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An Agent-Based Model of Ibn Khaldun's Asabiyah and Wellbeing: Mechanisms, Simulation, and Empirical Validation With World Values Survey

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ABSTRACT

This study develops an agent-based model (ABM) to examine how social cohesion, understood through Ibn Khaldun's concept of Asabiyah, emerges from microlevel interactions and influences collective wellbeing. We operationalize social cohesion as a composite state of positive and negative social interactions, shared values, and learning-driven alignment, *Total Social Cohesion* (TSC), and wellbeing as a composite outcome that blends material and value-driven wellbeing, *Total Wellbeing* (TWB). The ABM generates emergent trajectories of cohesion and wellbeing under varying social and environmental conditions. To ground and test the model, we map ABM-derived cohesion and wellbeing dynamics to two empirically derived indices: *the Social Cohesion Index (SCI) and the Wellbeing Index* (WBI) derived from WVS Wave 7 data. The two-stage design—simulation followed by empirical validation—offers a transparent bridge between theory and data, highlights emergent mechanisms, and reveals contexts in which cohesion translates into wellbeing. We report robustness checks across parameter ranges and discuss implications for computational social science and policy. Limitations are acknowledged where measurement, abstraction, and cross-country comparability constrain inference.

1 | Introduction

Ibn Khaldun's seminal concept, *Asabiyah*—often translated as social cohesion or group solidarity—offers a powerful lens for analyzing the rise and fall of civilizations. This paper operationalizes Asabiyah as a dynamic, measurable force within an agent-based model (ABM) and tests its link to wellbeing (WB) using World Values Survey (WVS) indicators.

While some scholars critique the predictive precision of Khaldun's cycles, many acknowledge that his integrative perspective—linking economic, social, and political spheres—continues to illuminate patterns of modernization, imperial overstretch, and systemic vulnerability in modern civilizations [1, 2]. The relevance of Asabiyah has gained renewed traction in Western scholarship, which argues that Khaldun's cyclical theory remains a valuable lens for understanding contemporary social dynamics, including state capacity, urban resilience, and the era of globalization-driven disruption [3, 4]. Proponents emphasize the interplay among economic vitality, social cohesion, and political power, viewing Asabiyah as a dynamic force-shaping collective fortunes [5]. They argue that cycles of prosperity and decline arise from fragile equilibria among governance, revenue, and public legitimacy, rather than inevitabilities, aligning with contemporary analyses of legitimacy and resilience [6, 7].

Against this backdrop, work on social capital and collective efficacy supports operationalizing Asabiyah through measurable indicators [8]. Yet the mechanisms by which Asabiyah evolves and influences WB remain insufficiently formalized. Bridging this gap requires translating Khaldun's qualitative insights into explicit pathways: how shifts in economic vitality, social cohesion, and political legitimacy produce tangible outcomes of WB, and how these dynamics can be captured with robust indicators.

Agent-based modelling provides a framework for simulating how microlevel trust and cooperation aggregate into macrolevel cohesion [9]. Building on this, we develop an ABM in which microlevel interactions give rise to macrolevel Asabiyah, and we calibrate the model against WVS indicators to test empirical relevance. By simulating and validating Asabiyah mechanisms using ABM and cross-national data, the study contributes to the nexus of social theory, computational social science, and global WB, offering a data-driven framework for policymakers and scholars.

The study addresses two core research questions:

1. How does Asabiyah influence WB through positive and negative social interactions?
2. Can an ABM-encoding Asabiyah dynamics reproduce observed cross-national patterns in social cohesion and WB?

The rest of the paper proceeds as follows: Section 2 reviews the literature; Section 3 outlines the methods (ABM structure, agent behaviors, energy dynamics, and operationalization of cohesion and WB, plus Alkire–Foster indices from WVS); Section 4 presents simulation results and regression analyses; Section 5 discusses implications, contributions, limitations, and future directions. Finally, Section 6 concludes the study.

2 | Literature

2.1 | Theoretical Lens

Ibn Khaldun's Asabiyah [10] provides a sociological lens on the rise (*Badawa*) and fall (*Hadara*) of civilizations [11]. He argues that cohesive groups rise to power, organize regimes, and eventually decline as internal solidarity wanes and external pressures mount [12–14]. Modern interpreters translate this dynamic into cyclical or regime-shifting models where cohesion, resources, and authority coevolve over time. Fahmi et al. [15] map Asabiyah onto contemporary institutional resilience, arguing that cohesion underwrites legitimacy and policy effectiveness but deteriorates under stress, thereby precipitating transitions—an interpretation directly compatible with ABM-driven cycles. Likewise, Anderson [16] emphasizes the social dynamics of Khaldun's cycles, presenting a framework wherein group solidarity catalyzes political power and administrative capacity but erodes with dilution of shared identity, a mechanism readily encoded as feedback loops in agent-based models.

Several scholars extend Khaldun's logic to modern social dynamics without abandoning his core premise that cohesion is the motor of social order [17, 18]. Ahmadi and Jamshidiha [19] integrate Khaldunian ideas into a broader theory of social change, highlighting how collective action and legitimacy mediate transitions between stability and upheaval. This body of work suggests that ABM and other modeling approaches can encode Asabiyah as a macrostructural variable that translates microlevel cooperation and shared norms into aggregate measures of social welfare, stability, and resilience [13, 17, 18].

ABM studies reveal that trust, cooperation, and resilience emerge from local interactions and learning [20], reflecting Khaldunian cycles in which cooperation expands capacity and erosion leads to decline.

2.2 | Model Conceptualization

In our ABM, Asabiyah sprouts from interagent learning, and value alignment via two feedbacks: (1) positive interactions boost mutual trust, prosocial learning, and cooperation, increasing total value energy (TVE) and total social cohesion (TSC) to raise total wellbeing (TWB) and (2) negative interactions foster envy, depletion, fragmentation, elevating total negative interactions (TNI) and total negative learning (TNL) to reduce cohesion and WB, embodying the Khaldunian cycle. It also integrates renewable and nonrenewable resource stocks to reflect sustainable versus unsustainable consumption, showing how agents' behaviors alter resource availability, feed back into learning, and drive evolving network cohesion via social-learning mechanisms.

Consistent with the generative modeling tradition in ABM research [21, 22], the purpose of the ABM is not microlevel prediction or parameter estimation but to demonstrate how Khaldunian mechanisms are sufficient to generate macrolevel cohesion–WB cycles under broad parameter ranges. Parameter values in the ABM are not empirical constants but normalized benchmarks within a theoretical framework.

2.3 | Empirical Bridge: WVS and WB Indicators

The literature links theory to data via WVS indicators, enabling cross-national indices that reflect sociocultural context and WB. The empirical bridge uses the following: Social Cohesion Index (SCI)—country-level aggregates of trust, reciprocity, neighborly helping, and social harmony; and Wellbeing Index (WBI)—a two-factor measure of hedonic (life satisfaction and materialism) and eudaimonic (purpose, meaning, and efficacy). Key references support construct validity and cross-national comparability [23]. Standard factor-analysis reductions yield latent constructs to compare with ABM signals [24]. The cross-national, cross-sectional (WVS Wave 7) empirical bridge faces ecological inference limitations; SCI and WBI serve as informative summaries aligned with ABM outputs, with measurement error and cross-country comparability caveats.

3 | Models and Methods

This is a two-stage study: Stage 1 involves ABM development and running and Stage 2 involves empirical validation mapping ABM signals to WVS Wave 7.

Figure 1 outlines a streamlined, eight-step research process—from theoretical framing (Asabiyah/H1–H6) and ABM design in NetLogo to time-series generation, empirical linking (SCI/WBI from WVS), regression analyses, robustness checks, causal interpretation, and replication materials.

3.1 | Theoretical Framing

The model links hedonic/eudaimonic processes, resource use, and emergent learning to WB; positive (H1) (Khaldunian

