Journal of Food and Drug Analysis

Volume 32 | Issue 1 Article 2

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Recommended Citation
Tu, Wen-Chin; Tsai, Wan-Ling; Lee, Chi-Hao; Tsai, Chia-Fen; Wei, Jen-Ting; Lin, King-Fu; Wu, Shou-Mei; and Weng, Yih-Ming (2024) "Application and effectiveness of artificial intelligence for the border management of imported frozen fish in Taiwan," *Journal of Food and Drug Analysis*: Vol. 32 : Iss. 1 , Article 2.
Available at: https://doi.org/10.38212/2224-6614.3490

ORIGINAL ARTICLE

Application and effectiveness of artificial intelligence for the border management of imported frozen fish in Taiwan

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Abstract

In Taiwan, the number of applications for inspecting imported food has grown annually and noncompliant products must be accurately detected in these border sampling inspections. Previously, border management has used an automated border inspection system (import food inspection (IFI) system) to select batches via a random sampling method to manage the risk levels of various food products complying with regulatory inspection procedures. Several countries have implemented artificial intelligence (AI) technology to improve domestic governmental processes, social service, and public feedback. AI technologies are applied in border inspection by the Taiwan Food and Drug Administration (TFDA). Risk management of border inspections is conducted using the Border Prediction Intelligent (BPI) system. The risk levels are analyzed on based on the noncompliance records of imported food, the country of origin, and international food safety alerts. The subjects of this study were frozen fish products, which have been under surveillance by the BPI system. The purpose of this study was to investigate the relevance between the noncompliant trend of frozen fish products using the adoption of the BPI system and the results of postmarket sampling inspections. The border inspection and postmarket sampling data were divided into two groups: IFI and BPI groups (corresponding to before and after the adoption of the BPI system, respectively). The Chi-square test was employed to analyze the noncompliant differences in products between before and after the BPI system adoption. Despite the number of noncompliance batches being statistically insignificant after the adoption of the BPI system, the noncompliance rate of frozen fish products at the border increased from 3.0% to 4.7%. Meanwhile, the noncompliance rate in the postmarket decreased from 2.1% to 1.9%. The results indicate that the BPI system improves the effectiveness of interception of noncompliant products at the border, thereby preventing the entrance of noncompliant products to the postmarket. The variables were further classified and organized according to the scope of this study and product characteristics. Furthermore, ordinal logistic regression (OLR) was employed to determine the correlations among border, postmarket, and major influencing factors. Based on the analysis of major influencing factors, small fish and fish internal organ products exhibited significantly high risk for fish body type and product type, respectively. The BPI system effectively utilizes the large amount of data accumulated from border inspections over the years. Additionally, real-time information on bilateral data obtained from the border and postmarket should be bidirectionally shared for effectively intercepting noncompliance products and used for improving the border management efficiency.

Keywords: Artificial intelligence, Border management, Imported frozen fish, Postmarket

1. Introduction

In the declaration process for imported food at the Taiwan border, the obligor or importer must submit an online application form (including product information), a copy of the import declaration, and other supporting documents required by the Taiwan Food and Drug Administration (TFDA). The inspection process for imported products includes document review, on-site inspection, and

Received 10 June 2023; accepted 30 November 2023.
Available online 15 March 2024

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https://doi.org/10.38212/2224-6614.3490

sampling. The complete declaration process is illustrated in Fig. 1.

The risk management concept for imported products is implemented as follows. First, all batches involving imported products are examined on a batch-by-batch basis for the reviewed documentation, followed by an on-site inspection or sampling according to the following inspection procedures.

(1) Batch-by-batch inspection. Each batch of imported products must pass an on-site inspection and sampling process with a sampling rate of 100%.

