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Configuring AI Capabilities for Export Competitiveness: A Fuzzy-Set Analysis of 50 Economies

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ABSTRACT: Artificial intelligence (AI) is increasingly reshaping export competitiveness (EC), yet existing research largely emphasizes the marginal effects of individual AI capabilities. This study conceptualizes AI-enabled EC as a configurational outcome arising from AI investment (AIINS), digital infrastructure (AIDINF), AI human capital and skills (AIHCS), AI-enabled global value-chain integration (AIGVC), and AI innovation (AIINN). Using fuzzy-set Qualitative Comparative Analysis (fsQCA) across 50 economies, we identify alternative pathways to high EC and assess their robustness using consistency, coverage, and proportional reduction in inconsistency (PRI). No individual condition is universally necessary, while five sufficient configurations demonstrate substantial equifinality (consistency = 0.891420; coverage = 0.726243). Stricter PRI analysis identifies AIINSAIDINF~AIHCS*AIINN as the most robust configuration (consistency = 0.951025; coverage = 0.525331; PRI = 0.806594). The findings show that export competitiveness depends on configurational fit rather than AI-capability accumulation, with digital infrastructure and AI innovation playing particularly stable complementary roles.

1. INTRODUCTION

Artificial intelligence (AI) is evolving from a general-purpose technology into a strategic capability that reshapes international competitiveness. Beyond automation and productivity, AI increasingly enhances market intelligence, product development, innovation, cross-border coordination, and global value chain (GVC) activities (Buckley et al., 2026; Menzies et al., 2024). For export-oriented economies, competitiveness depends not only on production efficiency but also on the ability to identify global opportunities, upgrade products, coordinate international operations, and reduce transaction costs. Recent studies consistently associate AI with export performance, international trade, export quality, green export sophistication, technological complexity, and export upgrading (Chen & Dong, 2024; Jakubik et al., 2025; Kumar et al., 2025; Liu et al., 2025; Xu & Tian, 2025; Fang & Liu, 2025; Rao & He, 2026; Xu, 2026).

Despite this growing evidence, an important theoretical question remains: Does export competitiveness arise from individual AI capabilities or from their combinations? Existing research is predominantly variable-centred, emphasizing net effects, mediation, and moderation, while offering limited insight into conjunctural causation, equifinality, and causal asymmetry. AI capabilities rarely operate independently; infrastructure, innovation, human capital, investment, and GVC integration interact in complementary or substitutable ways (Bai et al., 2026; Buckley et al., 2026; Chiappini & Gaglio, 2024; Delera et al., 2022; Jangam et al., 2024).

This study addresses that gap by conceptualizing export competitiveness (EC) as a configurational outcome of five AI-related capabilities: AI investment (AIINS), AI digital infrastructure (AIDINF), AI human capital and skills (AIHCS), AI-enabled GVC integration (AIGVC), and AI innovation (AIINN). Rather than assuming additive effects, we argue that export advantages emerge through complementary capability architectures in which technological, organizational, and international resources reinforce or substitute for one another.

Empirically, the study applies fuzzy-set Qualitative Comparative Analysis (fsQCA) to 50 economies. FsQCA is particularly appropriate because it captures conjunctural causation, equifinality, causal asymmetry, and heterogeneity, identifying multiple sufficient pathways to high EC while distinguishing conventional sufficiency from stricter PRI-based robustness (Ragin, 2008; Rihoux & Ragin, 2009; Schneider & Wagemann, 2012).

The study makes three contributions. First, it reframes AI-enabled export competitiveness as a configurational rather than additive phenomenon. Second, it demonstrates that AI capabilities perform distinct configurational roles, with digital infrastructure as the most stable backbone and AI innovation as a critical complement. Third, it identifies the robust pathway AIINSAIDINF~AIHCS*AIINN, illustrating that countries with similar export competitiveness may follow markedly different AI capability configurations, as exemplified by Vietnam.

2. LITERATURE REVIEW

Artificial intelligence (AI) has evolved from an automation technology into a strategic capability shaping productivity, innovation, market intelligence, internationalization, and global value-chain (GVC) activities. This transformation is particularly consequential for export-oriented economies, where competitiveness increasingly depends on identifying foreign-market opportunities, adapting products, coordinating cross-border activities, and achieving technological upgrading (Buckley et al., 2026; Menzies et al., 2024).

A growing body of evidence links AI capabilities to export-related outcomes. AI strengthens export performance through enhanced international marketing capabilities (Chen & Dong, 2024; Kumar et al., 2025), reshapes comparative advantage and trade patterns (Jakubik et al., 2025), and supports export-product quality, green export sophistication, technological complexity, and spatial export upgrading (Fang & Liu, 2025; Liu et al., 2025; Rao & He, 2026; Xu, 2026; Xu & Tian, 2025). Cross-country evidence likewise associates AI readiness with stronger export performance (Lahmeri, 2025). Collectively, these findings establish a positive AI–export relationship, while suggesting that its effects depend on complementary technological, organizational, human, and international capabilities rather than on AI adoption alone.

Five interrelated capabilities are particularly relevant. AI investment (AIINS) provides resources for computing, data, R&D, and organizational transformation, but its contribution to export performance appears contingent on complementary capabilities (Besiroglu et al., 2024; Chen & Dong, 2024; Kumar et al., 2025). AI digital infrastructure (AIDINF) enables AI deployment, digital transformation, market access, and supply-chain coordination while reducing transaction costs (Bai et al., 2026; Chiappini & Gaglio, 2024; Zhou et al., 2024). AI human capital and skills (AIHCS) provide the absorptive capacity required to translate AI into innovation, managerial efficiency, product upgrading, and export sophistication (He et al., 2024; Liu et al., 2025; Xu & Tian, 2025). AI-enabled GVC integration (AIGVC) facilitates access to foreign knowledge, technologies, standards, and upgrading opportunities, although its contribution varies across production structures (Buckley et al., 2026; Delera et al., 2022; Jangam et al., 2024). Finally, AI innovation (AIINN) converts AI-related resources into new products, processes, and technological upgrading, with implications for export quality, manufacturing complexity, and green competitiveness (Besiroglu et al., 2024; Fang & Liu, 2025; Liu et al., 2025; Rao & He, 2026; Xu, 2026).

Despite these advances, three limitations remain. First, the AI–export relationship is heterogeneous across institutional, market, and production contexts, suggesting that AI capabilities do not generate uniform competitive effects (Chen & Dong, 2024). Second, existing studies examine diverse mechanisms including productivity, market exploration, innovation, quality upgrading, transaction-cost reduction, and GVC coordination but predominantly through variable-centred net-effect or mediation models (Bai et al., 2026; Chiappini & Gaglio, 2024; Jakubik et al., 2025; Rao & He, 2026). Third, limited attention has been paid to how these capabilities operate jointly, leaving the role of complementarity and substitution insufficiently understood.

This gap is theoretically important because the effectiveness of one AI capability may depend on the presence or absence of others. Different capability combinations may therefore generate comparable export outcomes, while the absence of a capability associated with one successful configuration may not preclude high competitiveness. Such conjunctural causation, equifinality, and causal asymmetry are difficult to capture with conventional additive approaches.

