., seeking more about the future on Google) possess larger per capita GDP ($r = 0.78$, Preis et al., 2012). This strong correlation not only provides a strong correlation between the economic development level and future-oriented behavior at the country level but also reveals that a country's economic prosperity can be reflected in the online information-seeking behavior of its citizens. This research garnered tremendous academic and public attention: amassing over 255 citations on Google Scholar (as of August 2024) and being featured in prominent media, such as *The Guardian* (Sedghi, 2013).

Due to its unique and effortless data source, and compared with traditional assessments that solely rely on participant self-reports, the FOI has several inherent strengths in convenience and effectiveness. Through the freely available data of the Google Trends website, the FOI eliminates the need for administering questionnaires, making it significantly more accessible and cost-effective. Moreover, by relying on behavioral indicators from billions of Google users, the FOI results in less potential sampling bias compared to measurements based on questionnaires. Thus, FOI has emerged as a widely utilized measure for investigating the relationship between future orientation and features across various research domains, especially in cross-cultural contexts (Shepard & Turner, 2019), e.g., intertemporal decision preference (Burro et al., 2022), fertility (Cavalli, 2020), income taxes (Petutschnig, 2017), and environmental policy performance (Schaub, 2022).

However, due to its convenient data source, previous studies have directly calculated FOI from Google Trends without verifying its prior stability or efficacy. After over a decade of its use, it is appropriate to revisit the replicability of the FOI, especially its correlation with GDP, while examining the following key aspects:

1) Stability and generalizability of the FOI across countries with different dominant search engines. To the best of our knowledge, the majority of existing research has primarily relied on Google Trends to calculate FOI [Burro et al. (2022); Cavalli (2020); Schaub (2022)]. However, Google search data may fail to cover the trends of citizens' online behavior in certain non-Western/Educated/Industrialized/Rich/Democratic (WEIRD) countries where Google is not the dominant search engine. For instance, in China, Baidu is the dominant search engine, while Russia primarily uses Yandex, and South Korea primarily uses Naver. These countries also play important roles in the global economy and politics. Taking China as a non-WEIRD example (Henrich et al., 2010), Baidu (rather than Google) is the dominant search engine, holding a 59% share of the Chinese search engine market, and Google accounting for a mere 2% share (StatCounter, 2023). Thus, solely relying on Google Trends data in China to calculate FOI may introduce substantial sampling bias, as well as significant distortions and inaccuracies. This limitation was particularly evident given the contradiction between different measurements of country-level future orientation data. As measured by questionnaires, China ranks among the *most* future-oriented (i.e., long-term oriented) countries according to Hofstede's Cultural Dimensions Theory (Hofstede & Minkov, 2010), while measurement by the FOI, has China rated as one of the *least* future-oriented countries (41 out of 45) in the study of Preis et al. (2012). Therefore, to obtain a more representative FOI in these counties, a more suitable approach would be to calculate the index based on local search engine data (e.g., Baidu in China) and subsequently investigate the stability and replicative ability of the FOI, as well as its relationship with GDP, across countries with different dominant search engines, before its practical application.

2) Generalizability of the FOI across levels. It is also valuable to explore the efficacy of the FOI as a comprehensive tool to capture the variations of future orientation across different levels: from variables measured at the inter- to intra-country levels down to the individual level. Originally proposed as a country-level index, the FOI has mostly been utilized to examine variations in future orientation between countries. However, emerging research has shed light on notable differences in future orientation within cultures (Falk et al., 2018) and among individuals (Steinberg et al., 2009). Research has shown that these cultural heterogeneities within countries can be as significant, or even more significant, than inter-country variation (Falk et al., 2018). Recently, increasing studies have attempted to develop indices to quantify intra-country cultural differences in China. However, the majority of these efforts have focused on variations in the dimensions of tightness/looseness (Zhang et al., 2023) or individualism/collectivism (Gong et al., 2021), leaving a deficiency of available resources to capture the multifaceted aspects of future orientation within cultures.

To fill these gaps, the current study conducted a concept replication and exploratory generalization of the original study conducted by Preis et al. (2012). The original research tested the correlation between the FOI (based on Google Trends) and per capita GDP among 45 countries from 2008 to 2010. Consistent with this approach, we also collected the FOI and correlated it with the per capita GDP among the 31 provinces in China. Our study differs from the original research in three ways: first, to test the stability and generalizability of FOI across search engines, we used the dominant local search engine (i.e., Baidu) to calculate the FOI; second, to test the temporal stability of the correlation between FOI and GDP, we collected data from 2012 to 2021; and third, to test the generalizability of the FOI across measurement levels, we tested the correlation between the Baidu-based FOI and other variables related to future orientation, such as patience and delay discounting, measured at an individual level.