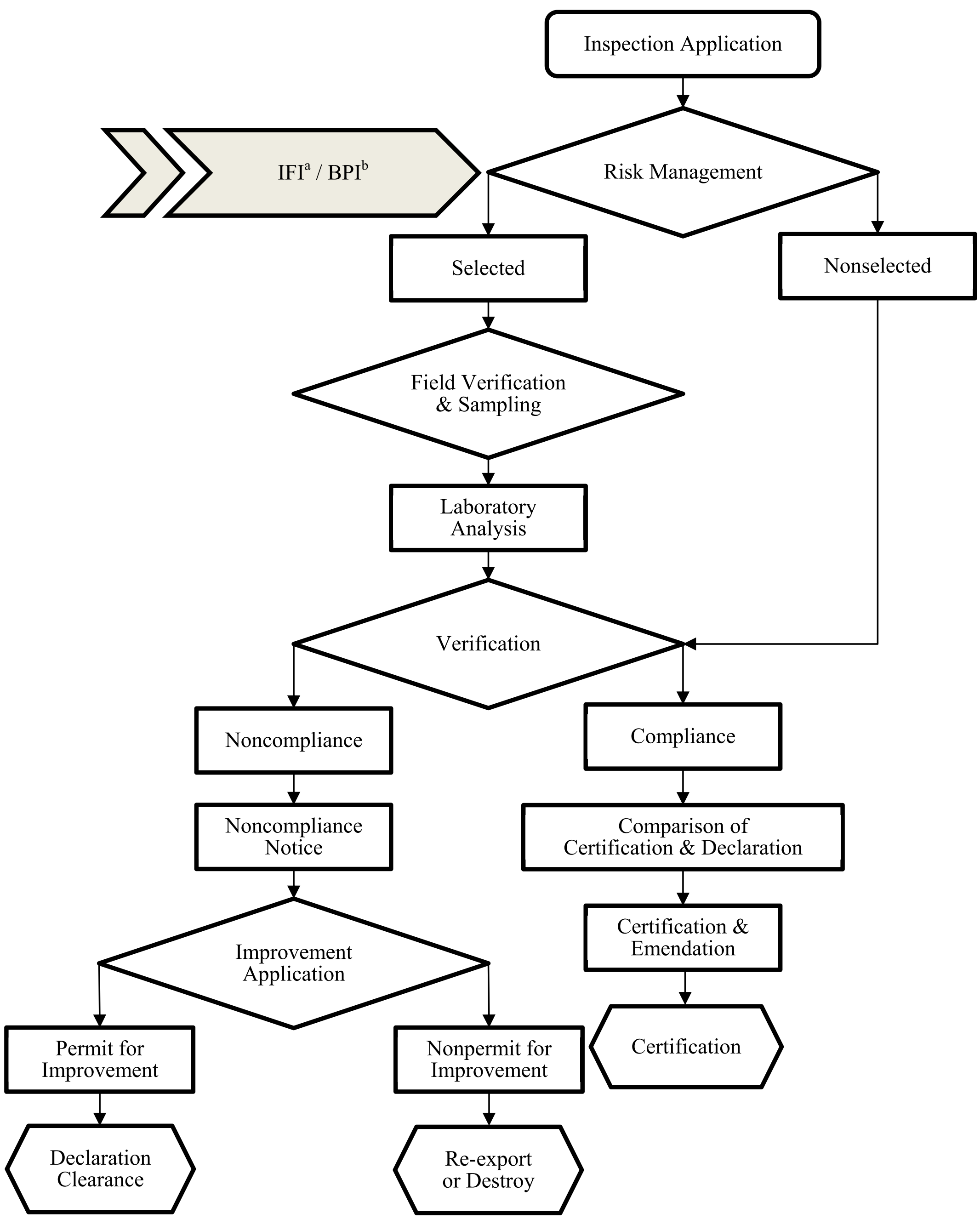

Fig. 1. Flowchart of inspection procedures for imported foods [1]. a: The Import Food Inspection (IFI) system. b: The Border Prediction Intelligent (BPI) system. The obligor or importer submits the application and the border system conducts risk assessment according to the inspection procedure to determine the selected batch. In the past, the IFI system would select batches via random sampling in the risk management step. However, the BPI system has been adopted to determine the risk. The selected batches will be sampled and analyzed in a laboratory. Importation is only permitted after conducting all inspections in compliance with the regulations.

(2) Randomly-selected batch inspection. Sampling is conducted according to two inspection rates: (a) regular randomly-selected batch inspection with an inspection rate of 2%−10% and (b) reinforced randomly-selected batch inspection with a 20%−50% inspection rate. The risk factors determine the inspection rate of batch testing that include records of import noncompliance, the country of origin, international food safety alerts, major domestic and international health and safety incidents, and high-concern or high-risk food products.
(3) Batch-by-batch verification. Each batch is checked on site.
(4) Certification inspection. Certified products can be released after verification. Here, the documentary proof must come from the manufacturer who signed an agreement or registered an agreement with the exporting country on behalf of the competent health and safety authorities in Taiwan. For inspection, the documentary evidence of compliance with the provisions of the agreement or agreements must be examined.
(5) Overseeing inspection. For specific products (rice or other staple foods), each batch should be inspected thoroughly and sampled on site, and the intensity of the inspection should not be reduced or the inspection method should not be affected by the inspection results [1]. Importation is only permitted after conducting all inspections in compliance with the regulations.

In the past, the risk management at the border used an automated border inspection system (the Import Food Inspection (IFI) system) to manage the risk levels of various food products. Fig. 1 shows that the obligor or importer submits an inspection application to the TFDA under the sampling rate that complies with the abovementioned inspection procedures. In the risk management step, the IFI system would select batches via random sampling. Maintaining sufficient imported food quality at the border primarily relies on accurately detecting products that do not comply with the quality standards during the sampling inspections, thereby preventing importation. In Taiwan, the number of inspection applications for imported food has grown annually, and border sampling inspections are of great significance to effectively strengthen control over high-risk products and detecting noncompliant products accurately. To effectively use the large amount of data accumulated from annual border inspections, the TFDA consulted the data sources and practices followed by the EU and US. After identifying and assessing the risk factors, TFDA developed the Border Prediction Intelligent (BPI) system [2] (Fig. 2). It is expected that artificial intelligence (AI) can play a role in early warning and prediction, assist in sampling high-risk products, and be used to improve the efficiency of border management.

The hypothesis in this study is that the BPI system adoption can improve the effectiveness of the border management process. The noncompliance by imported frozen fish products is used in this paper to test this hypothesis. Therefore, the purpose of this study is to investigate the noncompliance trend exhibited by the frozen fish products before and after the adoption of the BPI system and to analyze the results of sampling inspections in the postmarket to determine whether the application of AI at the border has improved the effectiveness of border management procedures. Additionally, the results of information from border and postmarket inspections are analyzed for identifying major influencing factors to implement effective management policy adjustments and system modifications.

2. Materials and methods

2.1. Data sources

The border inspection data considered in this study were extracted from the TFDA's IFI system, including the product name, region (country of origin), inspection methods, and test results of imported food products. This study analyzed 18,242 batches.

The postmarket data were retrieved from the Product Management Distribution (PMD) system developed by the TFDA. This system integrates information on postmarket food inspection and testing operations, including product names, sampling sites, region (country of origin), and test results, from the health bureaus of the local government. The total number of batches analyzed was 262.

2.2. Data collection

Risk management of imported frozen fish products as a target population adopted the BPI system for nearly one year. Here, the term “frozen fish products” refers to untreated fish and fish products, including (but not limited to) frozen codfish, water sharks, sailfish, and fish roe.

To prove the hypothesis of this study, the used statistical analysis interval was based on the start date of the adoption of the BPI system for frozen fish products at the border (April 15, 2020) and the same period of the previous year (April 15, 2019). Notably, the number of days in both analysis periods was set to 320. The border inspection data and postmarket sampling data were divided into two groups—before adoption of the BPI system (IFI group) and after adoption (BPI group)—to eliminate selection bias caused by different seasons or duration and ensure that the comparison between the groups remains the same. The analysis period is detailed in Table 1. To avoid the limitations of the aforementioned analysis intervals and deviation of the null hypothesis [3], (i.e., to confirm whether the analysis interval before and after the adoption of BPI is representative), this study employed sensitivity analysis for confirming the robustness of the analysis results and conducted analysis on two sets of sensitivity groups for different analysis periods (sensitivity analysis I: January 1–April 14, 2019; sensitivity analysis II: January 1, 2019–February 28, 2020) for determining whether the results of the different analysis periods still apply.

