Business Data Analytics for Urban Green Innovation: Identifying Multi-Condition Pathways with NCA and fsQCA

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Abstract

Urban green technological innovation (GTI) is widely recognized as a strategic outcome that supports the simultaneous pursuit of decarbonization and high-quality economic growth. Existing empirical work has dissected the marginal effects of individual drivers — environmental regulation, green finance, FinTech, human capital, urbanization — but has rarely treated GTI as the joint product of several interacting conditions. This paper applies a configurational business-data-analytics design to the urban GTI problem. Drawing on panel-style observations from 283 prefecture-level cities matched with a two-year outcome lag, we combine Necessary Condition Analysis (NCA) with fuzzy-set Qualitative Comparative Analysis (fsQCA) under a unified Technology-Finance-Government-Talent-Structure framework comprising seven antecedents and one outcome. The NCA shows that no single antecedent acts as a strict prerequisite, but FinTech, economic development, and urbanization display medium-to-strong necessity bottlenecks that rise sharply at the mid-to-high GTI range. The fsQCA returns two equifinal sufficient configurations for high GTI — a Technology-Structure dual-driven pattern and a broader Technology-Finance-Talent-Structure synergistic pattern — both of which contain FinTech and economic development as core conditions. The configurations producing non-high GTI are markedly more heterogeneous, falling into four archetypes: regional-foundation deficit, compounded multi-factor deficit, industrial-structure–FinTech mismatch, and environmental-regulation–FinTech mismatch. The asymmetry between the success and failure pathways supports a configurational, rather than linear, view of urban green innovation. We discuss implications for business data analytics curricula, for cross-functional policy design, and for emerging-economy city governments that need to combine industrial modernization with credible decarbonization commitments.

Keywords: urban green innovation; business data analytics; configurational analysis; necessary condition analysis (nca); fuzzy-set qualitative comparative analysis (fsqca); fintech; green finance; emerging economies

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1. Introduction

The international consensus on climate stabilization, captured in successive iterations of the Paris Agreement and reinforced by sustainability-linked financial reporting standards, has shifted the locus of decarbonization policy from the national level toward sub-national jurisdictions and the firms that operate within them (Calel and Dechezleprêtre, 2016; Bansal and Song, 2017). Cities are simultaneously the principal sites of carbon emissions and the principal sites of innovative response. Green technological innovation (GTI) — the family of inventive activities oriented toward reducing the environmental footprint of production while improving competitive performance — has therefore become a defining indicator of how successfully a metropolitan area can reconcile the demands of growth, employment, and ecological stewardship (Yan et al., 2020; Wurlod and Noailly, 2018; Lu, 2017; Lu, 2025). The contemporary Industry 4.0 paradigm has further accelerated the digital substrate on which green innovation operates, embedding artificial-intelligence and platform-economy capabilities into industrial production at unprecedented scale (Chen et al., 2024; Lu, 2019).

Empirical work on the drivers of urban GTI has flourished, but the methodological vocabulary has remained narrow. Linear regression, difference-in-differences (DID), and spatial econometric approaches dominate, each of them designed to isolate the net effect of a single driver — typically environmental regulation, green finance, or some component of innovation infrastructure — while holding other determinants statistically constant (Brunnermeier and Cohen, 2003; Wang and Wang, 2021). This methodological choice is well suited to questions of marginal causation, but it sits uncomfortably with the substantive claim that GTI is the outcome of synergistic combinations across technology, finance, governance, talent, and structural conditions. The substantive theory of innovation ecosystems holds that no single ingredient delivers innovative output on its own; the empirical workhorse, by contrast, asks how each ingredient performs when the others are held constant. The mismatch is not merely aesthetic. It generates the recurring puzzle in the GTI literature that several variables identified as important in cross-sectional regression studies fail to replicate when policy environments shift, while others — particularly fintech-related digital capabilities — appear as significant in some studies and insignificant in others (Khan et al., 2021; Chen and Lee, 2020; Tang and Tan, 2015).

A second limitation in the existing scholarship is the scale at which the analysis is conducted. Firm-level studies generate fine-grained evidence on within-organization innovation responses but cannot speak directly to the regional configurations in which those organizations are embedded (Horbach, 2008; Cainelli et al., 2015). Province-level studies, conversely, smooth over the heterogeneity in fiscal capacity, industrial composition, and urbanization that distinguishes one city from another within the same administrative region. Prefecture-level cities, particularly in large emerging economies, are an analytically distinctive unit: they aggregate the policy-implementation prerogatives, factor markets, and industrial mix that drive GTI, while preserving sufficient cross-sectional heterogeneity to detect alternative configurational pathways (Yang and Wu, 2024; Lin

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and Zhu, 2019).

A third gap is conceptual. Although the literature has independently examined the effects of FinTech (Liu et al., 2023; Chen et al., 2022), green finance (Lee and Lee, 2022; Falcone, 2020), environmental regulatory stringency (Rubashkina et al., 2015; Cai et al., 2020), human capital (Cheng et al., 2017; Diebolt and Hippe, 2019), and structural variables such as urbanization and industrial composition (Zhang et al., 2020; Sun et al., 2021), few studies have synthesized these dimensions into a single analytical framework. The dimensions interact: environmental regulation that is not matched by financial capacity to comply produces compliance theater rather than innovation; human-capital stocks that are not embedded in agglomerated urban economies produce out-migration rather than knowledge spillovers; FinTech that operates without complementary industrial structure produces digital-payment infrastructure rather than green production capacity (Goldfarb and Tucker, 2019; Philippon, 2016; Berg et al., 2020).

