Sensors and Materials, Vol. 38, No. 8 (2026) 4795–4816
MYU Tokyo

S & M 4594

A Sensing-information-assisted Gravity Model Integrating IoT Logistics and Maritime Sensing Indicators for TradePotential Assessment

Cong Pang,[1] Yucheng Geng,[1*] Fen Tan,[1] and Cheng-Fu Yang[2,3**]

[1]Business School, Dongguan City University, Dongguan 523419, China
[2]Department of Chemical and Materials Engineering, National University of Kaohsiung, Kaohsiung 811, Taiwan
[3]Department of Aeronautical Engineering, Chaoyang University of Technology, Taichung 413, Taiwan

(Received July 12, 2026; accepted July 29, 2026)

Keywords: IoT, maritime sensing data, AIS, trade potential, gravity model, logistics visibility, Portuguese-speaking countries, China exports

Conventional trade-potential studies based on gravity models explain bilateral trade mainly through economic scale, population, income differences, and geographic distance, while paying limited attention to logistics and maritime information obtained from sensing-enabled monitoring systems. In digital logistics and smart-port environments, IoT devices, tracking-and-tracing systems, automatic identification system (AIS)-based vessel monitoring, and port monitoring platforms provide sensing-derived information on shipment visibility, cargo traceability, maritime connectivity, route availability, and port efficiency. However, a remaining problem is how such heterogeneous sensing-derived operational information can be systematically transformed into quantitative indicators and incorporated into conventional trade-potential models. Accordingly, the objective of this study is to examine whether sensing-related logistics and maritime operational information can improve gravity-based trade-potential assessment beyond conventional economic and geographic variables. To achieve this objective, a sensing-information-assisted framework is proposed by incorporating IoT-enabled logistics indicators and maritime sensing variables into an extended gravity model. Using panel data on five Portuguese-speaking countries' exports to China from 2003 to 2022, the baseline gravity model is compared with models incorporating aggregated and disaggregated sensing-related indicators, including the IoT-enabled logistics sensing index (IOTLS), tracking-and-tracing capability (TRACE), AIS-based maritime connectivity (AISCON), port dwell time (DWELL), and shipping-route density (ROUTE). The results show that incorporating sensing-related indicators improves the explanatory performance of trade-potential assessment for total exports and major commodity categories. The disaggregated TRACE/ROUTE/DWELL specification outperforms the aggregate IOTLS/AISCON model, demonstrating the value of distinguishing individual sensing-derived operational components. A current limitation is the incomplete availability of historical AIS, port-operation, and shipment-level IoT datasets for the entire study period; therefore, consistently constructed and standardized sensing-related operational

*Corresponding author: e-mail: gengyucheng@dgcu.edu.cn
**Corresponding author: e-mail: cfyang@nuk.edu.tw
https://doi.org/10.18494/SAM6527

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

indicators are used to establish and evaluate the proposed framework. Further validation using high-resolution and directly observed sensing data remains an important issue for future research.

1. Introduction

International trade potential is commonly estimated using gravity models, in which bilateral trade flows are explained by economic size, market scale, population, geographic distance, and income differences.(1–3) International trade potential is commonly estimated using gravity models. In this context, “gravity” refers to an analytical concept analogous to the physical gravity principle: trade interaction between two economies tends to increase with their economic or market size and decrease with the resistance or separation between them, commonly represented by geographic distance and other trade-cost factors. A gravity model therefore estimates the expected level of bilateral trade from economic, demographic, and geographic characteristics. In this study, “trade potential” refers to the extent to which the observed trade flow differs from the level predicted by the gravity model. Comparing the actual trade with the predicted trade provides a quantitative basis for determining whether a bilateral trade relationship has additional expansion potential, is close to its expected level, or has already exceeded the predicted level. Later theoretical developments introduced multilateral resistance terms and more rigorous representations of trade costs, improving the theoretical foundation and empirical performance of gravity models.(2,3) In trade-potential studies, the predicted trade is generally compared with the actual trade to determine whether a bilateral relationship is underdeveloped, balanced, or overdeveloped.

However, conventional specifications rely primarily on macroeconomic and geographic variables, and treat distance as a broad proxy for trade costs. Consequently, they do not directly represent operational logistics conditions, including shipment visibility, cargo traceability, shipping-route availability, port congestion, and cargo-handling efficiency.(4) Because these conditions can change more rapidly than conventional economic and geographic variables, gravity-based assessments may incompletely represent the practical capacity of a trade corridor to support additional trade. The increasing digitalization of international logistics provides an opportunity to incorporate sensing and monitoring information into trade-potential assessment. Cross-border trade is physically supported by vessels, ports, containers, warehouses, transportation networks, and information systems that generate operational information through sensing-enabled technologies. IoT devices, radio-frequency identification (RFID), global positioning system (GPS) technologies, wireless sensors, tracking-and-tracing systems, and cloud-based monitoring platforms have been widely applied to improve supply-chain visibility, cargo monitoring, logistics coordination, and information sharing.(5–8)

From the perspective of sensing implementation, these technologies form a multilayer sensing environment for digital logistics and smart-port operations. RFID tags and readers provide cargo, container, and package identification and support event-based tracking at warehouses, terminals, and checkpoints, whereas GPS/global navigation satellite system (GNSS) devices provide continuous position and movement information for vehicles and transport assets.

Environmental and condition-monitoring sensors can further measure temperature, humidity, vibration, shock, pressure, and other physical parameters that are important for monitoring sensitive or high-value cargo. In maritime transportation, automatic identification system (AIS) transponders periodically transmit vessel identity, position, speed, course, and navigation status, enabling vessel-call frequency, voyage regularity, route activity, and maritime connectivity to be derived from sensing records. At ports, IoT-connected sensing systems can be combined with gate, terminal, cargo-handling, and operational records to characterize cargo movement, waiting conditions, and port dwell time (DWELL). Through wireless and IoT communication networks, these heterogeneous sensing data can be transmitted to logistics or port information platforms for integration, monitoring, and subsequent analytical processing.

In the proposed framework, these sensing technologies constitute the physical data-acquisition layer rather than independent explanatory variables. Their measurements are transformed into operational information that can subsequently be represented by the sensing-related indicators used in the gravity model. For example, identification and positioning records contribute to shipment visibility and tracking-and-tracing capability (TRACE); AIS vessel-position and voyage records provide information for AIS-based maritime connectivity (AISCON) and shipping-route density (ROUTE); and port monitoring and operational records can be used to determine vessel or DWELL. Therefore, the proposed sensing-information-assisted framework establishes a data pathway from physical sensing and monitoring, through operational-indicator construction, to gravity-model estimation and trade-potential assessment. This relationship enables sensor-generated information to be evaluated not only for real-time operational monitoring but also for its contribution to higher-level logistics, maritime transportation, and trade decision support. These systems provide information on cargo location, transportation status, shipment progress, storage conditions, customs procedures, and delivery timeliness. Logistics visibility and tracking capability can therefore be regarded as measurable dimensions of the sensing infrastructure supporting international trade.(9)

The value of IoT-enabled sensing systems in cross-border logistics lies in both operational data acquisition and the reduction in uncertainty among exporters, carriers, port operators, customs agencies, and importers. TRACE is particularly important for agricultural products, animal products, food, and beverages, for which traceability, transportation conditions, and delivery reliability can affect product quality and market access. From a sensing-oriented perspective, information generated by these systems can be transformed into quantitative indicators representing logistics visibility, cargo traceability, customs digitalization, and delivery efficiency.(9,10) Incorporating such indicators into trade models provides a means of connecting physical logistics monitoring with macro-level trade assessment. Maritime transportation represents another important source of sensing-derived operational information. The AIS records vessel identity, position, speed, course, navigation status, and other maritime information. AIS-based data have been widely used to monitor vessel movements, port calls, shipping routes, maritime connectivity, port congestion, and transportation activity.(11–14)