Accordingly, this study shifts the analytical question from “What matters?” to “What works together?” It conceptualizes high export competitiveness as a configurational outcome of AI investment, digital infrastructure, human capital and skills, GVC integration, and innovation, and examines how alternative combinations of these capabilities are associated with high EC.

3. THEORETICAL FRAMEWORK

Artificial intelligence (AI) is increasingly reshaping the technological and organizational foundations of international competitiveness. Its contribution to export competitiveness extends beyond productivity to product upgrading, technological sophistication, international market development, and cross-border coordination (Chen & Dong, 2024; Fang & Liu, 2025; Kumar et al., 2025; Liu et al., 2025; Xu & Tian, 2025). However, these benefits are unlikely to arise from AI capability in isolation. Rather, they depend on complementary technological, organizational, human, and international resources that enable AI to be deployed and converted into competitive value (Bai et al., 2026; Buckley et al., 2026; Chiappini & Gaglio, 2024; Delera et al., 2022; Jangam et al., 2024).

Building on this premise, the study adopts a capability-complementarity perspective, in which AI capabilities create export value through their interaction with complementary resources and through the configurations that these interactions generate:

AI capabilities → Complementary capabilities → Configurations → High export competitiveness (EC)

The central theoretical premise is therefore that high EC results from combinations of mutually reinforcing capabilities, rather than from the independent strength of individual AI-related factors. This perspective is consistent with international-business research emphasizing the interconnected nature of technological resources, organizational processes, knowledge, and cross-border activities (Buckley et al., 2026; Menzies et al., 2024). Accordingly, the analytical focus shifts from the marginal contribution of individual capabilities to the conditions under which they become jointly effective.

The framework specifies five theoretically distinct AI-related conditions: AI investment (AIINS), AI digital infrastructure (AIDINF), AI human capital and skills (AIHCS), AI-enabled GVC integration (AIGVC), and AI innovation (AIINN). AIINS represents the resource commitment required to develop and deploy AI; AIDINF provides the technological platform for its diffusion and coordination; AIHCS represents the knowledge and absorptive capacity required to exploit AI; AIGVC connects AI capabilities to international production and knowledge networks; and AIINN captures the capacity to transform AI-related resources into new products, processes, and technological upgrading. These conditions are therefore not treated as independent predictors but as potentially complementary or substitutable components of an AI-enabled capability architecture.

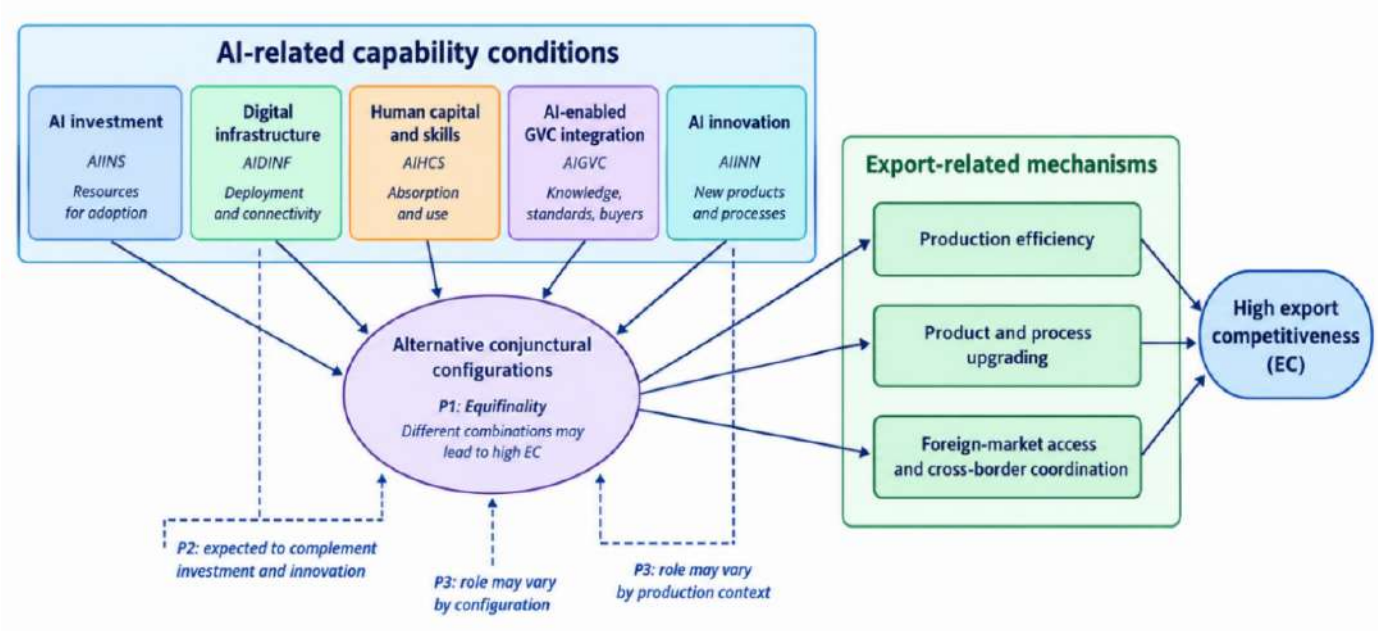


Figure 1. Theoretical framework linking AI-related capabilities to export competitiveness *(Arrows represent theorized enabling mechanisms and configurational relationships, not independently estimated causal effects.* ***P1*** *concerns alternative pathways;* ***P2*** *expects digital infrastructure to work especially effectively with investment and innovation;* ***P3*** *treats the roles of human capital and GVC integration as context-dependent.)*

The theoretical implication is complementarity rather than additivity. A capability may generate limited competitive value when critical complementary conditions are absent, whereas the same capability may become consequential when embedded in an appropriate configuration. Thus, investment may be less effective without adequate infrastructure, infrastructure may facilitate connectivity without generating upgrading without innovation, and human capital may not translate into export advantage without complementary technological and organizational conditions. High EC can consequently arise through multiple equifinal configurations rather than a single optimal combination.

This configurational perspective also implies that the role of a condition may vary across pathways. A capability that contributes to one successful configuration need not be present in all successful cases, because alternative capabilities may perform a compensating or substituting function. Accordingly, the framework does not assume that all five conditions must be simultaneously high. Instead, it allows for causal heterogeneity, equifinality, and causal asymmetry, whereby different combinations or the presence versus absence of a particular condition may be associated with the same outcome.

These theoretical properties provide the rationale for a set-theoretic approach. Rather than asking whether individual AI capabilities have positive average effects on exports, the study examines under what combinations of AI investment, digital infrastructure, human capital, GVC integration, and innovation these capabilities become sufficient for high EC. The resulting proposition is:

Proposition: High export competitiveness in the AI era emerges from configurations of complementary AI-related capabilities rather than from the independent strength or accumulation of any single capability.

4. RESEARCH METHOD

This study employs fuzzy-set Qualitative Comparative Analysis (fsQCA) to examine how combinations of AI-related capabilities are associated with high export competitiveness (EC) across 50 economies. FsQCA is appropriate for this purpose because it treats causal relationships as set relations and accommodates conjunctural causation, equifinality, causal asymmetry, and configurational heterogeneity (Ragin, 2008; Rihoux & Ragin, 2009; Schneider & Wagemann, 2012). The unit of analysis is the country/economy.