2. Methods

2.1. Data collection

Data collection occurred in three parts: calculation of the FOI, collection of the province-level data, and collection of the individual-level data.

2.1.1. Calculation of the FOI

FOI calculation followed the original formula proposed by Preis et al. (2012), which is the ratio of the volume of searches made for the coming year (represented in Arabic numerals) to the volume of searches for the previous year. To extend the original FOI protocol and test the stability of the FOI across search engines, the volume of searches was quantified by Baidu Index (a search index based on the biggest local search engines in China), rather than Google Trend. Taking the calculation of the FOI for 2018 as an example, the formula was as follows:

$$FOI_{2018} = \frac{Baidu\ Index\ for\ \text{“2019”}\ during\ 2018}{Baidu\ Index\ for\ \text{“2017”}\ during\ 2018}$$

Next, to show the robustness of the FOI across time periods, we obtained the Baidu-based FOI for the past decade. Because the earliest available Baidu Index started in 2011, the FOI was calculated from 2012 to 2021. The year 2013 was excluded as an outlier because the related previous year 2012 was also the name of a famous movie, which may have distorted regular patterns (see Supplementary Materials). All Baidu Index data across 31 provinces were extracted from https://index.baidu.com. To ensure Baidu Index data was free of typos or mismatches, an independent researcher cross-verified all extracted data and made necessary corrections (see Supplementary Materials for more detailed information about the cross-verification process).

2.1.2. Province-level data

Consistent with the previous study (Preis et al., 2012), per capita GDP was used to reflect the level of economic development across 31 provinces from 2012 to 2021. The data on per capita GDP were collected from the China National Bureau of Statistics (https://data.stats.gov.cn/).

In addition to per capita GDP, we added the human development index (HDI) as a more comprehensive assessment of development levels across provinces. HDI was defined as an average of achievements in three dimensions: health, education, and standard of living (Klugman et al., 2011). HDI data (Smits & Permanyer, 2019) were collected from the Global Data Lab (https://globaldatalab.org/shdi/). The HDI data were available from 2012 to 2019.

Although our data focused on China, we also collected the per capita GDP of subregions in Russia and South Korea where Google is not the dominant search engine. Detailed information about the data of Russia and South Korea are presented in our Supplementary Materials.

2.1.3. Data measured at the individual level

We used a public dataset to test the correlation between the FOI and one psychological variable related to future orientation (patience) measured at the individual level.

The patience index was measured by the Global Preference Survey 2012 (GPS 2012) (Falk et al., 2018, 2022). The data of Chinese respondents in the GPS 2012 covered 25 provinces in mainland China (N = 2,574). All respondents completed the survey from April to May 2012. This public dataset measured a series of economic preferences and has been widely used by previous studies investigating individual differences in patience (Burro et al., 2022; Nieminen, 2022). The patience index (Falk et al., 2022) combines a measurement of delay discounting (i.e., five delay discounting questions asking the respondent to choose between an immediate and a delayed payment) and a self-assessment of willingness to wait, and it is calculated as follows: Patience index = 0.712 × delay discounting + 0.288 × self-assessment. These weights are based on the regression coefficients of observed behavior from an experimental validation study on responses to the respective items (Falk et al., 2016). A higher patience index suggests that the respondent is more patient and more willing to wait. Previous research has shown this index to have good test-retest reliability (r = .73). For more information about this measurement approach, see www.briq-institute.org/global-preferences and [Falk et al. (2022)].

In addition to the patience index, we also tested the correlation between the FOI and delay discounting using a different dataset (China Household Finance Survey). These results were mainly consistent and can be found in our Supplementary Materials.

2.2. Data analysis

Our data analysis plan also consisted of three parts: first, a descriptive analysis of the Baidu-based FOI was conducted to show the general distribution and intra-cultural differences in future orientation among provinces. Then, to test the stability of the FOI across search engines at an intra-country level, we attempted to replicate the positive correlation between the Baidu-based FOI and the economic development of provinces in China. Moreover, this replication was repeated using the data from the past decade to test whether this correlation was robust across the time period. Finally, to generalize the relationship between the FOI and city development to individual preference, we tested the predicting effect of the FOI on individual-level patience.