Compared with annual trade statistics and static geographic distance, AIS-based information provides a more direct representation of maritime transportation conditions. Indicators derived from vessel movements, route activity, shipping connectivity, and DWELL can therefore complement conventional economic variables by representing the connectivity and operational efficiency of maritime trade corridors. This issue is particularly relevant to trade between Portuguese-speaking countries and China because many of these countries depend strongly on maritime transportation and resource- or commodity-based exports. Brazil, Angola, Mozambique, Portugal, and Equatorial Guinea differ substantially in economic scale, export composition, port conditions, logistics infrastructure, and maritime connectivity. Physical distance alone cannot sufficiently represent these differences because transportation conditions may vary with port congestion, customs digitalization, route frequency, shipping-network connectivity, and port operational efficiency. These differences provide an appropriate empirical setting for examining whether sensing-related logistics and maritime indicators improve country-level and commodity-level trade-potential assessment. Despite the increasing application of sensing technologies in logistics and maritime transportation, gravity-based trade assessment, IoT-enabled logistics, and AIS-based maritime monitoring have largely developed as separate research fields. Conventional trade-potential studies primarily use macroeconomic and geographic variables, whereas IoT and maritime sensing studies focus on monitoring shipments, vessels, ports, and transportation operations. Limited attention has therefore been paid to transforming sensing-derived logistics and maritime information into quantitative variables for gravity-based trade-potential assessment.

Accordingly, the principal research problem addressed in this study is how sensing-derived logistics and maritime operational information can be systematically transformed into quantitative variables and incorporated into gravity-based trade-potential assessment. The objective of this study is therefore to develop and evaluate a sensing-information-assisted gravity framework that determines whether such operational information provides additional explanatory value beyond conventional economic and geographic variables. More specifically, the study aims to (1) construct sensing-related indicators representing logistics visibility, tracking capability, maritime connectivity, shipping-route activity, and port operational efficiency; (2) compare conventional, aggregated sensing-enhanced, and disaggregated sensing-enhanced gravity specifications; and (3) evaluate whether the resulting sensing-enhanced estimates provide a more operationally informative basis for country- and commodity-level trade-potential and prospect assessment. This methodological gap is important because classifications based only on conventional variables may not sufficiently reflect whether logistics and maritime transportation systems are operationally capable of supporting additional trade.

To address this gap, we propose a sensing-information-assisted trade-potential assessment framework that incorporates IoT-enabled logistics indicators and maritime sensing variables into an extended gravity model. The empirical analysis examines exports from Angola, Brazil, Mozambique, Portugal, and Equatorial Guinea to China from 2003 to 2022, considering total exports and five major commodity groups: mineral products, vegetable products, animal products, pulp and paper, and food and beverages. The sensing-related variables include the IoT-enabled logistics sensing index (IOTLS), TRACE, AISCON, DWELL, and ROUTE, representing logistics visibility, cargo traceability, maritime connectivity, and port operational monitoring. By comparing conventional, aggregated, and disaggregated sensing-enhanced specifications, we evaluate whether sensing-related operational information improves the explanatory performance and interpretation of trade-potential assessment. The main contribution of this study is the establishment of an analytical connection between sensing-enabled logistics and maritime monitoring systems and gravity-based trade-potential assessment.

Compared with recent studies that mainly apply IoT technologies to logistics visibility and shipment monitoring, use AIS data to analyze vessel movements and maritime connectivity, or employ conventional gravity models to estimate bilateral trade flows, the novelty of the proposed framework lies in integrating these previously separate analytical dimensions within a unified trade-potential assessment procedure. Specifically, sensing-related information is incorporated at two complementary levels: aggregated indicators (IOTLS and AISCON) represent overall logistics sensing capability and maritime connectivity, whereas disaggregated indicators (TRACE, ROUTE, and DWELL) identify the individual effects of cargo tracking, shipping-route availability, and port operational efficiency. This two-level design enables a direct comparison of whether composite or operationally specific sensing indicators provide greater explanatory value. Furthermore, the sensing-enhanced gravity estimates are linked with trade-potential ratios, RCA, trade space, and prospect classification, thereby extending sensing information from operational monitoring to country- and commodity-level trade assessment and decision support. Rather than treating IoT and AIS technologies solely as operational monitoring tools, the proposed framework transforms the information associated with logistics sensing, vessel monitoring, route activity, and port operations into quantitative indicators for international trade analysis. The aggregated and disaggregated sensing-related indicators are evaluated for total exports and major commodity categories, followed by trade-potential estimation and prospect classification.

This approach examines whether individual sensing-derived operational variables provide more informative assessments than aggregated indicators across countries and commodity groups. Thus, the proposed framework extends conventional gravity analysis from a predominantly macroeconomic and distance-based approach toward a sensing-information-assisted method incorporating observable logistics and maritime operational conditions. The results further demonstrate the value of distinguishing specific sensing-related components in trade-potential assessment and provide a methodological basis for future higher-frequency trade monitoring, the identification of logistics bottlenecks, and sensing-assisted decision support in digital logistics and smart-port environments. From a sensor-development perspective, the framework can also help identify which sensing functions and operational measurements provide the greatest analytical value for logistics and maritime applications. For example, the importance of tracking capability, route monitoring, and DWELL information can provide application requirements for future sensing systems in terms of positioning accuracy, identification reliability, environmental monitoring, communication continuity, long-term stability, and operation under harsh maritime conditions. Although the present study does not directly develop new sensing devices or materials, the resulting requirements can support future research on sensor integration and on sensor-related materials with improved resistance to humidity, salt exposure, temperature variation, mechanical vibration, and long-term environmental degradation for smart-port and maritime IoT applications.

2. Data, Materials, and Methods

The research framework is shown in Fig. 1. It integrates conventional trade and macroeconomic data with sensing-related logistics and maritime operational information represented by IoT logistics and AIS-based maritime sensing indicators. The empirical sample and corresponding data sources are summarized in Table 1. The framework consists of four analytical layers. The first layer characterizes bilateral trade relationships using export values and conventional gravity variables. The second layer incorporates sensing-related indicators representing logistics visibility, tracking capability, maritime connectivity, shipping-route activity, and port operational efficiency. The third layer estimates the baseline gravity model and sensing-enhanced specifications to evaluate the contribution of sensing-derived operational information to trade-flow explanation. The fourth layer converts predicted export values into trade-potential measures and prospect classifications. Through this framework, sensing-related logistics and maritime information is transformed into quantitative variables that can be systematically incorporated into trade assessment while maintaining comparability with conventional gravity-model studies. The sensing-related indicators therefore extend rather than replace the conventional gravity variables, and geographic distance remains explicitly included in the sensing-enhanced model specifications.

To ensure data consistency and analytical repeatability, each variable is associated with a clearly defined data source, measurement method, or construction rule. Trade data are organized by exporter, importer, year, and harmonized system (HS) category using UN Comtrade data,[15] whereas macroeconomic indicators are matched at the country-year level and geographic distance is obtained from the CEPII GeoDist Database.[16] The sensing-related indicators, including IOTLS, TRACE, AISCON, DWELL, and ROUTE, are processed according to consistent construction rules and standardized before model estimation. This procedure reduces

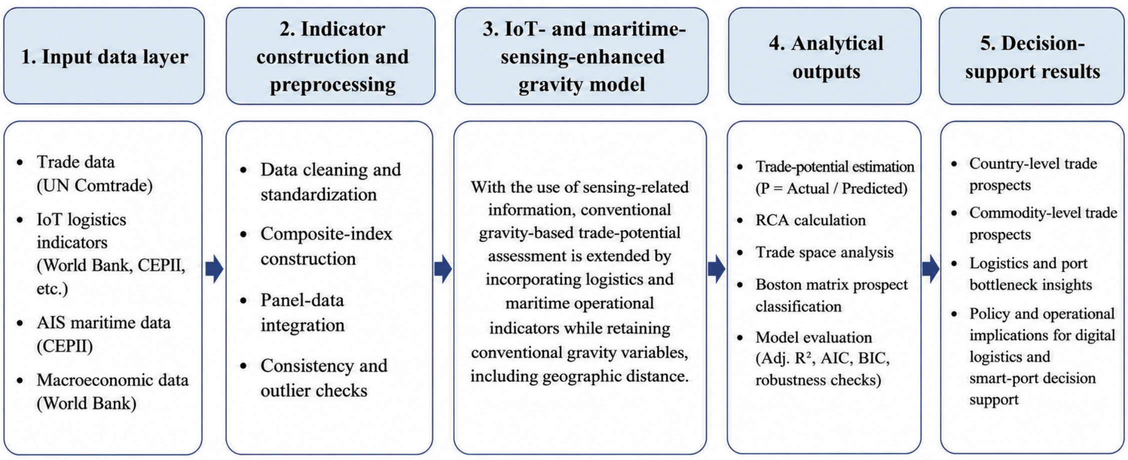

Fig. 1. (Color online) IoT- and maritime-sensing-data-based trade-potential assessment framework.