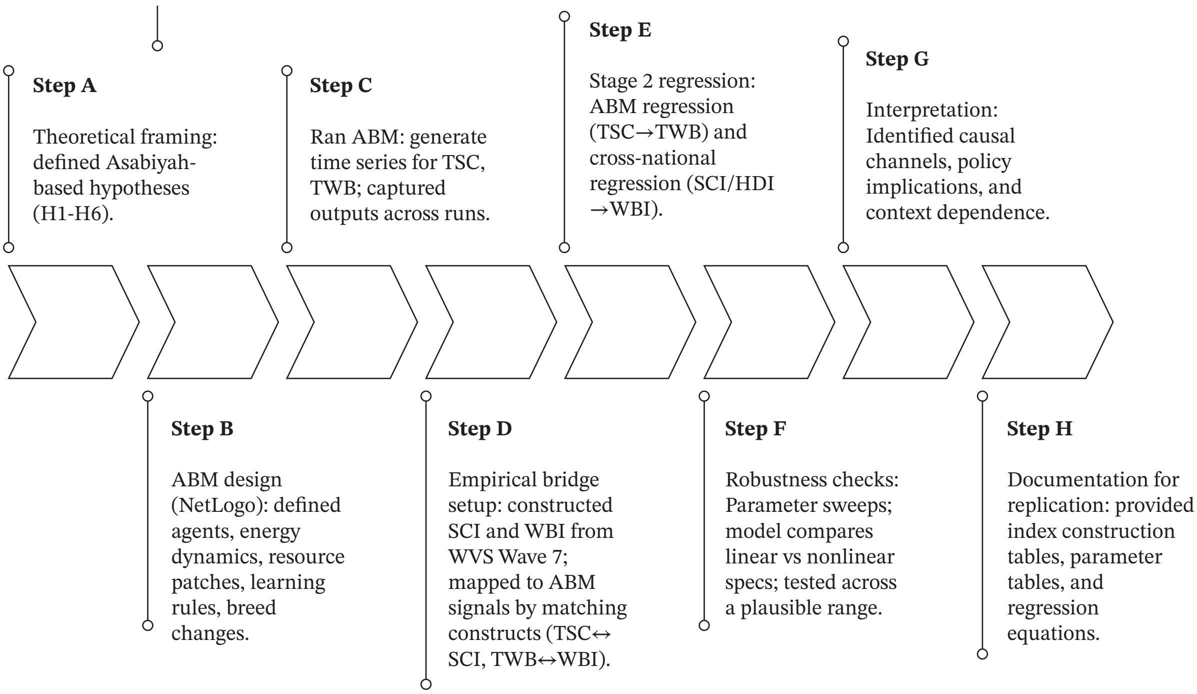

FIGURE 1 | Research process timeline.

resonance: tribal solidarity, or Asabiyah) [4] and negative (H2) (Khaldunian critique of internal factionalism) [2] interactions shape energy flows and learning, affecting cohesion (H5) (Khaldunian emphasis on social transmission within groups) [5] and WB (H6) (Khaldunian continuity of collective welfare) [25], while resource consumption (H3) (Khaldunian emphasis on provisioning and economy) [1] and internal energy (H4) (Khaldunian notions of vigor and communal vitality) [7] mediate individual-to-collective outcomes. Collectively, these hypotheses encode Asabiyah within a computational framework for simulating micro-to-macro trajectories of WB.

Figure 2 summarizes the model's causal structure, illustrating the hypothesized links among constructs; each hypothesis (H1–H6) tests a micro-to-macro pathway from agent interactions (social cohesion) to WB outcomes.

3.2 | ABM Description and Logic

The NetLogo 6.4.0 synthetic society model simulates a simple two-breed society—hedonics and eudemonics—within a patch-based landscape. The design remains deliberately straightforward to aid understanding, with agents transitioning between

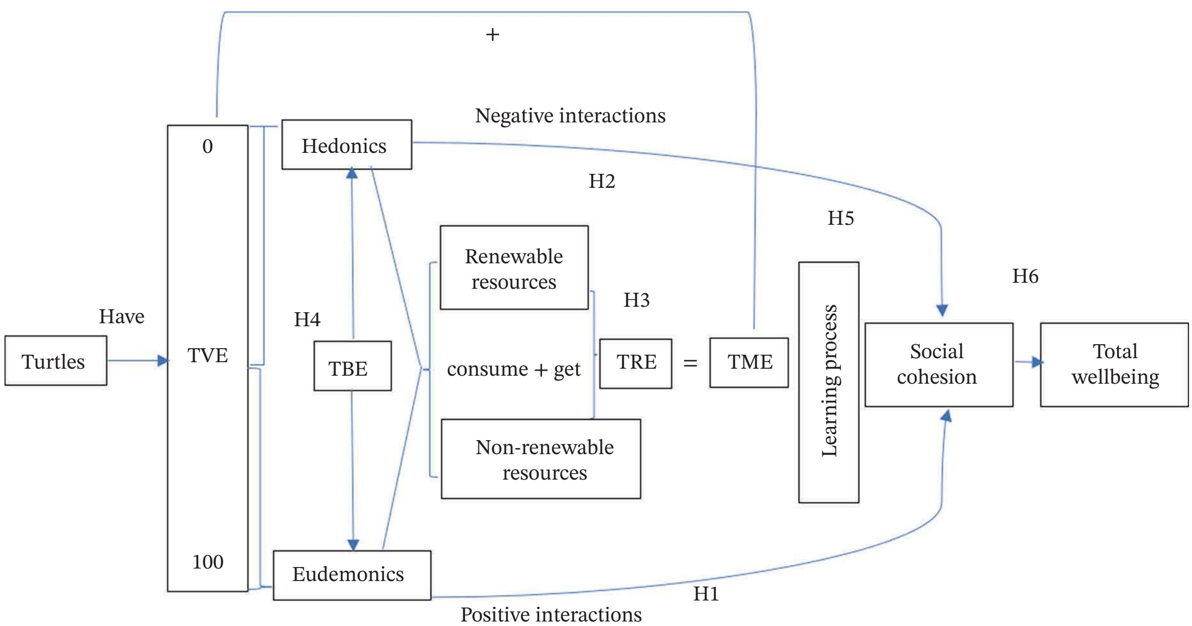

FIGURE 2 | Conceptual model of social cohesion and wellbeing.

breeds based on interactions and social learning. Hedonics are represented by low energy values (0–50), capturing selfish and greedy tendencies that can lead to negative interactions such as energy theft. Eudemonics, by contrast, are characterized by high energy values (51–100), reflecting positive emotional benefits from helping others and sharing energy with neighbors in need. The VE threshold of 50 is a neutral symmetry point on a 0–100 normalized scale, not an empirical cutoff, and serves to classify agents into hedonic- or eudaimonic-dominant orientations. Midpoint thresholds of this kind are common in ABMs to operationalize competing motivational regimes without assuming specific distributions [21, 22]. Robustness checks show that the qualitative dynamics persist under alternative thresholds (e.g., 40–60), making eudaimonic vs. hedonic orientations as orthogonal or competing motivational continua.

Interactions occur within a radius of two patches, capturing direct contact with immediate neighbors. This radius represents bounded local social influence rather than literal spatial distance; it supports clustering, diffusion, and local spillovers while avoiding global mixing, in line with standard spatial ABMs of cooperation and social learning [21]. Sensitivity analyses indicate that increasing the radius speeds up dynamics but does not eliminate the cohesion–WB cycles.

Each agent starts with birth energy to support survival, acquiring energy through two channels: resource energy (RE) (earned by consuming renewable green and nonrenewable yellow resources) and value energy (VE), which is assigned at birth and evolves with interactions via social learning. Changes in VE can flip an agent's breed when crossing the midpoint. Total societal WB sums material energy (ME) and VE, whereas TSC reflects a weighted balance between positive gains (positive interactions times positive learning) and negative losses (negative interactions times negative learning).

The (positive interactions) sharing and (negative interactions) stealing mechanisms are not ad hoc behaviors but computational representations of Ibn Khaldun's core distinction between solidaristic cooperation under strong Asabiyah and extractive behavior during moral decline. In the Muqaddimah, Khaldun emphasizes that the erosion of group solidarity leads ruling groups to replace mutual obligation with appropriation and coercion. The model operationalizes this transition at the microlevel through contrasting interaction rules; encoding moral regimes asymmetrically is a common ABM practice because directional consistency matters more than realism of each action [26]. Table 1 summarizes the model specification, with supporting literature.

Agents travel, interact, reproduce, consume resources, convert energy, update their WB and intensity, check for death, and update their total energy. ME costs drive movement, reproduction, and interactions, while VE updates through learning from positive and negative interactions (adaptation). Patches regenerate renewable resources to sustain activity. Agents consume available renewable or nonrenewable resources; both yield +2 RE and reduce the patch's RE by 1, when depleted patches turn brown. Reproduction incurs ME costs (5 units); offspring hatch with baseline energy and WB derived from energy components, with VE randomly assigned in the range 0–100. If $VE < 50$, offspring become hedonic (red, person-shaped); if $VE \geq 50$, they become eudaimonic (black, person-shaped).

Intensity value (IV) is defined as $(VE - 50)/50$, a linear metric guiding dynamics. Within a two-patch radius, hedonic agents may steal ME from lower-intensity neighbors (incurring self-cost and causing more harm to hedonics), whereas eudaimonic agents share ME with lower-intensity neighbors for mutual benefit. VE and WB update after each interaction; thresholds

TABLE 1 | Model specification table.