All analyses were conducted using R 4.0.3 (R Project for Statistical Computing). The following R packages or functions were used: *lm* and *lme4* (Bates et al., 2014) for linear (mixed) regression models, *lmrob* of *robustbase* (Maechler et al., 2023) for robust regression models, *ggplot2* (Wickham, 2011) for visualization, and *bruceR* (Bao, 2023) for presenting results. Significance levels for all analyses were set to 0.05. Because we aimed to replicate the *positive* correlation between FOI and economic development/patience/delay discounting, all correlation tests were one-tailed. We also used JASP (Love et al., 2019) and the R package *BayesFactor* (Richard et al., 2022) to calculate Bayes factors (BF_{10}) for our main analyses with the default prior. All raw data (including the FOI, province-level, and individual-level data) and R code for replicating our results are available at https://doi.org/10.57760/sciencedb.psych.00302.

2.2.1. Description of the FOI

For the descriptive analysis, we aggregated the FOI from 2012 to 2021 by mean for each province. The five highest-FOI and lowest-FOI provinces were listed. To geographically show FOI differences among different provinces, we drew an FOI map. Then, according to the geographic division of China (National Bureau of Statistics, 2020), we tested regional differences among three regions (i.e., Eastern, Central, and Western[1]) using a linear mixed model with year and city as random intercepts. Additionally, to compare the dispersion level of the FOI across the latest decade, we calculated the coefficient of variation (*CV*) of the FOI for each year using the formula *CV* = *SD/M*.

2.2.2. Correlation with province-level GDP/HDI

For each year, a pairwise correlation with FOI and two province-level variables (i.e., per capita GDP and HDI) was tested. In light of the small sample size (i.e., 31 pairs of data points) of the correlation test, a robust regression based on an M-estimator using iteratively reweighted least squares estimation (Field & Wilcox, 2017; Koller & Stahel, 2011) was also conducted as a robustness check in addition to the simple correlation. To directly view the data distribution, each correlation between the FOI and GDP (or HDI) was accompanied by a scatterplot.

2.2.3. Correlation with patience measured at the individual level

For the patience index in GPS 2012, a total of 202 respondents were excluded for being under 18 years of age or answering incompletely with missing values. After data cleaning, 2,372 respondents were considered valid for future analysis. We then aggregated the patience at a province level (mean value of the patience index) and tested its correlation with the FOI (in 2012). Aggregated values for each province can be found in our Supplementary Materials.

In addition to the correlation, we also used a hierarchical linear model to test the relationship between province-level FOI and patience (i.e., without province aggregation). This model showed similar results to our other models and can be found in Supplementary Materials.

3. Results

3.1. Descriptive results of the FOI across provinces

Table S1 lists FOI for each province from 2012 to 2021. Figure 1 provides an FOI map that details regional differences in FOI and lists provinces with the highest (or lowest) FOI.

These observed systematic differences in FOI across provinces showed an intra-cultural variation of future orientation in China. Specifically, Eastern China (e.g., Shanghai, Zhejiang, $M \pm SD$ = 0.981 ± 0.136) had significantly higher FOI than Central (e.g., Shanxi, Jilin, $M \pm SD$ = 0.826 ± 0.055, p = .008, BF_{10} = 6.24) and Western China (e.g., Tibet, Gansu, $M \pm SD$ = 0.791 ± 0.086, p < .001, BF_{10} > 100). Further, the degree of this intra-cultural variation was stable (*CV* ranges from 0.13 to 0.21), without an observable increasing (or decreasing) trend from 2012 to 2021. These results suggest that the Baidu-based FOI can detect regional differences among Chinese provinces.

3.2. Correlation with province-level GDP/HDI

According to correlation analyses, FOI and GDP (or HDI) were highly correlated (Table 1) through the decade (*p*s < .001, BF_{10} > 100, *r*s ranging from .72 to .87), suggesting that, at the province level, a higher FOI was related to a higher GDP and HDI. Robust regressions also consistently showed a significantly positive relationship between the FOI and GDP (or HDI), providing evidence for the stability of the correlation results. The year 2019 was taken as an example to plot a visualized scatterplot (Figure 2); scatterplots for all other years are shown in Figures S1 and S2. Consistent with the study of Preis et al. (2012), these results replicated that provinces may benefit from higher FOI, both in economic development (i.e., GDP) and generalized city development (i.e., HDI).