Table 1
Sample economies, commodity coverage, and data sources.

Data block	Coverage	Measurement	Source/status
Sample economies	Angola, Brazil, Mozambique, Portugal, Equatorial Guinea	Five exporters to China, 2003-2022; N = 100 country-year observations	Compiled from the uploaded manuscript and empirical workbook
Total exports	EXP	Total export value from each country to China	UN Comtrade [12], compiled in the empirical dataset
Commodity exports	EXP1-EXP5	HS25-27; HS06-14; HS01-05; HS47-49; HS16-24	UN Comtrade [12]; HS product groups compiled in the empirical dataset
Macroeconomic variables	PGDP, CGDP, PPOP, DRGDP	Exporter GDP, China GDP, population, income gap	World Bank World Development Indicators [6]
Geographic variable	DIS	Distance between exporter and China	CEPII GeoDist database [13]
Sensing variables	IOTLS, TRACE, AISCON, DWELL, ROUTE	IoT logistics and maritime sensing indicators	AIS and maritime sensing sources [9–11]; proxy-based indicators to be validated with AIS, port-operation, and shipping-network data
Prospect variables	P, RCA, TS, Prospect	Trade-potential ratio, comparative advantage, trade space, matrix class	Calculated by the authors based on model estimates, RCA, trade space, and Boston matrix framework

Note: EXP, total exports; EXP1–EXP5, exports of HS25–27, HS06–14, HS01–05, HS47–49, and HS16–24, respectively; PGDP, exporter gross domestic product; CGDP, China gross domestic product; PPOP, exporter population; DRGDP, difference in per capita gross domestic product; DIS, bilateral geographic distance; IOTLS, IoT-enabled logistics sensing index; TRACE, tracking-and-tracing capability; AISCON, AIS-based maritime connectivity; DWELL, port dwell time indicator; ROUTE, shipping-route density; P, trade-potential ratio; RCA, revealed comparative advantage; TS, trade space.

scale differences among indicators and enables their coefficients to represent relative variations in logistics sensing capability, maritime connectivity, route activity, and port operational efficiency. The resulting dataset therefore provides a consistent analytical basis for comparing conventional and sensing-enhanced gravity models and evaluating the contribution of sensing-related operational information to trade-potential assessment.

The dependent variables are the natural logarithms of total exports and five HS commodity groups. The conventional gravity variables include lnPGDP, lnCGDP, lnPPOP, lnDIS, and lnDRGDP, whereas IOTLS, TRACE, AISCON, DWELL, and ROUTE are incorporated as sensing-related logistics and maritime operational variables. These indicators represent logistics visibility, tracking capability, maritime connectivity, port operational efficiency, and shipping-route activity. Their definitions and expected signs are reported in Table 2, and the data-processing procedure is summarized in Fig. 2. The five commodity groups are retained because they represent major import categories from the sample economies and differ in their sensitivity to sensing-enabled logistics and maritime conditions. Mineral products are generally dependent on maritime connectivity, route availability, and transportation capacity, whereas vegetable

Table 2
Variable definitions, operational measurements, and expected signs.

Variable	Definition	Operational measurement	Expected sign
lnEXP	Total exports to China	Natural log of total export value from country p to China in year t	Dependent
lnEXP1-lnEXP5	Commodity exports	Natural log of HS25-27, HS06-14, HS01-05, HS47-49, and HS16-24 exports	Dependent
lnPGDP	Exporter economic scale	Natural log of exporter GDP	+
lnCGDP	China market scale	Natural log of China GDP	+
lnPPOP	Exporter population	Natural log of exporter population	+/-
lnDIS	Geographic distance	Natural log of bilateral distance	-
lnDRGDP	Income-level difference	Natural log of per capita GDP difference	+/-
IOTLS	IoT logistics sensing index	Composite of tracking, visibility, customs digitalization, and timeliness	+
TRACE	Tracking-and-tracing capability	Standardized cargo visibility and shipment traceability	+
AISCON	AIS-based maritime connectivity	Composite of vessel calls, route density, regularity, and China-bound connectivity	+
DWELL	Port dwell-time indicator	Average vessel/container dwell time; higher values indicate congestion	-
ROUTE	Shipping-route density	Density of regular routes between export and Chinese ports	+

Note 1: lnEXP, natural logarithm of total exports; lnEXP1–lnEXP5, natural logarithms of exports for HS25–27, HS06–14, HS01–05, HS47–49, and HS16–24, respectively; lnPGDP, natural logarithm of exporter GDP; lnCGDP, natural logarithm of China GDP; lnPPOP, natural logarithm of exporter population; lnDIS, natural logarithm of bilateral geographic distance; lnDRGDP, natural logarithm of the difference in per capita GDP; IOTLS, IoT-enabled logistics sensing index; TRACE, tracking-and-tracing capability; AISCON, AIS-based maritime connectivity; DWELL, port dwell-time indicator; ROUTE, shipping-route density.
Note 2: "Dependent variable" means that the variable is used as the outcome variable in the regression model. Specifically, lnEXP and lnEXP1–lnEXP5 are explained by conventional gravity variables, including lnPGDP, lnCGDP, lnPPOP, lnDIS, and lnDRGDP, and by sensing-related variables, including IOTLS, TRACE, AISCON, DWELL, and ROUTE. The symbols "+" and "–" indicate the expected sign of the estimated coefficient. "+" denotes an expected positive relationship with exports to China, whereas "–" denotes an expected negative relationship with exports to China. "+/–" indicates that the direction of the effect is theoretically ambiguous and may vary depending on commodity category, exporter characteristics, or model specification.

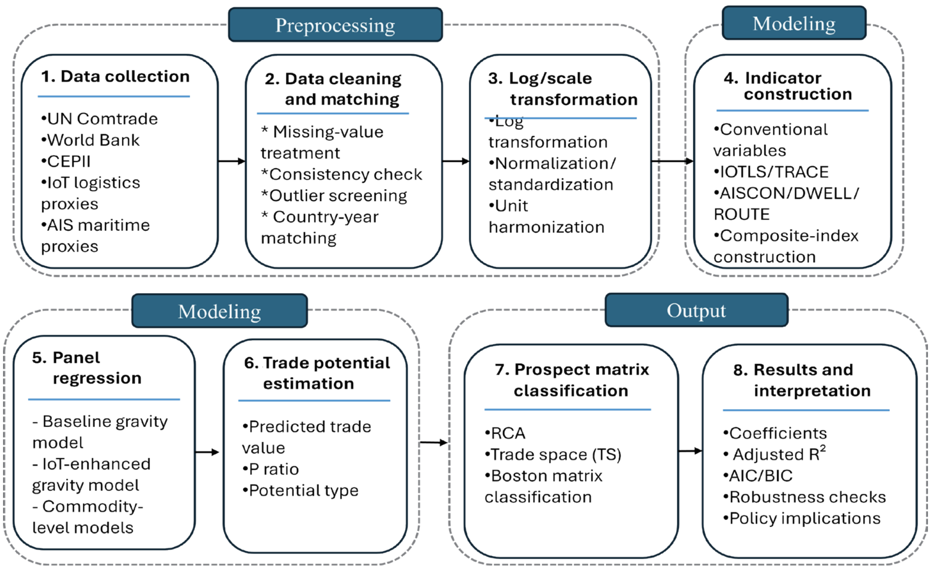

Fig. 2. (Color online) Data processing workflow.

products, animal products, and food and beverages are more sensitive to tracking capability, cargo traceability, inspection, delivery timeliness, and logistics visibility.