The empirical model comprises five causal conditions AI investment (AIINS), AI digital infrastructure (AIDINF), AI human capital and skills (AIHCS), AI-enabled GVC integration (AIGVC), and AI innovation (AIINN) and one outcome, high export competitiveness (EC). Each condition represents a theoretically distinct capability: resource commitment, technological infrastructure, absorptive capacity, international value-chain integration, and innovation capability, respectively. A codebook-first procedure specified the construct definition, indicator, measurement unit, data source, and membership direction before calibration to ensure consistency and avoid ex post adjustment (Schneider & Wagemann, 2012).

Calibration and set construction

Raw indicators were transformed into fuzzy-set membership scores using the direct three-anchor approach, with 0.95, 0.50, and 0.05 representing full membership, the crossover point, and full non-membership, respectively (Ragin, 2008; Schneider & Wagemann, 2012). Before calibration, the data were harmonized with respect to measurement units, directionality, and temporal consistency. Calibrated memberships were subsequently checked for ordering reversals, excessive compression, implausible extremes, and other inconsistencies. Thus, calibration was treated as a theoretically informed transformation into set membership rather than as conventional statistical normalization.

Analytical procedure

The analysis followed a sequential fsQCA procedure: calibration, necessity analysis, truth-table construction, Boolean minimization, and robustness assessment. Necessity analysis examined both the presence and absence of each condition, using set-theoretic consistency and coverage rather than statistical significance. With five causal conditions, the configurational space comprises 32 logically possible combinations. In the truth table, * denotes conjunction, + denotes alternative pathways, and ~ denotes the absence of a condition.

The baseline analysis applied a frequency threshold of 2 and a consistency threshold of 0.875057. Configurations not meeting these criteria were excluded from the sufficient solution. Boolean minimization was conducted using fsQCA 4.1, with Complex, Intermediate, and Parsimonious solutions examined to distinguish empirically grounded configurations from solutions that rely more heavily on logical remainders. Positive directional expectations were specified for the five causal conditions.

Robustness assessment

Robustness was assessed by systematically varying the analytical specifications, including frequency thresholds (1 versus ≥2), consistency thresholds (0.84–0.90), and pathway composition. In addition, Proportional Reduction in Inconsistency (PRI) was incorporated to evaluate whether configurations associated with high EC were also compatible with the negated outcome (~EC) (Schneider & Wagemann, 2012). The stricter C-PRI specification retained the baseline frequency and consistency criteria and imposed PRI ≥ 0.50.

The complete analytical sequence was preserved from raw indicators through calibration, truth-table assignment, minimization, and robustness testing to facilitate transparency and reproducibility. Detailed configurations, set-theoretic parameters, and country-level results are reported in Section 5.

5. RESULTS

5.1. Descriptive statistics and calibration profiles

The empirical analysis covers 50 economies and examines export competitiveness (EC) as the fuzzy-set outcome of five configurational conditions: AI investment (AIINS), AI digital infrastructure (AIDINF), AI human capital and skills (AIHCS), AI-enabled GVC integration (AIGVC), and AI innovation (AIINN). The fsQCA was conducted using the Quine–McCluskey algorithm on calibrated membership scores ranging from 0 to 1, which represent degrees of set membership rather than standardized variables (Ragin, 2008; Schneider & Wagemann, 2012).

The calibration profiles reveal substantial cross-country heterogeneity (Table 1 and Appendix A). For AIDINF, the United States, China, Ireland, and the United Kingdom achieve full membership (0.95), followed by Japan (0.8039) and Canada (0.7778). A similar pattern appears for AIINN, where these four economies again reach 0.95, with France (0.9149) and South Korea (0.8795) also exhibiting high membership.

EC varies considerably across countries. The United States and China score 0.95, whereas Israel (0.1787) and Finland (0.2600) remain substantially lower despite relatively strong AI capabilities. This divergence indicates that high export competitiveness is better explained by configurations of complementary capabilities than by isolated AI conditions. Overall, the calibration profiles provide the empirical foundation for the subsequent necessity and sufficiency analyses.

Table 1. Descriptive statistics of the calibrated fuzzy sets

Set	N	Mean	SD	Minimum	Maximum	≤ 0.05	≥ 0.95
AIINN	50	0.518	0.276	0.050	0.950	3	4
AIGVC	50	0.496	0.262	0.050	0.950	3	3
AIHCS	50	0.488	0.311	0.050	0.950	3	4
AIDINF	50	0.508	0.268	0.050	0.950	3	4
AIINS	50	0.534	0.253	0.050	0.950	3	3
EC	50	0.469	0.315	0.050	0.950	3	3

Note: Fuzzy-set scores range from 0 to 1, where 0.05 and 0.95 represent full non-membership and full membership, respectively. Mean and SD describe the distribution of calibrated set memberships and should not be interpreted as conventional standardized-variable statistics. Source: Authors' calculations based on the audited 50 × 6 fuzzy-set dataset.

5.2. Necessity analysis

Necessity analysis was conducted prior to sufficiency analysis to determine whether any individual AI-related capability constitutes a necessary condition for high export competitiveness (EC). In fuzzy-set terms, a condition is necessary when membership in the outcome is consistently contained within membership in the condition. Both the presence and absence of AIINS, AIDINF, AIHCS, AIGVC, and AIINN were therefore examined (Ragin, 2008; Schneider & Wagemann, 2012).

Table 2. Necessity analysis for the export competitiveness

Condition	Outcome	Consistency	Coverage	Interpretation
AIINS	EC	0.815598	0.718389	Not necessary
AIDINF	EC	0.893080	0.827409	Not necessary
AIHCS	EC	0.646838	0.624253	Not necessary
AIGVC	EC	0.753027	0.714093	Not necessary
AIINN	EC	0.889075	0.807944	Not necessary
~AIINS	~EC	0.715693	0.813591	Weak association with low EC
~AIDINF	~EC	0.834343	0.897702	Stronger association with low EC
~AIHCS	~EC	0.653780	0.675513	Weak association with low EC
~AIGVC	~EC	0.731897	0.769190	Moderate association with low EC
~AIINN	~EC	0.812065	0.891689	Stronger association with low EC

Note: Necessity is assessed as a set relation; consistency indicates the degree to which the outcome is contained in the condition, whereas coverage indicates the empirical relevance of the condition. The analysis tests both the presence and absence of each condition, following Ragin (2008) and Schneider and Wagemann (2012). The underlying fsQCA output reports the EC necessity results directly, with AIINN (0.889075) and AIDINF (0.893080) showing the highest positive-set consistency, but neither reaches a conventional necessity threshold.

From Table 2, the results show that no single condition is unequivocally necessary for high EC. Instead, the evidence supports a configurational structure in which alternative combinations of capabilities generate the same outcome. This interpretation is consistent with the subsequent intermediate solution, which identifies five sufficient pathways with overall consistency = 0.891420 and coverage = 0.726243.

Among the five conditions, AIDINF and AIINN exhibit the strongest structural relevance. Both recur across the sufficient solution space, with AIDINF appearing in all five baseline pathways. However, repeated occurrence should not be interpreted as formal necessity, since high EC can still emerge through alternative configurations. AIINS functions as a complementary resource, while AIHCS and AIGVC are clearly contingent: one principal pathway contains ~AIHCS, and AIGVC is present in some pathways but absent in others.