Parameter	Value/range	Literature support
Agent birth energy (BE)	100 (Fixed)	[27]
Resource energy per patch (RE)	Renewable: 8; nonrenewable: 20	[28]
Value energy (VE)	0–100 (random)	[26]
Hedonic/eudemonic threshold	50	[29]
Interaction radius	2	[21]
Max population per breed	200 (capped)	[27]
Reproduction ME threshold	30	[22]
Reproduction cost (ME)	10	[30]
Resource gain per move	4	[27]
Wellbeing death threshold	45	[31]
Renewable patch regeneration time	10 ticks	[28]
BE + RE relation in ME	$ME = BE + RE$	[32]
WB calculation	$WB = ME + VE$	[32]
TWB calculation	$TWB = TME + TVE$	[32]
TSC calculation	$TSC = TVE + 2 * [(TPI * TPL) - (TNI * TNL)]/(TPI + TNI)$	[33]
Patch depletion visualization	Patch turns brown when $RE = 0$	[22]
Renewable patch regeneration trigger	Regenerate when timer ≥ 10; reset to green with 6 RE	[34]

may trigger breed or appearance changes. A Khaldunian twist appears in the VE $\longrightarrow$ ME conversion rule: eudaimonic agents can convert VE to ME if WB $\geq$ 300, capturing a surplus logic where high collective WB enables material accumulation. This threshold represents a nonlinear transition from subsistence to surplus rather than an empirical constant; alternative thresholds were explored and did not eliminate the cyclical rise–decline dynamics. Death occurs if WB < 45. WB is computed as

$$\mathrm{WB} = \mathrm{ME}(\mathrm{BE} + \mathrm{RE}) + \mathrm{VE}, \tag{1}$$

So, for an agent

$$\begin{aligned} \mathrm{ME} &= \mathrm{BE} + \mathrm{RE}, \\ \mathrm{WB} &= \mathrm{ME} + \mathrm{VE}. \end{aligned} \tag{2}$$

TWB of the society = TWB

$$\mathrm{TWB} = \mathrm{TME} + \mathrm{TVE}. \tag{3}$$

Social cohesion in society is defined as the TSC.

$$\mathrm{TSC} = \mathrm{TVE} + 2 * \frac{(\mathrm{TPI} * \mathrm{TPL} - \mathrm{TNI} * \mathrm{TNL})}{(\mathrm{TPI} + \mathrm{TNI})}. \tag{4}$$

Model captures how TSC impacts TWB in a society.

4 | Results and Discussion

4.1 | ABM Runs[1]

The NetLogo interface tracks energy, WB, and social cohesion for hedonics and eudemonics (Figure 3). On the left, sliders adjust interaction costs and reproduction thresholds; the middle displays real-time energy metrics, population counts, and social cohesion; the right presents a color-coded grid of spatial distribution and interactions, offering a dynamic view of energy use, social behavior, and cohesion over time.

Figure 4 shows the model interface running for 60 ticks, illustrating dynamic changes in hedonics and eudemonics.

4.2 | ABM Sensitivity Analysis

In the behavioral space, the values of TNI, TPI, and the reproduction threshold are varied within their respective ranges to assess their impact on social cohesion and WB cycles. The model yields rich data and graphical outputs that reveal a strong correlation between TWB and TSC. This demonstrates how shifts in energy dynamics and interactions shape collective outcomes.

Figure 5 shows the simulation running for 500 ticks, with 2500 iterations.

Sensitivity analyses confirm that the cyclical Khaldunian dynamic remains robust across ranges (e.g., thresholds of 40–60 or radii of 1–5), suggesting the patterns are not artefacts of any single-point choice [26, 29]. The 200-agent cap represents environmental carrying capacity and simulates regime-level discontinuities (e.g., Great Plagues or dynastic resets) rather than individual mortality, aligning with Khaldun's cyclical and punctuated history. This population-reset mechanism—though not intended to model microlevel mortality—fits the broader use of ABMs to study social–ecological collapse and macrodynamics [27].

The data set is enormous: 2500 iterations × 500 ticks per iteration, totaling 1,250,000 readings. This scale makes plotting the full time series impractical. Therefore, TSC and TWB were recorded and averaged across runs to produce mean time series, resulting in the graph presented in Figure 6. It confirms the generation of endogenous cycles: *Asabiyah* (TSC) peaks during the growth phase (Badawa) and declines as WB (TWB) hits its minimum (Hadara), preceding the population collapse. This lagged correlation supports the model's validation of Khaldun's hypothesis that the seeds of decline are sown at the peak of prosperity, driven by shifts in social interactions based on value shifts.

4.3 | Regression Results for ABM

Results indicate a robust association between TSC and TWB. Across 2500 runs of 500 ticks each (12,50,000 data points for both variables), the ABMSCWB regression yields an R of 0.713, with $R^2 = 0.508$ and an adjusted R^2 also at 0.508, indicating that about 50% of the variance in TWB is explained by TSC after accounting for chance. The model summary in the table reports a standard

FIGURE 3 | Setup interface for ABM.

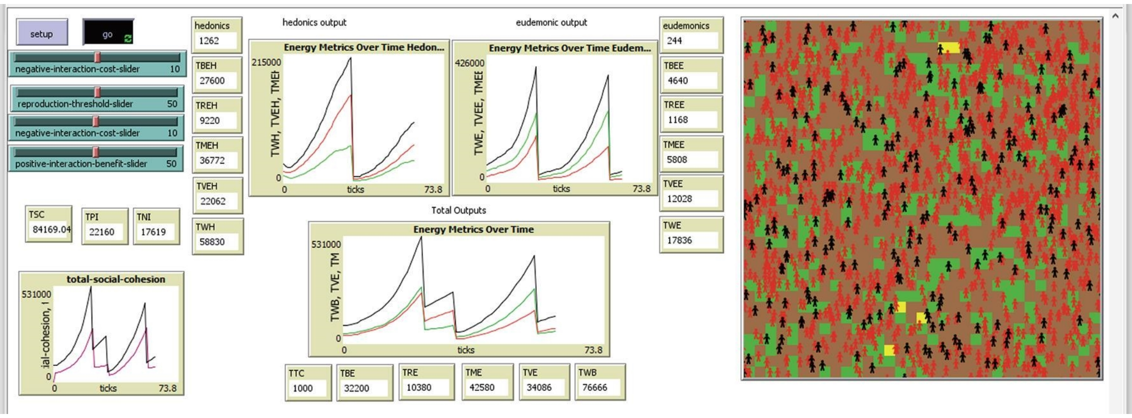

FIGURE 4 | ABM interface in model running.

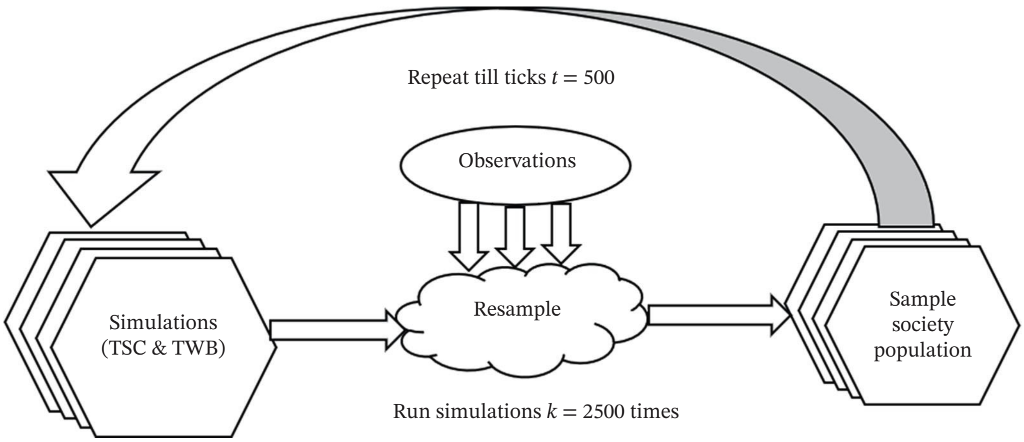

FIGURE 5 | Simulation steps.

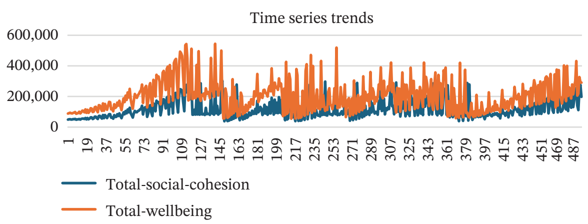

FIGURE 6 | Time-series trends and cycles for TSC and TWB.

TABLE 2 | Model summary of ABMSCWB regression.

Model	R	R square	Adjusted R-square	Std. error of the estimate
1	0.713[a]	0.508	0.508	87,237.84658

[a]Predictors: (constant), TSC.

error of the estimate at 87,237.85, reflecting the typical dispersion around the predicted values (see Table 2).

Table 3 shows a highly significant relationship: the regression coefficient for TSC is 0.945 (SE = 0.019, $t = 50.82$, $p < 0.001$). The intercept is −103,846.897 (SE = 5160.319, $t = -20.12$, $p < 0.001$), suggesting that TWB is driven positively by TSC, but there are

TABLE 3 | ABMSCWB regression coefficients.

Predictor	Coefficient	Standard error	t-value	p value
(Constant)	−103846.897	5160.319	−20.124	0.000
TSC	0.945	0.019	50.815	0.000

Note: Dependent variable: TWB.

additional factors lowering TWB when TSC is absent or minimal. The regression equation is

$$\text{TWB} = -103,846.897 + 0.945 \times \text{TSC}. \tag{5}$$

Each unit increase in TSC is associated with a 0.945 unit increase in TWB, reflecting a strong, statistically reliable positive link between social cohesion and WB. The substantial intercept implies other unmodeled influences reduce TWB when TSC is zero, underscoring that TSC is a major, but not sole, determinant of TWB.