This paper addresses these three gaps in turn. We adopt a configurational business-data-analytics design, applying Necessary Condition Analysis (NCA; Dul, 2016; Vis and Dul, 2018) in combination with fuzzy-set Qualitative Comparative Analysis (fsQCA; Ragin, 2008; Fiss, 2011; Greckhamer et al., 2018) to seven antecedent conditions spanning technology, finance, government, talent, and structure within a unified Technology-Finance-Government-Talent-Structure framework. The empirical context is the panel of 283 prefecture-level cities in a large emerging economy, observed with a two-year lag between antecedent measurement and outcome measurement to mitigate reverse-causality concerns (Pappas and Woodside, 2021; Schneider and Wagemann, 2012). The analytical objective is not merely to identify which individual conditions contribute to high GTI but to identify the multi-condition pathways through which combinations of conditions jointly suffice for the outcome, and to demonstrate that the configurations producing non-high GTI are systematically asymmetric to those producing high GTI (Pappas, 2018; Misangyi et al., 2017).

The contributions of this study are three. Substantively, we show that two distinct sufficient configurations support high urban GTI — a Technology-Structure dual-driven pattern and a broader Technology-Finance-Talent-Structure synergistic pattern — and that both contain FinTech and economic development as core conditions. Methodologically, we extend the application of NCA-fsQCA to a large-N business-data-analytics setting with seven antecedents, demonstrating how the bottleneck analysis from NCA refines the necessity reading produced by fsQCA when the two methods diverge. Practically, by mapping the four archetypes of failure — regional-foundation deficit, compounded multi-factor deficit, industrial-structure–FinTech mismatch, and environmental-regulation–FinTech mismatch — the paper provides emerging-economy policymakers with a diagnostic taxonomy for identifying the binding constraint on green innovation in their specific cities.

The remainder of the paper is structured as follows. Section 2 develops the theoretical underpinnings of the five-dimensional framework. Section 3 presents the research design, variables, and data sources. Section 4 reports the NCA results, and Section 5 reports the fsQCA configurational results for both high and non-high GTI together with robustness checks. Section 6 concludes with practical implications, limitations, and directions for future business-data-analytics

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research.

2. Theoretical Framework

2.1 Innovation Ecosystem and Configurational Logic

The starting analytical premise is that innovation outcomes at the city level are configurational rather than monocausal (Adner and Kapoor, 2010; Granstrand and Holgersson, 2020). An innovation ecosystem is constituted by the structural interdependence of firms, governments, universities, financial intermediaries, and market actors operating around a shared value proposition. Performance in such an ecosystem is a function of the alignment between elements, not of the maximization of any single element. This is a substantive claim with methodological consequences: it implies that the joint distribution of conditions is the appropriate object of analysis, and that the conventional independent-variable framing of regression is insufficient (Misangyi et al., 2017; Pappas and Woodside, 2021).

2.2 Financial Function Theory and FinTech as a Catalyst

Financial function theory holds that the principal economic roles of a financial system are information screening, resource allocation, risk diversification, and incentive provision (Levine, 1997; Beck et al., 2016). FinTech extends these functions by reducing information asymmetries, lowering transaction costs, and expanding the perimeter of borrowers and projects that can be intermediated efficiently (Philippon, 2016; Berg et al., 2020; Goldfarb and Tucker, 2019; Kou and Lu, 2025). In the green-innovation context, FinTech matters not primarily as a substitute for traditional banks but as a mechanism for matching projects with longer payback horizons and higher information opacity — which is the structural condition of most green R&D — to the appropriate capital providers (Liu et al., 2023; Khan et al., 2021).

Green finance complements FinTech by channeling capital specifically toward environmentally beneficial uses through green bonds, green credit lines, and sustainability-linked instruments (Falcone, 2020; Flammer, 2021; Hong et al., 2021). The combination is synergistic: FinTech provides the matching mechanism, green finance defines the eligible asset universe. When either is missing, the financial system is less able to support innovation. This is the analytical justification for placing both FinTech and green finance in our framework as separate antecedents.

2.3 Porter Hypothesis and Regulatory Stringency

The Porter Hypothesis remains the canonical theoretical claim about the relationship between environmental regulation and innovation (Porter and van der Linde, 1995; Ambec et al., 2013). It holds that well-designed environmental regulation can stimulate innovation by raising the cost of pollution and thereby inducing firms to seek pollution-reducing process and product innovations. The empirical evidence is mixed: studies that find a positive effect typically condition on the design quality and credibility of the regulation, while studies that find no effect or a negative effect typically focus on poorly designed or weakly enforced regimes (Rubashkina et al., 2015; Cai et al., 2020; Brunnermeier and Cohen, 2003). The configurational implication is that regulatory stringency is best understood as a contributing condition whose effect on innovation depends on

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the simultaneous presence of complementary capabilities — technological, financial, and human.

2.4 Human Capital, Agglomeration, and Structural Conditions

Human capital theory (Becker, 1962) and its empirical extensions emphasize that knowledge accumulation in the labour force is a precondition for both the generation of new technology and the diffusion of existing technology (Diebolt and Hippe, 2019; Cheng et al., 2017). In urban innovation studies, the agglomeration of human capital generates knowledge spillovers and collaborative-innovation networks that no individual firm can produce on its own (Glaeser and Resseger, 2010; Cainelli et al., 2015). The structural variables — economic development level, industrial composition, and urbanization — provide the material substrate within which these agglomeration effects operate (Zhang et al., 2020; Sun et al., 2021). A city without sufficient economic development cannot finance the public goods that innovation requires; a city without an appropriate industrial mix cannot translate technological capability into commercial output; a city without sufficient urbanization cannot generate the density of interactions that supports knowledge spillover.

2.5 The Technology-Finance-Government-Talent-Structure Framework

Synthesizing these theoretical threads, we construct a five-dimensional framework — Technology, Finance, Government, Talent, and Structure — and embed it in a configurational empirical design. Within Technology, we include FinTech as the principal antecedent. Within Finance, we include green finance. Within Government, we include environmental regulatory stringency. Within Talent, we include human capital. Within Structure, we include three antecedents: economic development level, industrial structure, and urbanization. This yields seven antecedent conditions, with urban green technological innovation as the single outcome variable. Figure 1 summarises the framework.