We also used Google Trends to calculate province-level FOI and tested its correlation with GDP/HDI (see Supplementary Materials). Consistent with our argument, the Google-based FOI performed worse than the Baidu-based FOI in China. The correlation with GDP was much weaker; most correlations were non-significant and even negative

1 Eastern: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; Central: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; Western: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

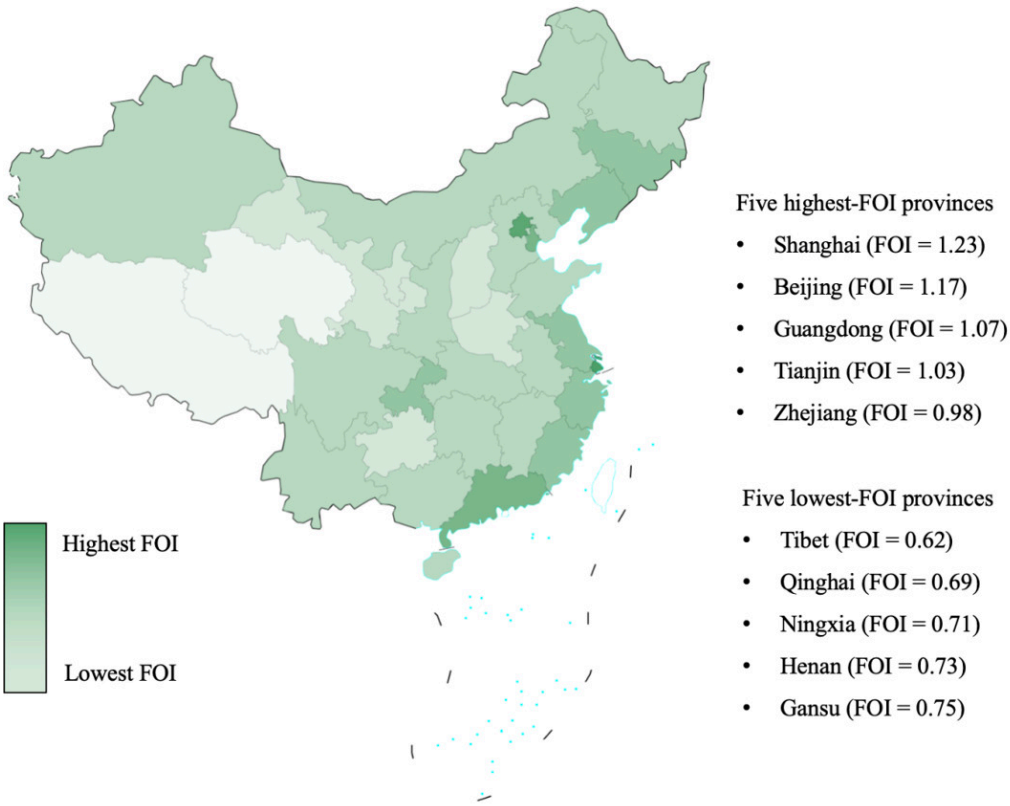

Figure 1. A FOI map of Chinese provinces. FOI used in this map is aggregated by mean from 2012 to 2021 (excluding 2013) for each province. Deeper/lighter green represents a higher/lower FOI. The white area represents areas excluded from the study. The five provinces with the highest/lowest FOI are listed on the right side.

Table 1. Relationship between Baidu-based FOI and GDP/HDI from 2012 to 2021 in China.

Year	Baidu-based FOI and GDP		Baidu-based FOI and HDI	
	Correlation (*r*)	Robust regression (β)	Correlation (*r*)	Robust regression (β)
2012	.785	.821	.852	.835
2014	.739	.742	.867	.844
2015	.822	.805	.851	.830
2016	.771	.610	.866	.865
2017	.848	.832	.790	.730
2018	.719	.686	.801	.773
2019	.860	.858	.848	.794
2020	.828	.829	/	/
2021	.749	.678	/	/

Note: *r*, the correlation coefficients between the Baidu-based FOI and GDP/HDI; β, the standardized regression coefficients from the robust regression using FOI to predict GDP/HDI. All coefficients were significant at $p < .001$ and with extreme evidence from $BF_{10} > 100$. The results of the FOI and HDI were missing for 2020 and 2021 because HDI data were not accessible.

for some years. The Google-based FOI also resulted in inexplicable missing values for some provinces. Additionally taking the year 2019 as an example, Figure 2 shows that there was significant deviation between the Baidu-based FOI and the Google-based FOI (r = .030, p = .876, BF_{10} = 0.282) and that, more importantly, the relationship between the Google-based FOI and GDP/HDI was weak (r = .221/.130, p = .247/.500, BF_{10} = 0.431/0.282) with a much wider error bar. The Google-based FOI also did not perform well in Russia and South Korea (see detailed report in our Supplementary Materials): the correlation between Google-based FOI and subregional GDP was much weaker than that