4.4 | Empirical Bridge

WVS Wave 7 (2022) data were used to calibrate and perform country-level regressions on a constructed SCI and a WBI, with the HDI as an explanatory variable. To ensure comparability, the

TABLE 4 | SCI questions and code WVS, Wave 7 (2022).

Question no. and question	Original coding	Recode assigned
1. Importance of family 2. Importance of friends 4. Importance of politics 5. Importance of work 6. Importance of religion	1 v.imp to 4 not imp at all	1–2 = 1, 3–4 = 0
7. Good manners 10. Responsibility 12. Tolerance 14. Determination/perseverance 15. Religious faith 16. Not being selfish 19. Tolerance of different races 21. Tolerance of immigrants/foreigners	1 mentioned, 2 not mentioned	1 = 1, 2 = 0
27. Importance of religion 29. Tolerance of parent's dreams	1 v.imp to 4 not imp at all	1–2 = 1, 3–4 = 0
34. If Scare jobs then locals preferred 38. Importance of parents care 40. Work as duty	1 agreed to 5 not at all	1–2 = 1, 3–5 = 0
57. Trust most people	1 yes, 2 no	1 = 1, 2 = 0
58. Trust family 59. Trust neighborhood 60. Trust personal acquaintance 61. Trust first-time met people 62. Trust another religion person 63. Trust another nationality	1 completely to 4 not at all	1–2 = 1, 3–4 = 0
118. Bribe	1 never to 4 always	1 = 1, 2–4 = 0
120. Risk to bribe	1 no risk to 10 very high risk	1–4 = 1, 5–10 = 0
132. Robberies 133. Alcohol 134. Police or military interference 135. Racism 136. Drugs 137. Street violence 138. Sexual harassment	1 very frequently to 4 not at all	1–3 = 0, 4 = 1
164. Importance of God	1 not at all to 10 very imp	1–4 = 0, 5–10 = 1
165. Belief in God 166. Belief in life hereafter 167. Belief in hell 168. Belief in heaven	1 yes, 2 no	1 = 1, 2 = 0
172. How often do you pray?	1 several times a day to 8 never	1–3 = 1, 4–8 = 0
177–184, 186–194. Lack of ethical values	1 disagree to 10 agree	1–5 = 1, 6–10 = 0
199, 200, 209–220. Political and social activities	1 have done to 3 never	1–2 = 1, 3 = 0
254. National pride	1 very to 5 not at all	1–2 = 1, 3–5 = 0

TABLE 5 | WBI questions and code WVS, Wave 7 (2022).

Question no. and question	Original coding	Recode assigned
46. Happiness	1 very to 4 not at all	1–2 = 1, 3–4 = 0
47. Health	1 very good to 5 not at all	1–3 = 1, 4–5 = 0
48. Choice 49. Life satisfaction 50. Financial satisfaction	1 not at all to 10 completely	1–4 = 1, 5–10 = 0
51. Life without food 52. Life without safety 53. Life without medicine 54. Life without cash income 55. Life without shelter	1 often to 4 never	1–3 = 0, 4 = 1
56. Life in comparison to parents	1 better, 2 worse, 3 same	1, 3 = 1, 2 = 0

TABLE 6 | KMO and Bartlett's test for SCI factor analysis (Stage 1).

Kaiser–Meyer–Olkin measure of sampling adequacy		0.909
Bartlett's test of sphericity	Approx. Chi-square	2,001,056.040
	df	2556
	Sig.	0.000

same or analogous cut points were used across items with similar response formats. Multicategory or yes/no indicators were converted into binary or simplified scales to improve interpretability and analysis consistency. Recoding ordinal survey items to dichotomous variables is common in cross-cultural attitude research to simplify interpretation and enhance comparability, with precedent in Kline [35] and DeVellis [36]; using theoretical anchors (e.g., high vs. low importance, trust, or risk) aligns with Rasch/Item Response Theory and logistic regression approaches noted by Bond and Fox [37]. Details of SCI formation follow in Table 4 and WBI in Table 5, respectively.

4.5 | 2-Stage Factor Analysis for SCI and WBI Construction

Stage 1 results of SCI factor analysis: KMO = 0.909, meritorious suitability for factor analysis; Bartlett's test $p = 0.000$ (< 0.05), rejecting the null hypothesis that the correlation matrix is an identity matrix (Table 6). Together, these indicate that the factor analysis is appropriate for Stage 1.

On the basis of total variance explained, 15 factors got a considerable percentage, and the rest were insignificant. Table 7 summarizes the PCA results, showing the variance explained by each component before extraction, after extraction, and after rotation. The first 7-8 components account for the most information, with cumulative variance increasing as more components are retained. Rotation tends to clarify the structure by reallocating variance across components, thereby aiding interpretation; however, the total variance approaches 100% only when many components are included (slso seen in Figure 7).

Second stage factor analysis (SCI) results: Table 8 shows KMO and Bartlett test results for the second stage. Again KMO 0.617 and Bartlett's test chi-square value of 118,720.484 with df 66 at sig < 0.005 (0.000) support factor analysis and identified 12 distinct dimensions, with each weighted equally at 1/12 (0.08333) based on eigenvalue percentages to form the overall index (see Table 9 and Figure 8).

Table 10 shows the KMO value of 0.806 and Chi-Sq value of 209,961.826 at p value (0.000). Both KMO and Bartlett's test results supported factor analysis.

On the basis of total variance explained, 2 factors got considerable percentage and rest were insignificant, as shown in the scree plot in Table 11 and Figure 9.

4.6 | Index Formation

Factor analyses yielded latent dimensions, with indicator weights determined by factor loadings. Pivot tables were then used to compute the total population (the count of SCI/WBI), the sum of weighted SCI/WBI scores, and the number of people with SCI/WBI (sum of recoded SCI/WBI). The SCI and WBI were constructed using the Alkire–Foster methodology, a well-established approach for multidimensional measurement [38, 39], where

$$H = \frac{\text{No. of people with SCI or WBI}}{\text{Total population}}, \tag{6}$$

$$A = \frac{\text{Sum of weighted SCI or WBI scores}}{\text{No. of people with SCI or WBI}}, \tag{7}$$

and

$$\text{Index} = H{*}A. \tag{8}$$

For each indicator, a country receiving a score exceeding 0.49 was assigned a binary value of 1, indicating not deprived, whereas a score of 0.49 or less was assigned a value of 0, indicating deprivation. Using dual cutoffs, countries were classified as

TABLE 7 | Total variance explained for SCI factor analysis (Stage 1).

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	8.362	11.614	11.614	8.362	11.614	11.614	6.109	8.484	8.484
2	5.005	6.952	18.566	5.005	6.952	18.566	4.305	5.979	14.463
3	4.557	6.329	24.895	4.557	6.329	24.895	3.885	5.395	19.859
4	3.634	5.048	29.943	3.634	5.048	29.943	3.544	4.923	24.781
5	2.433	3.379	33.322	2.433	3.379	33.322	2.770	3.848	28.629
6	2.012	2.794	36.116	2.012	2.794	36.116	2.500	3.472	32.101
7	1.600	2.222	38.338	1.600	2.222	38.338	2.493	3.462	35.563
8	1.473	2.046	40.384	1.473	2.046	40.384	2.097	2.912	38.475
9	1.394	1.936	42.320	1.394	1.936	42.320	1.704	2.367	40.843
10	1.342	1.864	44.184	1.342	1.864	44.184	1.601	2.223	43.066
11	1.220	1.694	45.878	1.220	1.694	45.878	1.515	2.104	45.170
12	1.118	1.553	47.431	1.118	1.553	47.431	1.250	1.737	46.907
13	1.109	1.540	48.971	1.109	1.540	48.971	1.229	1.707	48.614
14	1.068	1.483	50.454	1.068	1.483	50.454	1.199	1.665	50.278
15	1.060	1.472	51.925	1.060	1.472	51.925	1.134	1.575	51.853
16	1.025	1.424	53.349	1.025	1.424	53.349	1.077	1.496	53.349
17	0.982	1.364	54.713						
18	0.963	1.338	56.050						
19	0.946	1.313	57.364						
20	0.927	1.287	58.651						
21	0.917	1.273	59.924						
22	0.900	1.250	61.173						
23	0.885	1.229	62.402						
24	0.857	1.191	63.592						
25	0.844	1.172	64.764						
26	0.825	1.146	65.911						
27	0.813	1.130	67.041						
28	0.796	1.105	68.146						
29	0.786	1.091	69.237						
30	0.778	1.080	70.318						
31	0.754	1.047	71.365						
32	0.744	1.034	72.398						
33	0.714	0.992	73.390						
34	0.704	0.978	74.368						
35	0.701	0.974	75.342						
36	0.689	0.957	76.299						
37	0.668	0.928	77.226						
38	0.666	0.925	78.152						
39	0.654	0.908	79.059						
40	0.644	0.895	79.954						
41	0.598	0.831	80.785						
42	0.592	0.822	81.607						
43	0.584	0.812	82.419						
44	0.567	0.788	83.207						

(Continues)

TABLE 7 | (Continued)

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
45	0.564	0.784	83.990						
46	0.552	0.766	84.756						
47	0.540	0.750	85.506						
48	0.529	0.735	86.241						
49	0.524	0.727	86.968						
50	0.519	0.721	87.689						
51	0.505	0.701	88.391						
52	0.501	0.695	89.086						
53	0.497	0.690	89.776						
54	0.492	0.683	90.459						
55	0.477	0.663	91.123						
56	0.474	0.658	91.780						
57	0.462	0.642	92.422						
58	0.450	0.625	93.048						
59	0.439	0.610	93.657						
60	0.433	0.601	94.259						
61	0.427	0.593	94.852						
62	0.406	0.564	95.415						
63	0.386	0.536	95.951						
64	0.380	0.527	96.479						
65	0.372	0.516	96.995						
66	0.366	0.508	97.503						
67	0.355	0.493	97.995						
68	0.319	0.443	98.438						
69	0.316	0.439	98.877						
70	0.312	0.433	99.310						
71	0.298	0.413	99.723						
72	0.199	0.277	100.000						

Note: Extraction method: principal component analysis.