Analysis of negated conditions further demonstrates causal asymmetry. The highest consistency values for the low-EC outcome are observed for ~AIDINF (0.897702) and ~AIINN (0.891689), indicating that weak digital infrastructure and innovation are strongly associated with low export competitiveness. In contrast, ~AIHCS (0.675513) shows a much weaker relationship, suggesting that limited AI human capital does not systematically imply low EC.

Overall, the necessity analysis confirms that export competitiveness is not driven by any universally necessary AI capability but by complementary configurations of technological, organizational, and international resources.

5.3. Truth-table analysis and contradictory configurations

Following the necessity analysis, a truth-table analysis was conducted to identify configurations associated with high export competitiveness (EC). With five causal conditions AI investment (AIINS), digital infrastructure (AIDINF), AI human capital and skills (AIHCS), AI-enabled GVC integration (AIGVC), and AI innovation (AIINN) the configurational space contains 32 (2^5)

logically possible combinations. The truth table links calibrated fuzzy-set memberships to Boolean minimization by evaluating each configuration's empirical frequency and set-theoretic consistency (Ragin, 2008; Schneider & Wagemann, 2012).

Under Model C, a frequency cutoff of 2 and consistency threshold of 0.875057 were applied. The calibrated 50-country dataset produced a highly uneven distribution, with many logical remainders and only two configurations satisfying both criteria. Configuration 11001 (AIINSAIDINF~AIHCS~AIGVCAIINN) includes China and Thailand (frequency = 2; consistency = 0.879997), while 11011 (AIINSAIDINF~AIHCSAIGVCAIINN) includes the United States, South Korea, Singapore, and India (frequency = 4; consistency = 0.878804). Because both share the same four-condition backbone AIINSAIDINF~AIHCS*AIINN Boolean minimization eliminates AIGVC, yielding a baseline pathway with consistency = 0.951025, raw coverage = 0.525331, and unique coverage = 0.00749665. The overall Model C solution comprises five sufficient pathways with solution consistency = 0.891420 and coverage = 0.726243, supporting the principle of equifinality (Appendix B).

To distinguish genuine sufficiency from contradictory configurations, the analysis incorporates Proportional Reduction in Inconsistency (PRI). Whereas ordinary consistency evaluates whether X ⊆ EC, PRI additionally tests whether the same configuration is associated with ~EC. Although both retained rows satisfy the conventional consistency criterion, neither reaches the robustness threshold of PRI ≥ 0.50. Configuration 11001 records PRI = 0.005365, while 11011 achieves PRI = 0.231761, indicating limited discrimination between high and low EC. Overall, the truth-table analysis demonstrates that only a small subset of the 32 possible configurations is empirically supported and establishes AIINSAIDINF~AIHCS*AIINN as the common configurational backbone for subsequent robustness assessment.

5.4. Baseline sufficiency results: Model C

Sufficiency was assessed using Model C with a frequency cutoff of 2, consistency threshold of 0.875057, and the Quine–McCluskey algorithm for Boolean minimization. Positive directional expectations were specified for all five conditions. The Complex and Intermediate solutions are identical, indicating that the baseline results are stable and do not depend on additional simplifying assumptions. The overall solution achieves consistency = 0.891420 and coverage = 0.726243, demonstrating that the retained pathways explain approximately 72.6% of membership in high export competitiveness (EC).

Table 3. Baseline Sufficiency Results for High Export Competitiveness: Model C

Pathway	Configuration	Consistency	Raw coverage	Unique coverage	Cases with membership > 0.50
P1	AIINS * AIDINF * ~AIGVC * AIINN	0.919320	0.515878	0.031311	China; Israel; Canada; Spain; Thailand; Sweden
P2	~AIINS * AIDINF * AIGVC * AIINN	0.912368	0.458651	0.034365	Switzerland; Finland; Austria; France; Italy; Japan; Malaysia
P3	AIINS * AIDINF * AIHCS * AIGVC * ~AIINN	0.875057	0.372295	0.019373	Poland; Belgium
P4	AIINS * AIDINF * ~AIHCS * AIINN	**0.951025**	**0.525331**	0.007497	China; United States; South Korea; India; Singapore; Thailand
P5	AIDINF * ~AIHCS * AIGVC * AIINN	0.943921	0.454275	0.005916	United States; Singapore; South Korea; India; Malaysia; Japan
Overall solution	**P1 + P2 + P3 + P4 + P5**	**0.891420**	**0.726243**	—	—

Notes: * indicates logical conjunction; + indicates alternative configurations; ~ indicates the absence (negation) of a condition. The frequency cutoff is **2** and the consistency cutoff is **0.875057**. Complex and Intermediate solutions are identical under Model C. The five pathways are therefore interpreted as alternative sufficient configurations rather than mutually exclusive country groups. The underlying fsQCA output reports identical pathway statistics for the Complex and Intermediate solutions.

From Table 3, there are five sufficient configurations emerge. P1 (AIINSAIDINF~AIGVC*AIINN) achieves consistency = 0.919320 and raw coverage = 0.515878, showing that strong AI investment, infrastructure, and innovation can compensate for weaker GVC integration. P2 (~AIINSAIDINFAIGVC*AIINN) records consistency = 0.912368 and illustrates that high AI investment is not indispensable when digital infrastructure, GVC integration, and innovation coexist. P3 (AIINSAIDINFAIHCSAIGVC~AIINN) lies exactly at the prespecified threshold (consistency = 0.875057), representing a valid but comparatively weaker pathway. P4 (AIINSAIDINF~AIHCS*AIINN) is the strongest configuration with consistency = 0.951025 and raw coverage = 0.525331, demonstrating that high EC can emerge despite relatively low AI human-capital membership. P5 (AIDINF~AIHCSAIGVC*AIINN) achieves consistency = 0.943921, further confirming that AI investment is not universally required.

Collectively, the pathways provide strong evidence of equifinality. AIDINF appears in all five configurations, making it the most pervasive capability, while AIINN appears in four. By contrast, AIINS, AIHCS, and AIGVC vary across pathways, indicating that

their contributions are contingent rather than universal. The presence of ~AIHCS in P4 and P5 should therefore be interpreted as configurational substitution rather than evidence against the importance of human capital.

The Parsimonious solution yields a more simplified structure (consistency = 0.828945; coverage = 0.825672), but because it relies more heavily on logical remainders, the Complex/Intermediate solution is retained as the principal baseline. Overall, Model C demonstrates that high export competitiveness is generated through multiple complementary configurations rather than a single optimal AI capability profile.

5.5. Parsimonious solution and configurational core

The Parsimonious solution is examined alongside the Complex and Intermediate solutions to distinguish stable core conditions from peripheral or contingent elements. While the Complex and Intermediate solutions are identical, providing a robust baseline, the Parsimonious solution allows greater use of logical remainders and serves as a structural diagnostic rather than the preferred empirical model (Ragin, 2008; Schneider & Wagemann, 2012).

The parsimonious output identifies AI digital infrastructure (AIDINF) and AI innovation (AIINN) as independent minimized terms, with raw coverage of 0.893080 and 0.889075, respectively. However, these values derive from a less restrictive specification (frequency = 1; consistency = 0.848707) and should not be interpreted as the final Model C results, which use frequency ≥2 and consistency ≥0.875057. Their primary value lies in identifying conditions that remain stable across different levels of Boolean minimization.