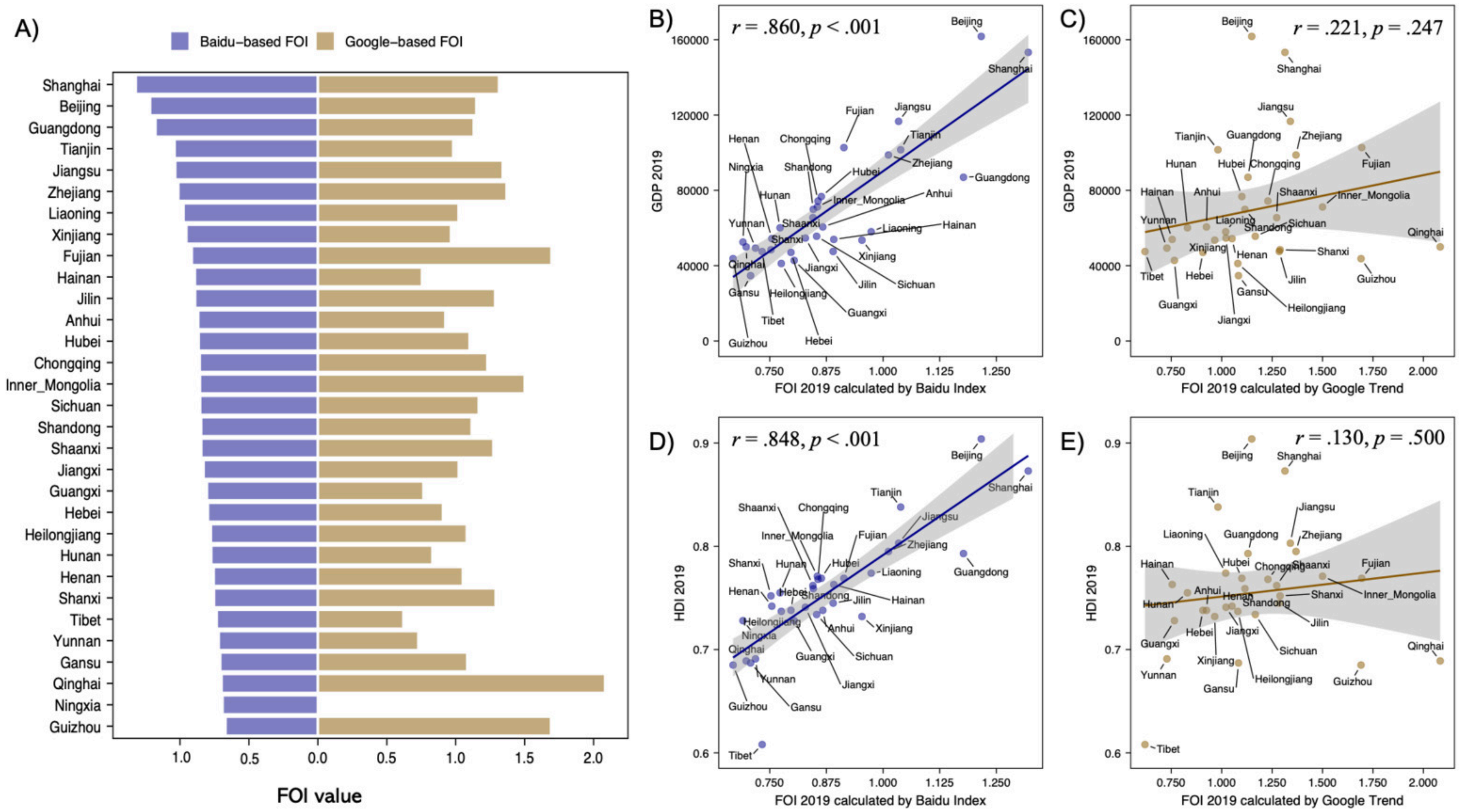

Figure 2. (A): FOI of Chinese provinces in 2019 calculated by Baidu Index (blue bar) and Google Trends (brown bar). The order of the provinces was sorted by Baidu-based FOI. Google-based FOI for Qinghai Province was missing. (B & D): Scatterplots between the Baidu-based FOI and GDP/HDI of Chinese provinces in 2019. (C & E): Scatterplots between the Google-based FOI and GDP/HDI of Chinese provinces in 2019. Each dot represents a province in China and is labeled with the province name. The trendline (blue for Baidu-based and yellow for Google-based) represents the fitted regression line, and the error bar represents the 95% confidence intervals.