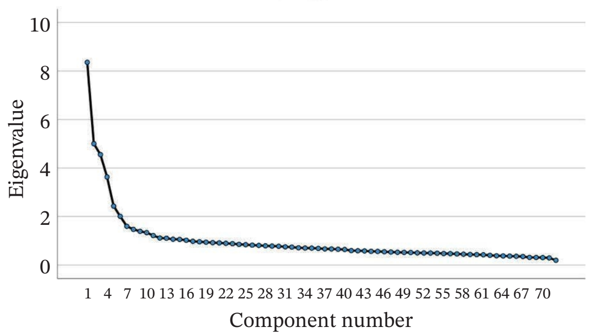

FIGURE 7 | Scree plot for SCI factor analysis.

TABLE 8 | KMO and Bartlett's test for SCI factor analysis (Stage 2).

Kaiser–Meyer–Olkin measure of sampling adequacy		0.617
Bartlett's test of sphericity	Approx. Chi-square	118,720.448
	df	66
	Sig.	0.000

nondeprived if they meet a specified threshold on the number of indicators. Tables 12 and 13 depict the abbreviation of dimensions, indicator weights, and literature support of SCI and WBI, respectively.

TABLE 9 | Total variance explained for SCI factor analysis (Stage 2).

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	2.090	17.417	17.417	2.090	17.417	17.417	1.708	14.237	14.237
2	1.708	14.234	31.651	1.708	14.234	31.651	1.686	14.053	28.290
3	1.237	10.308	41.958	1.237	10.308	41.958	1.491	12.422	40.712
4	1.169	9.743	51.701	1.169	9.743	51.701	1.319	10.989	51.701
5	0.995	8.295	59.996						
6	0.950	7.919	67.915						
7	0.869	7.239	75.154						
8	0.774	6.453	81.607						
9	0.639	5.322	86.929						
10	0.602	5.020	91.949						
11	0.487	4.056	96.004						
12	0.479	3.996	100.000						

Note: Extraction method: principal component analysis.

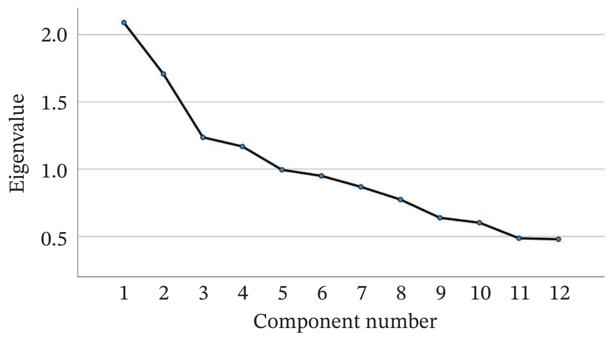

FIGURE 8 | Scree plot for Factor Analysis S2.

TABLE 10 | KMO and Bartlett's test for WBI factor analysis.

Kaiser–Meyer–Olkin measure of sampling adequacy		0.837
Bartlett's test of sphericity	Approx. Chi-square	209,961.862
	df	55
	Sig.	0.000

Therefore,

$$SCI = PR*(0.08333) + R*(0.08333) + NS*(0.08333) + SE*(0.08333) + PE*(0.08333) + PnE*(0.08333) + T*(0.08333) + SR*(0.08333) + PI*(0.08333) + CT*(0.08333) + To*(0.08333) + WLB*(0.08333). \quad (9)$$

Table 13 lists two dimensions of WB—Safety from deprivations (SfD) and Happiness and satisfaction (HaS)—with their respective question indicators (and associated weights) used to calculate the overall scoring.

Also, $WBI = SfD * (0.50) + HaS * (0.50)$.

4.7 | Regression Analysis of WVS Data

When the SCI and WBI indices were built for each country, iterative regressions were run, and beta values were recorded in Table 14.

The regression results indicated significant relationships across various countries. For instance, Andorra had a beta value of 0.392 ($p < 0.001$), and the highest beta value was observed in the Netherlands at 0.876 ($p < 0.001$). While some countries such as Bangladesh (beta = 0.046, $p = 0.573$) showed no significant relationship, the overall average beta across all countries was approximately 0.394. These results support the validity of the ABMSCWB, demonstrating consistent predictive power of SCI and HDI on WBI when analyzed both individually and collectively.

5 | Country-Wise Regression

5.1 | Robustness Checks

This analysis evaluates all combinations of 5 machine learning algorithms and 8 feature specifications for predicting the WBI.

TABLE 11 | Total variance explained for WBI factor analysis.

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	3.289	29.903	29.903	3.289	29.903	29.903	2.769	25.173	25.173
2	1.692	15.384	45.287	1.692	15.384	45.287	2.213	20.114	45.287
3	0.914	8.313	53.600						
4	0.883	8.023	61.623						
5	0.767	6.973	68.596						
6	0.712	6.475	75.071						
7	0.659	5.992	81.064						
8	0.624	5.677	86.740						
9	0.531	4.827	91.568						
10	0.471	4.280	95.848						
11	0.457	4.152	100.000						

Note: Extraction method: principal component analysis.

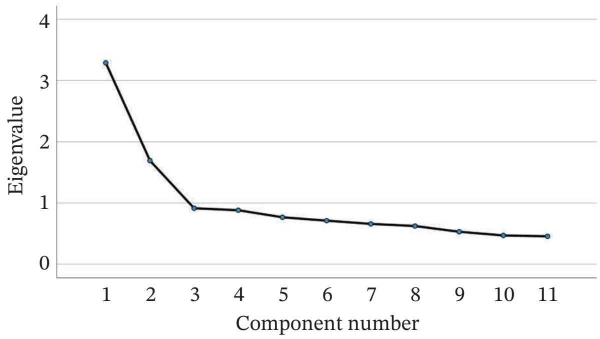

FIGURE 9 | Scree plot for WBI.

TABLE 12 | SCI dimensions and indicator weights.

Sr. no.	Abbreviation	Dimension	Indicators (question no.'s)	Weights for indicators	Literature support
1	PR	Political responsibility	219, 218, 211, 215, 212, 210, 217, 220, 209, 216, 214, 213	0.091, 0.088, 0.087, 0.085, 0.084, 0.084, 0.082, 0.082, 0.081, 0.080, 0.072	[40, 41]
2	R	Religiosity	168, 167, 166, 165, 164, 6, 172	0.170, 0.162, 0.157, 0.140, 0.130, 0.121, 0.121	[41–43]
3	NS	Neighborhood safety	137, 138, 136, 135, 134, 133, 132	0.154, 0.151, 0.150, 0.140, 0.139, 0.134, 0.132	[41, 44, 45].
4	SE	Social ethics	193, 183, 186, 182, 184, 188, 187	0.160, 0.156, 0.156, 0.148, 0.142, 0.123, 0.114	[46, 47]
5	PE	Protection ethics	192, 194, 191, 189	0.291, 0.284, 0.232, 0.193	[46]
6	PnE	Personal ethics	178, 177, 180, 179, 181	0.218, 0.210, 0.202, 0.190, 0.181	[46, 48].
7	T	Trust	62, 63, 61	0.347, 0.343, 0.310	[41, 45, 49].
8	SR	Social responsibility	40, 38, 34	0.356, 0.350, 0.292	[41, 50].
9	PI	Political interest	199, 4, 200	0.370, 0.333, 0.296	[40].
10	CT	Community trust	58, 59	0.561, 0.439	[41, 44].
11	To	Tolerance	21, 19	0.503, 0.497	[51–53].
12	WLB	Work-life balance	3, 5	0.527, 0.473	[54, 55].

TABLE 13 | WBI dimensions and indicator weights.

Sr. no.	Abbreviation	Dimension	Indicators (question no.'s)	Weights for indicators
1	SfD	Safety from deprivations	53, 51, 54, 55, 52	0.211, 0.210, 0.206, 0.191, 0.182
2	HaS	Happiness and satisfaction	49, 50, 46, 48	0.283, 0.256, 0.241, 0.220

TABLE 14 | Country-wise regression results from WVS Wave 7 data.