2.3. Research methodology

The inspection results obtained for the IFI and BPI groups were further divided into two categories

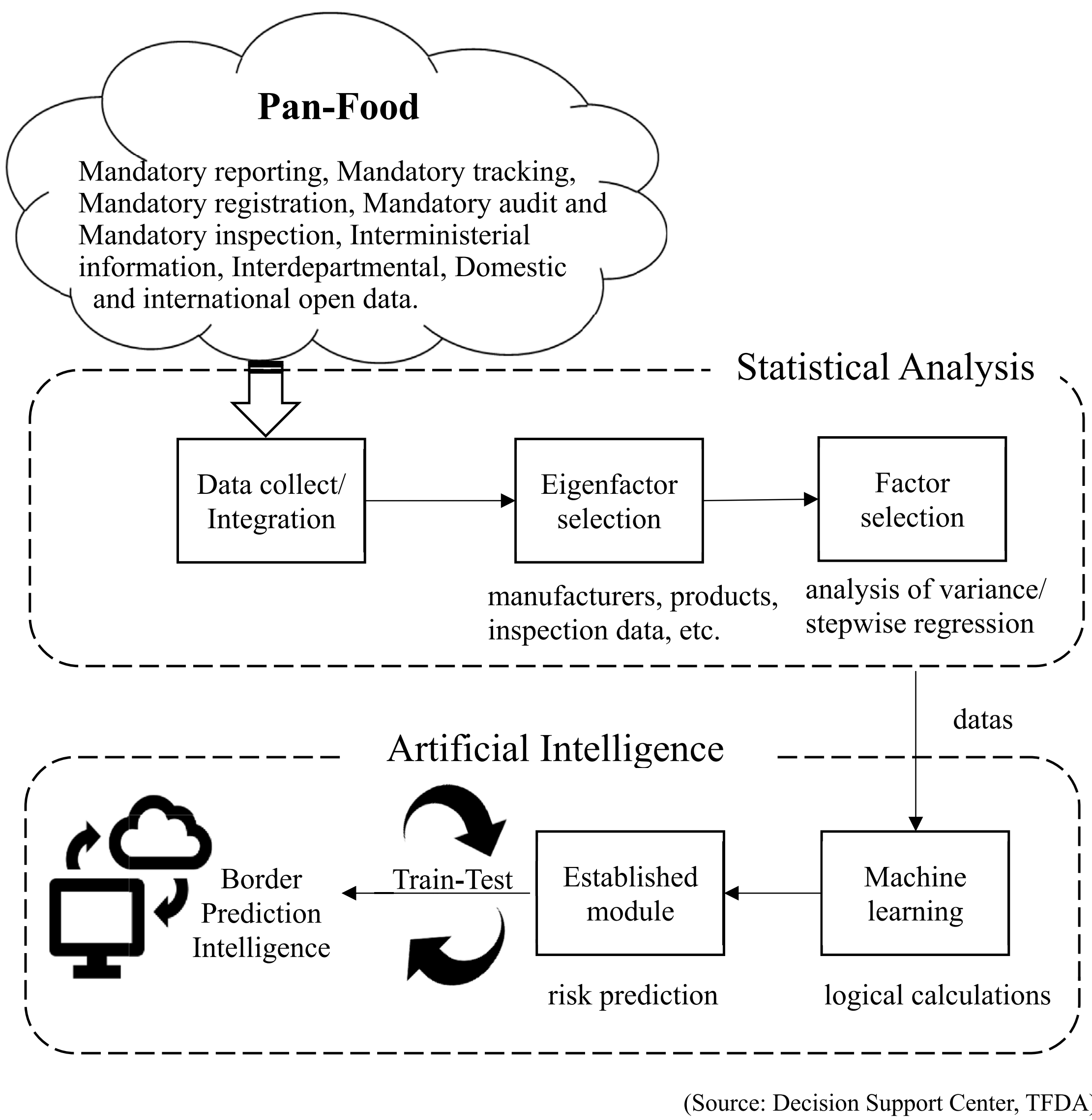

Fig. 2. Schematic of the Border Prediction Intelligence (BPI) system. The model was collated and linked to the food cloud data to perform various statistical analyses and utilized computer analysis data to determine the best algorithms and influencing factors. The system was iteratively tested to adjust the model and develop the BPI system.

Table 1. Analysis periods.

	IFI[a]	BPI[b]	Sensitivity analysis group[c]	
			I	II
Analysis period[d] (YYYY.MM.DD)	2019.04.15–2020.02.28 (320 days)	2020.04.15–2021.02.28 (320 days)	2019.01.01–2020.04.14 (469 days)	2019.01.01–2020.02.28 (424 days)

[a] The Import Food Inspection system.
[b] The Border Prediction Intelligent system.
[c] To avoid the limitations of the aforementioned analysis intervals and deviation of the null hypothesis, this study conducted analysis on two sets of sensitivity groups for different analysis periods: sensitivity analysis I: January 1–April 14, 2019 and sensitivity analysis II: January 1, 2019–February 28, 2020).
[d] The analysis period was grouped into IFI and BPI groups (before and after the adoption, respectively, of the BPI system). To eliminate selection bias caused by different seasons or durations and ensure that the comparison between the groups was the same under different conditions, analysis periods were set the same—320 d—under different conditions.

based on the analysis after the adoption of the BPI system in the border and postmarket: compliance and noncompliance. The Chi-squared test was employed to analyze the differences before and after the BPI system adoption at the border. This method explores the significance of these differences after adopting the BPI system and the system's effectiveness for improving the border management.

The risk levels in the EU, US, and BPI systems were analyzed based on the noncompliance records of imported food, country of origin, and international food safety alerts. Therefore, the fish species and country of the noncompliance products were listed as variables while analyzing the major influencing factors. Because the border inspection and postmarket sampling data are very complex, they were analyzed as category (qualitative/discrete) data. To this end, the variables were further classified and organized based on the scope of the study and product characteristics. For example, according to the fish body type of the Taiwan Fish Database [4], variables with respect to fish species were grouped into three subvariables: large, medium, and small variables. Moreover, based on their type, the products were classified into internal and noninternal organ products. The countries were grouped into seven continents and the Organization for Economic Cooperation and Development (OECD) to assess the relevance of each region or country's level of economic development to noncompliance batches. The original border inspection and postmarket data were organized into countable subvariable data. The classification of the subvariables is shown in Table 2. Additionally, the ordinal logistic regression (OLR) method [5] was employed for estimating the correlation among the border, postmarket, and major influencing factors to evaluate the effectiveness of the border AI application and establish an effective two-way feedback mechanism (Fig. 3).

2.4. Statistical analysis

This study was conducted using IBM's SPSS Statistics for Windows, Version 25.0. (IBM Corp., Armonk, NY). After the adoption of the BPI system at the border and postmarket, IBM SPSS statistics was equipped with the Chi-squared test to analyze the noncompliance differences between the IFI and BPI groups.

As the inspection and postmarket data contain several variables, descriptive statistical analysis was conducted based on the variables classified into subvariable data (Table 2) to investigate the major influencing factors between the border and postmarket and evaluate the efficiency of AI at the border. Additionally, IBM SPSS statistics was used with the OLR method to perform multivariate analysis for identifying the major influencing factors of noncompliance at the border and calculate the odd ratio (OR), 95% confidence interval (CI), and p value for each subvariable. This analysis employed a

Table 2. Classification of subvariables: Variable (product name and region) classification basis.