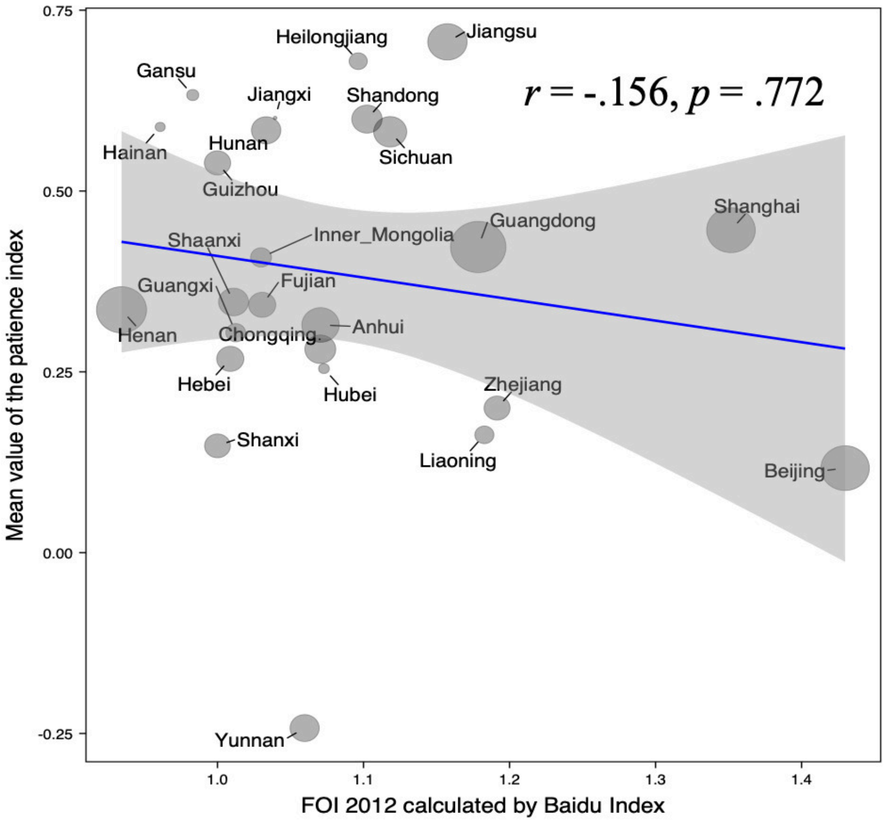

Figure 3. Scatterplots between Baidu-based FOI and the province mean of the patience index. Each dot represents a province in China and is labeled by the province name. The size of the dot represents the sample size of the province (i.e., a bigger dot means more respondents from that province). The trendline represents the fitted regression line, and the error bar represents the 95% confidence intervals.

reported in the original research in Russia (r = .293, p = .007; in the original research, the results reached r = 0.78) and was insignificant in South Korea (r = −.273, p = .306). Given that the correlation between Google-based FOI and GDP is weaker in countries where Google is not the dominant search engine, these results highlight the necessity of using local search engines rather than relying solely on Google.

3.3. Correlation with patience measured at individual level

Figure 3 shows that the results from the GPS 2012 did not support the positive correlation between the FOI and patience (r = −.156, p = .772, BF_{10} = 0.153). This result remained unchanged after controlling for the mean age and proportion of the female population in the province: the relationship between the FOI and patience (β = −.194, p = .400, BF_{10} = 0.735) remained negligible. For a deeper examination of the potential mechanism, we also tested the mediating effect of patience/delay discounting between FOI and GDP/HDI. However, none of the mediating effects were significant (see Supplementary Materials).

Surprisingly, these correlations did not support our hypothesis and were even opposite (negative) in direction. These results reveal a huge gap between easily obtained FOI and individual-level patience or delay discounting (even aggregated at the province level), which could be a weakness of the FOI. In other words, despite being solidly linked to province-level GDP/HDI, it remains difficult to apply FOI to variables measured at the individual level.