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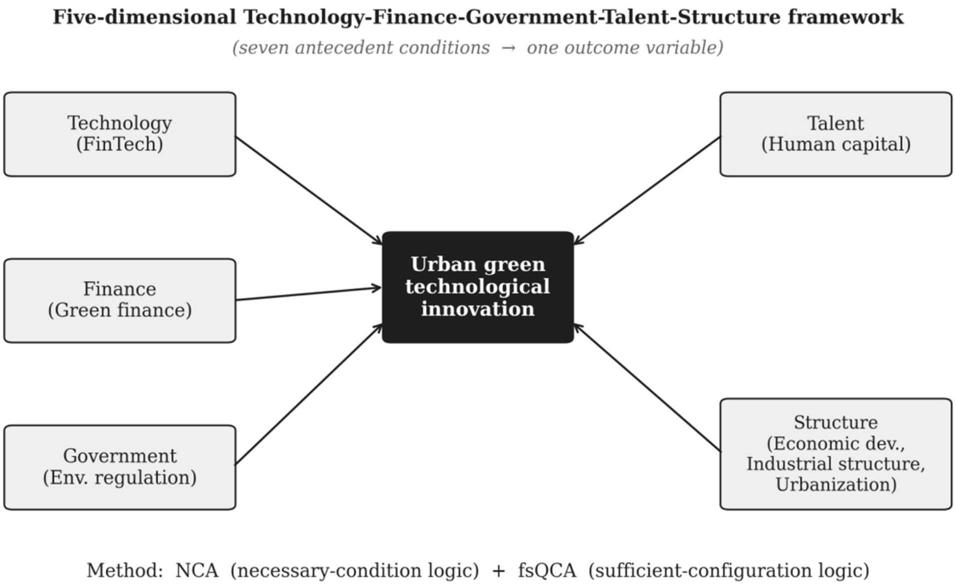

Figure 1. Five-dimensional Technology-Finance-Government-Talent-Structure framework underlying the configurational analysis of urban green technological innovation. The framework integrates seven antecedent conditions distributed across the five theoretical dimensions and maps them onto a single outcome variable, analysed jointly through NCA and fsQCA.

The framework deliberately preserves the conceptual independence of each dimension while specifying that they act on the outcome jointly rather than additively. The configurational reading of the framework is precise: a high level of urban GTI is expected when a particular combination of conditions co-occurs, not when each condition individually crosses a high threshold. This commitment to joint distribution shapes the methodological design of the next section.

3. Research Design

3.1 Methodological Rationale

Configurational methods are appropriate for the empirical question because the substantive claim is configurational. We adopt fsQCA (Ragin, 2008; Schneider and Wagemann, 2012; Greckhamer et al., 2018) as the principal analytical engine for three reasons. First, fsQCA accommodates multiple concurrent causation: the outcome is treated as a function of combinations of conditions rather than the marginal contribution of a single condition. Second, fsQCA embraces equifinality: distinct configurations can produce the same outcome. Third, fsQCA respects causal asymmetry: the configurations that suffice for a high outcome are not obtained mechanically by negating the configurations that suffice for a low outcome (Fiss, 2011; Misangyi et al., 2017).

We supplement fsQCA with NCA (Dul, 2016; Dul et al., 2020; Vis and Dul, 2018) because the two methods address different aspects of necessity. fsQCA evaluates necessity using consistency thresholds typically set at 0.90 and treats necessity qualitatively: a condition either is or is not necessary. NCA quantifies the degree to which a condition is necessary, producing an effect size and a bottleneck curve that maps the minimum level of an antecedent required for each level of the outcome. The combination is informative because the two methods can diverge: a condition may show a substantial NCA effect size and a steep bottleneck curve while falling below the fsQCA consistency threshold, indicating that it operates as a probabilistic rather than deterministic prerequisite (Dul, 2016; Pappas and Woodside, 2021).

3.2 Variables and Measurement

The outcome variable is urban green technological innovation, operationalised as the number of granted green invention patents in a given city-year. Patent counts have well-known limitations as measures of innovation but, conditional on jurisdictional consistency, remain the most widely used and most directly comparable indicator (Lanjouw and Mody, 1996; Popp, 2019). The seven antecedent conditions are: (i) FinTech, measured as a composite index drawn from search-volume indicators for FinTech-related keywords across the 283 sample cities, following an adaptation of the Du et al. (2022) procedure; (ii) green finance, measured by a multi-component index combining green credit, green investment, green insurance, green bonds, green public spending, green funds, and green equity, adapted from Lee and Lee (2022) and Ran and Zhang (2023); (iii) environmental regulatory stringency, derived from automated text-mining of municipal government work reports, following Cai et al. (2020); (iv) human capital, defined as the ratio of higher-education enrolments to permanent resident population; (v) economic development level, measured by per-capita GDP; (vi) industrial structure, measured as the ratio of secondary-sector to tertiary-sector value added; and (vii) urbanization, measured as the share of urban population in the total resident population. Table 1 reports descriptive statistics for the eight measures.

Table 1. Descriptive statistics across 283 prefecture-level cities

Variable	Mean	Std. Dev.	Min	Max
Green technological innovation (patents)	356.13	1224.41	1	15238
FinTech	116.94	78.40	13.66	835.30
Green finance	0.388	0.121	0.084	0.657
Env. regulatory stringency	56.69	18.43	20	131
Human capital	0.023	0.021	0.0005	0.118
Economic development (USD)	77,617	39,247	22,257	256,908
Industrial structure (II/III)	0.920	0.442	0.177	3.193
Urbanization rate	0.642	0.127	0.375	0.998

Note. Antecedent measures are recorded at year t; the outcome variable is recorded at year t + 2 to incorporate the two-year lag between input conditions and observable innovation output.