Cross-solution comparison reveals a clear configurational hierarchy. AIDINF appears in all five baseline pathways (P1–P5), establishing it as the most stable configurational backbone (Appendix C)). Despite its structural centrality, its necessity consistency (0.893080) remains below the conventional 0.90 threshold, indicating that backbone status is not equivalent to individual necessity. AIINN appears in four of five pathways (P1, P2, P4, and P5) and similarly functions as a strong enabling condition, although P3 demonstrates that high EC can still emerge under ~AIINN through alternative capability combinations.

The remaining conditions are substantially more contingent. AIINS appears in P1, P3, and P4 but is absent in P2 and P5, confirming its substitutable role (necessity consistency = 0.815598). AIGVC is present in P2, P3, and P5 but absent in P1 and P4 (0.753027), indicating that GVC integration complements some pathways without being universally required. AIHCS is the most pathway-specific capability, appearing positively only in P3 while ~AIHCS characterizes P4 and P5; its low necessity consistency (0.646838) highlights its highly contingent contribution.

Overall, the comparison suggests that AIDINF + AIINN form a relatively stable backbone of AI-enabled export competitiveness, whereas AIINS, AIGVC, and AIHCS operate as complementary or substitutable capabilities. This reinforces the configurational proposition that high EC emerges from alternative architectures of mutually reinforcing capabilities rather than the simultaneous maximization of all five AI conditions.

5.6. PRI-based robustness test: C-PRI solution

To evaluate the robustness of the baseline sufficiency solution, a PRI-based robustness test (C-PRI) was conducted. While conventional consistency assesses whether a configuration approximates a subset of high export competitiveness (EC), Proportional Reduction in Inconsistency (PRI) additionally tests whether the same configuration is also associated with the negated outcome (~EC). This provides a stricter assessment of configurational sufficiency (Ragin, 2008; Schneider & Wagemann, 2012).

Table 4. Final C-PRI Solution for High Export Competitiveness

Criterion	**C-PRI Result**
Outcome	High Export Competitiveness (EC)
Number of causal conditions	5
Frequency cutoff	**2**
Consistency cutoff	**0.875057**
PRI cutoff	**0.50**
Baseline sufficient pathways	5
Robust pathways retained	**1**
Final robust configuration	**AIINS * AIDINF * ~AIHCS * AIINN**
Consistency	**0.951025**
Raw coverage	**0.525331**
Unique coverage after C-PRI filtering	**0.525331**
PRI	**0.806594**
Robustness assessment	**Retained**

\Note: The undrlying Model C output confirms P4's baseline consistency of **0.951025**, raw coverage of **0.525331**, and baseline unique coverage of **0.00749665**, while the full five-pathway solution has consistency **0.891420** and coverage **0.726243**.

The C-PRI analysis retained the Model C thresholds (frequency ≥2 and consistency ≥0.875057) and introduced PRI ≥0.50 (Table 4 and Appendix E). A pathway was therefore considered robust only if it satisfied all three criteria: sufficient empirical frequency, strong consistency with EC, and clear discrimination from ~EC.

This stricter screening substantially narrows the baseline solution. Although Model C identifies five sufficient pathways (solution consistency = 0.891420; coverage = 0.726243), P1, P2, P3, and P5 fail the PRI requirement despite satisfying conventional consistency. Only P4 remains robust: AIINS * AIDINF * ~AIHCS * AIINN. This configuration achieves consistency = 0.951025, raw coverage = 0.525331, and PRI = 0.806594, substantially exceeding the robustness threshold. As the sole retained pathway, its raw coverage equals its unique coverage (0.525331), unlike the overlapping baseline solution.

Substantively, the robust pathway combines high AI investment, strong digital infrastructure, and high AI innovation with relatively low AI human-capital membership. The presence of ~AIHCS should not be interpreted as evidence that human capital is detrimental; rather, it reflects configurational substitution, whereby investment, infrastructure, and innovation jointly compensate for lower AIHCS within this specific pathway.

Overall, the C-PRI analysis distinguishes baseline sufficiency from robust sufficiency, identifying AIINSAIDINF~AIHCS*AIINN as the strongest empirical explanation of high export competitiveness.

5.7. Robustness across solution specifications

To assess the stability of the configurational findings, the baseline solution was evaluated against alternative solution specifications that varied the frequency and consistency thresholds and the composition of the retained pathways. This robustness assessment follows established fsQCA practice, which emphasizes examining the sensitivity of configurational results to analytic specifications rather than treating a single solution as definitive (Ragin, 2008; Schneider & Wagemann, 2012).

The comparison indicates that the core configurational structure is stable across the examined specifications. In particular, the configuration retained under the stricter PRI assessment in Section 5.6 remains substantively supported across the alternative specifications. The agreement between the Complex and Intermediate solutions further indicates that the principal configurational pattern does not depend on additional simplifying assumptions. This distinction is important because different solution types can rely to different degrees on logical remainders and therefore should not be treated as interchangeable representations of the same empirical evidence (Ragin, 2008; Schneider & Wagemann, 2012).

The sensitivity analysis also supports the use of the baseline specification as the principal empirical solution. The more restrictive thresholding strategy excludes configurations supported by insufficient empirical frequency while preserving the central pathway identified in the PRI analysis. This provides evidence that the main configurational finding is not an artifact of a particular truth-table cutoff or Boolean minimization specification, but remains substantively stable when the analytical criteria are varied.

Taken together, the robustness checks strengthen confidence in the stability of the retained configurational pathway while preserving the broader finding of configurational equifinality. The baseline analysis establishes that high export competitiveness can arise through multiple sufficient combinations, whereas the stricter robustness assessment identifies the configuration that remains most consistently supported under alternative specifications. This distinction allows the study to separate the plurality of sufficient pathways from the stability of the most robust pathway, thereby providing a more conservative interpretation of the fsQCA evidence.

5.8. Configurational interpretation

The configurational results indicate that high export competitiveness (EC) is not generated by a uniform bundle of AI capabilities. Rather, different capabilities assume different roles across alternative sufficient configurations, consistent with the principles of conjunctural causation and equifinality underlying fsQCA (Ragin, 2008; Schneider & Wagemann, 2012).

Within this broader configurational structure, the pathway retained under the stricter PRI assessment provides a particularly informative illustration of capability complementarity. Its combination of AI investment, digital infrastructure, and AI innovation suggests that resource commitment to AI becomes more consequential when embedded in an infrastructure environment capable of supporting its deployment and complemented by innovation capacity. The interpretation therefore shifts attention from the accumulation of individual AI inputs toward the conditions under which these capabilities can be jointly converted into export competitiveness (Appendix E).

Digital infrastructure (AIDINF) occupies a particularly central position in this configurational architecture. It recurs across the sufficient pathways and also forms part of the robust configuration, indicating that infrastructure functions as an enabling platform through which other AI-related capabilities can be mobilized and translated into internationally competitive activities. Importantly, however, configurational centrality should not be equated with individual necessity: the necessity analysis does not establish AIDINF, or any other single condition, as universally necessary for high EC.