Serial no.	Code	Country name	Beta-value	Sig.
1	20	Andorra	0.392	< 0.001
2	32	Argentina	0.248	< 0.001
3	36	Australia	0.553	< 0.001
4	50	Bangladesh	0.046	0.573
5	51	Armenia	0.283	< 0.001
6	68	Bolivia	0.414	< 0.001
7	76	Brazil	0.427	< 0.001
8	104	Myanmar	0.444	< 0.001
9	124	Canada	0.685	< 0.001
10	152	Chile	0.622	< 0.001
11	156	China	0.101	0.033
12	158	Taiwan ROC	0.344	< 0.001
13	170	Colombia	0.212	< 0.001
14	196	Cyprus	0.588	< 0.001
15	203	Czechia	0.445	< 0.001
16	218	Ecuador	0.352	< 0.001
17	231	Ethiopia	0.375	< 0.001
18	276	Germany	0.392	< 0.001
19	300	Greece	0.413	< 0.001
20	320	Guatemala	0.269	< 0.001
21	344	Hong Kong SAR	0.502	< 0.001
22	356	India	0.352	< 0.001
23	360	Indonesia	0.415	< 0.001
24	364	Iran	0.365	< 0.001
25	368	Iraq	0.318	< 0.001
26	392	Japan	0.433	< 0.001
27	398	Kazakhstan	0.6	< 0.001
28	400	Jordan	0.315	< 0.001
29	404	Kenya	0.089	0.103
30	410	South Korea	0.16	< 0.001
31	417	Kyrgyzstan	0.178	< 0.001
32	422	Lebanon	0.478	< 0.001
33	434	Libya	0.414	< 0.001
34	446	Macau SAR	0.784	< 0.001
35	458	Malaysia	0.334	< 0.001
36	462	Maldives	0.151	0.045
37	484	Mexico	0.188	< 0.001
38	496	Mongolia	0.068	0.277
39	504	Morocco	0.299	< 0.001
40	528	Netherlands	0.876	< 0.001
41	554	New Zealand	0.605	< 0.001

(Continues)

TABLE 14 | (Continued)

Serial no.	Code	Country name	Beta-value	Sig.
42	558	Nicaragua	0.35	< 0.001
43	566	Nigeria	0.169	0.02
44	586	Pakistan	0.191	< 0.001
45	604	Peru	0.428	< 0.001
46	608	Philippines	0.161	< 0.001
47	630	Puerto Rico	0.362	< 0.001
48	642	Romania	0.388	< 0.001
49	643	Russia	0.391	< 0.001
50	688	Serbia	0.184	0.002
51	702	Singapore	0.437	< 0.001
52	703	Slovakia	0.413	< 0.001
53	704	Vietnam	0.23	< 0.001
54	716	Zimbabwe	−0.021	0.78
55	762	Tajikistan	0.176	0.002
56	764	Thailand	−0.054	0.448
57	788	Tunisia	0.21	0.037
58	792	Türkiye	0.696	< 0.001
59	804	Ukraine	0.299	< 0.001
60	818	Egypt	0.938	< 0.001
61	826	Great Britain	0.517	< 0.001
62	840	United States	0.727	< 0.001
63	858	Uruguay	0.279	< 0.001
64	860	Uzbekistan	0.47	< 0.001
65	862	Venezuela	0.511	< 0.001
66	909	Northern Ireland	0.692	< 0.001
	Total	Avg beta	0.373,833,333	
Without outliers		Avg beta	0.39345	
Average beta			0.39345	

Note: Standard errors are robust for heteroscedasticity.

Model performance is assessed via 5-fold cross-validation to ensure out-of-sample generalization.

Feature specifications are as follows:

M1 Linear-Level: Raw feature values (X).

M2 Linear-LogX: Log-transformed features $\ln(X)$.

M3 Quadratic-Level: Raw features + Squared features (X, X^2).

M4 Quadratic-LogX: Log features + Squared log features [$\ln(X)$, $\ln(X)^2$].

M5 Level + Log (Mixed): Raw + Log features (X, $\ln(X)$)

M6 Level + Sq + Log + LogSq: All: X, X^2, $\ln(X)$, $\ln(X)^2$

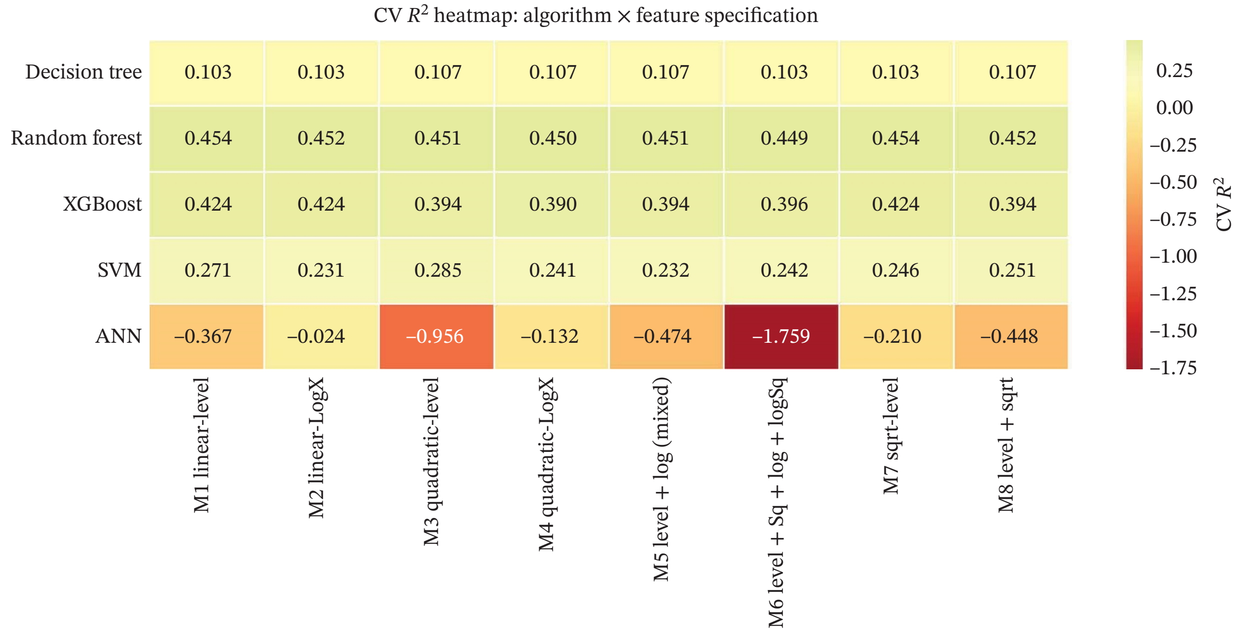

FIGURE 10 | CV R^2 heatmap algorithm × feature specification. Green = better fit. Bold = highest value per row.

M7 Sqrt-Level: Square-root–transformed features $\sqrt{X}$.

M8 Level + Sqrt: Raw + Square-root features (X, $\sqrt{X}$).

5.1.1 | Performance Heatmaps—CV R^2 and CV RMSE

Figures 10, 11, 12, and 13 visualize how every algorithm performs across all 8 feature specifications. Green cells indicate higher CV R^2/lower RMSE. This allows immediate identification of the best algorithm specification pairing.

5.1.2 | Best Model per Algorithm

Figure 14 and Table 15 show each algorithm's best-performing specification and its performance metrics. Figure 15 and Table 16 rank algorithms by average CV R^2 across all 8 specs.

5.2 | Country-Level Regression as per Selected Model

The country-level analysis (Figure 16) shows predominantly positive, significant links between social cohesion (SCI), development (HDI), and WB (WBI) across 66 countries, with betas

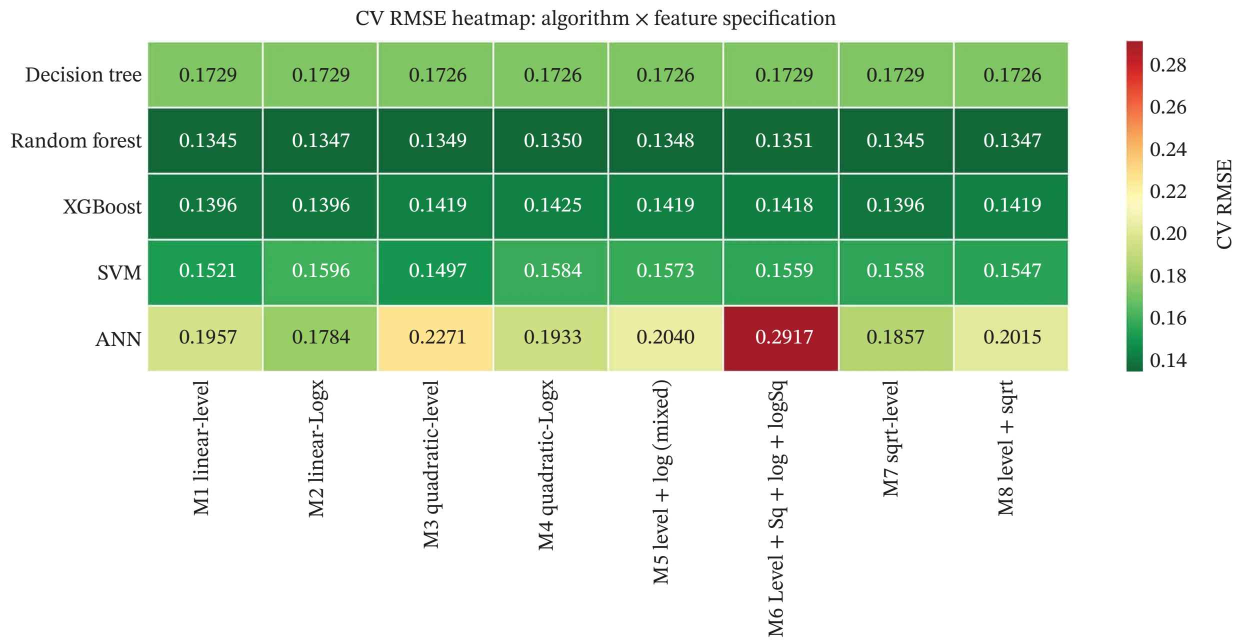

FIGURE 11 | CV RMSE heatmap, lower is better. Note: RF consistently achieves the lowest RMSE.

