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Fulfilment Efficiency, AI Capability, and Cross-Border E-Commerce Development in China: Complementarities, Regional Heterogeneity, and Resource-Saving Potential

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Abstract

China's cross-border e-commerce (CBEC) has expanded rapidly, yet province-level evidence remains limited on how AI development conditions the contribution of logistics fulfilment efficiency (LEF) to cross-border e-commerce development (CBED), especially across regions with uneven digital maturity. This study tests whether AI capability amplifies the marginal effect of logistics fulfilment efficiency (LEF) for CBED and whether this complementarity varies across eastern, central, and western China. Using a balanced panel of thirty-one provinces over 2017–2023 ($N = 217$), we combine a Super-SBM DEA logistics fulfilment efficiency measure (LEF), a four-pillar AI Development Index (AIDI), and customs-based CBED indicators. Two-step System GMM models are estimated for the full sample and regional subsamples to account for dynamic persistence and endogeneity concerns. Results indicate that higher LEF is associated with higher CBED and that AIDI strengthens this relationship via the interaction term; the complementarity is the largest in eastern provinces and remains positive but smaller in central and western regions. Overall, the evidence suggests that logistics fulfilment efficiency and AI capability act as complementary enablers of cross-border e-commerce development, supporting provincial competitiveness as CBEC scales. Sustainability implications are therefore discussed via operational-efficiency channels rather than direct environmental outcomes.

Keywords: cross-border e-commerce development; logistics fulfilment efficiency; AI development index; digital-logistics complementarity; System GMM; DEA; regional heterogeneity; endogeneity; resource-saving potential



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1. Introduction

Official customs statistics put China's cross-border e-commerce (CBEC) trade at RMB 2.38 trillion in 2023, a 15.6% year-on-year increase [1]. This growth adds pressure on logistics systems that already account for a large share of economic activity and involve substantial resource use. Industry reports estimate that cross-border activities accounted for around RMB 2.56 trillion in 2022, or roughly 20–30% of national logistics expenditure [2]. At this scale, cross-border logistics can entail high transport and packaging intensity, especially where operational mitigation practices remain limited [3,4]. Logistics performance is therefore a core determinant of CBED and a key driver of fulfilment frictions and operational intensity as the sector scales. Prior work on cross-border flows has underscored

that logistics solutions, risk exposure, and fulfilment reliability play a decisive role in shaping platform competitiveness [5,6]. Yet China's cross-border e-commerce still faces structural bottlenecks in logistics, regulation, and digital infrastructure, and these constraints can undermine service quality and delay shifts toward more resource-efficient fulfilment configurations, particularly through operational frictions and underutilised capacity [7–9].

Recent studies suggest that advanced data analytics and automation increasingly influence how logistics networks support CBEC, with implications for operational efficiency and resource use. Empirical and review studies suggest that AI-related applications are shifting toward predictive and optimisation functions, improving planning accuracy, service reliability, and cost efficiency [10–12]. In cross-border settings, AI-enabled demand sensing, inventory repositioning, and dynamic routing help platforms respond to live order flows and network conditions, shortening cycle times and reducing empty miles, which can lower operational frictions and improve capacity utilisation at the margin [13–15]. At the same time, work on digitalisation and supply chain sustainability warns that such technologies can have “double-edged” effects on operational efficiency and resource use, depending on how they are deployed and governed [13,16,17]. When layered on an already efficient logistics backbone, these capabilities can support higher conversion, fewer returns, and more resilient cross-border market positions. Any sustainability implications are framed in operational terms, emphasising lower frictions and better utilisation within fulfilment operations.

China's regions differ in their capacity to leverage data-driven logistics tools, with implications for competitiveness and the scope for more resource-efficient fulfilment. Eastern coastal provinces typically combine dense digital infrastructure, mature transport networks, and wider adoption of warehouse and transport management systems, whereas many central and western provinces still face connectivity gaps, skills shortages, and fragmented data architectures [18,19]. These differences suggest that the same underlying logistics efficiency may yield different CBED outcomes once AI capabilities are considered and may shape the scope for more resource-efficient fulfilment as CBEC scales. However, existing empirical work provides limited province-level evidence on how logistics efficiency and AI development interact in shaping CBED and seldom compares regions that differ in digital maturity and logistics upgrading [20,21]. Prior studies often adopt firm-/platform-level designs that are well-suited to analysing adoption choices and operational outcomes, whereas comparable province-level evidence remains thinner in the CBEC setting. A provincial lens is nonetheless informative because it captures ecosystem-wide foundations—digital infrastructure, interoperability, public investment, and institutional coordination—that condition how AI capability translates into cross-border fulfilment performance across regions. Existing work on CBEC and logistics therefore leaves the following three issues underexplored: the joint role of logistics efficiency and AI capability in shaping CBED, the multidimensional nature of AI development beyond single indicators, and the role of regional digital maturity as a boundary condition for these relationships.

Building on these observations, this study asks how logistics fulfilment efficiency (LEF) and AI development jointly shape CBED at the provincial level. It first examines whether provinces with higher logistics efficiency exhibit stronger cross-border e-commerce development. It then tests whether AI development strengthens the association between logistics efficiency and CBED. Finally, it explores whether this AI-logistics complementarity varies across regions with different levels of digital maturity—namely eastern, central, and western China.

To answer these questions, we compile a provincial panel for thirty-one provinces over 2017–2023. LEF is measured as logistics fulfilment efficiency using Super-SBM DEA,

and AIDI is constructed across innovation, application, infrastructure, and market pillars. We estimate dynamic panel models to test the LEF effect, the AIDI interaction, and regional heterogeneity. Conceptually, LEF captures a core fulfilment capability, while AIDI captures a higher-order AI-specific digital capability—spanning innovation, application, infrastructure, and market readiness—linked to sensing, prediction, and operational reconfiguration beyond baseline digital connectivity, consistent with resource-based and dynamic capability views [22–25].

The study contributes to research on digital commerce and logistics fulfilment in three ways. It reframes provincial logistics efficiency as a fulfilment capability underpinning CBED. It introduces a province-level AIDI and embeds it in a dynamic panel setting to quantify how digital capability conditions the CBED–logistics link. It also documents regional heterogeneity in this complementarity across eastern, central, and western China, highlighting the digital divide as a boundary condition and supporting differentiated digital–logistics policy design [26].

For platforms and policymakers, the arguments imply practical priorities. For cross-border platforms and logistics providers, AI-integrated forecasting and routing are most effective where logistics fundamentals and digital infrastructure are already in place; under such conditions, similar physical logistics efficiency can support different CBED trajectories depending on AI readiness [11,27]. For less-developed provinces, strengthening data interoperability, connectivity, and human capital is a prerequisite for realising the operational gains of AI-enabled logistics in supporting CBED and improving fulfilment efficiency, with lower operational frictions when digital and logistics capabilities are strengthened in tandem [13,28,29]. From a policy perspective, the provincial lens shows how AI and logistics capabilities jointly shape electronic commerce development under pronounced regional heterogeneity and provides a basis for region-tailored investment roadmaps primarily linked to SDG 9 (Industry, Innovation, and Infrastructure), with indirect relevance to SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action) through more efficient resource use within fulfilment operations, reflected in reduced operational frictions and improved utilisation [30–32].

2. Literature Review and Theoretical Framework

2.1. Resource-Based View, Dynamic Capabilities, and Sustainable Logistics in Electronic Commerce

The resource-based view (RBV) explains performance differences by the heterogeneous and hard-to-imitate resource bundles that organisations accumulate [22]. In electronic commerce, data assets, logistics infrastructure, and service routines can function as VRIN resources, shaping reliability, cost efficiency, and innovation. For cross-border e-commerce (CBEC), provincial logistics efficiency—including coordinated warehousing, transportation, and customs handling—represents a core operational capability that supports shorter lead times, greater reliability, and lower unit costs [7,21]. Sustainable logistics research further shows that network design shapes service quality under disruption and is often discussed alongside resource-use constraints and externality concerns, linking logistics capabilities to resilience and broader sustainability debates [13,33]. Here, logistics efficiency is interpreted as fulfilment (service) efficiency; sustainability is discussed via operational efficiency channels.