AI innovation (AIINN) plays a complementary upgrading role. Its recurrence across the sufficient pathways suggests that innovation capability helps transform AI-related resources and infrastructure into new products, processes, and forms of technological upgrading. This pattern is consistent with a conjunctural interpretation in which innovation generates greater competitive value when combined with complementary capabilities rather than operating as an isolated source of advantage.

The presence of ~AIHCS in the robust configuration requires particular caution. It should not be interpreted as evidence that AI-related human capital is unimportant or detrimental to export competitiveness. Rather, it represents a configuration-specific form of

substitution: within this particular pathway, strong AI investment, digital infrastructure, and innovation capability can coexist with relatively lower membership in the high-AIHCS set. In fsQCA terms, the same condition may assume different roles across alternative sufficient configurations, reflecting causal heterogeneity rather than a universal negative effect. This interpretation is consistent with the manuscript's broader finding that AIHCS is pathway-dependent, appearing positively in some configurations and negatively in others.

AI investment (AIINS) and AI-enabled GVC integration (AIGVC) likewise exhibit contingent rather than universal roles across the sufficient configurations. Their varying presence indicates that high EC can be achieved through alternative capability combinations rather than through a single standardized AI development profile. The resulting pattern is therefore better characterized as configured AI capability than as simply "more AI": export competitiveness depends on how resources, infrastructure, innovation, human capital, and GVC integration are combined within particular country contexts.

Overall, the configurational interpretation indicates that AI-related export competitiveness is characterized by capability complementarity, configurational substitution, and pathway dependence. Digital infrastructure provides an important enabling platform, AI innovation contributes an upgrading function, while AI investment, human capital, and GVC integration assume different roles across alternative configurations. The evidence therefore supports a configurational rather than additive understanding of the AI–export competitiveness relationship.

5.9. Country-level positioning and the Vietnam case

The configurational analysis provides a country-level perspective by examining how individual economies are positioned within the sufficient pathways associated with high export competitiveness (EC). This complements the aggregate solution analysis by distinguishing membership in the outcome set from membership in particular sufficient configurations. In fsQCA, relatively high outcome membership does not require strong membership in every sufficient pathway, because alternative configurations can produce the same outcome (Ragin, 2008; Schneider & Wagemann, 2012).

A relatively small group of economies exhibits membership above the crossover point in the configuration retained under the stricter PRI assessment. This concentration indicates that the robust pathway is not a universal representation of high-EC economies, but one stable capability architecture within a broader pattern of configurational heterogeneity. Thus, high EC does not necessarily correspond to strong membership in the same AI-capability configuration.

From Table 5 and Appendix F, Vietnam provides a particularly informative boundary case. Its relatively high membership in the high-EC outcome set is not matched by strong membership in the robust AI-capability configuration. This divergence is not contradictory; rather, it illustrates that export competitiveness and AI-enabled configurational capacity represent related but analytically distinct dimensions. Vietnam can therefore be characterized as a boundary/transitional case, in which established export competitiveness has not yet translated into strong membership in the AI-capability architecture identified as most robust.

Table 5. Country-level positioning in baseline and final robust configurations

Economy	AIINS	AIDINF	AIHCS	AIGVC	AIINN	EC	P1	P2	P3	P4 (C-PRI)	P5	Positioning
China	0.925630	0.950000	0.067802	0.158767	0.950000	0.950000	0.841233	0.074370	0.050000	0.925630	0.158767	Strong final-pathway member
United States	0.818940	0.950000	0.098674	0.726908	0.950000	0.950000	0.273092	0.181060	0.050000	0.818940	0.726908	Strong final-pathway member
South Korea	0.805560	0.661612	0.078093	0.674514	0.879526	0.765663	0.325486	0.194440	0.078093	0.661612	0.661612	Final-pathway member
India	0.689140	0.606870	0.417677	0.899815	0.664819	0.633777	0.100185	0.310860	0.335181	0.582323	0.582323	Final-pathway member
Singapore	0.572198	0.908197	0.114109	0.701320	0.812840	0.702161	0.298680	0.427802	0.114109	0.572198	0.701320	Final-pathway member
Thailand	0.574631	0.517542	0.054425	0.070633	0.545594	0.555608	0.517542	0.070633	0.054425	0.517542	0.070633	Borderline final-pathway member
Vietnam	0.206655	0.468180	0.050000	0.499349	0.466088	0.723630	0.206655	0.466088	0.050000	0.206655	0.466088	High-EC boundary/transitional case

The case does not imply an absence of relevant AI capabilities. Instead, it suggests a capability-conversion challenge: existing competitive strengths have not yet formed the combination associated with the robust pathway. Vietnam therefore illustrates how

economies can achieve substantial export competitiveness through existing configurations while remaining in transition toward a more AI-enabled capability structure.

Overall, the country-level evidence reinforces the central configurational argument: AI-related export competitiveness depends not simply on the level of individual capabilities, but on how those capabilities are combined within country-specific configurations.

5.10. Summary of empirical findings

The empirical analysis yields five main findings.

First, no individual AI capability is universally necessary for high export competitiveness (EC). High EC therefore cannot be attributed to any single AI-related condition in isolation.

Second, high EC is associated with multiple sufficient configurations. The five identified pathways demonstrate configurational equifinality, whereby different combinations of AI capabilities can generate the same outcome.

Third, digital infrastructure (AIDINF) emerges as the most stable configurational backbone. Its recurrent presence across the sufficient pathways indicates an enabling role in connecting other AI capabilities to export competitiveness.

Fourth, AI innovation capability (AIINN) functions as an important complementary upgrading condition, while the roles of AI investment, human capital, and AI-enabled GVC integration vary across configurations.

Fifth, the PRI analysis identifies a particularly robust configuration, while the country-level evidence demonstrates substantial heterogeneity in configurational membership. The Vietnam case further shows that relatively high EC does not automatically imply strong membership in the dominant AI-capability configuration.

Taken together, these findings support a configurational rather than additive interpretation of the relationship between AI capability and export competitiveness.

6. DISCUSSION

The findings reshape how AI-related capabilities contribute to export competitiveness (EC). Rather than supporting a universal hierarchy of individual determinants, the fsQCA results reveal a configurational architecture in which digital infrastructure, AI innovation, investment, human capital, and GVC integration assume different roles across alternative pathways. The theoretical question therefore shifts from whether AI improves exports to under what combinations of capabilities AI generates high EC.

The five sufficient pathways demonstrate equifinality, indicating that comparable export outcomes can emerge from different capability combinations. This finding complements evidence that the effects of AI vary across institutional, competitive, and structural environments (Chen & Dong, 2024; Fang & Liu, 2025; Jakubik et al., 2025; Kumar et al., 2025). The implication is that AI capability should be understood relationally rather than as a uniform country-level attribute.

Among the conditions, digital infrastructure (AIDINF) emerges as the most stable configurational backbone. Its recurrent presence suggests that infrastructure provides an enabling platform through which AI-related resources can support learning, innovation, coordination, and cross-border activities (Buckley et al., 2026; Menzies et al., 2024). AI innovation (AIINN) provides an important complementary upgrading function, reinforcing the view that AI generates greater competitive value when embedded in innovation-producing capabilities (Besiroglu et al., 2024; Liu et al., 2025).

By contrast, AI investment (AIINS) and AI-enabled GVC integration (AIGVC) operate more contingently across configurations. Their varying roles suggest configurational substitutability and are consistent with evidence that AI investment creates value when aligned with complementary organizational and technological capabilities (Besiroglu et al., 2024; Buckley et al., 2026; Rao & He, 2026; Xu, 2026).