Pulp and paper products also require stable transportation networks and efficient port operations. Commodity-level estimation therefore enables the framework to evaluate the different explanatory effects of sensing-related indicators across products with heterogeneous logistics and monitoring requirements. The workflow shown in Fig. 2 provides a consistent procedure for integrating conventional economic data with sensing-related logistics and maritime information. Country names and HS classifications are harmonized across data sources, and monetary values are converted into comparable annual series. Logarithmic transformations are applied to export and macroeconomic variables, whereas sensing-related indicators are normalized to reduce scale differences. The processed variables are then matched by country and year to construct a unified panel dataset for baseline and sensing-enhanced model estimation. This procedure provides a repeatable basis for integrating heterogeneous economic and sensing-related operational information and evaluating their contribution to trade-potential assessment.

The baseline gravity model is specified in Eq. (1).

$$\begin{aligned} lnEXP_{pc,t} = \alpha_0 + \alpha_1 lnPGDP_{p,t} + \alpha_2 lnCGDP_t + \alpha_3 lnPPOP_{p,t} \\ + \alpha_4 lnDIS_{pc} + \alpha_5 lnDRGDP_{pc,t} + \varepsilon_{pc,t} \end{aligned} \tag{1}$$

In Eq. (1), p denotes the Portuguese-speaking exporting country, c denotes China, and t denotes year. $lnXP_{pc,t}$ denotes the natural logarithm of the export value from country p to China in year t; $lnPGDP_{p,t}$ is the natural logarithm of the GDP of exporting country p ; $lnCDP_t$is the natural logarithm of China's GDP; $lnPPOP_{p,t}$ is the natural logarithm of the population of exporting country p; $lnDIS_{pc}$ is the natural logarithm of the geographic distance between country p and China; and $lnDRGDP_{pc,t}$ is the natural logarithm of the per capita GDP difference between country p and China. α_0 denotes the constant term, α_1–α_5 are the estimated coefficients, and $\varepsilon_{pc,t}$ is the random error term. To evaluate whether sensing-related logistics and maritime operational information improves trade-flow explanation, the aggregate sensing model incorporates IOTLS and AISCON into the baseline specification, as shown in Eq. (2).

$$\begin{aligned} lnEXP_{pc,t} = \alpha_0 + \alpha_1 lnPGDP_{p,t} + \alpha_2 lnCGDP_t + \alpha_3 lnPPOP_{p,t} + \alpha_4 lnDIS_{pc} + \alpha_5 lnDRGDP_{pc,t} \\ + \alpha_6 IOTLS_{p,t} + \alpha_7 AISCON_{pc,t} + \varepsilon_{pc,t} \end{aligned} \tag{2}$$

In Eq. (2), $IOTLS_{p,t}$ denotes the IOTLS of exporting country p in year t and $AICON_{pc,t}$ denotes the AISCON between exporting country p and China in year t. α_6 and α_7 denote the estimated coefficients of IOTLS and AISCON, respectively. The other variables and parameters are defined as in Eq. (1). The disaggregated sensing model replaces the composite indicators with TRACE, ROUTE, and DWELL to distinguish the explanatory effects of specific sensing-related logistics and maritime operational components, as shown in Eq. (3). The same model specifications are applied to total exports and each commodity group.

$$lnEXP_{pc,t} = \alpha_0 + \alpha_1 lnPGDP_{p,t} + \alpha_2 lnCGDP_t + \alpha_3 lnPPOP_{p,t} + \alpha_4 lnDIS_{pc} + \alpha_5 lnDRGDP_{pc,t} + \alpha_6 TRACE_{p,t} + \alpha_7 ROUTE_{pc,t} + \alpha_8 DWELL_{p,t} + \varepsilon_{pc,t} \quad (3)$$

In Eq. (3), $TRACE_{p,t}$ denotes the TRACE of exporting country p in year t, $ROUTE_{pc,t}$ denotes the ROUTE between exporting country p and China in year t, and $DWELL_{p,t}$ denotes the DWELL indicator of exporting country p in year t. α_6–α_8 denote the estimated coefficients of TRACE, ROUTE, and DWELL, respectively. The other variables and parameters are defined as in Eq. (1). The aggregate specification evaluates whether overall logistics sensing capability and maritime connectivity provide additional explanatory information beyond conventional gravity variables. In contrast, the disaggregated specification identifies the contributions of individual sensing-related components representing tracking capability, shipping-route activity, and port operational efficiency. In this study, "aggregated" sensing indicators refer to composite variables that combine several related sensing and operational dimensions into an overall measure, whereas "disaggregated" indicators retain individual operational components as separate explanatory variables. This distinction allows the model to determine whether overall sensing capability or specific operational conditions provide more informative explanations of trade flows. This comparison is important because composite indicators may conceal heterogeneous operational effects. For example, greater route density may support trade flows by improving maritime connectivity and transportation availability, whereas longer DWELL may indicate congestion or operational inefficiency and therefore constrain trade. The baseline and sensing-enhanced models are compared using adjusted R^2, AIC, and BIC to determine whether incorporating sensing-related information provides meaningful improvements in model performance. Adjusted R^2 evaluates explanatory power while accounting for additional variables, whereas AIC and BIC assess model fit with penalties for model complexity. A sensing-enhanced specification is considered preferable only when it improves explanatory performance and reduces the information criteria relative to the baseline model. This comparison provides a consistent basis for evaluating the contribution of sensing-related logistics and maritime operational information while avoiding the attribution of improved model performance solely to the inclusion of additional variables.

Trade potential is calculated from the actual and predicted export values obtained from the baseline and sensing-enhanced models, as shown in Eq. (4).

$$P_{pc,t} = (Actual\ export_{pc,t}) / (Predict\ export_{pc,t}) \quad (4)$$

The resulting trade-potential ratio provides a quantitative measure for evaluating whether observed trade flows are above, close to, or below the levels predicted from conventional economic variables and sensing-related logistics and maritime operational information. In practical terms, the trade-potential ratio compares realized trade with the trade level expected from the explanatory conditions included in the model. A ratio below the reference range indicates that actual trade remains below the model-predicted level and may therefore have room for further development, whereas a ratio above the reference range indicates that realized trade already exceeds the predicted level. The ratio is used here as an assessment indicator rather than as a direct measure of future trade growth. A value of $P \geq 1.2$ indicates the reconstruction type, $0.8 < P < 1.2$ indicates the exploratory type, and $P \leq 0.8$ indicates the high-potential type. Because the predicted export values generated by the sensing-enhanced models incorporate logistics visibility, tracking capability, maritime connectivity, route activity, and port operational efficiency, the resulting trade-potential assessment reflects both conventional economic conditions and sensing-related operational factors. Prospect classification further combines the trade-potential ratio with RCA and trade space using a Boston matrix. RCA is calculated using Eq. (5).

$$RCA_{k,p,t} = (X_{k,p,t} / X_{p,t}) / (M_{k,c,t} / M_{c,t}) \tag{5}$$

The Boston matrix is used as an interpretive classification tool rather than as a substitute for regression analysis. For readers outside the field of international trade, revealed comparative advantage (RCA) is used in this study as an indicator of the relative competitiveness or specialization of a country in a particular product category. Trade space (TS) represents the remaining room for trade development by considering the relationship between realized and estimated trade conditions. The Boston matrix is adopted as an interpretive classification framework that combines trade potential, comparative advantage, and trade space to distinguish different development prospects. Accordingly, the resulting prospect categories are intended to support the comparative interpretation of country- and commodity-level trade opportunities rather than to replace the statistical results obtained from the gravity models. The regression models estimate expected trade levels on the basis of conventional and sensing-related explanatory variables, whereas RCA and trade space provide complementary information on product competitiveness and market-development conditions. Combining these measures reduces the risk of interpreting all low actual-to-predicted trade ratios as equally attractive opportunities and enables a more differentiated evaluation of country- and commodity-level trade prospects. Figure 3 illustrates the maritime sensing and connectivity logic underlying AISCON, ROUTE, and DWELL. These indicators represent complementary dimensions of maritime operational monitoring: AISCON reflects the overall connectivity of maritime transportation networks, ROUTE represents the availability and density of shipping routes, and DWELL reflects port operational efficiency through the time associated with vessel or cargo handling. Incorporating these sensing-related maritime indicators into model estimation and subsequent trade-potential classification establishes a consistent analytical link between AIS-based operational information, predicted trade flows, and prospect assessment.