RBV is largely static and emphasises what resources an organisation holds at a given point in time, whereas CBEC operates under regulatory change, volatile demand, and recurrent disruptions. Dynamic capabilities theory addresses this limitation by focusing on how actors sense opportunities and threats, seize them through timely decisions and investments, and reconfigure their resource base when conditions shift [23,24]. Recent work extends this view to AI and digital technologies, treating AI-enabled operations

as higher-order capabilities that combine data, analytics, and routines to enhance agility, resilience, and logistics performance [34]. Sustainability-oriented studies suggest that AI-based optimisation is most useful when it balances cost and service objectives while improving operational efficiency, for example, through better routing and load planning, with potential gains in utilisation and lower operational frictions [13,14,30].

Although RBV and dynamic capabilities were developed for firms, regional research has applied these ideas to territorially embedded innovation systems [35]. Provinces can be viewed as ecosystems in which logistics infrastructure, digital networks, firms, and public institutions jointly shape bundles of operational and higher-order capabilities. In this setting, dynamic capability is reflected in coordinated upgrading and orchestration across actors—public investment and regulation, platform integration, logistics-network organisation, and border-process alignment—rather than in decisions made by a single unitary actor. In more digitally mature provinces, AI-related capabilities are expected to strengthen the contribution of logistics efficiency to CBED and expand the scope for lower-friction, lower-waste fulfilment operations; in less mature regions, the same efficiency gains may translate into smaller CBED responses.

2.2. AI and Sustainable Logistics in Cross-Border E-Commerce

In cross-border e-commerce, logistics performance is the critical link between online orders and realised value. Slow or unreliable delivery undermines repeat purchasing, while poorly designed routes, modes, and packaging can increase operational waste and, in many settings, raise the resource intensity of fulfilment [3,7]; sustainability relevance is discussed via operational-efficiency channels. Evidence from CBEC and sustainability-oriented logistics studies indicates that service design, last-mile solutions, and network configuration jointly shape competitiveness and can influence the operational intensity of fulfilment, especially where cross-border flows rely heavily on time-sensitive express services with higher resource demands [6,21,30].

AI-related applications in CBEC logistics span the fulfilment chain; where data and governance permit, optimisation can incorporate resource-use constraints alongside cost and service objectives. Upstream, AI-based demand forecasting and inventory planning help platforms anticipate order flows and reduce stockouts, overstocking, and associated waste [34,36]. In mid-stream operations, AI-supported routing and scheduling adjust transport plans in response to network conditions and can incorporate efficiency-related constraints in route and mode choices, including time and load-factor constraints and, where data permit, resource-use constraints [13,30]. At the last mile, AI-enabled consolidation, dynamic locker allocation, and differentiated delivery options can support more efficient fulfilment in dense markets and may reduce avoidable waste through better utilisation [37,38].

Packaging and reverse logistics are another focal area for sustainable e-commerce. Reviews of e-commerce packaging stress that material choices, packaging formats, and returns policies strongly influence the material intensity and return-handling burden of online orders [3]. Reverse logistics studies show that reusable and returnable packaging can reduce waste but require careful process design to avoid disruptions and extra cost [39–41]. AI-based analytics can support these initiatives by identifying where reusable packaging is most viable and by optimising collection and consolidation [13,42].

Firm-level evidence suggests that AI-enabled logistics capabilities are most effective when embedded in broader digital strategies and service architectures. Studies on self-built delivery and digitally reconstructed logistics services show that platforms can reshape collaboration with carriers and improve perceived service quality, continuance intention, and logistics performance [20,38,43]. Evidence from China also points to regional variation

in the pay-offs from AI-enabled logistics upgrading: eastern coastal provinces typically combine more developed logistics and digital infrastructure, whereas many central and western provinces still face fragmented systems and weaker connectivity [7,18]. In more digitally mature regions, studies report wider use of data-driven tools for routing, packaging management, and coordination-intensive initiatives, while in less mature regions adoption is more often tied to basic efficiency and service reliability, with sustainability benefits discussed as conditional rather than guaranteed [30,37,44]. Existing research thus offers detailed insights into AI and sustainable logistics but still offers limited province-level evidence on whether AI development conditions the CBED returns to logistics efficiency, and whether this complementarity differs across eastern, central, and western China—questions we test using provincial panel data.

2.3. Hypothesis Development

Drawing on RBV and dynamic capabilities, we develop three testable hypotheses linking logistics efficiency, AI development, and regional digital maturity to CBED.

H1. *Logistics fulfilment efficiency (LEF) is positively associated with cross-border e-commerce development (CBED).*

At the provincial level, logistics efficiency reflects a fulfilment-efficiency capability (LEF) that supports reliable and cost-effective cross-border transactions. More efficient networks shorten lead times, reduce variability, and lower fulfilment costs, which should encourage CBED [5,6]. Related logistics studies link higher efficiency to more robust service under disruption and discuss potential reductions in avoidable resource use, suggesting that provinces with more efficient logistics can support stronger CBED [7,21]. Any sustainability discussion is kept at the level of operational potential.

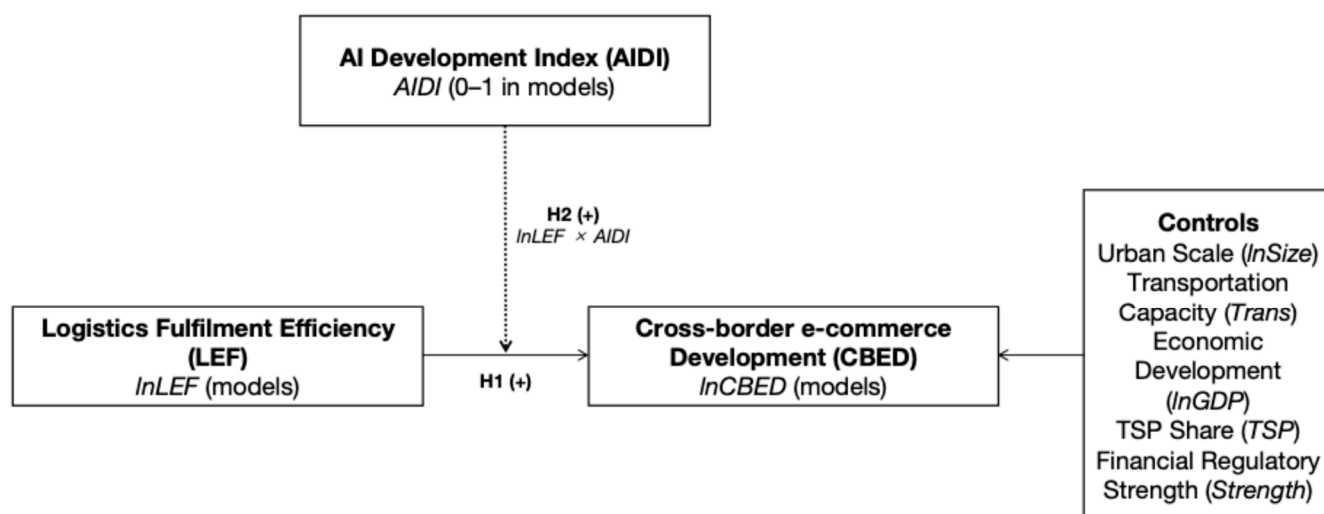
H2. *AI development (AIDI) positively moderates the relationship between logistics fulfilment efficiency (LEF) and cross-border e-commerce development (CBED).*

Within an RBV–dynamic capabilities view, AI development functions as a higher-order capability that supports data-enabled planning and coordination in fulfilment operations. In this study, AIDI is intended to proxy the maturity of operational routines such as forecasting, routing, inventory positioning, and exception handling, which are consistent with lower operational frictions and improved utilisation in cross-border fulfilment [23,24]. Evidence on AI-enabled supply chains shows that data, analytics, and embedded routines enhance agility and resilience, while optimisation can incorporate cost and service indicators and, where data allow, resource-use constraints alongside efficiency considerations [13,30,34]. In provinces with stronger AI development, the CBED returns to logistics efficiency are expected to be larger, reflecting lower frictions and better utilisation.

H3. *The positive moderating effect of AI development (AIDI) on the LEF–CBED relationship is stronger in eastern provinces than in central and western provinces.*

The moderating effect of AIDI is expected to be heterogeneous. Provinces with deeper AI ecosystems and more advanced digital infrastructure—features more common in eastern coastal China—are more likely to convert AI capability into larger improvements in logistics fulfilment efficiency, thereby strengthening the fulfilment efficiency–CBED relationship [7,8,21,37].

These hypotheses guide the empirical analysis of how provincial logistics fulfilment efficiency, AI development, and their interaction relate to CBED across eastern, central, and western regions. Figure 1 summarises the conceptual framework and hypotheses.