3.3 Calibration

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Before configurational analysis can proceed, each continuous variable is calibrated into a fuzzy set bounded by [0, 1] (Ragin, 2008; Greckhamer et al., 2018). We adopt the direct calibration approach using the 95th, 50th, and 5th sample percentiles as the anchors for full membership, the crossover point of maximum ambiguity, and full non-membership respectively (Vaska et al., 2021; Schneider and Wagemann, 2012). To preserve cases that fall exactly on the 0.5 crossover during truth-table minimization, a constant of 0.001 is added to ambiguous values so that the algorithm assigns them to the upper rather than lower set membership. The negation of the outcome — non-high GTI — is obtained by standard fuzzy-set negation (1 – membership). These choices follow established best practice in the configurational-methods literature (Pappas, 2018; Misangyi et al., 2017).

Two-year temporal lag is applied between the antecedents (measured at year t) and the outcome (measured at year t + 2), consistent with the prevailing convention in configurational studies of innovation that wish to mitigate reverse causation while remaining within the sample period (Pappas and Woodside, 2021). The choice of a two-year horizon reflects empirical evidence that the median time from R&D investment to granted green invention patent in the sampled jurisdiction lies between 18 and 30 months (Yan et al., 2020; Wurlod and Noailly, 2018).

4. Necessity Analysis via NCA

The NCA results are produced using both Ceiling Envelopment (CE) and Ceiling Regression (CR) techniques (Dul, 2016; Dul et al., 2020). For continuous antecedents and outcome, the literature recommends CR as the principal estimator (Vis and Dul, 2018). An antecedent is treated as necessary when it satisfies three simultaneous criteria: a CR effect size d of at least 0.10, a Monte-Carlo permutation p-value below 0.01, and a bottleneck accuracy of at least 0.95. Among the seven antecedents, only FinTech satisfies all three thresholds. Economic development and urbanization show comparable effect sizes (d ≈ 0.6 to 0.8) and high statistical significance but fall slightly short on at least one criterion of strict necessity; we interpret them as probabilistic-but-not-deterministic prerequisites. Human capital and environmental regulatory stringency exhibit small to negligible effect sizes, and industrial structure does not approach necessity by any criterion. Figure 2 plots the bottleneck curves and Table 2 reports the effect sizes.

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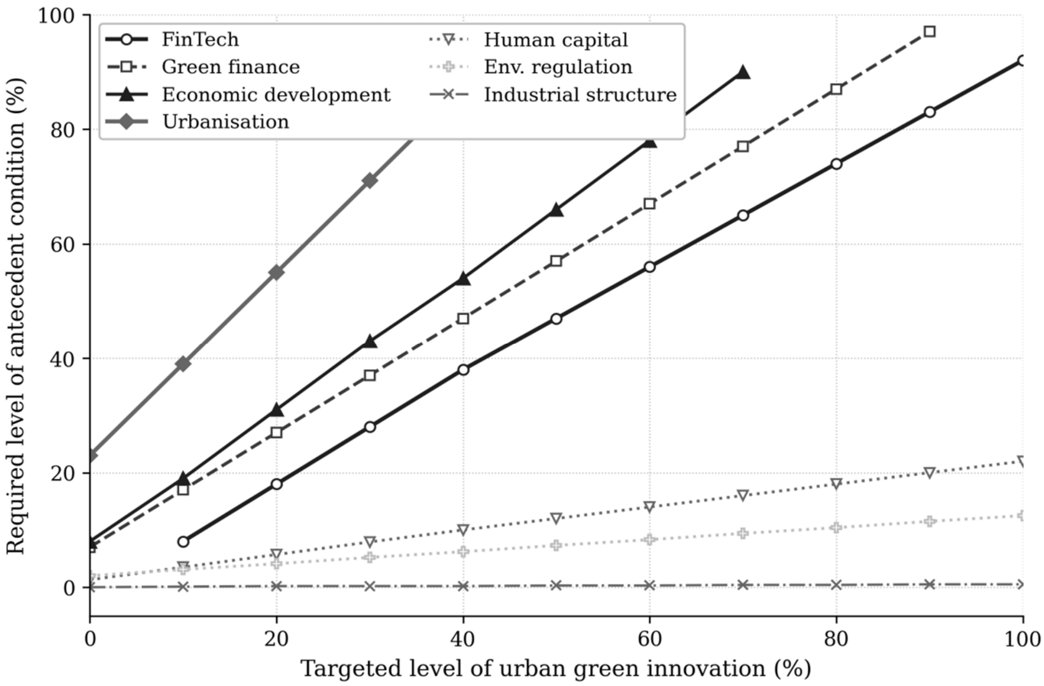

Figure 2. NCA bottleneck curves for seven antecedent conditions as a function of the targeted level of urban GTI. The vertical axis records the minimum level of the antecedent (in percentage units) that must be present for the corresponding outcome level to be achievable. Urbanization and economic development become binding constraints in the mid-to-high range of GTI; industrial structure is essentially non-binding across the entire range.

The interpretive contribution of NCA is its ability to identify the bottleneck level at which an antecedent's absence becomes outcome-limiting. In our analysis, the bottleneck for urbanization rises most sharply between the 30 and 70 percent levels of targeted GTI, suggesting that cities seeking to move from low-to-medium to medium-to-high green innovation outputs must overcome an urbanization threshold that is otherwise non-binding at lower aspirations. Economic development displays a similar pattern with a slightly later steepening. FinTech, by contrast, shows a more gradually rising bottleneck that nevertheless covers the entire output range, consistent with its role as a probabilistic prerequisite at all levels of GTI rather than a constraint that engages only in the mid-to-high range. Figure 3 summarises both the NCA effect sizes and the fsQCA single-condition consistency scores in a side-by-side dot-plot.