The presence of ~AIHCS in the robust configuration should likewise be interpreted relationally, rather than as evidence against human capital. It indicates that strong EC can arise through alternative combinations in which infrastructure, investment, and innovation compensate for weaker membership in the calibrated AIHCS set. This is consistent with the broader importance of skills, learning, and managerial capabilities (Buckley et al., 2026; Menzies et al., 2024).

Overall, the findings support a configurational rather than additive view of AI-enabled export competitiveness: competitive advantage emerges from the complementarity, substitution, and country-specific combination of AI capabilities rather than from their isolated accumulation.

7. POLICY IMPLICATIONS

The configurational evidence suggests that export competitiveness (EC) in the AI era cannot be achieved through isolated AI policies. Rather, governments need complementary capability portfolios in which digital infrastructure, AI innovation, investment, and other country-specific capabilities reinforce one another. The robust pathway identified by the C-PRI analysis should therefore be interpreted as an empirical reference point, not as a universal policy template. Its principal implication is the need for sequenced and context-sensitive capability building.

First, policy should shift from an AI-adoption paradigm toward an AI capability-configuration paradigm. The existence of multiple sufficient pathways indicates that no single policy sequence is appropriate for all economies. Governments should consequently prioritize mutually reinforcing capability portfolios rather than maximize individual AI indicators. This approach is consistent with

evidence that AI creates value through technological, organizational, and knowledge complementarities rather than adoption alone (Buckley et al., 2026; Menzies et al., 2024).

Second, digital infrastructure (AIDINF) should constitute the foundational policy layer. Priorities include broadband and advanced mobile connectivity, cloud and high-performance computing, secure data infrastructure, interoperable digital platforms, digital public infrastructure, data-center ecosystems, and cross-border digital connectivity. The policy objective should be to remove infrastructure bottlenecks that constrain AI adoption, innovation, and export upgrading rather than to expand infrastructure independently of productive use.

Third, AI investment (AIINS) should be strategically oriented toward export capability rather than investment volume alone. Policy can target AI-enabled production and logistics, intelligent supply-chain management, quality control, export-market intelligence, digital customs, and productivity-enhancing applications in export-oriented industries (Kumar et al., 2025; Liu et al., 2025; Xu, 2026). The relevant policy criterion is whether investment strengthens the broader export-capability configuration.

Fourth, AI innovation (AIINN) requires stronger innovation ecosystems linking research to commercialization. Priorities include university–industry collaboration, AI-focused R&D, technology transfer, startups, commercialization mechanisms, and intellectual-property systems. Such policies can strengthen an AI-to-export innovation pipeline, connecting research and innovation with industrial application, product and process upgrading, and export competitiveness (Besiroglu et al., 2024; Fang & Liu, 2025; Liu et al., 2025).

Fifth, AI-enabled GVC integration (AIGVC) should be pursued selectively rather than treated as a universal requirement. Where GVC participation is strategically important, governments should promote AI-enabled supply-chain coordination, traceability, interoperability, intelligent logistics, digital standards, and upgrading of domestic firms toward higher-value segments (Buckley et al., 2026; Rao & He, 2026; Xu, 2026).

Finally, the role of AI human capital (AIHCS) should be interpreted as complementary and configuration-dependent. The appearance of ~AIHCS in the robust pathway does not justify reducing investment in skills. Rather, human-capital policies should focus on capabilities that enable firms and workers to integrate AI into export-oriented activities, including AI research, engineering, digital management, and AI-enabled production.

For Vietnam, the policy priority is therefore capability conversion rather than simply further export expansion. The evidence points toward a sequenced strategy that strengthens digital infrastructure, develops domestic AI innovation, directs AI investment toward export-oriented applications, selectively deepens AI-enabled GVC upgrading, and subsequently broadens organizational and human capabilities. The broader lesson is that policy convergence is not necessary for configurational convergence: countries need not replicate the institutional models of leading economies, but should construct feasible capability combinations consistent with their own institutional, industrial, and sectoral conditions. The central policy principle is therefore to maximize configurational fit rather than individual AI indicators.

8. CONCLUSION

This study examined how combinations of AI capabilities shape export competitiveness across 50 economies using a configurational approach. The findings show that high export competitiveness is not associated with a single universally necessary AI capability. Instead, several sufficient configurations demonstrate that countries can reach comparable competitive outcomes through alternative combinations of capabilities.

The analysis further identifies digital infrastructure as a particularly stable enabling element and AI innovation as an important complementary capability. The PRI-based robustness assessment strengthens this conclusion by showing that one configuration remains particularly stable under a stricter assessment of sufficiency. Importantly, the configuration-specific role of human capital demonstrates that the contribution of AI capabilities depends on their interaction with other conditions rather than on their isolated effects.

The country-level analysis also highlights substantial heterogeneity in how economies combine AI capabilities. The Vietnam case illustrates that relatively strong export competitiveness does not automatically translate into membership in the most robust AI-capability configuration. This distinction points to an important policy challenge: transforming existing export capacity into a broader AI-enabled capability base.

Overall, the study advances a configurational perspective on AI and export competitiveness, emphasizing capability complementarity, alternative pathways, and the country-specific conditions under which AI capabilities can be converted into export advantage.

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Appendix A. Calibration profiles and empirical anchors

Set	Raw Min	P5 / Full Non-membership Anchor	Median / Crossover Anchor	P95 / Full Membership Anchor	Raw Max
AIINN	18.390	28.423	47.465	65.280	83.600
AIGVC	2.300	5.008	29.034	44.404	45.595
AIHCS	12.000	13.270	57.000	76.000	78.000
AIDINF	40.610	47.471	56.875	74.960	89.270
AIINS	44.625	48.819	79.573	92.521	96.135
EC	−8.079	−4.179	2.474	24.786	36.266

Appendix B. Truth-table analysis and contradictory configurations

Configuration	AIINS	AIDINF	AIHCS	AIGVC	AIINN	Frequency	Cases	Consistency	PRI	Decision
11001	●	●	⊗	⊗	●	2	China, Thailand	0.879997	0.005365	Retained by consistency; PRI-contradictory
11011	●	●	⊗	●	●	4	United States, South Korea, Singapore, India	0.878804	0.231761	Retained by consistency; PRI-contradictory

Notes: ● = presence of a condition; ⊗ = absence of a condition. Configuration codes follow the condition order AIINS, AIDINF, AIHCS, AIGVC, AIINN. Thus, 11001 represents AIINSAIDINF~AIHCS~AIGVCAIINN, whereas 11011 represents AIINSAIDINF~AIHCSAIGVCAIINN. The frequency cutoff was 2, and the consistency cutoff was 0.875057. Both configurations satisfy the baseline frequency and consistency criteria but fail the robustness criterion of PRI ≥ 0.50. Their shared configurational backbone is AIINSAIDINF~AIHCS*AIINN, from which AIGVC is eliminated through Boolean minimization. The resulting Model C solution comprises five sufficient pathways, with overall consistency = 0.891420 and coverage = 0.726243.