H3: The positive moderating effect of AI development (AIDI) on the LEF–CBED relationship is stronger in eastern provinces than in central and western provinces.

Figure 1. Conceptual framework and hypotheses. Note: LEF and CBED enter the econometric models in logs (lnLEF, lnCBED). AIDI is normalised to 0–1 in regressions. Controls include lnSize, Trans, lnGDP, TSP, and Strength.

3. Materials and Methods

3.1. Data Sources and Sample

The analysis uses a balanced panel for 31 mainland Chinese provinces (excluding Hong Kong, Macao, and Taiwan) over 2017–2023, yielding 217 province–year observations. Provinces are grouped into eastern (11), central (8), and western (12) regions following the National Bureau of Statistics classification, allowing AI–logistics fulfilment relationships to be compared across development zones.

All variables are taken from official and widely used statistical sources. Cross-border e-commerce development (CBED) is measured using customs-recorded cross-border e-commerce (CBEC) import and export values from the China Customs Statistics Yearbook. Logistics inputs and outputs for the efficiency measures come from the China Logistics Yearbook and official yearbooks. Indicators for the Artificial Intelligence Development Index (AIDI) are drawn from the China Statistical Yearbook on Science and Technology, China National Intellectual Property Administration (CNIPA) patent statistics, Web of Science and CNKI records, and the China Electronic Information Industry Statistical Yearbook. The five control variables—urban scale (Size), transportation capacity (Trans), economic development (lnGDP), transportation, storage and postal services (TSP), and financial regulatory strength (Strength)—are constructed from the China Statistical Yearbook, the China Transport Statistical Yearbook, provincial yearbooks, and financial supervision reports.

We then apply a conservative data-cleaning procedure across all indicators and province–year entries. Missing values are limited and confined to a small number of province–year entries. Linear interpolation is applied only when adjacent observations support a smooth year-to-year pattern; it is used to preserve sample continuity rather than to reconstruct discontinuous shocks. Where the pattern suggests a structural shift, we avoid trend-based interpolation and instead use within-province time-series mean imputation for that indicator; series with clear discontinuities are left unimputed to prevent introducing

artificial jumps. All monetary variables are deflated to 2017 constant prices using provincial consumer price indices and then logged. The dataset contains no individual-level information and does not raise ethical concerns. All raw inputs draw on customs and statistical yearbooks and cannot be redistributed in raw form. Upon reasonable request, the corresponding author can provide replication code and derived indices, subject to source and licencing constraints.

3.2. Variable Measurement

3.2.1. Dependent Variable: Cross-Border E-Commerce Development (CBED)

Cross-border e-commerce development (CBED) is measured as the natural logarithm of the sum of provincial CBEC import and export values recorded in customs statistics (lnCBED). All underlying monetary series are deflated to 2017 constant prices using provincial consumer price indices. For descriptive summaries, CBED is reported as a normalised index for presentation, while the regression models use lnCBED. This specification follows recent work that treats customs-recorded CBEC transaction values as a systematic proxy for China's cross-border e-commerce activity. Detailed definitions, data sources, and processing steps for the CBED indicator are summarised in Appendix A.1 (Table A1).

3.2.2. Independent Variable: Logistics Fulfilment Efficiency (LEF)

Logistics fulfilment performance rests on multiple inputs—capital, labour, and energy. To capture this multi-input, multi-output structure, we use a data envelopment analysis (DEA) super-efficiency slacks-based measure (Super-SBM) model under variable returns to scale (VRS). This specification benchmarks provinces with different economic sizes and network densities against a best-practice frontier and yields a full ranking of decision-making units. The model structure is compatible with undesirable outputs in principle; however, in this study, LEF is constructed as a fulfilment-efficiency measure using harmonised logistics inputs and desirable service outputs and is interpreted as an operational efficiency indicator rather than a direct environmental-performance metric [45,46]. Undesirable outputs are not incorporated because province-level proxies that can be consistently measured and credibly attributed to fulfilment activities are not available in a harmonised form over the full 2017–2023 period.

The input set includes investment in transportation, storage, and postal services, employment in logistics-related sectors and energy consumption. Energy consumption is included as part of the operational input bundle for fulfilment activities; accordingly, LEF should be interpreted as a composite fulfilment-efficiency measure under a harmonised input–output specification. The main desirable output is freight turnover (ton-kilometres), capturing the volume of transport services. Although some logistics DEA studies incorporate undesirable outputs (e.g., environmental-externality proxies), our implementation prioritises comparability and coverage across provinces and years. Accordingly, the Super-SBM set-up is applied using consistently available logistics inputs and service outputs, and sustainability is interpreted later in operational terms—lower frictions and better utilisation [16,17]. Super-SBM inputs/outputs underpinning the fulfilment-efficiency measure (LEF) are defined in Section 3 and listed in Appendix A.2 (Table A2). Appendix A.2 clarifies that LEF is linearly rescaled to the 0–1 interval for descriptive reporting, whereas regressions use lnLEF computed from the raw Super-SBM efficiency scores (not truncated).

Provincial Super-SBM fulfilment-efficiency scores are computed annually. LEF is transformed as $\ln\text{LEF} = \ln(\max(\text{LEF}, \varepsilon))$, where $\varepsilon = 0.001$ is used to avoid undefined values when Super-SBM scores are close to zero. This treatment ensures numerical stability and preserves cross-provincial variation for the log-linear dynamic panel specifications in Section 3.3.

3.2.3. Moderating Variable: Artificial Intelligence Development Index (AIDI)

Provincial AI maturity is measured by an Artificial Intelligence Development Index (AIDI) spanning the following four dimensions: innovation, digital infrastructure, application, and market environment [9,47]. The innovation pillar aggregates AI-related patents granted by the China National Intellectual Property Administration (CNIPA) and AI-focused academic publications in Web of Science and CNKI, capturing the codified AI knowledge base. The digital infrastructure pillar uses indicators on 5G base-station density, broadband penetration, and data-centre capacity from official statistical yearbooks, proxying the connectivity and computing backbone for large-scale AI deployment.

The application pillar uses proxies for firm-level AI adoption, such as counts of AI-oriented software and information-service enterprises and deployments of intelligent systems in logistics and manufacturing [27,28]. The market-environment pillar combines operating revenue or value added in AI-related industries with counts of AI-oriented firms from the China AI Development Report and provincial yearbooks, reflecting the local AI business ecosystem.

All indicators are coded so that higher values reflect more advanced AI development and are min–max normalised to [0, 1]. Pillar scores are the mean of the normalised indicators within each dimension and entropy-based weights are applied across pillars; AIDI is the weighted sum of the four pillars (0–1). For descriptive tables, AIDI is rescaled to 1–9, while regressions use the original 0–1 index. Alternative indices with equal weights or principal components yield similar results [12,48], indicating that the findings are not sensitive to the weighting scheme. Construction steps are documented in Appendix A.3, and the principal-component-based alternative index (AIDI_alt) is reported in Appendix A.4 (Table A3).

3.2.4. Control Variables

To isolate the effects of logistics fulfilment efficiency and AI development, the models include the following five provincial controls: urban scale (Size), transportation capacity (Trans), economic development (lnGDP), the share of transportation, storage, and postal services (TSPs), and financial regulatory strength (Strength). Size is the natural logarithm of the urban population, capturing agglomeration forces that typically boost logistics demand and e-commerce activity, while Trans is an index combining road density and freight turnover per capita as a proxy for network capacity. lnGDP is the natural logarithm of provincial GDP per capita in 2017 prices, and TSP is the share of transportation, storage, and postal services in provincial value added, indicating the maturity and relative importance of logistics-related services. Strength is a composite index based on provincial financial supervision and regulation indicators and summarises the local institutional framework for digital- and logistics-related innovation [25].

In the regressions, Size and lnGDP enter in logarithmic form and Trans, TSP, and Strength as indices; descriptive statistics for all variables are reported in Table 1. Additional digital-economy indicators such as internet penetration and human-capital measures were examined but were highly collinear with components of AIDI and unevenly available across provinces. Because AIDI already captures much of the digital infrastructure and skills environment, these variables are excluded, and any residual omitted-variable bias is acknowledged as a limitation in Section 5.4.

3.3. Model Specification

To test the hypotheses while accounting for dynamic persistence, endogeneity, and unobserved provincial heterogeneity, we estimate dynamic panel models using the two-step System GMM estimator [49–51], which is suited to panels with a short time dimension and a lagged dependent variable.

