Domain importance in well-being frameworks: a Gradient Boosting Quantile Regression approach

Beyond-GDP frameworks are gaining traction, and policymakers are increasingly aiming to enhance (regional) well-being or quality of life rather than focusing solely on material wealth. As governments adopt these beyond-GDP frameworks as policy goals, there are many efforts to monitor and study the development of well-being. Well-being is a multidimensional concept, influenced by domains such as health, wealth, housing, social cohesion, and environmental quality. While the relationship between these domains and well-being or life satisfaction has been widely studied, little attention has been paid to their relative importance (Clark, 2018; Samavati & Veenhoven, 2024). We know that different aspects of well-being impact life satisfaction, but we do not know which domains are most important. We can make educated guesses that some domains are more important than others based on effect sizes and theoretical models, but we have little insight into actual relative importance. This study aims to address this by explicitly examining the relative importance of different domains of well-being. The main goal is to understand which domains most significantly shape life satisfaction and for whom. Understanding the key drivers of life satisfaction is as important for theoretical insights into well-being as it is for well-being-centered policymaking. If increasing well-being is to be the ultimate policy goal rather than increasing GDP, our understanding of what drives it needs to catch up with our understanding of economic growth.

We base our analysis on the theoretical framework of broad prosperity, which is widely used in Dutch policymaking. This model of well-being includes eight domains, with well-being (measured as life satisfaction) as the overarching one (CBS, 2023). We study the relative importance of its seven subdomains in explaining well-being. A secondary aim of this study is to gain a deeper understanding of the distribution of life satisfaction. As well-being-centered policymaking typically includes aims of equality or equity, we apply quantile regression to gain insight into what is most important not only for explaining mean life satisfaction but also for explaining life satisfaction at the extreme ends of the distribution. Additionally, we apply age group stratification to examine whether this distribution varies across different age groups.

Alongside these empirical contributions to understanding life satisfaction and well-being, we provide a methodological contribution. Well-being research typically employs linear regression models. The application of machine learning (ML) techniques is fairly new but promising (Oparina et al., 2025). ML techniques are valuable as they can handle non-linear relationships without imposing a functional form on the data. As explained further in the methods section, non-linear relationships are commonly found in well-being research. For instance, some factors (such as income) may have decreasing marginal benefits, or different functional forms, such as the U-shaped age-life satisfaction relationship. In this study, we apply Gradient Boosting Quantile Regression (GBQR). This technique combines Gradient Boosting, which utilizes decision trees to capture complex non-linear relationships, with Quantile Regression, which estimates conditional quantiles of life satisfaction, providing a more comprehensive understanding of the distribution beyond the mean. To the best of our knowledge, this is the first study to use GBQR for predicting life satisfaction across the distribution. Our third aim is to evaluate the effectiveness of GBQR in capturing life satisfaction and to assess its performance compared to traditional linear approaches. We use survey data from 2024 for a diverse group of individuals spatially distributed across two Dutch provinces. By applying ML techniques, we analyze how important different domains of well-being are in shaping life satisfaction across the distribution.

We find that some domains are indeed more important than others, that there is fairly limited variation in domain importance across age groups and across the distribution of life satisfaction, and that GBQR has both advantages and disadvantages compared to linear regression in explaining life satisfaction. The results indicate clear differences in the relative importance of domains. Health, particularly mental health, is consistently the most important domain. This underscores the importance of not only good healthcare but also good access to mental health services. Material wealth, which has long been the focus of regional development, ranked fifth among the domains at most quantiles for both the full model and the separate age group models. This is somewhat nuanced by the fact that the labor and leisure domain (which includes satisfaction with work) ranks as the second most important domain. However, it is clear from the results that life satisfaction is driven by much more than just material wealth and work. For example, the social domain is consistently important.

We also find that across different age groups, there are small differences in the relative importance of the domains, but the overall ranking is consistent. While one domain may be more important to a certain age group (at a specific quantile or in general), the order of importance remains similar. For the stratified age groups, we see that the models for individuals under 35 and between 35 and 55 have the highest explained variance. This suggests that the conceptual model of broad prosperity best captures what is important for the life satisfaction of people in these age groups. It also suggests a need to further investigate whether the conceptual models used to monitor regional well-being adequately capture the diversity of needs among older people. There may be domains or elements not currently included that are important for this group.

There are some differences in importance across the quantiles, particularly within the age group models. In the full model, while there are small differences in SHAP values across quantiles, few domains exhibit a defined pattern. When we look at the age groups and consider all the elements, some distinct patterns emerge, particularly for those under 35. Elements of wellbeing that have much greater importance for young people compared to other age groups include satisfaction with free time and social cohesion. Another unexpected upward trend appears toward the upper quantiles for the relative importance of housing for younger and older people.

In terms of the theoretical framework of broad prosperity, our research shows that the domains do not contribute equally to life satisfaction. While satisfaction with financial situation and work makes a relevant contribution, other aspects impact life satisfaction to a similar or even greater extent. This provides further evidence that focusing solely on GDP and economic growth is insufficient to increase well-being and offers empirical validation for the conceptual framework of well-being. We show that all included domains significantly impact life satisfaction, albeit to different degrees. Understanding these differences is crucial for regional development and well-being policy, as domains are often treated as equal or weighted based on theoretical frameworks. This research provides empirical support for assigning different levels of importance to various domains. However, it also highlights some challenges in domain-based weighting for well-being monitoring. Our most important contribution is thus an improved understanding of the dynamics of domain importance in well-being frameworks. Additionally, the age group models provide policy-relevant information about which domains are most important for improving the well-being of the least satisfied groups. In particular, the importance of social cohesion for younger people and the significance of work or daily activities for older individuals provide actionable insights. Our methodological contribution is demonstrating the usefulness of GBQR (or Gradient Boosting in general) in well-being research. In combination with SHAP values, it is highly effective for establishing domain importance but does not provide as much detail into the effect of specific variables as linear (quantile) regression. As such it should be used for analysis like this where the main goal is to better understand the conceptual framework of wellbeing and provide empirical evidence for it. However, in cases where the goal is to understand the expected effect of certain changes or interventions linear regression may be a better choice.

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