Coding note: In the truth-table notation, 1 = presence and 0 = absence of the corresponding condition. The table therefore presents only the two empirically supported rows that meet both baseline selection criteria; the remaining 30 of the 32 logically possible configurations are not retained under the specified frequency and consistency thresholds.

Appendix C. Cross-solution structure

Cross-solution comparison and configurational stability in model C

Condition / Solution Term	Complex / Intermediate Solution	Parsimonious Solution	Necessity Consistency	Configurational Interpretation
AIDINF	Present in P1–P5 (5/5)	Standalone term	0.893080	Core / configurational backbone
AIINN	Present in P1, P2, P4, P5 (4/5); ~AIINN in P3	Standalone term	0.889075	Core-like / strong enabling condition
AIINS	Present in P1, P3, P4 (3/5); absent in P2, P5	Not retained as standalone term	0.815598	Peripheral / substitutable
AIGVC	Present in P2, P3, P5 (3/5); absent in P1, P4	Not retained as standalone term	0.753027	Contingent
AIHCS	Present in P3; ~AIHCS in P4, P5	Not retained as standalone term	0.646838	Highly contingent / peripheral
Parsimonious solution	—	AIDINF + AIINN	—	Structural diagnostic

Notes: Complex and Intermediate solutions are identical under Model C. The Parsimonious run uses frequency cutoff = 1 and consistency cutoff = 0.848707; it yields AIDINF (raw coverage = 0.893080; unique coverage = 0.053628; consistency = 0.827409)

and AIINN (raw coverage = 0.889075; unique coverage = 0.049623; consistency = 0.807944). Necessity consistency values are reported in the fsQCA necessity analysis.

Configurational core–peripheral hierarchy of model C

Condition	Presence / Polarity across P1–P5	Role in Sufficient Configurations	Necessity Consistency	Classification
AIDINF	5/5 positive	Common to all five pathways; also retained as a standalone parsimonious term	0.893080	Core / configurational backbone
AIINN	4/5 positive; 1/5 negative	Present in most pathways; retained as a standalone parsimonious term	0.889075	Core-like / strong enabling
AIINS	3/5 positive; 2/5 absent	Substitutable across alternative pathways	0.815598	Peripheral / substitutable
AIGVC	3/5 positive; 2/5 absent	Pathway-specific complement	0.753027	Contingent
AIHCS	1/5 positive; 2/5 negative; absent elsewhere	Strongly pathway-dependent; polarity varies across configurations	0.646838	Highly contingent / peripheral

Note: "Core" refers to configurational stability, not individual necessity. No condition reaches the conventional 0.90 necessity-consistency threshold; AIDINF is the closest at 0.893080.

Appendix E. Interpretation

Interpretation of the final C-PRI configuration

Configurational component	Condition	Interpretation
AIINS	Present	High AI investment
AIDINF	Present	High digital infrastructure
~AIHCS	Negated	Relatively low membership in the calibrated AIHCS set
AIINN	Present	High AI innovation
Overall configuration	AIINS * AIDINF * ~AIHCS * AIINN	Robust pathway to high EC

Note: The negative AIHCS condition should not be interpreted as evidence that AI human capital is detrimental. Rather, it indicates that, within this calibrated configurational space, high EC can occur when strong AI investment, digital infrastructure, and AI innovation jointly compensate for relatively lower AIHCS membership. This interpretation is consistent with the baseline solution, where AIHCS appears with different polarities across pathways. The baseline output confirms that AIHCS is positive in P3 but negative in P4 and P5.

Cross-specification stability of configurational conditions and pathways

Element	Baseline Model C	Parsimonious / Alternative Specification	Robustness assessment	Interpretation
AIDINF	Present in 5/5 pathways	Emerges as standalone term	Highest stability	Configurational backbone
AIINN	Present in 4/5 pathways	Emerges as standalone term	High stability	Core-like enabling condition
AIINS	Present in 3/5 pathways	Not independently retained	Moderate stability	Substitutable/peripheral
AIGVC	Present in 3/5 pathways	Not independently retained	Moderate/contingent	Pathway-specific complement
AIHCS	Positive in P3; negative in P4 and P5	Not independently retained	Lowest stability	Highly contingent
P4: AIINSAIDINF~AIHCS*AIINN	Consistency = 0.951025; raw coverage = 0.525331	Survives C-PRI; PRI = 0.806594	Strongest cross-specification stability	Final robust pathway

P1	Consistency = 0.919320	Not retained under C-PRI	Baseline only	Non-robust
P2	Consistency = 0.912368	Not retained under C-PRI	Baseline only	Non-robust
P3	Consistency = 0.875057	Fails stricter PRI assessment	Threshold-level	Borderline
P5	Consistency = 0.943921	Not independently retained under C-PRI	High baseline consistency but limited unique coverage	Contingent

Note: Complex and Intermediate solutions are identical under Model C, with the same five pathways and solution statistics (consistency = 0.891420; coverage = 0.726243). AIDINF occurs in all five baseline pathways, while AIINN occurs in four. The parsimonious representation identifies AIDINF and AIINN as standalone terms.

Configurational role of AI-related capabilities

Condition	Presence across baseline pathways	Role in final robust configuration	Configurational interpretation	Empirical assessment
AIDINF	5/5	Present	Stable enabling backbone	Most stable condition
AIINN	4/5	Present	Core-like complementary capability	Second-most stable condition
AIINS	3/5	Present	Resource/enabling capability	Substitutable across pathways
AIGVC	3/5	Absent	Alternative/contingent capability	Pathway-specific complement
AIHCS	Positive in 1 pathway; negative in 2	~AIHCS	Polarity-sensitive condition	Highly pathway-dependent

Note: “Core” or “backbone” refers to configurational stability, not individual necessity. AIDINF appears in all five baseline pathways, AIINN in four, AIINS and AIGVC in three each, while AIHCS changes polarity across pathways.

Final robust configurational architecture

Component	Fuzzy-set role	Interpretation
AIINS	● Present	Provides the resource base for AI deployment and scaling
AIDINF	● Present	Provides the stable digital enabling environment
AIHCS	⊗ Absent / low membership	Pathway-specific negative condition; not evidence that AI human capital is detrimental
AIINN	● Present	Converts AI-related resources and infrastructure into innovation capability
AIGVC	Not included	Contingent rather than universal capability
Outcome: EC	High membership	Configuration associated with high export competitiveness
Consistency	0.951025	Strong set-theoretic sufficiency
Raw coverage	0.525331	Covers 52.5% of outcome membership
PRI	0.806594	Strong discrimination between EC and ~EC

The final C-PRI configuration is AIINS * AIDINF * ~AIHCS * AIINN. Its statistics are directly supported by the audited fsQCA output and the final robustness analysis.

Appendix F. Country-level detailed data

Selected country-level calibration profiles

Economy	AIINN	AIDINF	AIINS	EC
United States	0.950	0.950	0.819	0.950
China	0.950	0.950	0.926	0.950
Japan	0.870	0.804	0.436	0.777

South Korea	0.880	0.662	0.806	0.766
Ireland	0.950	0.950	0.950	0.524
United Kingdom	0.950	0.950	0.950	0.697
Canada	0.900	0.778	0.677	0.349
France	0.915	0.918	0.470	0.836
Israel	0.790	0.618	0.904	0.566
Finland	0.710	0.624	0.449	0.260
Vietnam	0.466	0.468	0.207	0.724