The baseline specification without the AI–logistics interaction is:

$$\ln CBED_{\{i,t\}} = \alpha + \beta_1 \ln CBED_{\{i,t-1\}} + \beta_2 \ln LEF_{\{i,t\}} + \gamma X_{\{i,t\}} + \mu_i + \lambda_t + \varepsilon_{\{i,t\}} \quad (1)$$

where i indexes provinces and t indexes years; $\ln CBED_{\{i,t\}}$ denotes cross-border e-commerce development, $\ln LEF_{\{i,t\}}$ is the logistics fulfilment-efficiency measure, $X_{\{i,t\}}$ is the vector of control variables (Size, Trans, $\ln GDP$, TSP, and Strength), and μ_i and λ_t are province and year fixed effects.

To incorporate AI development, we extend the model by adding $AIDI_{\{i,t\}}$ and its interaction with $\ln LEF_{\{i,t\}}$:

$$\ln CBED_{\{i,t\}} = \alpha + \beta_1 \ln CBED_{\{i,t-1\}} + \beta_2 \ln LEF_{\{i,t\}} + \beta_3 AIDI_{\{i,t\}} + \beta_4 (\ln LEF_{\{i,t\}} \times AIDI_{\{i,t\}}) + \gamma X_{\{i,t\}} + \mu_i + \lambda_t + \varepsilon_{\{i,t\}} \quad (2)$$

The interaction term ($\ln LEF_{\{i,t\}} \times AIDI_{\{i,t\}}$) captures AI–fulfilment complementarity; β_4 shows how AI development changes the marginal effect of fulfilment efficiency on CBED.

In the System GMM specifications, $\ln CBED_{\{i,t-1\}}$ is treated as predetermined and instrumented using deeper lags, while $\ln LEF_{\{i,t\}}$ is treated as endogenous given potential simultaneity between fulfilment upgrading and CBED. In Equation (2), $AIDI_{\{i,t\}}$ and the interaction term ($\ln LEF_{\{i,t\}} \times AIDI_{\{i,t\}}$) are also treated as endogenous to preserve consistency of the moderation test. The remaining controls enter as weakly exogenous (or predetermined where appropriate), and year dummies are treated as strictly exogenous. To limit instrument proliferation with a small number of groups ($N = 31$), we use collapsed instrument sets and restrict the GMM-style lag window to lags $t - 2$ and $t - 3$, balancing relevance and parsimony in a short panel [51]. We report two-step estimates with Windmeijer [52] finite-sample corrections and evaluate model adequacy using AR(1)/AR(2) tests and the Hansen J-test. The estimates are therefore interpreted as dynamic associations identified by internal instruments and potential feedback between CBED and AI development cannot be fully excluded. While difference-in-Hansen subset tests can be informative, instrument validity is assessed here through the Hansen test together with conservative instrument construction.

For regional heterogeneity, Equation (2) is estimated separately for eastern, central, and western subsamples, and Wald tests assess whether β_4 differs across regions. For clarity, each hypothesis corresponds to a specific estimand in the empirical models. H1 is tested using the coefficient on $\ln LEF$ in Equation (1). H2 is tested using the interaction coefficient $\ln LEF \times AIDI$ in Equation (2), and the implied marginal effect of $\ln LEF$ is evaluated at representative $AIDI$ values. H3 is assessed by comparing the interaction estimates across eastern, central, and western subsamples using pairwise Wald tests. For regional heterogeneity, Equation (2) is estimated separately for eastern, central, and western subsamples, and Wald tests assess whether β_4 differs across regions. Robustness checks include difference GMM, alternative DEA specifications for LEF, different $AIDI$ constructions (entropy-weighted, equal-weighted, and principal-component based), variations in lag and instrument structure, and fixed-effects models with Driscoll–Kraay standard errors. The corresponding robustness outputs are reported in Appendices A.4–A.6 [34,48,53].

4. Empirical Results

4.1. Descriptive Statistics

Table 1 reports descriptive statistics for the main variables based on 217 province–year observations. For presentation, the CBED index is reported as a normalised index for presentation (mean = 0.369, SD = 0.050; range = 0.333–0.571), indicating moderate dispersion

across provinces and sizable differences in cross-border e-commerce development within a common national regulatory framework. Logistics fulfilment efficiency (LEF) also varies substantially (mean = 0.442, SD = 0.261), with some provinces close to the lower bound. For descriptive reporting, LEF is shown on a 0–1 scale as a presentation rescaling (Table 1), whereas the regressions use $\ln\text{LEF}$ derived from the underlying Super-SBM DEA fulfilment-efficiency scores (Section 3), without imposing a 0–1 bound in estimation. These LEF scores summarise the fulfilment-efficiency capability (LEF) available to CBEC platforms, with lower-efficiency provinces offering weaker fulfilment capacity than high performers.

Table 1. Descriptive statistics (CBED reported as a normalised index for presentation; regressions use $\ln\text{CBED}$).

Variable	Symbol	Observation	Mean	Std. Dev.	Min	Max
Cross-Border E-Commerce Development	CBED	217	0.369	0.050	0.333	0.571
Logistics Fulfilment Efficiency	LEF	217	0.442	0.261	0.000	1.000
Urban Scale	$\ln\text{Size}$	217	21.980	1.204	19.740	25.710
Transportation Capacity	Trans	217	0.414	0.207	0.047	0.885
Economic Development	$\ln\text{GDP}$	217	0.062	0.133	−0.679	0.351
Transportation, Storage, and Postal Services	TSP	217	0.347	0.151	0.085	0.749
Financial Regulatory Strength	Strength	217	0.187	0.448	−0.575	2.896
AI Development Index	AIDI	217	6.382	1.079	1.000	9.000

Note: CBED = cross-border e-commerce development (reported as a normalised index for presentation; regressions use $\ln\text{CBED}$). LEF = logistics fulfilment efficiency (reported as a 0–1 presentation rescaling; regressions use $\ln\text{LEF}$ based on the underlying Super-SBM DEA fulfilment-efficiency scores). AIDI = AI Development Index (reported on a 1–9 scale; regressions use the 0–1 normalised index). $\ln\text{Size}$ = transformed measure of urban scale used in the regressions (see Appendix A.2); $\ln\text{GDP}$ = transformed (and scaled) provincial GDP per capita used in the regressions and may take negative values after transformation (see Appendix A.2); Trans = transportation capacity; TSP = share of transportation, storage, and postal services in provincial value added; Strength = financial regulatory strength. N = 217 province-year observations (31 provinces), 2017–2023.

The AI Development Index (AIDI), reported on a 1–9 scale for ease of comparison (mean = 6.382, SD = 1.079; range = 1.000–9.000), points to pronounced heterogeneity in AI innovation, infrastructure and application across provinces. This dispersion is consistent with evidence of uneven CBEC development and digital readiness in China [8]. By contrast, the transformed controls $\ln\text{Size}$ and $\ln\text{GDP}$ (constructed and scaled as described in Appendix A.2) show more limited dispersion in this sample than LEF and AIDI, suggesting that differences in logistics conditions and AI readiness may be more salient sources of cross-provincial heterogeneity in CBED.

Descriptive regional comparisons indicate that eastern provinces generally combine higher logistics fulfilment efficiency and stronger AI development than central and western provinces. This pattern is consistent with recent evidence on regional digital divides in cross-border e-commerce and logistics services, where platform performance reflects complementarities between fulfilment capabilities and digital infrastructure [20,43]. Overall, these descriptive patterns suggest that digitally advanced regions tend to combine stronger AI readiness with more efficient fulfilment conditions, consistent with lower operational frictions and better capacity utilisation.

4.2. Correlation Analysis

Table 2 reports pairwise Pearson correlations among the main variables and variance inflation factors (VIFs) for the regressors. $\ln\text{CBED}$ is positively associated with both $\ln\text{LEF}$ and AIDI ($r = 0.42$ and $r = 0.50$, respectively; $p < 0.01$), indicating that provinces with higher fulfilment efficiency and more advanced AI ecosystems tend to exhibit higher cross-border e-commerce development. The correlation between $\ln\text{LEF}$ and AIDI is also

positive but moderate in size ($r = 0.48$; $p < 0.01$), suggesting that fulfilment capability and digital capability are related but not mechanically overlapping. Across all pairs, correlation coefficients remain below 0.70. VIF values for the regressors range from 1.24 to 3.56, which is below common rule-of-thumb thresholds, indicating that multicollinearity among the main covariates is unlikely to be a major concern. The interaction term is introduced in the next section within the dynamic panel framework, with inference based on the System GMM specification.