Variables	Subvariables
Product name	1. Body type[a]: large fish (>70 cm), medium fish (15–70 cm), and small fish (<15 cm). 2. Internal organ product: internal organ, noninternal organ.
Region[b] (country of origin)	1. Continent: Asia, Africa, North America, South America, Antarctica, Europe, and Oceania. 2. OECD: member states, and nonmember states.

[a] Body type: According to the Taiwan Fish Database [4], fish were divided into large (>70 cm), medium (15–70 cm), and small fish (<15 cm).
[b] Countries are grouped into seven continents and the Organization for Economic Cooperation and Development (OECD) to assess the relevance of each region or country's level of economic development for noncompliance batches.

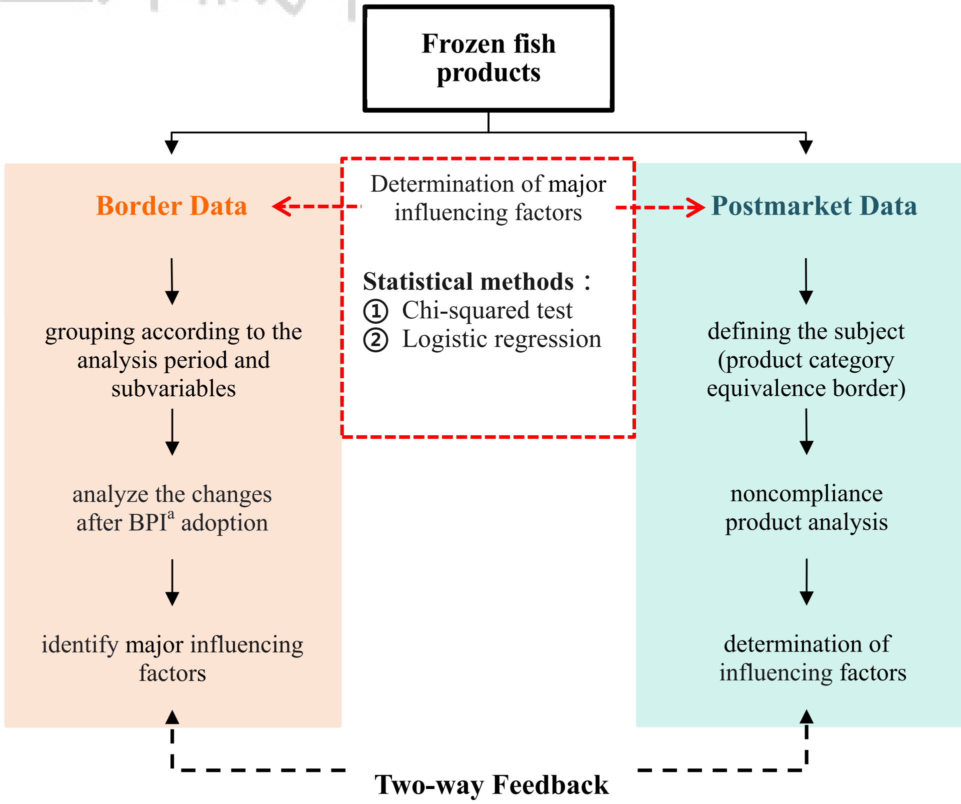

Fig. 3. Experimental framework. a: The Border Prediction Intelligent (BPI) system. The border inspection and postmarket data of frozen fish products were grouped and classified. The Chi-squared test was employed to analyze the bilateral differences. The logistic regression method was used to explore the correlation and major influencing factors between the border and postmarket, evaluate the effectiveness of AI (BPI system), and establish a two-way feedback mechanism.

strict criterion (p value) as the significance level. Here, when the p value was <0.001, the corresponding subvariable was considered a major influencing factor. Because the border and postmarked data belong to category data, their statistical graphics primarily present its frequency distribution in the bar chart or table format.

3. Results and discussion

3.1. Applications of AI in public policy

As learning algorithms and computational capability continue to evolve, AI applications have made significant advances and could even replace human intervention in various tasks [6]. AI technologies can provide faster and more precise answers to increasingly complex social problems, and such technologies can be utilized to improve public service in a highly technological, ever-changing, and complex context. Using AI, numerous data can be processed and modeled and public policies can be evaluated in a fast, accurate, and cost-effective manner, making government administration more efficient, accurate, and transparent to satisfy the requirements and expectations of the general public. AI can improve government efficacy and be applied to implement effective changes at various governmental levels, including administrative processes, public interactions, service delivery, decision-making processes, and the design and evaluation of public policies [7–9]. In practice, AI can derive meaningful results from complex big data to help humans make decisions or provide valuable information to decision makers. In turn, the acquired information can be transformed into knowledge to support the formulation of effective public policy strategies [10,11]. Numerous multinational organizations and countries (e.g., the European Union (EU) and United States (US)) have adopted AI to improve domestic governmental operation, service delivery, and public interaction, or used it to develop relevant national strategies [12].

AI has become an international priority and a key factor that should be adopted. For instance, the policy guide—the National Approach to Artificial Intelligence—of the Nordic nation Sweden is the most concise document among all the national strategy documents. The guide focuses on (1) education and training, (2) research, (3) innovation and use, and (4) framework and infrastructure areas of AI development [13]. On border management applications, the EU's Rapid Alert System for Food and Feed constructed a Bayesian network model to predict the types of food fraud that can occur in imported products from known food product categories and countries of origin. The findings can assist border risk management and control and serve as an important reference for EU governments when conducting inspections and law enforcement [14–16]. The US utilizes the Predictive Risk-based Evaluation for Dynamic Import Compliance Targeting (PREDICT) system for risk prediction. Big data are employed to collect relevant data from products, e.g., the history of the facility, inspection records, and country of origin. The PREDICT system can perform data mining and analysis, enabling the use of AI techniques to predict the potential risks of imported goods and intercept them in a timely manner [17].