4. Discussion

The primary aim of the present study was to replicate and extend the findings of Preis et al. (2012) by exploring the correlation between a Baidu-based FOI and GDP/HDI at the province level in China, as well as the association between FOI and patience/delay discounting measured at the individual level. Our study consistently suggested that: 1) the correlation between the FOI and GDP reported in the study of Preis et al. (2012) is replicable across different search engines (from Google to Baidu); 2) the positive correlation between the Baidu-based FOI and GDP is stable across time period (from 2012 to 2021); and 3) the Baidu-based FOI may be valid at the inter-country or intra-country level but not at the individual level. These results showed the robustness and stability of the FOI as a convenient tool to quantify the future orientation at a country/province level and also highlighted the necessity to calculate FOI based on locally dominant search engines, as opposed to defaulting to using data reported by Google.

Despite the seemingly straightforward calculation of the FOI (solely based on the ratio of two search indices), our study found remarkably stable results, consistently indicating a positive correlation between the FOI and GDP/HDI. Notably, we successfully replicated this correlation across different search engines (using Baidu instead of Google) and over a span of time (from 2012 to 2021). Consistent with previous studies (Preis et al., 2012), these results add solid evidence to the association between the economic prosperity of a city and the online information-seeking behavior of its citizens. It is important to recognize that the FOI is primarily concerned with the behavioral components of future orientation (i.e., future-oriented behaviors). While this index may indirectly reflect future-oriented thinking or cognition, it does not necessarily capture the psychological states of individuals or countries.

These positive correlations between FOI and GDP should *not* be interpreted as evidence of a causal relationship (Preis et al., 2012). Here, we highlight the potential for a bidirectional relationship between FOI and GDP. On the one hand, greater economic success may result from more future-oriented behaviors (i.e., higher FOI may contribute to higher GDP), as a higher level of future orientation could drive greater long-term planning (Kooij et al., 2018) and also predict more innovative activities (Barreto et al., 2022), both of which can generate wealth and enhance economic development. Conversely, greater economic success may also create a more stable and secure environment, thus enabling individuals to focus more on thinking and planning for their future. This implies an alternative explanation: higher GDP may increase an individual's future orientation, and a higher FOI merely reflects (rather than contributes to) the underlying economic prosperity.

Beyond cross-country comparisons, our results also suggest that the Baidu-FOI can effectively capture province-level differences in future orientation within China. While most previous studies have primarily used FOI as a country-level measure (Burro et al., 2022; Preis et al., 2012; Schaub, 2022), our results extend the correlation between the FOI and GDP/HDI from an inter-cultural to an intra-cultural context. In China, although various intra-cultural differences have been identified [Gong et al. (2021); Talhelm et al. (2014); Zhang et al. (2023)], intra-cultural differences in future orientation (or long-term orientation) among provinces remain to be elucidated. Here, our results suggest that a Baidu-based FOI could be an effective and stable method to detect the intra-cultural variation of future orientation among Chinese provinces. It could not only reveal general regional differences (i.e., Eastern China showed higher future orientation than Central and Western China) but also precisely predict province development (i.e., strong positive correlations between the FOI and GDP/HDI). Based on our primary example of using a Baidu-based FOI to investigate intra-cultural differences, researchers in the field of cultural psychology can access the FOI from the open dataset (https://doi.org/10.57760/sciencedb.psych.00302) and use it to investigate any related hypotheses.

Despite these successful replications and extensions, our results failed to support the positive correlation between the FOI and individual's patience/delay discounting. Despite the gap between the FOI and future-related variables measured at the individual level, there may be alternative explanations for these insignificant results. First, these insignificant correlations (even negative in direction) may be related to a potential sampling bias in the measurement of patience. Specifically, there is a significant positive relationship between sample size from each province and its FOI/GDP (r = .516, p = .008), indicating that provinces with lower FOI/GDP are underrepresented. Moreover, as noted by Keidel et al. (2021), the relationship between future orientation and delay discounting may be complex and moderated by other psychological variables. Future research should consider incorporating additional variables that have not been controlled for in this study and exploring alternative variables, such as innovation (Barreto et al., 2022), to better explain the relationship between FOI and GDP.