Table 2. Pearson correlation matrix and variance inflation factors (N = 217).

Variable	lnCBED	lnLEF	AIDI (0–1)	lnSize	Trans	lnGDP	TSP	Strength	VIF
lnCBED	1	0.42 ***	0.50 ***	0.29 ***	0.34 ***	0.44 ***	0.31 ***	0.18 *	—
lnLEF	0.42 ***	1	0.48 ***	0.11	0.26 ***	0.35 ***	0.27 ***	0.15	2.17
AIDI (0–1)	0.50 ***	0.48 ***	1	0.23 ***	0.29 ***	0.38 ***	0.21 **	0.12	2.35
lnSize	0.29 ***	0.11	0.23 ***	1	0.19 **	0.64 ***	0.28 ***	0.07	2.84
Trans	0.34 ***	0.26 ***	0.29 ***	0.19 **	1	0.41 ***	0.25 ***	0.09	1.73
lnGDP	0.44 ***	0.35 ***	0.38 ***	0.64 ***	0.41 ***	1	0.39 ***	0.11	3.56
TSP	0.31 ***	0.27 ***	0.21 **	0.28 ***	0.25 ***	0.39 ***	1	0.10	1.67
Strength	0.18 *	0.15	0.12	0.07	0.09	0.11	0.10	1	1.24

Note: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Pearson correlations use N = 217 province–year observations (31 provinces), 2017–2023. VIFs are reported for regressors (max = 3.56). AIDI is the 0–1 normalised index.

4.3. Baseline Dynamic Panel Results

Table 3 reports baseline estimates for the relationship between logistics efficiency and cross-border e-commerce development using OLS, fixed effects (FE), and two-step System GMM. For the preferred System GMM specification (Column 3), the diagnostics indicate the expected first-order serial correlation in differences (AR(1) $p < 0.01$), no evidence of second-order serial correlation (AR(2) $p > 0.10$), and Hansen test results that do not reject the validity of the instrument set (see Table 3).

Table 3. Baseline regression results for cross-border e-commerce development.

Variable	(1) OLS	(2) FE	(3) System GMM
L.lnCBED	—	—	0.157 *** (4.12)
lnLEF	0.013 (0.76)	0.029 (0.43)	0.323 *** (3.54)
lnSize	−0.327 *** (−3.11)	0.027 *** (4.11)	0.213 *** (3.43)
Trans	0.021 (0.84)	−0.023 (−0.54)	0.005 ** (2.34)
lnGDP	−0.073 *** (−3.55)	−0.213 (−0.43)	0.121 *** (4.21)
TSP	0.012 ** (2.34)	0.005 (0.34)	0.054 ** (2.45)
Strength	0.012 *** (2.89)	−0.121 *** (−4.21)	0.032 *** (3.53)
AR(1) p -value	—	—	0.000
AR(2) p -value	—	—	0.457
Hansen p -value	—	—	0.572
No. of groups	—	—	31
Observations (N)	217	217	217

Note: OLS/FE report province-clustered robust standard errors; System GMM reports Windmeijer-corrected two-step standard errors. ** $p < 0.05$; *** $p < 0.01$. Column (3) uses two-step System GMM with year fixed effects, collapsed instruments, and lags $t - 2$ to $t - 3$ for GMM-style regressors; the number of instruments is 24 (<31 groups). AR(1)/AR(2) are Arellano–Bond tests and Hansen is the J-test.

The lagged dependent variable is positive and statistically significant, indicating persistence in lnCBED and supporting the use of a dynamic estimator (see Table 3).

For the main regressors, logistics fulfilment efficiency (LEF)—interpreted as the provincial fulfilment-efficiency capability (LEF) supporting CBEC platforms—is positive and highly significant in the GMM specification. The estimated elasticity of lnCBED with respect to lnLEF is about 0.32 in Column (3), implying that a 1% increase in fulfilment efficiency is associated with an approximate 0.32% increase in lnCBED. This magnitude is economically meaningful and is consistent with better utilisation of transport capacity and fewer avoidable detours, suggesting reduced operational frictions and operational potential for more efficient resource use, rather than any directly measured environmental effect. This result supports H1 and aligns with recent evidence that more efficient logistics and fulfilment systems are associated with stronger cross-border e-commerce performance [8,20,43].

In Column (3), the controls behave as expected: larger and richer provinces are associated with higher lnCBED, and provinces with a larger transport-services sector also exhibit higher lnCBED. Financial regulatory strength is likewise positively associated with lnCBED, consistent with a more supportive institutional environment for digital and logistics innovation.

As static benchmarks, the OLS and FE estimates (Columns 1–2) differ in sign and magnitude from the dynamic estimates, which further motivates reliance on the System GMM framework to address persistence and endogeneity concerns and to introduce the interaction specification reported next.

4.4. Moderating Effect of AI Development

Table 4 reports the two-step System GMM estimates for the specification that includes the interaction between logistics efficiency and AI development ($\ln\text{LEF} \times \text{AIDI}$). The diagnostic tests indicate the expected first-order serial correlation in differences (AR(1) $p < 0.01$), no evidence of second-order serial correlation (AR(2) $p > 0.10$), and Hansen test results that do not reject the validity of the instrument set (see Table 4).

Table 4. Moderating effect of artificial intelligence on cross-border e-commerce development.

Variable	(1) System GMM	(2) System GMM + Interaction
L.lnCBED	0.157 *** (4.12)	0.106 *** (3.89)
lnLEF	0.323 *** (3.54)	0.416 *** (3.34)
AIDI		0.232 *** (3.45)
lnLEF $\times$ AIDI (0–1)		0.212 *** (4.44)
lnSize	0.213 *** (3.43)	−0.105 (−0.65)
Trans	0.005 ** (2.34)	0.005 (0.45)
lnGDP	0.121 *** (4.21)	−0.101 *** (−3.87)
TSP	0.054 ** (2.45)	0.032 *** (3.87)
Strength	0.032 *** (3.53)	0.025 *** (4.11)
AR (1) p -value	0.000	0.000
AR (2) p -value	0.457	0.284
Hansen p -value	0.572	0.497
No. of groups	31	31
Observations (N)	217	217

Note: Windmeijer-corrected two-step standard errors are in parentheses. ** $p < 0.05$; *** $p < 0.01$. Both columns use two-step System GMM with year fixed effects, collapsed instruments, and lags $t - 2$ to $t - 3$; instruments = 24 (Column 1) and 28 (Column 2), both below the number of groups ($N = 31$). AR(1)/AR(2) are Arellano–Bond tests and Hansen is the J-test.

The interaction term $\ln\text{LEF} \times \text{AIDI}$ is positive and statistically significant ($\beta = 0.212$, $p < 0.01$), supporting H2 and indicating that higher AI development is associated with a

stronger lnLEF–lnCBED relationship. Consistent with the interaction, the implied marginal effect of lnLEF on lnCBED increases with AIDI; across $AIDI \in [0, 1]$, the marginal effect rises by 0.212 (see Table 4). This result aligns with the view of AI-enabled logistics as a higher-order capability that amplifies the returns to fulfilment efficiency in platform settings [20,43,54]. From an operations-oriented perspective, this complementarity suggests greater scope for lower operational frictions and better capacity utilisation in AI-mature provinces, consistent with the study’s operational focus.

The main effects remain positive and significant in Column (2): lnLEF ($\beta = 0.416$, $p < 0.01$) and AIDI ($\beta = 0.232$, $p < 0.01$). Among controls, lnGDP turns negative and significant and lnSize becomes insignificant in Column (2), indicating that adding AIDI and the interaction alters the partial associations captured by these covariates. Trans, TSP, and Strength retain small, generally positive coefficients, consistent with enabling roles rather than primary drivers.

Here, AIDI refers to the 0–1 normalised index used in the regressions. Based on Column (2) in Table 4, the marginal effect of lnLEF on lnCBED is $0.416 + 0.212 \times AIDI$, implying a marginal effect of 0.416 when $AIDI = 0$ and 0.628 when $AIDI = 1$. Using the reported System GMM standard errors, a conservative delta-method approximation (ignoring the covariance term) yields 95% confidence intervals of approximately [0.172, 0.660] at $AIDI = 0$ and [0.367, 0.889] at $AIDI = 1$.