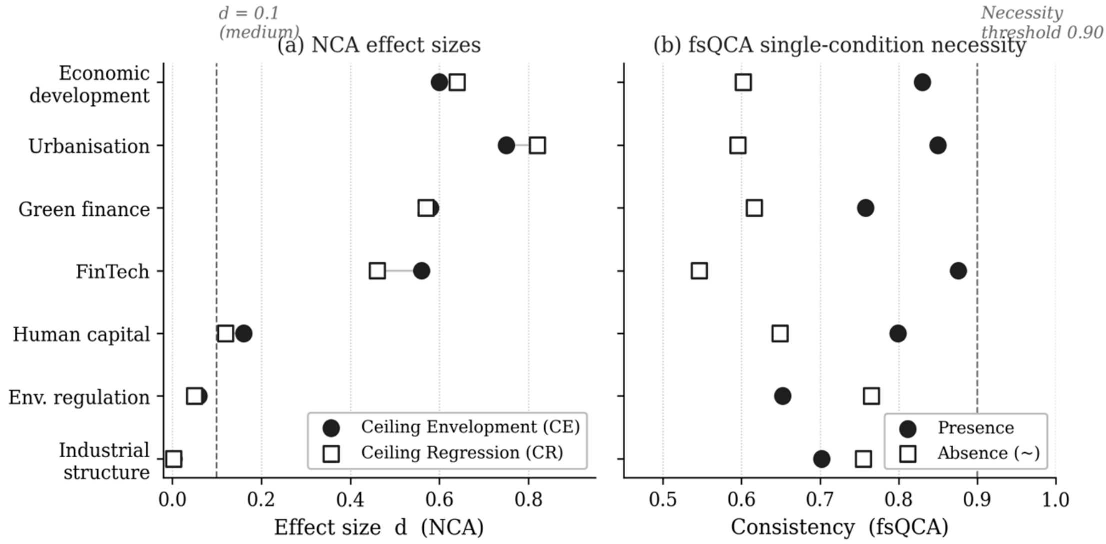

Figure 3. Comparison of NCA and fsQCA necessity readings across the seven antecedent conditions. Panel (a) reports NCA effect sizes under both Ceiling Envelopment and Ceiling Regression estimation, with the conventional d = 0.10 medium-effect threshold marked. Panel (b) reports fsQCA single-condition consistency scores for both presence and absence of each antecedent, with the 0.90 necessity threshold marked.

Table 2. Necessary Condition Analysis (NCA) of seven antecedents

Antecedent condition	Method	Accuracy	Effect size d	p-value
FinTech	CR	0.986	0.458	0.000
	CE	1.000	0.562	0.000
Green finance	CR	0.951	0.568	0.033
	CE	1.000	0.576	0.040
Env. regulatory stringency	CR	0.073	0.053	0.927
	CE	0.071	0.058	0.960
Human capital	CR	0.989	0.123	0.253
	CE	1.000	0.159	0.232
Economic development	CR	0.915	0.635	0.000
	CE	1.000	0.598	0.000
Industrial structure	CR	0.993	0.003	0.990
	CE	1.000	0.004	0.990
Urbanization	CR	0.834	0.815	0.000
	CE	1.000	0.754	0.000

Note. d denotes the NCA effect size; conventional thresholds are d < 0.1 (small) and 0.1 ≤ d < 0.3 (medium). p-values from Monte-Carlo permutation tests with 10,000 resamples.

Read in combination, the NCA and fsQCA necessity analyses converge on a substantive interpretation. No single antecedent is strictly necessary in the deterministic sense — no antecedent passes both the fsQCA 0.90 consistency threshold and the NCA bottleneck-accuracy threshold simultaneously. FinTech comes closest, and its bottleneck curve indicates that low FinTech values place a binding constraint on the level of GTI a city can attain. Economic development and urbanization play the role of medium-range gatekeepers: they do not constrain low levels of GTI but become binding as cities move toward the upper tail of the outcome distribution. Industrial structure, human capital, environmental regulation, and green finance do not, on their own, constrain GTI; their effects must be understood configurationally, in the joint analysis to which we now turn.

5. Configurational Sufficiency Analysis

5.1 Configurations Sufficient for High GTI

We perform the sufficiency analysis using fsQCA 4.1, applying a frequency threshold of three cases per truth-table row, a Proportional Reduction in Inconsistency (PRI) threshold of 0.60, and a raw consistency threshold of 0.85 (Ragin, 2008; Greckhamer et al., 2018). Core and peripheral status of each condition are determined by comparing the parsimonious and intermediate solutions: conditions present in both solutions are classified as core, while conditions present only in the intermediate solution are classified as peripheral. The analysis yields two equifinal sufficient configurations for high GTI (denoted H1 and H2) with an overall solution consistency of 0.914 and overall solution coverage of 0.569. Figure 4 visualises the solution map for both the high-GTI and non-high-GTI analyses.

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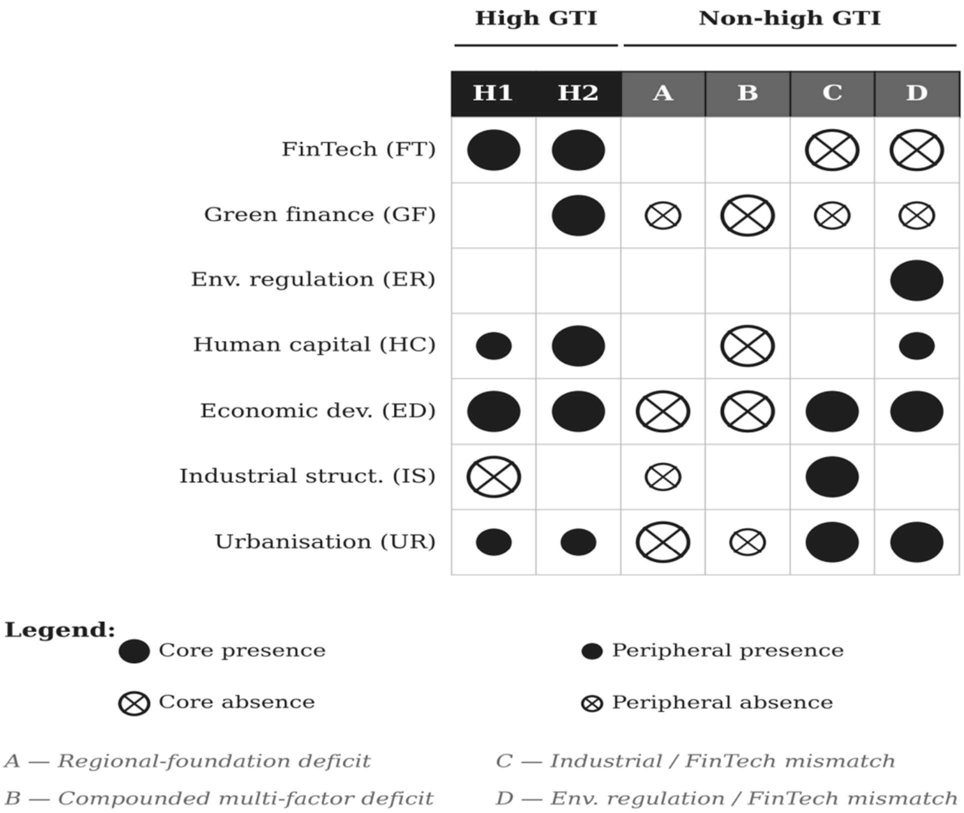