The IoT and maritime sensing indicators are constructed through a consistent procedure of indicator selection, direction identification, normalization, and aggregation. The purpose of this procedure is to transform heterogeneous logistics and maritime operational information into comparable quantitative variables that represent sensing-related capabilities and conditions. Before aggregation and model estimation, all indicators are standardized according to their operational directions. For positive indicators, where larger values represent stronger logistics sensing capability, maritime connectivity, or operational performance, Eq. (6) is used.

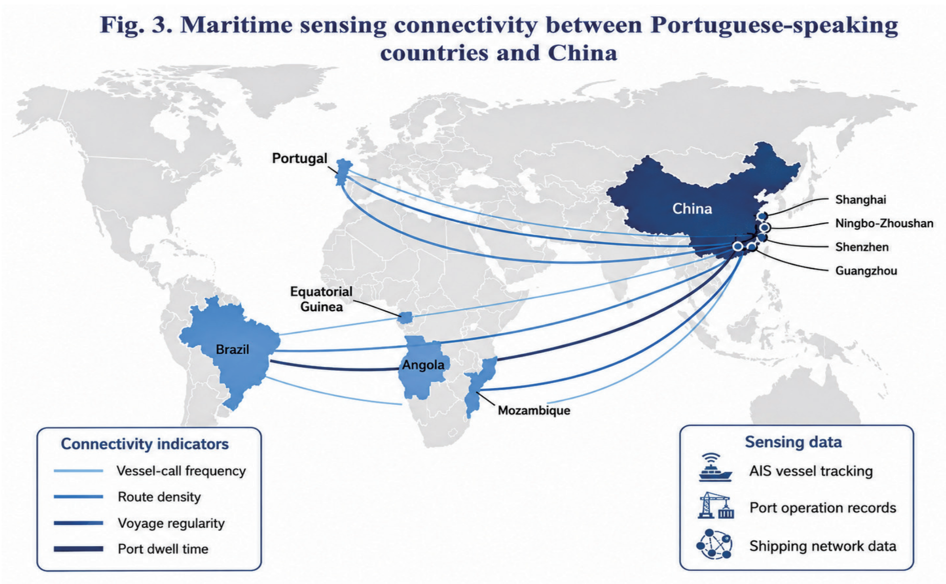

Fig. 3. (Color online) Maritime sensing connectivity between Portuguese-speaking countries and China.

$$Z_{i,t}^{+} = (X_{i,t} - \min X) / (\max X - \min X) \tag{6}$$

For negative indicators such as DWELL, where larger values indicate lower operational efficiency, Eq. (7) is applied.

$$Z_{i,t}^{-} = (\max X - X_{i,t}) / (\max X - \min X) \tag{7}$$

These transformations place the indicators on a common scale from 0 to 1 and reduce differences in measurement units. For the normalized indicators used in composite-index construction, higher values consistently represent stronger sensing-related logistics capability or maritime operational performance. This procedure enables heterogeneous information obtained from logistics monitoring, tracking systems, maritime connectivity, and port operations to be integrated into a common analytical framework. Owing to the limited availability of complete historical AIS trajectories, port-operation records, and shipment-level IoT logs for the entire 2003–2022 panel, the current implementation constructs sensing-related indicators using available proxy-based operational information. These proxies represent logistics visibility, tracking capability, customs digitalization, shipment timeliness, maritime connectivity, route activity, and port efficiency. Therefore, in the present study, we focus on establishing a repeatable procedure for constructing sensing-related indicators and demonstrating their applicability to trade-potential assessment. When higher-resolution sensing data become available, the same construction procedure can be applied directly to electronic tracking events, RFID/GPS records, customs-platform usage, shipment timeliness logs, AIS-derived vessel calls, voyage regularity, and port-operation records. IOTLS is constructed as a composite indicator representing multiple dimensions of sensing-enabled logistics capability, including TRACE, logistics visibility, customs digitalization, and shipment timeliness. After normalization, these components are aggregated according to Eq. (8).

$$IOTLS_{p,t} = w_1 TRACE_{p,t} + w_2 VIS_{p,t} + w_3 CUSTOM_{p,t} + w_4 TIME_{p,t} \tag{8}$$

TRACE represents the capability to monitor cargo location, shipment status, and delivery progress and therefore reflects the availability of sensing-supported information throughout the logistics process. VIS represents the accessibility and sharing of logistics information among supply-chain participants, whereas CUSTOM reflects the digitalization of customs procedures and associated information processing. TIME represents shipment timeliness and delivery reliability. The resulting IOTLS provides an aggregated measure of the sensing-related logistics capability supporting cross-border trade. AISCON is constructed to represent maritime sensing and connectivity conditions derived from vessel activity, shipping-network operations, and port efficiency. Its components include vessel-call frequency, ROUTE, voyage regularity, and dwell-time efficiency, as expressed in Eq. (9).

$$AISCON_{pc,t} = v_1 CALL_{pc,t} + v_2 ROUTE_{pc,t} + v_3 REG_{pc,t} + v_4 DWELL\_EFF_{p,t} \tag{9}$$

CALL represents vessel-call activity associated with maritime transportation demand and connectivity, ROUTE measures the density of regular shipping routes between major export and Chinese ports, and REG represents the regularity of maritime services. DWELL_EFF is obtained by directionally transforming DWELL and represents port operational efficiency. Together, these components transform maritime sensing and monitoring information into a composite indicator that reflects the operational connectivity and efficiency of maritime trade corridors. The aggregate and disaggregated indicators are used to evaluate different dimensions of sensing-related logistics and maritime conditions. IOTLS and AISCON provide composite measures of overall logistics sensing capability and maritime connectivity, whereas TRACE, ROUTE, and DWELL enable the model to identify the effects of specific operational components. IOTLS, TRACE, AISCON, and ROUTE are expected to have positive coefficients because stronger logistics visibility, tracking capability, maritime connectivity, and route availability are expected to support trade flows.

In contrast, DWELL is retained as a direct dwell-time indicator in the disaggregated model and is expected to have a negative coefficient because longer port stays generally indicate congestion, waiting time, or lower cargo-handling efficiency. The distinction between DWELL and DWELL_EFF is maintained throughout the indicator-construction procedure. A higher DWELL value represents longer port stays and lower operational efficiency, whereas a higher DWELL_EFF value represents faster handling and better port performance. Therefore, DWELL_EFF is used as a positive component in the construction of AISCON, while the original DWELL indicator is retained in the disaggregated model to directly evaluate the negative effect of port delays. This construction strategy ensures a consistent directional interpretation of the sensing-related indicators and enables aggregated and disaggregated models to provide complementary information on the contribution of logistics sensing and maritime operational conditions to trade-potential assessment.