4.5. Regional Heterogeneity in the AI–Fulfilment Synergy

Table 5 reports region-specific two-step System GMM estimates of Equation (2) for eastern, central, and western provinces based on the official National Bureau of Statistics east–central–west classification. Across all three subsamples, diagnostic tests remain consistent with the expected first-order serial correlation in differences (AR(1) $p < 0.01$), no evidence of second-order serial correlation (AR(2) $p > 0.10$), and Hansen test results that do not reject the instrument set at conventional levels (see Table 5). In line with H3, this section examines whether the complementarity between AI development and fulfilment efficiency is stronger in the more digitally mature eastern region than in the central and western regions.

Table 5. Regional heterogeneity in the AI–logistics efficiency relationship.

Variable	(1) Eastern	(2) Central	(3) Western
L.lnCBED	0.112 * (1.98)	0.059 *** (4.64)	0.351 *** (2.89)
lnLEF	0.123 *** (3.34)	0.087 ** (2.38)	0.023 * (1.94)
AIDI	0.078 *** (3.65)	0.034 *** (4.23)	0.132 ** (2.57)
lnLEF $\times$ AIDI (0–1)	0.213 *** (4.43)	0.178 ** (2.54)	0.166 *** (3.40)
lnSize	−0.121 *** (−4.21)	−0.112 *** (−3.74)	0.011 *** (6.23)
Trans	0.054 ** (2.45)	0.041 *** (3.54)	0.009 *** (2.81)
lnGDP	0.025 *** (4.34)	0.020 *** (3.75)	0.112 ** (2.79)
TSP	0.156 *** (3.65)	0.221 ** (3.57)	0.045 ** (2.67)
Strength	0.226 *** (3.81)	0.247 *** (4.23)	0.134 ** (2.87)
AR(1) p -value	0.000	0.000	0.000
AR(2) p -value	0.159	0.254	0.349
Hansen p -value	0.628	0.471	0.514
No. of groups	11	8	12
Observations(N)	77	56	84

Note: Windmeijer-corrected two-step standard errors are in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Columns (1)–(3) report region-specific two-step System GMM estimates with year fixed effects, collapsed instruments, and lags $t - 2$ to $t - 3$ to limit instrument proliferation in small subsamples. AR(1)/AR(2) are Arellano–Bond tests and Hansen is the J-test. Pairwise Wald tests indicate that the interaction coefficient is larger in the eastern subsample than in the central and western subsamples ($p < 0.05$), while the central–western difference is not statistically significant ($p > 0.10$).

The interaction term between fulfilment efficiency and AI development ($\ln\text{LEF} \times \text{AIDI}$) is positive and statistically significant in all three regions, indicating that the marginal effect of higher fulfilment efficiency on $\ln\text{CBED}$ increases with AI maturity in each subsample. However, as summarised in the note to Table 5, pairwise Wald tests on the interaction coefficient indicate that the eastern interaction effect is significantly larger than the corresponding coefficients for central and western provinces at the 5% level, whereas the central–western difference is not statistically significant. This pattern is consistent with H3 and suggests that AI–fulfilment complementarity operates nationwide but is most pronounced in the east.

The stronger eastern complementarity can be discussed along two dimensions. First, higher AI development levels may strengthen the interaction between AIDI and fulfilment efficiency. Second, structural advantages—such as denser logistics networks and more mature digital ecosystems—may facilitate the integration of AI capability into fulfilment operations [20,43]. In central and western provinces, the interaction remains positive but smaller, which is consistent with both lower AI development levels and tighter ecosystem constraints, including infrastructure gaps, weaker interoperability, and more limited specialised human capital. Overall, the results indicate a spatial divide in coupling capacity: the east appears better positioned to translate AI capability into fulfilment-enabled CBED gains, while other regions may face higher implementation frictions.

4.6. Robustness Checks and Endogeneity Diagnostics

Robustness checks are reported in Appendix Tables A3–A5. We also verified that the key conclusions are not sensitive to conservative instrument choices in System GMM (short lag windows and collapsed instrument sets): the sign and statistical significance of the interaction term remain stable across alternative instrument specifications. Using total e-commerce transaction value as an alternative CBED measure and a PCA-weighted AI index (AIDI_{alt}) leaves the signs and significance of $\ln\text{LEF}$, AIDI_{alt} , and $\ln\text{LEF} \times \text{AIDI}_{\text{alt}}$ unchanged (Table A3). Re-estimating with difference GMM yields the same qualitative conclusions (Table A4). Excluding Guangdong and Zhejiang and dropping year 2020 does not alter the main interaction result (Table A5). AR(1)/AR(2) and Hansen diagnostics remain acceptable across these specifications.

Endogeneity remains a concern because logistics and AI investment may respond to CBED growth and time-varying provincial shocks. We therefore rely on the dynamic System GMM strategy in Section 3.3, using lagged levels and differences with collapsed instruments. The baseline, interaction, and regional models (Tables 3–5) pass AR(2) and Hansen diagnostics. Estimates are interpreted as dynamic panel associations identified by internal instruments, rather than definitive causal effects. Accordingly, we treat the results as evidence of a stable dynamic relationship conditional on the instrument strategy, rather than a fully causal estimate.

5. Discussion and Implications

5.1. Purpose and Integrated Summary of Findings

This study examines how provincial logistics fulfilment efficiency (LEF) and artificial intelligence development (AIDI) relate to cross-border e-commerce development (CBED) in China, and whether these relationships vary across regions. Using a balanced panel of thirty-one provinces (2017–2023), we estimate two-step System GMM models with LEF, AIDI, CBED, and standard controls, and repeat the analysis for eastern, central, and western subsamples. We focus on complementarity—whether AIDI changes the marginal return of LEF for CBED and what this implies for region-calibrated development paths.

The estimates align with H1–H3 in three respects. First, logistics fulfilment efficiency (LEF) is consistently associated with higher CBED after accounting for persistence and structural differences in provincial economic conditions. Substantively, LEF captures fulfilment capability: better warehousing, connectivity, and clearance capacity reduce operational frictions in cross-border fulfilment. LEF is interpreted as a fulfilment-efficiency capability (LEF) and discussed through operational channels (e.g., frictions and utilisation).

Second, higher AI development is associated with a stronger—rather than substitutive—relationship between logistics fulfilment efficiency (LEF) and CBED in the dynamic estimates. The link between LEF and CBED becomes more pronounced as AI maturity rises, which is consistent with provinces with deeper AI ecosystems being more capable of scaling cross-border activity from a given fulfilment base. Operationally, AI-enabled forecasting, routing, and inventory decisions are often linked to higher throughput and lower coordination waste in platform fulfilment settings. This pattern is consistent with AI–fulfilment complementarity: higher AIDI is associated with a larger marginal association between LEF and CBED, potentially reflecting lower coordination frictions and improved utilisation within fulfilment operations.

Third, the strength of this synergy differs across space. The interaction is most pronounced in the eastern region and remains positive but smaller in central and western provinces, consistent with gaps in platform ecosystems, digital infrastructure, interoperability, and skills. The divide is also about coupling capacity: where foundations are mature, AI is embedded in routine decisions and LEF improvements translate into larger CBED gains. Where foundational digital conditions and skills lag, comparable physical upgrades may deliver slower payoffs and smaller CBED responses to comparable fulfilment upgrades. These findings motivate the region-calibrated implications that follow.

5.2. Theoretical Contributions

This study shows that AIDI acts as a higher-order capability that raises the return to LEF, rather than a stand-alone input. In the resource-based and dynamic capability tradition, advantage comes from integrating and reconfiguring operational assets as conditions change [22,23]. The stable, positive interaction between $\ln\text{LEF}$ and AIDI ($\ln\text{LEF} \times \text{AIDI}$) reported in Section 4 supports the following logic: provinces with stronger AI ecosystems obtain larger CBED gains from a comparable improvement in fulfilment efficiency (LEF). This mechanism sharpens the contribution to platform-oriented research. The key issue is capability matching: how AIDI aligns with the fulfilment environment to shape differentiated CBED paths across provinces [10,36,55].