3.2. Border Prediction Intelligent system

Because of the extensive AI applications in various fields internationally, the TFDA has consulted the data sources and practices of the EU and US to identify and assess risk factors to establish effective prediction model planning. An ensemble learning prediction model was introduced to border food management, and a food border risk analysis model was developed to collate and link the food cloud (mandatory reporting, tracking, registration, audit, and inspection), interministerial information and domestic and international open data, and incorporate border inspection data (vendor and product attributes) to perform various statistical analyses (single factor and rank-by-rank analyses) and utilize computer analysis data to determine the best algorithms and influencing factors. The system was tested iteratively to adjust the model and develop the Border Prediction Intelligent (BPI) system (Fig. 2). In the early stage, the BPI system primarily assessed the risk of imported food by combining five algorithms, and the optimal prediction model was extracted from the prediction results to determine whether quality sampling should be performed on imported food at the border. This process is established using a set of independent machine learning classifiers, combined their respective prediction results, and implemented an integration strategy to reduce the total error and improve the performance of a single classifier [18,19]. Each classifier may have different generalization capabilities (i.e., different inference abilities) for various samples, which is consistent with the opinions of various experts. Finally, combining the output of these individual classifiers can provide the final classification results, substantially reducing the probability of classification errors in the results [20]. The purpose of implementing an integration strategy is to combine multiple different classifiers for improving the classification accuracy of the overall classification system. To improve and stabilize the model's predictive performance, a second-generation ensemble learning prediction model was developed based on seven algorithms to enhance the "detection rate of unqualified batches" [2]. Since 2020, the BPI system has been adopted in phases for different categories of products to perform risk management, and the risk verification intervention points refer to the risk management steps shown in Fig. 1.

In terms of inspection results, 9101 batches were submitted to the inspection authority, and 798 batches of frozen fish products were selected for inspection via sampling analysis before the adoption of the BPI system at the border. Here, 9141 batches were submitted, and 1024 batches were selected for the period after BPI adoption at the border. The inspection rate increased to 11.2% (Table 3), and the noncompliance rate increased from 3.0% to 4.7%. The Chi-squared test was performed with SPSS; the results demonstrate that the odds of border noncompliance when BPI was

Table 3. Analysis of border inspection batches and rate after the adoption of the BPI system.

	Number of batches	Number of inspected batches	Inspection rate	P value
	N	N	%	
IFI[a]	9101	798	8.8	<0.001[c]
BPI[b]	9141	1024	11.2	

SPSS was employed with the Chi-squared test to analyze the inspection rate between the IFI and BPI groups. The number of inspection batches and rate increased, indicating statistical significance.
(Source: TFDA's IFI system).
[a] The Import Food Inspection system.
[b] The Border Prediction Intelligent system.
[c] P-values less of 0.001 were considered statistically significant.

adopted was estimated to be 1.59 times (95% CI = 0.96−2.61, p value = 0.068), while those in the absence of BPI were not statistically significant. With the BPI system implementation at the border, the postmarket noncompliance rate was reduced from 2.1% to 1.9%. The odds of postmarket noncompliance when BPI was adopted was estimated to be 0.88 times (95% CI = 0.14−5.35, p value = 0.890) those of BPI non-adoption (Table 4).

The application of AI is expected to improve the effectiveness of the BPI risk management at the border by intercepting noncompliance batches and reducing the flow of noncompliance products to the postmarket, i.e., increasing the noncompliance rate at the border and decreasing the postmarket noncompliance rate. The trends in border and postmarket noncompliance rates were consistent with the intended purpose of applying AI. However, there was no statistically significant difference. Subsequently, descriptive statistics were utilized to identify and investigate the correlation between the influencing factors of the border and application of AI at the border and the correlation of bilateral data.

3.3. Postmarket management of imported food

When imported food enters the domestic market (hereafter postmarket), it could be inspected and sampled at the distribution end as part of controlling the imported food safety. In the postmarket monitoring, the health bureaus of central and local governments are integrated. Here, the central government is responsible for identifying high-risk and high-concern products and working with the local government health bureaus to ensure that the products comply with the required food safety and hygiene in the postmarket. The TFDA's 2019 Animal Drug Residue Monitoring Program for commercially available livestock and aquatic products has demonstrated that aquatic products have the lowest compliance rate among the three categories of poultry products, livestock products and aquatic products [21]; therefore, they are generally considered a high-risk category internationally. Thus, fish products have the high priority for the adoption of the BPI system for risk management of frozen fish products, and the system has been applied on April 15, 2020.

Based on the frozen fish subvariable classification, frozen fish products were divided into Fish species and Body Type, Fish Internal Organ Products, and Region sections for discussing the border and postmarket relevance.

3.3.1. Fish species and body type

With the adoption of the BPI risk management system at the border, the highest increase in the noncompliance rate for the size category was for small fish (3.7%), demonstrating an increase of 28.9% (Fig. 4). The majority of the noncompliance small fish were slender sprat (*Spratelloides gracilis*) (Table 5). The noncompliance rate of this product increased from 20.0% (one noncompliant batch of five sampled batches) to 91.67% (11 noncompliant batches of 12 sampled batches). The reasons for noncompliance were that all heavy metals were detected in excess of the standard. In the analysis of the major influencing factors at the border, SPSS was employed to perform OLR multivariate analysis. The odds of small fish was estimated to be 23.94 times (95% CI = 7.13−80.40, p value < 0.001) that of large fish, thereby exhibiting a statistically significant difference (Table 6). These results indicate that body type was a high-risk factor. Large fishes exhibit the lowest risk compared to medium and small fishes. However, the number of noncompliance batches was higher for large fish at the border before and after adoption of the BPI system (21 and 33 batches before and after the adoption, respectively), and its noncompliance rate exhibited a slight

Table 4. Analysis of border and postmarket inspection results.

		Compliance		Noncompliance		P value
		N	%	N	%	
Border	IFI[a]	774	97.0	24	3.0	0.068
	BPI[b]	976	95.3	48	4.7	
Postmarket	IFI[a]	95	97.9	2	2.1	0.890
	BPI[b]	162	98.1	3	1.9	

(Source: TFDA's IFI system and PMD[c] system).

SPSS was employed with the Chi-squared test to analyze the noncompliance rate between the IFI and BPI groups. There was no statistical difference.

[a] The Import Food Inspection system.

[b] The Border Prediction Intelligent system.

[c] The Product Management Distribution system.