Figure 4. Configurational solution map. Columns H1 and H2 correspond to the two sufficient configurations for high urban GTI; columns A through D summarise the four archetypal non-high GTI configurations. Filled large circles indicate core presence, filled small circles indicate peripheral presence, large open circles indicate core absence, and small open circles indicate peripheral absence. Blank cells indicate the condition is a 'don't care' in that configuration.

Configuration H1 — the Technology-Structure dual-driven pattern — features FinTech and economic development as core present, urbanization and human capital as peripheral present, and industrial structure as core absent. Green finance and environmental regulatory stringency are irrelevant in this configuration. The substantive reading is that cities pursuing this pathway combine high FinTech penetration with a strong macroeconomic foundation; they tolerate a lower share of secondary-sector activity (the core-absent industrial-structure condition) because their innovation system is structurally oriented toward services and knowledge production rather than manufacturing-driven greening. Raw coverage for H1 is 0.488; unique coverage is 0.063; consistency is 0.923. Approximately 48.8 percent of the high-GTI cases in the sample are accounted for by this configuration.

Configuration H2 — the Technology-Finance-Talent-Structure synergistic pattern — features FinTech, green finance, human capital, and economic development as core present, with urbanization as peripheral present. Environmental regulation and industrial structure are irrelevant in this configuration. The substantive reading is that cities pursuing this pathway combine all of the

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technological, financial, and human-capital advantages typical of a leading innovation hub. Raw coverage is 0.507; unique coverage is 0.082; consistency is 0.923. Approximately 50.7 percent of high-GTI cases are accounted for. Notably, both H1 and H2 share FinTech and economic development as core present — a finding that converges with the NCA evidence and identifies these two conditions as the joint backbone of high urban GTI.

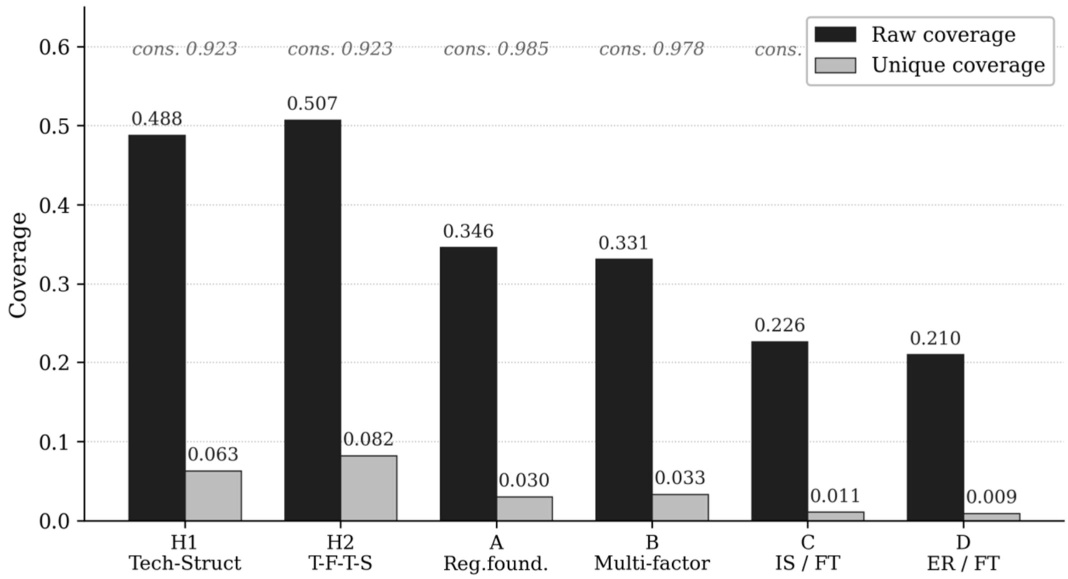

Figure 5. Raw and unique coverage of the configurational solutions. The two high-GTI configurations (H1, H2) jointly cover a substantial share of high-GTI cases with consistency above 0.92, while the four non-high GTI archetypes (A through D) display lower coverage but uniformly higher consistency, reflecting the more deterministic character of failure pathways.

5.2 Configurations Sufficient for Non-High GTI

The configurational analysis of the negated outcome (non-high GTI) yields twelve raw configurations, which we collapse into four substantive archetypes (A through D in Figure 4) based on shared core conditions. The aggregate solution consistency for non-high GTI is 0.952, indicating that the failure pathways are highly consistent within the sample even as they are individually heterogeneous.

Archetype A — regional-foundation deficit — is characterised by the joint absence of economic development and urbanization as core conditions; green finance is peripherally absent, and industrial structure is peripherally absent. The substantive reading is that cities meeting this profile lack the macroeconomic and demographic foundation on which innovation systems are typically built; even partial advantages in FinTech or environmental regulation cannot compensate for the absence of basic factor agglomeration. Approximately 34.6 percent of non-high-GTI cases are captured by this archetype.