The study also extends smart logistics and digital supply chain research by shifting “AI-enabled logistics” from firm-level KPI outcomes to a provincial ecosystem mechanism that matters for CBEC scale-up. Much of the literature evaluates AI through firm-level outcomes such as cost, service levels, or resilience [10,56]. By combining a DEA-based fulfilment-efficiency measure (LEF) with a composite AI development index in a dynamic System GMM framework, this study connects upstream fulfilment capability to downstream CBED growth at the provincial level. Fulfilment performance is shaped by a coupled system—public infrastructure, 3PL capacity, regulatory interfaces, and platform orchestration [8,14]. In this framing, AI contributes by improving coordination—forecasting, routing, inventory planning, and exception handling—so that existing physical networks are used with lower frictions and higher utilisation. This aligns with Industry 4.0 arguments that digital tools raise logistics productivity, conditional on the physical layer [11,57].

Finally, the regional heterogeneity documented in Section 4 advances the digital divide literature by highlighting capability matching as a distinct source of spatial divergence, beyond average gaps in income or infrastructure. Prior work on China emphasises uneven in-

novation capacity, digital foundations, and institutional conditions across regions [19,21,58]. The present findings add that provinces differ in the strength of AI–fulfilment complementarity itself: some regions can embed AI into routine fulfilment decisions and convert logistics improvements into stronger CBED responses, while others see weaker payoffs from similar physical upgrading because interoperability, skills, and ecosystem readiness lag. This “capability-mismatched” pattern offers a tighter interpretation of H3 than a level-only explanation. It also matters for the Sustainability-oriented repositioning of the paper, because smart logistics gains are closely tied to reducing operational inefficiencies (e.g., idle capacity, avoidable detours, and fragmented planning). Regions with weaker operationalisation may face a spatial divide in aligning CBED expansion with lower-waste fulfilment trajectories [9,17].

5.3. Implications for Sustainability, Policy, and Practice

The implications align primarily with SDG 9, with indirect relevance to SDG 12 and SDG 13. In this study, higher LEF reflects fewer frictions in warehousing, transport connectivity, and clearance capacity, and is therefore consistent with more reliable fulfilment for cross-border transactions. LEF is discussed through operational efficiency channels, reflecting lower operational waste and better utilisation potential in fulfilment. AIDI matters because it strengthens the LEF–CBED link, consistent with planning and coordination functions—forecasting, routing, inventory allocation, and exception handling—that can reduce avoidable delays and redundant movements. The regional results further indicate unequal coupling capacity: provinces with stronger digital foundations and ecosystem readiness appear better able to embed data-driven tools into routine fulfilment decisions. Accordingly, the sustainability-relevant message concerns enabling conditions for more efficient resource use in fulfilment, framed through operational efficiency channels; LEF is interpreted as fulfilment efficiency rather than environmental performance.

For platforms, merchants, and solution providers, the evidence points to sequenced investments rather than uniform deployment. In higher-AIDI provinces, platforms may prioritise integration-intensive fulfilment solutions (e.g., demand planning, routing, inventory positioning, and exception management), because the interaction pattern indicates stronger returns to LEF where digital capability is deeper. In lower-AIDI provinces, the first-order constraint is often basic readiness—data quality, interface standards, interoperability across actors, and targeted training—before more complex modules can be expected to yield comparable payoffs. For third-party logistics providers and vendors, the AIDI–LEF profile can guide rollout choices: end-to-end solutions are more feasible where integration capacity is present, whereas modular tools that work under partial interoperability may be more appropriate where systems remain fragmented. Across contexts, the managerial implication is to treat fulfilment capability and digital capability as complements and to calibrate implementation to local coupling capacity.

For governments, the policy implication is to invest in complements—data governance, interoperability, and human capital—while coordinating across provinces. In the eastern region, where coupling capacity is stronger, policymakers can pilot measures with diffusion potential: common data standards, supervised sharing mechanisms, and regulatory sandboxes for AI-assisted customs risk screening and clearance coordination. These efforts support SDG 9 and have indirect relevance to SDG 12 and SDG 13 through operational efficiency channels. In central and western regions, priorities may lie in expanding digital infrastructure, building interoperable data platforms, and developing applied analytics skills so that physical upgrades are not pursued in isolation. The results caution against an “assets-without-data” path: capacity expansion without interoperability and skills may yield slower CBED gains and more limited operational efficiency improvements.

The broader implication is that inclusive, efficiency-oriented CBED development is more likely when policies and firm strategies are sequenced and region-calibrated: where foundations are stronger, coordination tools can be embedded more readily and incremental improvements in LEF translate into larger CBED responses; where foundations lag, interoperability and skills remain binding constraints.

5.4. Limitations and Directions for Future Research

Two identification concerns merit caution. Two-step System GMM mitigates heterogeneity and simultaneity concerns but cannot remove all endogeneity. Unobserved policy shocks, changes in provincial regulatory intensity, or platform-side strategy shifts may raise CBED while coinciding with upgrades in LEF or AIDI, and such shocks are only partially absorbed by year effects. In addition, some finer-grained digital-economy and human-capital factors (e.g., skills, platform competition intensity) are not included because of coverage limits and collinearity with AIDI. We also note that future work may complement coefficient-based moderation tests with association-based tools that accommodate mixed-type covariates, especially when key drivers are ordinal, categorical, or potentially nonlinear. One option is to use surrogate-based partial association measures for mixed data to quantify conditional dependence within a unified framework, which may offer a useful robustness or exploratory check alongside interaction regressions [59]. Future work should strengthen causal leverage through quasi-experimental variation (e.g., staggered CBEC policy pilots, exogenous infrastructure expansions, or discrete changes in customs facilitation) and, where feasible, incorporate a small set of complementary digital indicators using designs that explicitly manage collinearity (e.g., alternative index construction or parsimonious proxies). Diagnostics are reported in Section 4, but endogeneity cannot be fully ruled out.

A second set of limitations relates to measurement, aggregation, and scope. Province-level panels necessarily average over heterogeneous platforms, merchants, and logistics providers, so the estimates cannot pinpoint which operational routines or contracting arrangements generate higher coupling capacity between AIDI and LEF. Moreover, both LEF and AIDI rely on publicly available statistics: this supports consistent coverage but may introduce measurement error and limits granularity. For instance, AIDI does not isolate optimisation-oriented applications from customer-facing AI, and LEF cannot fully distinguish conventional capacity expansion from digitally coordinated fulfilment improvements. The 2017–2023 window captures an early phase of AI diffusion in logistics, and the models do not explicitly account for cross-province spillovers even though fulfilment networks can span administrative borders. Future research could integrate platform transaction data, logistics tracking records, or customs processing measures to test micro-level mechanisms, refine LEF/AIDI with more specific indicators (e.g., automation intensity, algorithmic routing adoption, and data-sharing coverage), extend the panel beyond 2023, and apply spatial econometric or multi-level designs. Beyond extending the time window, another direction is to allow the effect of AI–fulfilment complementarity to vary over time rather than being constant within a short panel specification. Functional data analysis frameworks can model province-level outcomes as trajectories and enable time-varying relationships, for example, through adaptive function-on-scalar regression approaches [60].

Finally, external validity and sustainability inferences are bounded. China's dense platform ecosystems, strong state involvement in infrastructure, and pronounced regional disparities may condition the strength of AIDI–LEF complementarity, so generalisation should be treated as suggestive. Sustainability is discussed through operational channels as follows: LEF does not measure emissions or energy intensity, so decarbonisation outcomes cannot be inferred from the estimates. Future studies can directly link CBED expansion

and fulfilment upgrading to environmental indicators (e.g., CO₂ intensity, energy use, and packaging waste) where data allow, and test whether higher coupling capacity is associated with measurable environmental outcomes. Cross-country comparisons in other emerging markets and designs that combine econometric evidence with life-cycle assessment or multi-objective optimisation would further clarify when AI–fulfilment complementarity aligns growth in CBED with demonstrable sustainability gains.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AIDI	AI Development Index
CBEC	Cross-Border E-Commerce
CBED	Cross-Border E-Commerce Development
LEF	Logistics Fulfilment Efficiency
DEA	Data Envelopment Analysis
GMM	Generalised Method of Moments
PCA	Principal Component Analysis
CPI	Consumer Price Index
PPI	Producer Price Index
TSP	Transportation, Storage, and Postal Services

Appendix A

This appendix provides implementation details for the construction of the key measures. Appendix A.1 documents the CBED indicator (Table A1). Appendix A.2 summarises the measurement of the fulfilment environment (LEF) and the AI Development Index (AIDI). Appendices A.3–A.5 reports robustness checks and alternative GMM estimates (Tables A2–A4).

*Appendix A.1. Details of the Cross-Border E-Commerce Development Indicator (CBED)***Table A1.** Construction and sources of the cross-border e-commerce development (CBED) indicator.