3. Construction of IoT and Maritime Sensing Indicators

Table 3 reports the estimation results of the baseline extended gravity model. For total exports, the model yields an R^2 of 0.665 and an adjusted R^2 of 0.648. For the baseline total-export model, the adjusted R^2 value of 0.648 was calculated from the reported R^2 value of 0.665, the number of observations (n = 100), and the number of explanatory variables in the baseline model (k = 5). The calculation follows the standard adjusted R^2 formula.

$$Adjusted\ R^2 = 1 - \left(1 - R^2\right)\frac{n-1}{n-k-1} \tag{10}$$

Substituting R^2 = 0.665, n = 100, and k = 5 gives an adjusted R^2 of approximately 0.648. Exporter GDP and China GDP are significantly positive, confirming the importance of exporter capacity and China's market scale in explaining bilateral trade flows. The commodity-level results differ across product groups, indicating that total trade cannot be interpreted as a uniform relationship and that different commodity categories respond differently to economic and transportation conditions. The baseline model performs relatively well for animal products and food and beverages but shows lower explanatory power for mineral products. This suggests that conventional economic variables explain some commodity groups more effectively than others. However, the baseline specification cannot identify whether the remaining variation is associated with logistics visibility, tracking capability, maritime connectivity, shipping-route activity, or port operational efficiency. Some coefficients, particularly that of geographic distance, also differ from conventional expectations. This may reflect the maritime-oriented characteristics and commodity structures of the sample economies. For resource-based exports, large geographic distance may not strongly constrain trade when transportation capacity, regular

Table 3
Baseline extended gravity model results.

Variable	Total	Mineral	Vegetable	Animal	Pulp/paper	Food/bev.
lnPGDP	0.721***	0.911***	−0.275	0.495*	3.629***	1.764***
lnPPOP	−0.551***	−1.216***	4.109***	4.140***	0.937**	2.688***
lnDIS	5.345***	9.589***	6.428*	−9.363***	−4.901	−4.263
lnDRGDP	−0.496***	−0.562**	2.597***	1.646***	1.554***	2.254***
lnCGDP	0.902***	1.819***	−0.220	1.187***	−0.810	0.489
N	100	100	100	100	100	100
Adj. R^2	0.648	0.430	0.702	0.830	0.787	0.780

Note: N = number of observations; Adj. R^2 = adjusted coefficient of determination; AIC = Akaike information criterion; BIC = Bayesian information criterion. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

shipping services, and stable maritime connections are available. These results support the incorporation of sensing-related logistics and maritime operational indicators to complement conventional gravity variables.

After incorporating IOTLS and AISCON, the explanatory performance improves for all dependent variables. For total exports, the adjusted R^2 increases from 0.648 to 0.752, indicating that aggregated sensing-related information provides additional explanatory value beyond conventional economic and geographic variables. AISCON is positive for total exports and significant for pulp and paper and food and beverages, suggesting that stronger maritime connectivity and operational conditions support trade flows for these commodity groups. After incorporating IOTLS and AISCON, the explanatory performance improves for all dependent variables. For total exports, the adjusted R^2 increases from 0.648 for the baseline model to 0.752 for the aggregate IoT/AIS sensing-enhanced model, as reported in Table 4. The adjusted R^2 value of 0.752 was calculated from R^2 = 0.769, with n = 100 observations and k = 7 explanatory variables, using the standard adjusted R^2 formula. This improvement indicates that aggregated sensing-related information provides additional explanatory value beyond conventional economic and geographic variables. In contrast, the coefficients of IOTLS vary across product categories, indicating that an aggregated logistics sensing indicator may conceal differences among specific operational components.

The positive effects associated with AISCON are consistent with the maritime characteristics of the investigated trade corridors. More regular vessel services, stronger port-to-port connectivity, greater route availability, and efficient port operations can reduce effective trade friction even when geographic distance remains unchanged. The mixed IOTLS results should therefore not be interpreted as evidence against sensing-enabled logistics systems. Instead, they indicate that composite indicators may simultaneously capture logistics visibility, tracking capability, digital processing, and operational or compliance requirements, which may affect different commodity categories in different ways. For example, stronger tracking capability can improve shipment visibility and logistics coordination but may also be associated with stricter documentation, inspection, and quality-control requirements for certain commodities. These requirements may increase short-term transaction costs while improving traceability and

Table 4
Core sensing-variable results in the enhanced gravity models.

Variable	Total	Mineral	Vegetable	Animal	Pulp/paper	Food/bev.
IOTLS	−14.722***	−30.587***	49.974***	14.099	−1.630	9.849
AISCON	14.363*	22.127	−15.609	8.385	104.077***	60.530**
TRACE	−6.835	−6.945	−36.775	−59.345*	−135.620***	−72.488**
ROUTE	15.696	22.434	39.840	57.111	235.103***	148.748***
DWELL	6.724	22.507	−80.506**	−69.865***	−134.669***	−81.712***
Best Adj. R2	0.775	0.615	0.827	0.851	0.853	0.863

Note: IOTLS, IoT-enabled logistics sensing index; AISCON, AIS-based maritime connectivity; TRACE, tracking-and-tracing capability; ROUTE, shipping-route density; DWELL, port dwell-time indicator; N = number of observations; Adj. R^2 = adjusted coefficient of determination; AIC = Akaike information criterion; BIC = Bayesian information criterion. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

operational transparency. Therefore, the disaggregated sensing model is necessary to distinguish the individual effects of TRACE, ROUTE, and DWELL and to identify which sensing-related logistics and maritime operational conditions contribute most directly to trade-flow explanation.

Table 4 presents the main sensing-related coefficients obtained from the aggregate and disaggregated models. ROUTE is positive across the investigated commodity groups and strongly significant for pulp and paper and food and beverages, indicating that greater shipping-route availability and service density support export flows. In contrast, DWELL is negative and significant for vegetable products, animal products, pulp and paper, and food and beverages. This result indicates that longer port stays, which reflect congestion, waiting time, or lower cargo-handling efficiency, constrain trade performance. The commodity-level results further demonstrate the operational relevance of sensing-related indicators. ROUTE is particularly important for products requiring regular and predictable maritime services, whereas DWELL has a stronger effect on time-sensitive, inspection-sensitive, or logistics-dependent products.

Therefore, incorporating sensing-related operational information not only improves model performance but also provides a more detailed explanation of how maritime connectivity and port efficiency affect the trade potential of different commodity categories. The results also show that sensing-related indicators do not affect trade flows uniformly. ROUTE generally supports export expansion, whereas DWELL constrains trade performance. TRACE exhibits more heterogeneous effects because it may represent both improved cargo visibility and additional traceability or regulatory requirements. These differences confirm the methodological importance of distinguishing individual sensing-related components rather than relying solely on aggregated digital logistics indicators. The disaggregated specification therefore provides greater interpretability by identifying the distinct operational effects associated with logistics tracking, maritime route activity, and port efficiency.

Table 5 shows the baseline, aggregate IOTLS/AISCON, and disaggregated TRACE/ROUTE/DWELL models. The disaggregated sensing model yields the lowest BIC values for all six dependent variables and is therefore selected as the preferred specification. The improvements in adjusted R^2 range from 0.030 for animal products to 0.211 for mineral products, demonstrating that the contribution of sensing-related operational information differs across commodity categories. The improvements are observed across all dependent variables rather than being limited to a single commodity group, indicating that the sensing-enhanced framework provides additional explanatory information across different trade structures. The largest improvement is observed for mineral products, suggesting that maritime connectivity, shipping-route activity, and port operational conditions are particularly important for bulk commodity trade.

Smaller but positive improvements for animal products and food and beverages indicate that conventional gravity variables already explain a substantial proportion of their trade variation, while sensing-related indicators provide additional operational information. From the perspective of model reliability, the preferred disaggregated specification is supported by both explanatory performance and information criteria. An improvement only in adjusted R^2 can potentially result from the inclusion of additional explanatory variables. In this study, however, the simultaneous improvement in adjusted R^2, AIC, and BIC indicates that the sensing-related indicators provide meaningful explanatory information rather than merely increasing model complexity. These

Table 5
Model comparison and robustness-check results.