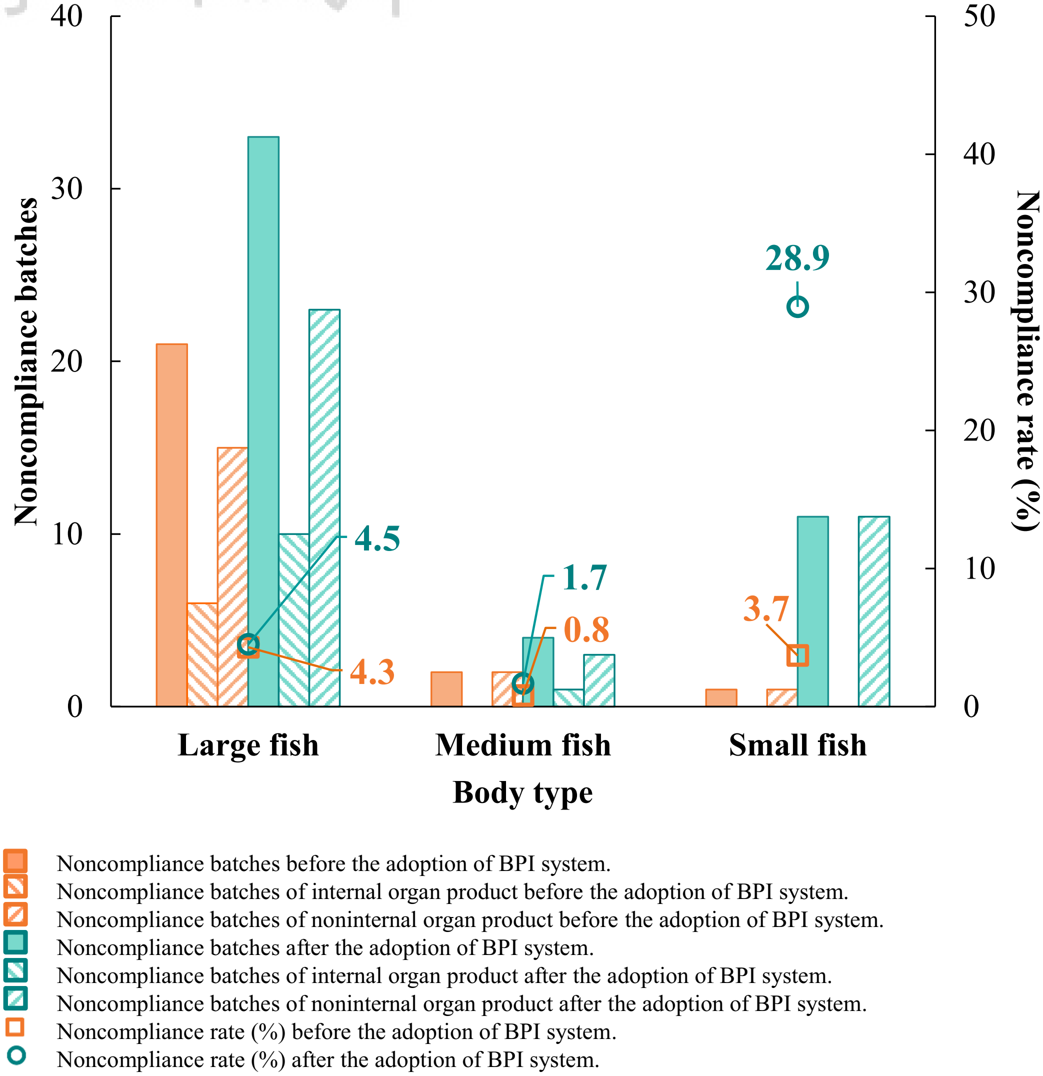

Fig. 4. Noncompliance batches and noncompliance rate based on fish body types in border inspections. (Source: TFDA's IFI system). BPI: The Border Prediction Intelligent system, IFI: The Import Food Inspection system. Among border noncompliance batches, the order of noncompliance rates after the adoption of the BPI system was as follows: (from highest to lowest) small, large, and medium fishes. The noncompliance rate of small fish increased the most (from 3.7% to 28.9%), and the number of noncompliance batches was the highest among large fish (21 batches before and 33 batches after adoption).

increment from 4.3% to 4.5%, with the most relevant species being primarily water sharks (*Prionace glauca*) and sailfish (*Tetrapturus angustirostri*) (Table 5). The slight increase in the number of noncompliance batches after adoption of the BPI indicates that the BPI system classified these two species of large fish as high-risk. Thus, these items should receive continuous attention at the border environments.

As shown in Fig. 5, after adoption of the BPI system, the highest increase in the noncompliance rate of postmarket samples was for small fish, from 7.7% (one noncompliant batch of 13 sampled batches) to 14.3% (one noncompliant batch of seven sampled batches). Although the noncompliance rate increased, the number of samples and identified noncompliance batches in the postmarket were very small. The correlation between the border and postmarket should be monitored continuously. All the noncompliant items were slender sprat (Tables 5 and 7). The causes of noncompliance were also excessive detection of heavy metals. This was the same as the noncompliant fish species and reasons at the border, indicating that the slender sprat in the postmarket was also an important concern. Slender sprat primarily inhabits the sand-reef mixed zone along the offshore coast [4]. This area is susceptible to anthropogenic sewage outfall, and industrial pollution has increased the heavy metal content in this regional marine environment. When benthic organisms are exposed to polluted marine environments, they will ingest heavy metals in the dissolved and

Table 5. Noncompliance batch results of frozen fish products in the border inspection. (Source: TFDA's IFI system). a: Kenya. b: Mauritius. c: Mozambique. d: Seychelles. e: Senegal. f: China. g: Indonesia. h: Japan. i: Sri Lanka. j: Philippines. k: Singapore. l: Viet Nam. m: Belize. n: Panama. o: United States. p: Australia. q: Fiji. r: Marshall Islands. s: Vanuatu. t: Brazil. u: Peru. v: The Import Food Inspection system. w: The Border Prediction Intelligent system.