No.	Indicator	Description	Unit	Data Source	Notes on Processing
A1	CBEC import value	Total import value processed through customs CBEC platforms	CNY 100 million	China Customs Statistics Yearbook	Deflated to 2017 constant prices using provincial consumer price indices (CPI), consistent with Section 3.2.1.
A2	CBEC export value	Total export value processed through customs CBEC platforms	CNY 100 million	China Customs Statistics Yearbook	Deflated to 2017 constant prices using the same CPI-based deflator to ensure comparability with A1 and with Section 3.2.1.
A3	Import order count	Number of declared CBEC import orders	10,000 orders	Provincial Statistical Yearbooks	Used to compute average order values and cross-checked against customs statistical releases where available. Outliers in this order-based indicator are winsorised at the 1% and 99% tails to reduce the influence of extreme observations.
A4	Export order count	Number of declared CBEC export orders	10,000 orders	Provincial Statistical Yearbooks	Processed using the same validation and winsorisation procedures as A3 to maintain import–export comparability for this order-based indicator.
A5	Number of CBEC firms	Registered CBEC firms with operating licences	Firms	Provincial commerce departments	Used in additional entropy-weighted robustness checks. Firm counts are harmonised across provinces based on published registration criteria.
	CBED (composite)	Cross-border e-commerce development indicator	—	See Section 3.2.1 and Appendix A.1	The main CBED measure is constructed as the sum of A1 and A2 in 2017 constant prices; A3–A5 are incorporated in supplementary entropy-weighted CBED indices used in robustness checks (results available on request). The log-transformed indicator $\ln\text{CBED}$ is used in all regressions.

Note: The baseline CBED indicator is constructed as the inflation-adjusted sum of CBEC import and export values (A1 + A2). Order counts and firm numbers (A3–A5) serve as auxiliary measures in entropy-weighted robustness checks. All monetary series are deflated to 2017 constant prices. Winsorisation at the 1% and 99% tails is applied only to the order-based indicators (A3–A4), in line with the description in Section 3.2.1, to improve cross-provincial comparability without altering the value-based CBED series.

Appendix A.2. Construction of the Logistics Fulfilment Efficiency Index (LEF)

The logistics fulfilment efficiency measure (LEF) is obtained from the Super-SBM DEA model described in Section 3. Because the Super-SBM formulation permits super-efficiency, the raw efficiency scores may exceed one. For descriptive reporting in Table 1, LEF is linearly rescaled to the 0–1 range for ease of interpretation; for estimation, the regressions use $\ln\text{LEF}$ computed from the underlying (unbounded) DEA scores, without imposing a 0–1 truncation. LEF is interpreted as a fulfilment-efficiency measure rather

than an environmental performance indicator. $\ln\text{Size}$ and $\ln\text{GDP}$ are transformed controls; definitions and scaling are reported in Appendix A.2 to match Table 1 and the regressions.

Table A2. Super-SBM specification for provincial logistics fulfilment efficiency (LEF): inputs and outputs.

Item	Type	Definition	Unit	Data Source
I1	Input	Fixed asset investment in transportation, storage and postal services	CNY 100 million	China Statistical Yearbook; Provincial Statistical Yearbooks
I2	Input	Employment in logistics-related sectors (transportation, storage and postal services)	10,000 persons	China Statistical Yearbook; Provincial Statistical Yearbooks
I3	Input	Energy consumption (logistics-related)	10,000 tons of standard coal equivalent	China Energy Statistical Yearbook; Provincial Statistical Yearbooks
O1	Desirable output	Freight turnover (transport service volume)	100 million ton-kilometres	China Statistical Yearbook; Provincial Statistical Yearbooks

Note: the Super-SBM model uses consistently available logistics inputs and a service output to ensure cross-province and intertemporal comparability.

Appendix A.3. Construction of the AI Development Index (AIDI)

The AI Development Index (AIDI) is designed to capture provincial AI maturity along four broad pillars:

- Innovation: AI-related invention patents and scientific publications.
- Application: proxies for AI adoption by firms, including warehouse automation rates, adoption of AI-enabled logistics management systems, and reported deployment of intelligent systems in logistics and manufacturing.
- Infrastructure: 5G base-station density, broadband penetration, data-centre/cloud capacity, and other logistics-relevant IoT deployments.
- Market: share of logistics firms using AI tools and value added of the provincial AI sector.

For each indicator, values are normalised within year across provinces to the 0–1 interval using min–max scaling. Within each pillar, the normalised indicators are combined into a pillar score as the arithmetic mean of the constituent indicators. Cross-pillar (inter-pillar) weights are then obtained by the entropy method and normalised to sum to one, and the composite AIDI is calculated as the weighted sum of the four pillar scores.

In the econometric analysis, the 0–1 scaled AIDI is used directly, including in the interaction term with $\ln\text{LEF}$ in Equation (2). For descriptive statistics in Table 1, the index is linearly rescaled back to the original 1–9 reporting scale to aid interpretation.

Sensitivity checks indicate that the main results are robust to equal pillar weights and to equal indicator weights within pillars, as well as to a principal-component-based AI index (AIDI_alt) used in the robustness specification reported in Table A2. Data are drawn from the China Statistical Yearbook on Science and Technology, CNIPA patent statistics, Web of Science/CNKI, provincial statistical yearbooks, and sectoral reports, consistent with the description in Section 3.2.3.

Appendix A.4. System-GMM Estimates with Alternative CBED and AIDI Definitions

Table A3. System-GMM estimates using alternative CBED and AIDI definitions.

Variable	Coefficient	z-Statistic
lnLEF	0.395 ***	4.12
AIDI_alt	0.215 ***	3.67
lnLEF $\times$ AIDI_alt	0.205 ***	3.01
Controls	Yes	—
AR(1) <i>p</i> -value	0.000	—
AR(2) <i>p</i> -value	0.312	—
Hansen <i>p</i> -value	0.524	—
Observations	217	—

Note: the alternative CBED indicator replaces the baseline CBED measure with total e-commerce transaction value. AIDI_alt is a PCA-weighted AI index based on the same underlying indicators as the baseline AIDI. System GMM is estimated in two steps with collapsed instruments and restricted lag depth, corresponding to the robustness checks discussed in Section 4.6. Windmeijer-corrected two-step standard errors are used to compute z-statistics. *** $p < 0.01$.

Appendix A.5. Difference-GMM Estimates

Table A4. Difference-GMM estimates of Equations (1) and (2).

Variable	Equation (1)	Equation (2)
lnLEF	0.372 *** (3.45)	0.359 *** (3.18)
AIDI	—	0.194 *** (2.80)
lnLEF $\times$ AIDI	—	0.198 ** (2.25)
Controls	Yes	Yes
AR(1) <i>p</i> -value	0.000	0.000
AR(2) <i>p</i> -value	0.298	0.274
Hansen <i>p</i> -value	0.489	0.501
Observations	217	217

Note: difference GMM (Arellano–Bond) estimators are applied to Equations (1) and (2) as an alternative to System GMM. For Equation (1), lagged levels of lnCBED and lnLEF are used as instruments for first differences; for Equation (2), lags of AIDI are also included in the instrument set. Instrument sets are collapsed to prevent proliferation. Robust two-step standard errors are used, and z-statistics are reported in parentheses, in line with the diagnostic discussion in Section 4.6. ** $p < 0.05$; *** $p < 0.01$.

Appendix A.6. System-GMM Estimates Excluding Outliers

Table A5. System-GMM estimates excluding outlier provinces and years.

Variable	Coefficient	z-Statistic
lnLEF	0.409 ***	3.96
AIDI	0.228 ***	3.21
lnLEF $\times$ AIDI	0.214 ***	2.89
Controls	Yes	—
AR(1) <i>p</i> -value	0.000	—
AR(2) <i>p</i> -value	0.301	—
Hansen <i>p</i> -value	0.538	—
Observations	191	—

Note: system-GMM estimates exclude Guangdong and Zhejiang provinces and the year 2020 to test sensitivity to highly developed coastal provinces and the COVID-19 shock. The specification and instrument strategy mirror the baseline models, with collapsed instrument sets and restricted lag depth. Windmeijer-corrected two-step standard errors are used to compute z-statistics. Coefficients on lnLEF, AIDI, and their interaction remain positive and statistically significant, and diagnostic tests continue to indicate acceptable serial-correlation and over-identification properties, as reported in Section 4.6. *** $p < 0.01$.

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