Dependent variable	Baseline Adj.R^2; AIC; BIC	IoT/AIS Adj.R^2; AIC; BIC	TRACE/ROUTE/ DWELL Adj.R^2; AIC; BIC	Delta Adj.R^2	Preferred
Total exports	0.648; 63.570; 79.201	0.752; 30.457; 51.298	0.775; 21.520; 44.967	+0.127	TRACE/ROUTE/ DWELL
Mineral	0.404; 231.437; 247.068	0.571; 200.415; 221.257	0.615; 190.449; 213.895	+0.211	TRACE/ROUTE/ DWELL
Vegetable	0.716; 346.581; 362.212	0.805; 310.960; 331.802	0.827; 299.567; 323.014	+0.111	TRACE/ROUTE/ DWELL
Animal	0.821; 271.412; 287.043	0.835; 265.409; 286.250	0.851; 255.880; 279.327	+0.030	TRACE/ROUTE/ DWELL
Pulp/paper	0.763; 325.438; 341.069	0.824; 297.615; 318.456	0.853; 280.249; 303.695	+0.090	TRACE/ROUTE/ DWELL
Food/bev.	0.799; 293.880; 309.511	0.849; 267.596; 288.437	0.863; 258.248; 281.695	+0.064	TRACE/ROUTE/ DWELL

Note: Adj. R^2, adjusted coefficient of determination; AIC, Akaike information criterion; BIC, Bayesian information criterion; IoT, Internet of Things; AIS, automatic identification system; TRACE, tracking-and-tracing capability; ROUTE, shipping-route density; DWELL, port dwell-time indicator.

results demonstrate that distinguishing specific logistics sensing and maritime operational components provides a more informative and statistically supported basis for trade-flow explanation and subsequent trade-potential assessment.

4. Trade Potential, Prospect Classification, and Discussion

Because Table 5 identifies the TRACE/ROUTE/DWELL specification as the preferred model, the trade-potential values reported in Table 6 are calculated using the predicted exports generated by the disaggregated sensing-enhanced model. The resulting assessment therefore reflects not only conventional economic and geographic factors but also sensing-related operational conditions associated with tracking capability, shipping-route activity, and port efficiency. At the aggregate level, all five countries are classified as exploratory types, whereas Angola, Brazil, and Equatorial Guinea exhibit bright total-export prospects because of their stronger RCA values. The prospect classification is not determined by the trade-potential ratio alone. Low P may indicate room for trade expansion, but low RCA suggests that such potential may be difficult to realize without improvements in competitiveness and supporting capabilities. Conversely, high RCA combined with limited trade space may indicate a mature category requiring structural upgrading rather than simple volume expansion.

Therefore, in Table 6, we combine P, RCA, TS, and prospect type to provide a multidimensional assessment. At the country level, Brazil exhibits broad competitiveness across several commodity groups, whereas Angola and Equatorial Guinea depend more strongly on resource-related exports. Mozambique shows selected advantages in vegetable and animal

Table 6
Trade potential and prospect classification in 2022.

Category	Country	P	Type	RCA	TS	Prospect
Total	Angola	1.11	Exploratory	3.82	0.09	Bright
Total	Brazil	0.99	Exploratory	2.40	0.21	Bright
Total	Mozambique	1.00	Exploratory	0.46	0.20	Promising
Total	Portugal	0.95	Exploratory	0.07	0.25	Promising
Total	Equatorial Guinea	0.98	Exploratory	1.68	0.22	Bright
Mineral	Angola	1.16	Exploratory	1.07	0.04	Bright
Mineral	Brazil	0.95	Exploratory	1.49	0.25	Bright
Mineral	Mozambique	1.05	Exploratory	1.07	0.15	Bright
Mineral	Portugal	0.87	Exploratory	0.95	0.33	Promising
Mineral	Equatorial Guinea	0.95	Exploratory	0.96	0.25	Promising
Vegetable	Angola	0.41	High-potential	0.00	0.79	Promising
Vegetable	Brazil	1.14	Exploratory	1.68	0.06	Bright
Vegetable	Mozambique	1.13	Exploratory	2.44	0.07	Bright
Vegetable	Portugal	1.48	Reconstruction	0.15	-0.28	Dim
Vegetable	Equatorial Guinea	0.00	High-potential	0.00	1.20	Promising
Animal	Angola	0.86	Exploratory	0.22	0.34	Promising
Animal	Brazil	1.10	Exploratory	1.52	0.10	Bright
Animal	Mozambique	0.92	Exploratory	3.83	0.28	Bright
Animal	Portugal	1.11	Exploratory	2.25	0.09	Bright
Animal	Equatorial Guinea	0.00	High-potential	0.00	1.20	Promising
Pulp/paper	Angola	0.69	High-potential	0.00	0.51	Promising
Pulp/paper	Brazil	1.11	Exploratory	1.12	0.09	Bright
Pulp/paper	Mozambique	1.80	Reconstruction	0.05	-0.60	Dim
Pulp/paper	Portugal	1.19	Exploratory	2.41	0.00	Bright
Pulp/paper	Equatorial Guinea	0.00	High-potential	0.00	1.20	Promising
Food/bev.	Angola	0.93	Exploratory	0.06	0.27	Promising
Food/bev.	Brazil	1.07	Exploratory	0.26	0.13	Promising
Food/bev.	Mozambique	0.98	Exploratory	0.01	0.22	Promising
Food/bev.	Portugal	1.13	Exploratory	0.57	0.07	Promising
Food/bev.	Equatorial Guinea	0.00	High-potential	0.00	1.20	Promising

Note: P, trade-potential ratio; RCA, revealed comparative advantage; TS, trade space. Prospect categories: bright, high comparative advantage with favorable trade potential; Promising, positive trade opportunities with moderate competitiveness; Dim, limited trade prospects under current conditions; Exploratory, trade close to the predicted level with potential requiring further evaluation; High-potential, trade below the predicted level indicating considerable expansion potential; Reconstruction, trade above the predicted level suggesting limited room for further expansion under the current framework.

products, whereas Portugal has stronger prospects in animal products and pulp and paper but weaker prospects in categories where actual exports exceed sensing-enhanced predicted levels without sufficient RCA support. The classification results show that mineral products remain the most mature category for Angola, Brazil, and Mozambique. Vegetable and animal products exhibit stronger prospects for Brazil and Mozambique, whereas pulp and paper show more favorable prospects for Brazil and Portugal. Food and beverages are generally classified as promising but have not yet reached the bright category. These results indicate that future expansion may depend on not only economic demand and comparative advantage but also sensing-enabled logistics conditions, including cargo traceability, route stability, logistics visibility, and port operational efficiency.

From the perspective of logistics and trade planning, different prospect categories require different operational priorities. Bright categories should maintain stable maritime services and prevent deterioration in port efficiency, whereas promising categories may benefit from improved tracking capability, product traceability, quality monitoring, and market access. Dim or reconstruction categories require greater caution because current trade performance may not be supported by sufficient comparative advantage or future trade space. The sensing-enhanced classification therefore provides more operationally interpretable information than a classification based solely on macroeconomic variables. For example, food and beverage exports may benefit from stronger tracking, traceability, and quality-monitoring systems, whereas mineral products depend more strongly on route density, port capacity, and reliable vessel services. The empirical results demonstrate that incorporating sensing-related operational information improves trade-potential assessment by representing logistics and maritime conditions that conventional gravity variables cannot directly capture. GDP and geographic distance describe economic capacity and spatial separation, whereas TRACE, ROUTE, and DWELL provide quantitative representations of tracking capability, maritime service availability, and port operational efficiency.

Incorporating these indicators establishes a connection between sensing-enabled monitoring systems and macro-level trade assessment and enables predicted trade flows to reflect observable operational conditions. This distinction also has methodological significance. Conventional gravity models commonly approximate trade costs using geographic distance, which is time-invariant and cannot represent changes in shipping networks, port congestion, logistics digitalization, tracking capability, or maritime service availability. In contrast, sensing-related operational indicators introduce time-varying information associated with logistics and maritime transportation into trade assessment. The resulting framework therefore extends conventional trade-potential analysis by incorporating measurable operational conditions that more closely represent the physical movement and monitoring of goods. The findings further suggest that sensing-enabled logistics and maritime monitoring systems can be considered part of the operational infrastructure supporting international trade. Conventional infrastructure includes ports, roads, warehouses, vessels, and cargo-handling facilities, whereas sensing-related infrastructure includes tracking systems, AIS-based vessel monitoring, customs information platforms, logistics visibility systems, and data-sharing mechanisms.