Based on these results, we argued that our results may contribute to future research by highlighting the following two prerequisites when using FOI as a measurement of future orientation:

1) Choose a locally dominant search engine and unambiguous keywords to calculate FOI. Our comparison between the Baidu-based and Google-based FOI pointed out one notable concern for FOI: potential sampling bias caused by using a non-dominate search engine (e.g., Google in China or Russia). From our results, the correlation between the FOI and GDP/HDI among Chinese provinces can be heavily distorted (only significant in 2012) when using data from Google Trends as a non-dominant search engine. Indeed, prior research has reminded us of the importance of considering potential disparities between distinct online platforms in the realm of online behavior analysis. For instance, studies have highlighted notable systematic distinctions between Weibo and Twitter as two microblogging services (Gao et al., 2012). Thus, we strongly emphasize the importance of a crucial prerequisite for using FOI to capture future orientation differences: basing data on a search engine that is dominant in the respective country. Researchers must remain cognizant of the nuances of specific search engines and be diligent in choosing a suitable data source (not necessarily a default to Google Trends) to calculate FOI and exercise caution when interpreting previous results obtained from a potentially biased FOI.

Moreover, another concern about FOI is its susceptibility to ambiguity, especially when Arabic numerals are used in search queries that have multiple meanings. For instance, we observed this issue with search data from 2012, which can refer to both the calendar year and the popular Hollywood movie titled *2012*. This ambiguity could also lead to biased FOI scores and distort its relationship with GDP/HDI.

2) Use the FOI as an aggregate-approach, group-level (but not individual-level) measurement for future oriented behaviors. Previous reviews have pointed out that the level of analysis should be a primary concern when using online query data (Lai et al., 2017): most analyses of these data are limited to the group level, and caution is advised when applying them to the individual level. Echoing this, our results found that although FOI is useful in capturing differences in future orientation at the provincial (intra-country) level, its correlation with individual-level variables, such as patience or delay discounting, was found to be weak. This lack of a significant relationship between the FOI and patience or delay discounting measured at the individual level aligns with previous research findings (Burro et al., 2022).

These results highlight the importance of distinguishing between individual-level and group-level measurements of future orientation. Negligible correlations with individual-level variables could be a common issue for group-level measurements of future orientation. As noted by Hofstede and Minkov (2013) in their Values Survey Module (another measurement for country-level culture differences), country-level correlations can differ significantly from individual-level correlations. They even stated that a country-level cultural variable is not suitable and should never be used for comparing individuals.

To highlight the applicable aspects, we argue that the FOI based on online search data should be considered as a group-level measurement of future orientation. As such, it shares the limitations of other group-level measurements: it is only suitable for comparing or describing group differences, not for any individual-level purposes. In addition to the measurement level, it should also be noted that the FOI places particular emphasis on the behavioral components of future orientation. While it may indirectly reflect future-oriented behavioral trends, it does not necessarily capture future-oriented thinking or cognition. Despite the convenience of obtaining FOI, researchers must decide whether it is an appropriate measurement tool based on the specific components of their interest in future orientation (cognitive or behavioral) and their research purposes (group or individual-level).

The current replications and extensions also warrant consideration of several inherent limitations: 1) the correlation between the FOI and GDP/HDI was tested across only one local search engine (i.e., Baidu). In future studies, researchers may try to investigate the reliability and validity of the FOI based on more local search engines, such as Yandex or Naver. 2) It is notable that the Baidu-based FOI we used here and the widely utilized Google-based FOI are not directly interchangeable or comparable. Due to the incongruity that arises from the distinct calculation methodologies underlying Baidu Index and Google Trends, these two FOIs are difficult to apply to one cross-cultural research, i.e., research can only choose either Baidu or Google (but not mix them) to calculate FOI. A promising avenue for future research could involve the development of an adjusted algorithm, similar to the approach proposed by Cavalli (2020), aimed at standardizing FOI derived from disparate search engines while preserving the online query information of each region at the same time.

5. Conclusions

This study aimed to replicate and extend the findings of the FOI proposed by Preis et al. (2012). Our results provide compelling evidence that the positive correlation between the FOI and GDP/HDI reported in study of Preis et al. (2012) is replicable in China, suggesting the robustness and stability of the FOI across search engines (from Google to Baidu), time periods (from 2012 to 2021), and level (inter-country and intra-country level but not individual level). We also highlighted two prerequisites when using FOI as a measurement of future orientation: 1) the selection of a locally dominant search engine and unambiguous keywords to calculate FOI; 2) the application of the FOI within a group-level context (but not at the individual level).

Contributions

Contributed to conception and design: YX, ZY-L
Contributed to acquisition of data: YX, LY
Contributed to analysis and interpretation of data: YX, LY, ZY-L
Drafted and/or revised the article: YX, LY, ZY-L
Approved the submitted version for publication: YX, LY, ZY-L

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Competing Interests

None.

Data Accessibility Statement

All the code and data used in this study can be found at https://doi.org/10.57760/sciencedb.psych.00302.

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