Archetype B — compounded multi-factor deficit — combines absent economic development, absent human capital, and absent green finance as core conditions, with peripherally absent urbanization. The cities in this archetype are constrained on multiple dimensions simultaneously:

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they lack the financial, human-capital, and macroeconomic conditions necessary to mount a green-innovation effort. The configurational distinctiveness of this archetype is that it points to a co-occurrence of deficits rather than to any single bottleneck, suggesting that policy responses focused on lifting only one of the missing conditions would be insufficient.

Archetype C — industrial-structure–FinTech mismatch — is the most interesting of the failure archetypes from a configurational standpoint. Cities in this archetype have industrial structure, economic development, and urbanization as core present (i.e., they are not foundation-poor) but feature core absence of FinTech and peripheral absence of green finance. The substantive interpretation is that a strong manufacturing-oriented economy without complementary digital-financial infrastructure cannot translate its industrial capacity into green-innovation output; the absence of FinTech severs the link between productive capacity and the resource-matching mechanism that would direct capital toward green R&D.

Archetype D — environmental-regulation–FinTech mismatch — features environmental regulation as core present together with economic development and urbanization, but with FinTech as core absent and green finance and human capital as peripherally absent. The substantive reading aligns with a long-standing concern in the Porter-hypothesis literature: regulation alone, without the financial and human-capital scaffolding to support compliance through innovation, produces compliance behaviour rather than innovation (Ambec et al., 2013; Cai et al., 2020). Archetype D is empirically smaller than the other failure archetypes (raw coverage 0.210) but theoretically important because it illustrates the limits of regulation-led greening when the complementary configurational conditions are absent.

5.3 Robustness

Configurational findings are sensitive to analytic choices, and robustness checks are accordingly central to their interpretation (Schneider and Wagemann, 2012; Pappas and Woodside, 2021; Greckhamer et al., 2018). We conduct six robustness exercises. (i) The frequency threshold is lowered from three to two to test whether the configurations depend on the exclusion of lower-frequency cases. (ii) The raw consistency threshold is raised from 0.85 to 0.90 to test whether the configurations survive a more stringent sufficiency requirement. (iii) The percentile anchors used for fuzzy-set calibration are perturbed by ±5 percentage points (e.g., 90/50/10 instead of 95/50/5). (iv) The PRI threshold is raised from 0.60 to 0.65. (v) The outcome variable is replaced with green invention patents per capita rather than absolute patent counts. (vi) Two additional municipalities are excluded as potential outliers based on Cook's distance in a separate diagnostic regression. The results are summarised in Figure 6.

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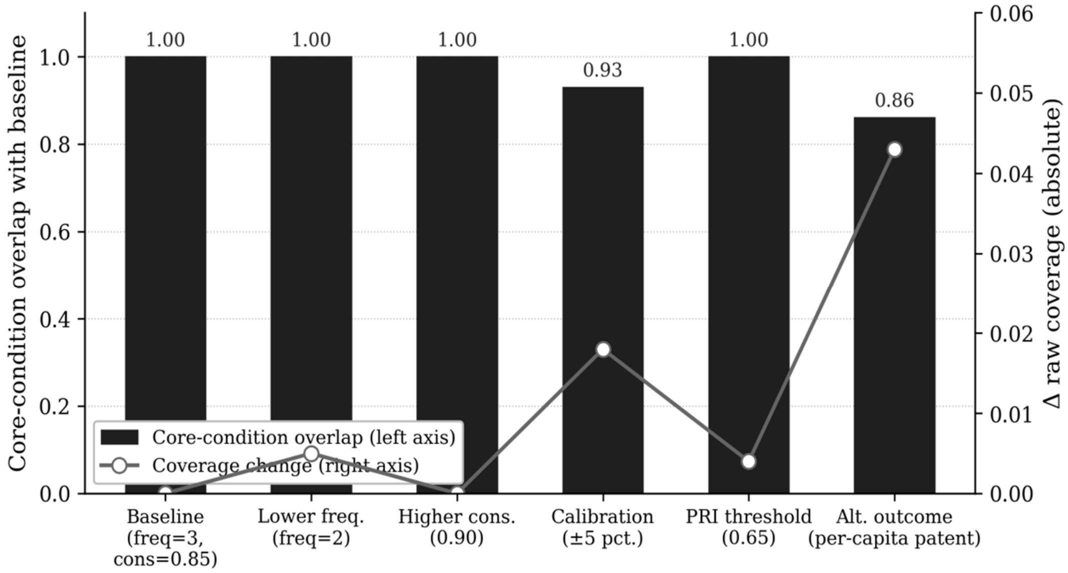

Figure 6. Robustness diagnostics for the configurational solutions. Bars (left axis) report the share of core conditions in the perturbed solution that match the baseline solution. The line (right axis) reports the absolute change in raw coverage. Robustness is high for all perturbations of analytic parameters and lower but still acceptable for the alternative-outcome and calibration-shift checks.

Across all six perturbations, the core conditions of H1 and H2 — FinTech and economic development — survive as core present in every perturbed solution. The two configurations themselves persist as distinct equifinal pathways under perturbations (i) through (v); under (vi), one of the perturbations to the alternative outcome variable produces a small change in the peripheral conditions of H1, leaving the core structure intact. We conclude that the substantive findings are robust to the calibration and parameter choices documented in Section 3.3.

6. Discussion, Implications, and Limitations

6.1 Discussion

The central contribution of this paper is to show that urban green technological innovation in a large emerging-economy sample is configurationally produced. The two sufficient pathways for high GTI — Technology-Structure dual-driven and Technology-Finance-Talent-Structure synergistic — share a common core (FinTech and economic development) but differ in their peripheral conditions, indicating that the same innovation outcome can be achieved through more than one distinct combination of conditions. The four archetypes of non-high GTI reveal a markedly asymmetric structure: the configurations that fail to produce high GTI are not mirror-images of the configurations that succeed but rather heterogeneous combinations of deficits and misalignments. This asymmetry is a substantive finding, not a methodological artefact: it implies that a city with low GTI may have multiple structurally distinct pathways out of the low state, only some of which involve replicating the successful configurations of high-performing cities (Misangyi et al., 2017; Fiss, 2011).