These physical and digital infrastructures jointly affect the capacity and efficiency of international trade corridors, but sensing-related operational conditions are rarely incorporated explicitly into conventional gravity models. The superior performance of the disaggregated TRACE/ROUTE/DWELL specification compared with the aggregate IOTLS/AISCON model indicates that sensing-related information should not necessarily be represented only through broad composite indicators. ROUTE and DWELL provide direct and interpretable measures of specific maritime operational conditions. Greater route density can improve transportation availability and reduce uncertainty, whereas longer dwell time reflects congestion, waiting time, and lower cargo-handling efficiency. The heterogeneous effects of TRACE suggest that tracking capability may represent both improved logistics visibility and additional compliance requirements. Stronger traceability can improve transparency and coordination but may also be associated with increased documentation, inspection, and quality-control costs. The commodity-level results further demonstrate the importance of distinguishing different sensing and operational requirements. Mineral products are strongly affected by resource endowment, bulk transportation capacity, route availability, and port operations, whereas vegetable products, animal products, and food and beverages are more sensitive to tracking capability, timeliness, traceability, and logistics visibility.

Pulp and paper products also depend on stable maritime services and efficient port handling. Therefore, sensing-enhanced trade-potential assessment provides a more differentiated basis for logistics planning and port-development decisions than aggregate trade analysis. The findings also have practical implications for trade cooperation between China and Portuguese-speaking countries. Future trade expansion may benefit not only from tariff reduction and market development but also from improved IoT-enabled shipment monitoring, port-data sharing, AIS-based maritime monitoring, customs information integration, and port-efficiency management. These sensing-enabled logistics and maritime systems can generate measurable operational information that supports the evaluation of trade corridors and the identification of transportation constraints. For port authorities and logistics enterprises, the proposed framework provides a methodological basis for corridor-level operational monitoring. Changes in ROUTE or DWELL may indicate emerging transportation constraints before their effects are fully reflected in annual export values. For policymakers, sensing-related indicators can provide complementary evidence for prioritizing investments in smart-port systems, digital customs infrastructure, logistics data-sharing platforms, and traceability systems.

The framework therefore demonstrates how sensing-enabled operational information can be transformed into quantitative inputs for trade assessment and decision support. The present study nevertheless has limitations related to sensing-data availability. The current indicators are constructed from standardized proxy-based operational information because complete historical AIS trajectories, vessel-call records, port-operation datasets, and shipment-level IoT logs are unavailable for the entire study period. Therefore, the empirical results should be interpreted as a demonstration of a sensing-information-assisted analytical framework rather than a direct real-time sensing-data implementation. Future studies should incorporate observed AIS trajectories, vessel-call records, port-stay and container dwell-time datasets, and IoT shipment-tracking logs. Such data would enable higher-frequency assessment, port-level comparisons, commodity-specific route analysis, and a more direct validation of the contribution of sensing technologies to trade-potential evaluation.

5. Conclusions

In this study, we proposed a sensing-information-assisted trade-potential assessment framework by incorporating IoT-enabled logistics indicators and maritime sensing variables into an extended gravity model. Compared with the baseline gravity model, the sensing-enhanced specifications consistently improve adjusted R^2 and reduce AIC and BIC values for total exports and major commodity groups, demonstrating that sensing-related operational information provides additional explanatory value beyond conventional economic and geographic variables. Among the evaluated specifications, the disaggregated TRACE/ROUTE/DWELL model achieves the best overall performance. These results indicate that trade potential should be assessed not only through production capacity, market demand, income differences, and geographic distance but also through observable logistics and maritime operational conditions associated with tracking capability, shipping-route activity, and port efficiency. Using the preferred sensing-enhanced model, we further integrate predicted trade potential, RCA, trade space, and Boston matrix classification to evaluate the country- and commodity-level export prospects of Portuguese-speaking countries to China. The results demonstrate that distinguishing individual sensing-related operational components provides more informative trade-potential assessments than relying solely on aggregated sensing indicators. The proposed framework establishes a repeatable analytical connection between sensing-enabled logistics and maritime monitoring systems and international trade assessment and can be extended to other maritime trade corridors with suitable logistics, maritime, and commodity-level data. However, the current implementation relies on proxy-based indicators because complete historical sensing datasets are unavailable for the entire study period. Future studies should incorporate observed AIS trajectories, vessel-call records, port-stay and container dwell-time data, and IoT shipment-tracking records to enable higher-frequency analysis, port-level validation, and a more direct evaluation of sensing technologies in trade-potential assessment and decision support.

Acknowledgments

This work was supported by the 2021 Quality-oriented Project, Guangdong Provincial Department of Education: Outstanding Digital-Intelligent Accounting Talent Training Program with No. 2021zlgc205, by the 2023 Youth Project of Guangdong Province's Philosophy and Social Sciences Planning: Research on the Trade Efficiency and Impact of Mechanical and Electrical Products between Guangdong and RCEP Member Countries with No. GD23YYJ02, and by the Teaching-Mode Reform and Practice of the Course Cross-border E-commerce Practice Empowered by Digital Technologies with No. 2025yjjg004.

References

1 J. Tinbergen: Shaping the World Economy: Suggestions for an International Economic Policy (The Twentieth Century Fund, New York, 1962).
2 J. E. Anderson and E. van Wincoop: Am. Econ. Rev. **93** (2003) 170.
3 K. Head and T. Mayer: Handbook Int. Econ. **4** (2014) 131.
4 D. Hummels: J. Econ. Perspect. **21** (2007) 131.
5 S. Ahmed, T. Kalsoom, N. Ramzan, Z. Pervez, M. Azmat, B. Zeb, and M. Ur Rehman: Sensors **21** (2021) 4158.
6 M. Ben-Daya, E. Hassini, and Z. Bahroun: Int. J. Prod. Res. **57** (2019) 4719.
7 M. Caridi, A. Moretto, A. Perego, and A. Tumino: Int. J. Prod. Econ. **151** (2014) 1.
8 F. Bibi, C. Guillaume, N. Gontard, and B. Sorli: Trends Food Sci. Technol. **62** (2017) 91.
9 J.-F. Arvis, L. Ojala, C. Wiederer, B. Shepherd, A. Raj, K. Dairabayeva, and T. Kiiski: Connecting to Compete 2018: Trade Logistics in the Global Economy—The Logistics Performance Index and Its Indicators (World Bank, Washington, DC, 2018).

10 World Bank: Logistics Performance Indicators 2.0, https://lpi.worldbank.org/ (accessed June 2026).
11 International Maritime Organization: AIS Transponders, https://www.imo.org/en/ourwork/safety/pages/ais.aspx (accessed June 2026).
12 S. Arslanalp, M. Marini, and P. Tumbarello: Big Data on Vessel Traffic: Nowcasting Trade Flows in Real Time, IMF Working Paper 19/275 (2019).
13 G. Pilgrim, E. Guidetti, and A. Mourougane: An Ocean of Data: The Potential of Data on Vessel Traffic, OECD Statistics Working Papers No. 2024/02 (OECD Publishing, Paris, 2024).
14 K. Kanamoto, L. Murong, M. Nakashima, and R. Shibasaki: Marit. Econ. Logist. **23** (2021) 211.
15 United Nations Statistics Division: UN Comtrade Database, https://comtrade.un.org/ (accessed June 2026).
16 T. Mayer and S. Zignago: Notes on CEPII's Distances Measures: The GeoDist Database, CEPII Working Paper No. 2011-25 (CEPII, Paris, 2011).