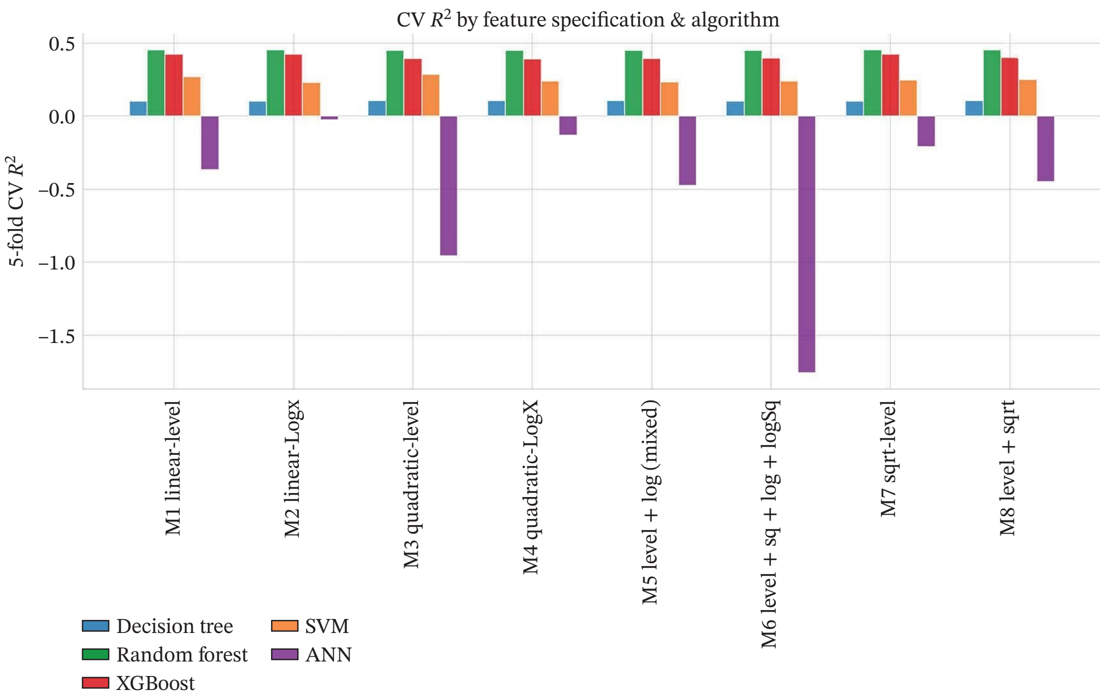

FIGURE 12 | Grouped bar chart of CV R^2 across all 8 specifications per algorithm. Random forest (green) dominates consistently.

ranging roughly 0.1–0.9; notable outliers include the Netherlands (0.876) and Egypt (0.938) as high points, and Bangladesh and Zimbabwe with weaker or nonsignificant effects. These exceptions reflect broader contextual factors—weak institutions, governance gaps, high inequality, cultural/political instability, and data issues—that can dampen the SCI-HDI to WBI pathway. Despite these outliers, the average beta of approximately 0.39 indicates moderate positive predictive power of SCI and HDI for WBI across countries. The model summary is presented in Table 17.

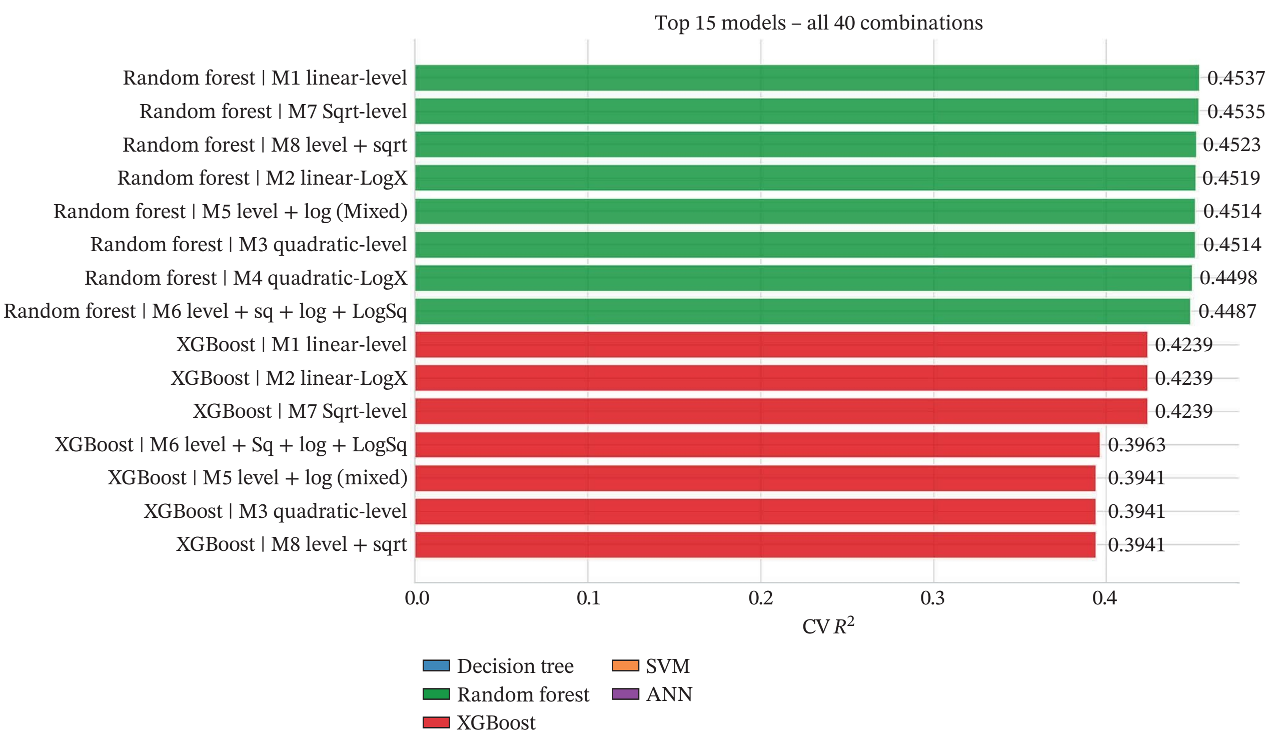

FIGURE 13 | Top 15 models ranked by CV R^2 across all 40 algorithm × specification combinations. Color = algorithm.

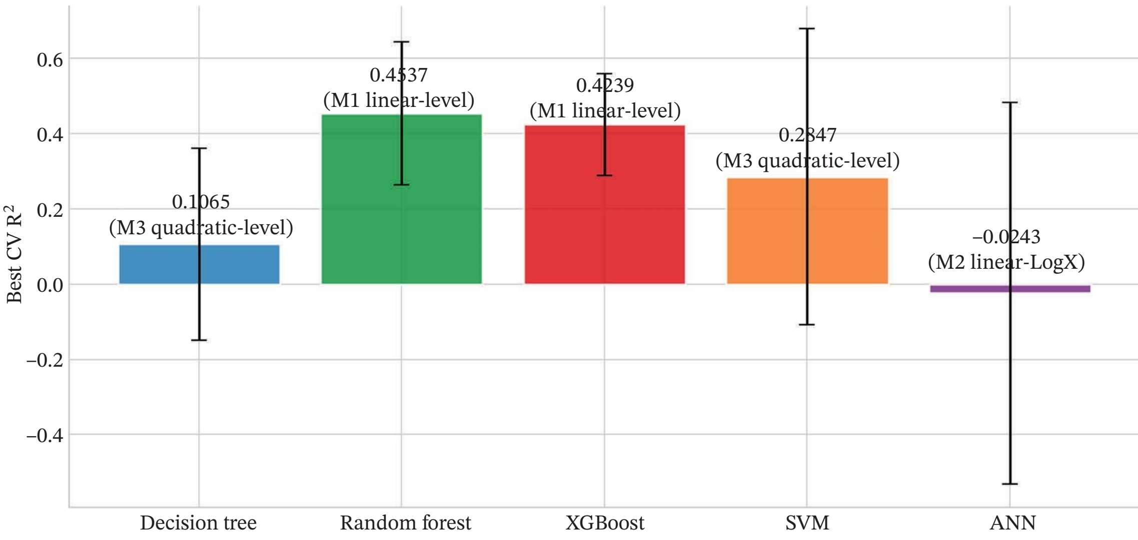

FIGURE 14 | Best CV R^2 per algorithm (best spec label shown above each bar).