	Body type	Species	Africa					Asia							North America			Oceania				South America		Total	
			KE[a]	MU[b]	MZ[c]	SC[d]	SN[e]	CN[f]	ID[g]	JP[h]	LK[i]	PH[j]	SG[k]	VN[l]	BZ[m]	PA[n]	US[o]	AU[p]	FJ[q]	MI[r]	VU[s]	BR[t]	PE[u]		
IFI[v]	Large fish	*Prionace glauca*			1													1						2	24
		Isurus paucus	1																					1	
		Thunnus alalunga				2																		2	
		Carcharhinus barchyurus	1																					1	
		Thunnus albacares									1													1	
		Thunnus albacares (internal organ product)					1																	1	
		Tetrapturus angustirostris		2		1							2								1			6	
		Tetrapturus angustirostris (internal organ product)		1		1															1			3	
		Scomberomorus guttatus																				1		1	
		Mola mola (internal organ product)																		1	1			2	
		Lateolabrax japonicus																1						1	
	Medium fish	*Lampris guttatus*																			1			1	
		Eumegistus illustris																			1			1	
	Small fish	*Spratelloides gracilis*												1										1	
BPI[w]	Large fish	*Salmo salar*								1														1	48
		Prionace glauca						1	3						1						3			8	
		Isurus paucus				1																		1	
		Muraenesox cinereus						1																1	
		Theragra chalcogramma															1							1	
		Coryphaena hippurus				1											1							2	
		Coryphaena hippurus (internal organ product)																					1	1	
		Thunnus albacares				1																		1	
		Thunnus albacares (internal organ product)				1																		1	
		Tetrapturus angustirostris				2		1								2	1							6	
		Tetrapturus angustirostris (internal organ product)					2												1		1			4	
		Ruvettus pretiosus (internal organ product)				2			1															3	
		Mola mola (internal organ product)					1																	1	
		Lepidocybium flavobrunneum				1																		1	
		Lateolabrax japonicus												1										1	
	Medium fish	*Hemiculter leucisculus*						1																1	
		Cephalopholis miniata										1												1	
		Eumegistus illustris																			1			1	
		Lophius litulon (internal organ product)					1																	1	
	Small fish	*Spratelloides gracilis*												11										11	

Table 6. Analysis of influencing factors for frozen fish products at the border: OLR[a].

Variables	Subvariables	OR	95% CI	P value
Body type	Large fish	1.00		
	Medium fish	2.78	(0.97, 07.92)	0.056
	Small fish	23.94	(7.13, 80.40)	<0.001[c]
Internal organ product	Noninternal organ	1.00		
	Internal organ	6.34	(3.03, 13.28)	<0.001[c]
Continent	South America	1.00		
	Asia	2.46	(0.33, 18.60)	0.382
	Europe	—[b]		
	Africa	3.83	(0.49, 30.16)	0.202
	Oceania	2.15	(0.25, 18.27)	0.484
	North America	4.61	(0.54, 39.45)	0.163
OECD	Member states	1.00		
	Nonmember states	2.29	(0.81, 06.45)	0.118

(Source: TFDA's IFI system)
In the analysis of the major influencing factors at the border, the internal organ product and small fish exhibited statistical significance. These results indicate that the body type of small fish and internal organ products were high-risk factors.

[a] SPSS was used with the OLR method to conduct multivariate analysis to identify the major influencing factors of noncompliance at the border and calculate the odd ratio (OR), 95% confidence interval (CI), as well as p value for each subvariable.

[b] The number of noncompliance batches from Europe was 0 (from 45 inspected batches), and the number of samples was too low to calculate the odds ratio (OR).

[c] P values less of 0.001 were considered statistically significant.

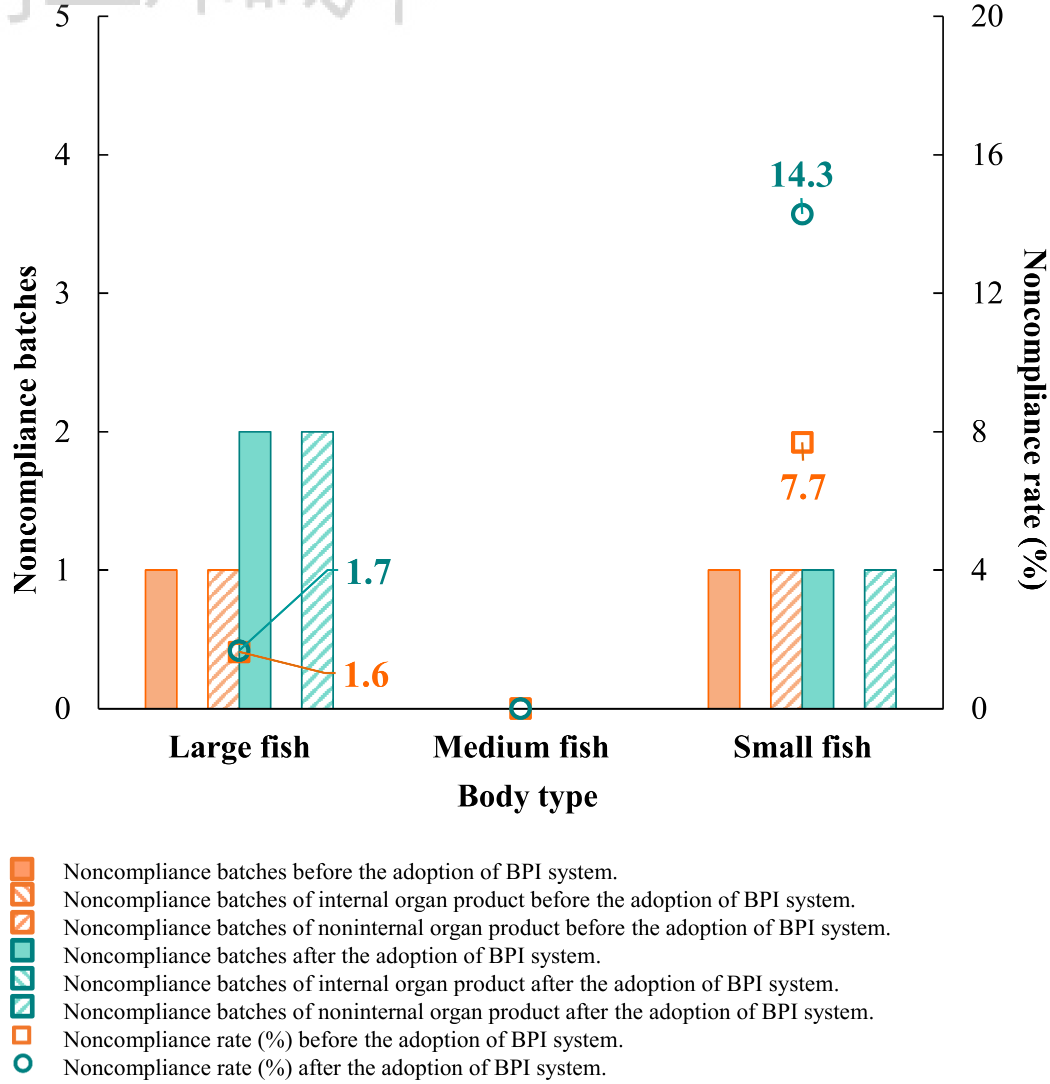

Fig. 5. Noncompliance batches and noncompliance rate based on fish body types in postmarket inspections. (Source: TFDA's PMD system). BPI: The Border Prediction Intelligent system, PMD: The Product Management Distribution system. The number of noncompliance batches in the postmarket and the noncompliance rates after the adoption of the BPI system were in the following order: (from highest to lowest) small, large, and medium fishes. Small fish had the largest increase in noncompliance rate (from 7.7% to 14.3%).