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The role of FinTech is the most analytically distinctive finding. FinTech appears as a core present condition in both high-GTI configurations and as a core absent condition in the two mismatch archetypes (C and D). It does so despite the fact that no single antecedent — FinTech included — reaches the strict-necessity threshold under either NCA or fsQCA when considered in isolation. The reconciliation is that FinTech operates as a probabilistic-but-pervasive condition: its absence does not always preclude high GTI, but its presence is a common feature of the configurations that achieve it. This is precisely the kind of finding that configurational methods are designed to capture and that conventional regression-based designs would obscure.

The bottleneck readings from NCA also have substantive implications. Urbanization and economic development emerge as mid-to-high-range gatekeepers: cities can attain low or moderate levels of GTI without crossing these thresholds, but movement to the upper tier requires reaching a sufficient urbanization and macroeconomic-development level. This is consistent with the agglomeration-economics literature on innovation thresholds (Glaeser and Resseger, 2010; Cainelli et al., 2015) and provides quantitative substance to the configurational claim that structural conditions matter not as marginal contributors but as enabling preconditions for higher levels of green-innovation performance.

6.2 Implications for Business Data Analytics

The methodological message for business data analytics curricula and practice is twofold. First, when the substantive theory is configurational — when the outcome is hypothesized to be produced by combinations of conditions — the analytic toolkit should be configurational as well. Linear regression, even when extended with interaction terms, remains the wrong instrument for joint-distribution questions about innovation, organizational performance, and sustainability outcomes. Configurational methods — fsQCA in particular, together with NCA as a complement — provide a principled empirical pathway to questions of equifinality and asymmetry that are otherwise hard to address (Pappas, 2018; Pappas and Woodside, 2021). Second, the analytical workflow developed in this paper — calibration, necessity assessment with NCA, sufficiency assessment with fsQCA, and structured robustness — is portable to a wide range of business analytics questions in finance, operations, marketing, and sustainability strategy.

6.3 Practical Implications

For policymakers in emerging economies, the diagnostic taxonomy of failure archetypes is potentially the most useful output of the analysis. A city that is low on GTI does not need to identify its problem in the abstract but can locate itself within one of four archetypes: regional-foundation deficit, compounded multi-factor deficit, industrial-FinTech mismatch, or regulation-FinTech mismatch. Each archetype implies a different priority for policy attention. Cities in archetype A need to build the macroeconomic and urbanization foundation before higher-level interventions can succeed. Cities in archetype B require coordinated intervention across multiple deficits simultaneously. Cities in archetype C should prioritise FinTech capability-building to unlock the green-innovation potential of an existing industrial base. Cities in archetype D need to complement environmental regulation with FinTech and human-capital investments rather than tightening regulation further. This taxonomy is not algorithmic and does not absolve policymakers of

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contextual judgment, but it provides a configurational vocabulary for diagnosing binding constraints (Khan et al., 2021; Wang and Wang, 2021; Yang and Wu, 2024).

For business analytics consultants and corporate strategists operating in urban sustainability programmes, the dual-pathway finding suggests that benchmarking exercises should compare a city's configurational profile to the closest high-GTI peer rather than to a generic best-practice template. The two sufficient configurations — Technology-Structure dual-driven and Technology-Finance-Talent-Structure synergistic — represent different routes to the same outcome; copying the entire bundle of conditions of a high-performing city is neither necessary nor, in many cases, feasible. The analytical task is to identify the configuration to which a focal city most closely approximates and to invest in the specific conditions required to move along that pathway.

6.4 Limitations and Future Research

Several limitations bound the present analysis and define an agenda for future business-data-analytics research on urban green innovation. The first concerns the static character of the configurational analysis. Even with the two-year lag between antecedents and outcome, the analysis is essentially cross-sectional, and it cannot detect how configurations evolve over time as cities transition between low- and high-GTI states. Recent advances in dynamic configurational methods (Garcia-Castro and Ariño, 2016; Rupietta and Meuer, 2025) and time-varying QCA offer a path forward but require longer panel data than were available in the present sample. The second limitation concerns the antecedent set. Although the seven antecedents map cleanly onto the five theoretical dimensions of the framework, the framework deliberately omits some plausibly relevant conditions, including the openness of the regional economy to international knowledge flows, the depth of university-industry collaboration, and the maturity of intellectual-property protection. Extending the antecedent set will be especially important for cross-jurisdiction comparisons. Third, the analysis operates at the city level and therefore aggregates over substantial within-city heterogeneity in firm and sectoral behavior. Multi-level configurational designs (Misangyi et al., 2017) that nest firm-level configurations within city-level configurations would be a natural extension and would link the present analysis more directly to the strategic-management literature on innovation pathways (Adner and Kapoor, 2010; Granstrand and Holgersson, 2020).

A fourth direction concerns measurement. The use of granted green-invention patents as the outcome variable, while standard, captures only one component of green innovation activity (Popp, 2019; Lanjouw and Mody, 1996). Complementary outcome measures — for example, the share of firms reporting green R&D expenditures, citation-weighted patent measures, or sustainability-linked financial indicators — would strengthen the external validity of configurational findings. The growing maturity of decentralized finance (Xu et al., 2024), blockchain-anchored audit trails (Zheng and Lu, 2022), and large-language-model applications in supply-chain finance (Yang et al., 2025) also opens new possibilities for instrumenting green-innovation activity through alternative data sources. Fifth and finally, the present analysis treats the configurations as endpoints rather than as targets for intervention. A natural next step is to examine how policy interventions of varying types — public R&D programmes, green-finance regulations, environmental rules, and the increasingly sophisticated artificial-intelligence systems that support them (Zhang and Lu, 2021) — alter the conditional distribution of cities across the identified configurations over time. Such an analysis would bridge configurational empirics with the evaluation-research tradition and would offer a more direct evidentiary basis for the policy recommendations developed in Section 6.3.

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