TABLE 15 | Best-performing specification.

Algorithm	Best spec	CV R^2	CV R^2 std	CV RMSE	CV MAE	Train R^2
Random forest*	M1 Linear-Level	0.4537	0.1909	0.1345	0.1058	0.8453
XGBoost	M1 Linear-Level	0.4239	0.1351	0.1396	0.1082	0.9666
SVM	M3 Quadratic-Level	0.2847	0.3937	0.1497	0.1228	0.8756
Decision tree	M3 Quadratic-Level	0.1065	0.2549	0.1726	0.1345	0.7456
ANN	M2 Linear-LogX	−0.0243	0.5080	0.1784	0.1444	0.4729

*Best algorithm overall.

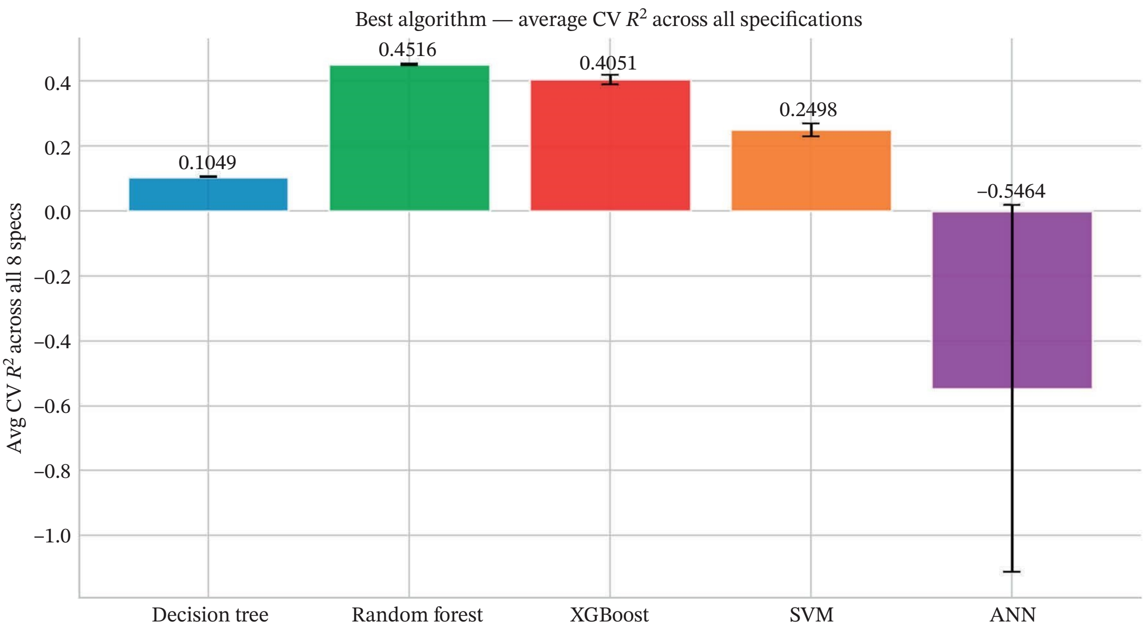

FIGURE 15 | Average CV R^2 per algorithm across all 8 feature specifications (error bars = ±1 SD).

TABLE 16 | Algorithm ranking average CV R^2 across all specifications.

Algorithm	Avg CV R^2	Best CV R^2	Best spec	Rank
Random forest ★	0.4516	0.4537	M1 Linear-Level	#1
XGBoost	0.4051	0.4239	M1 Linear-Level	#2
SVM	0.2498	0.2847	M3 Quadratic-Level	#3
Decision tree	0.1049	0.1065	M3 Quadratic-Level	#4
ANN	−0.5464	−0.0243	M2 Linear-LogX	#5

Note: ★ The top-ranked or best-performing algorithm.

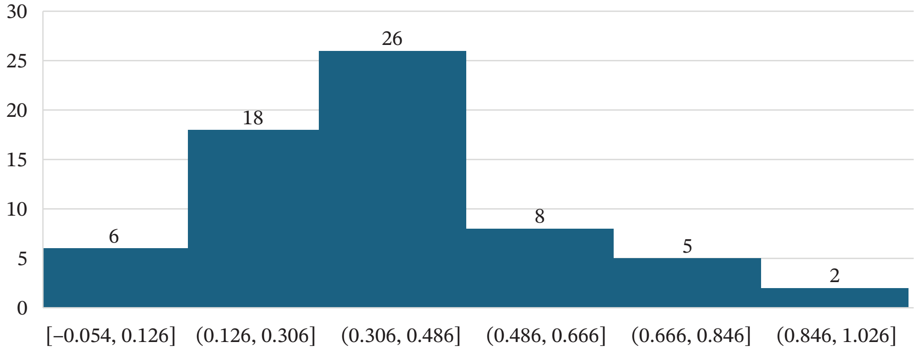

FIGURE 16 | Country-level beta values from the regression.

TABLE 17 | Model summary of overall regression.

Model	R	R square	Adjusted R square	Std. error of the estimate
1	0.495[a]	0.245	0.208	8.994

Note: Dependent variable: WBIp.
[a]Predictors: (Constant), HDIp, SCIp.

TABLE 18 | ABMSCWB regression coefficients.

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. error	Beta		
1	(Constant)	20.814	14.544		1.431	0.160
	SCIp	0.425	0.194	0.297	2.190	0.034
	HDIp	0.385	0.134	0.390	2.876	0.006

Note: Dependent variable: WBIp.

It shows a moderate R-value of 0.495 (R-squared = 0.245), indicating that about 24.5% of the variance in WB is explained by the SCI and Human Development Index.

Both the SCI ($\beta = 0.297$, $p = 0.034$) and the Human Development Index ($\beta = 0.390$, $p = 0.006$) significantly and positively influence WB, indicating that improvements in these areas may enhance overall WB.

Based on the regression results, the equation of the line for predicting TWB based on SCI and HDI is as follows:

$$\text{TWB} = 20.814 + 0.425 * \text{SCI} + 0.385 * \text{HDI}. \quad (10)$$

These results depict that increasing social cohesion by one unit can increase overall WB of a country by 42.5%. Similarly, increasing human development by one unit can also impact TWB by 38.5% (Table 18).

6 | Conclusion

Consistent with the generative modeling tradition in ABM, the purpose of this ABM is not microlevel prediction but to demonstrate that Khaldunian mechanisms are sufficient to generate macrolevel cohesion–WB cycles under broad, theoretically grounded parameter ranges. The analysis shows robust country-level associations between social cohesion (SCI) and WB (WBI) in both the ABM and WVS analyses. Beyond documentation, the findings invite interpretation of how cohesion interacts with material development to shape WB. High development without cohesion may fail to translate resources into WB, as social norms, trust, and collective efficacy—key for cooperative service use and fair resource distribution—are weak. This can lead to fragmentation and stress, thereby dampening gains in prosperity. Conversely, strong cohesion can frontload development benefits into everyday life through inclusive support and coordinated public goods, translating the HDI into tangible WB more efficiently.

Cultural and spiritual factors shape these effects. Collectivist or high-trust cultures may amplify WB returns to development and cohesion, while rule of law, transparency, and social protection can reinforce or undermine this coupling. In settings with weak institutions or inequities, even strong cohesion may not yield broad gains in WB if resources are misallocated, indicating a contingent, context-dependent relationship.

A plausible micro-to-macro pathway is as follows: (1) community alignment enhances collective action and institutional trust; (2) this improves access to and use of public services and social supports, mediating the HDI-WBI link; (3) better service experiences and perceived fairness elevate WB, reinforcing cohesion in a virtuous cycle. If development outpaces social integration, relative deprivation may erode cohesion and limit gains. Thus, policy should synchronize growth with institutions, inclusive norms, and socially integrative programs.

Policy implications include trust building and inclusive norms through participatory governance and transparent budgeting, strengthening safety nets and public services to reinforce social ties, tailor approaches to cultural and institutional contexts given varied effects of cohesion policies, and future work should model causal channels with longitudinal data to test mediation (cohesion ⟶ institutional trust ⟶ service use ⟶ WB) while exploring context interactions, showing that cohesion and development jointly drive WB via context-sensitive causal pathways.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in Comses.net at https://www.comses.net/codebases/a62efcea-bec7-4b5a-961c-aa655ca01cb1/releases/1.0.0/.

Endnotes

[1]See https://doi.org/10.25937/sqh5-8241.

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