Table 7. Noncompliance batch results of frozen fish products in the postmarket inspection.

	Body type	Species	Asia		Total	
			CN[a]	VN[b]		
IFI[c]	Large fish	*Larimichthys crocea*	1		1	2
	Small fish	*Spratelloides gracilis*		1	1	
BPI[d]	Large fish	*Larimichthys crocea*	2		2	3
	Small fish	*Spratelloides gracilis*		1	1	

(Source: TFDA's PMD[e] system).
[a] China.
[b] Viet Nam.
[c] The Import Food Inspection system.
[d] The Border Prediction Intelligent system.
[e] The Product Management Distribution system.

suspended phase and subsequently accumulate hazardous metals [22]. Slender sprat feed on plankton and benthic organisms, and the accumulation of hazardous metals may occur through the biomagnification effect of the food chain. Among large fish in the postmarket, the noncompliance rate of large yellow croaker (*Larimichthys crocea*) was up to 15.4% (two noncompliant batches of 13 sampled batches) (Table 7) for veterinary drugs. However, no noncompliance batches were observed at the border. That could be a feedback to the border for adjusting the BPI system by including the large yellow croaker in the supervision target.

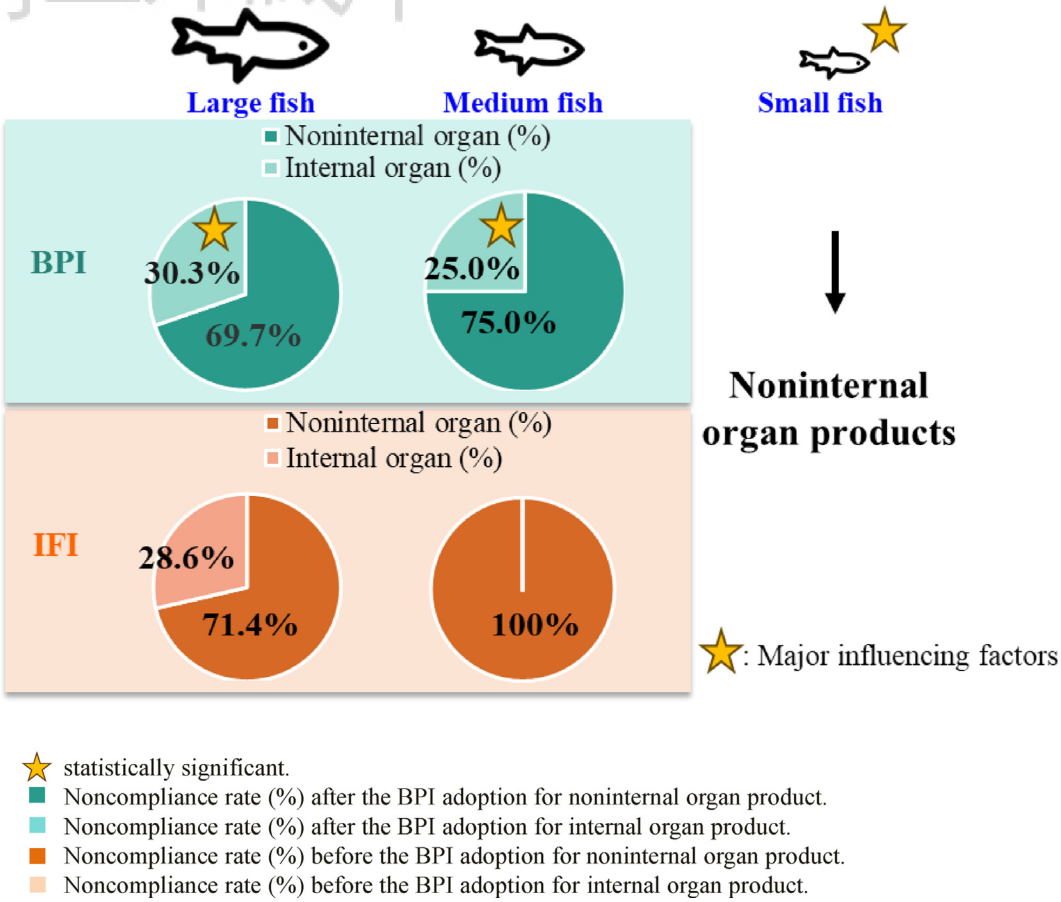

Fig. 6. Analysis of influencing factors of body type and internal organ product at the border. (Source: TFDA's IFI system). BPI: The Border Prediction Intelligent system, IFI: The Import Food Inspection system. The adoption of the BPI system, the proportion of noncompliance internal organ products for medium fish increased to 25.0%. Noncompliance internal organ products accounted for approximately 30% of the noncompliance rate for large fish. The internal organ products and small fish were the major influencing factors.

With the adoption of the BPI system, we found that the noncompliance rates at the border and postmarket in terms of body type were in the same order, i.e., (from highest to lowest) small, large, and medium fishes (Figs. 4 and 5). Regardless of whether BPI was implemented, the high similarity between the items sampled at the border and postmarket demonstrates that both were consistent in their concerns about high-risk products.

3.3.2. Fish internal organ products

For fish internal organ product, roe, intestine, and liver were examined. With the adoption of the BPI system at the border, the noncompliance rate of internal organ product was 20.8% (11 noncompliant batches of 53 sampled batches). Among such products, the largest number of noncompliance batches was for fish roe (eight batches). The causes of noncompliance were all heavy metals detected in excess of the standard. The noncompliance rate of noninternal organ product was 3.9%. In the OLR multivariate analysis of major influencing factors at the border conducted with SPSS, the odds of internal organ product were estimated to be 6.34 times (95% CI = 3.03–13.28, p value < 0.001) those of noninternal organ product, representing a statistically significant difference (Table 6) and indicating a high-risk factor.

The correlation between body type and internal organ product was compared further. For medium fish, no batches of noncompliance internal organ product were identified before adopting the BPI system. After its adoption, the proportion of noncompliance internal organ product for medium fish increased to 25.0%. For large fish, internal organ product was identified as a high-risk factor irrespective of whether BPI is adopted, accounting for ~30% of the noncompliance rate for large fish (Fig. 6). Thus, the internal organs of large and medium fishes at the border represented a high-risk factor.

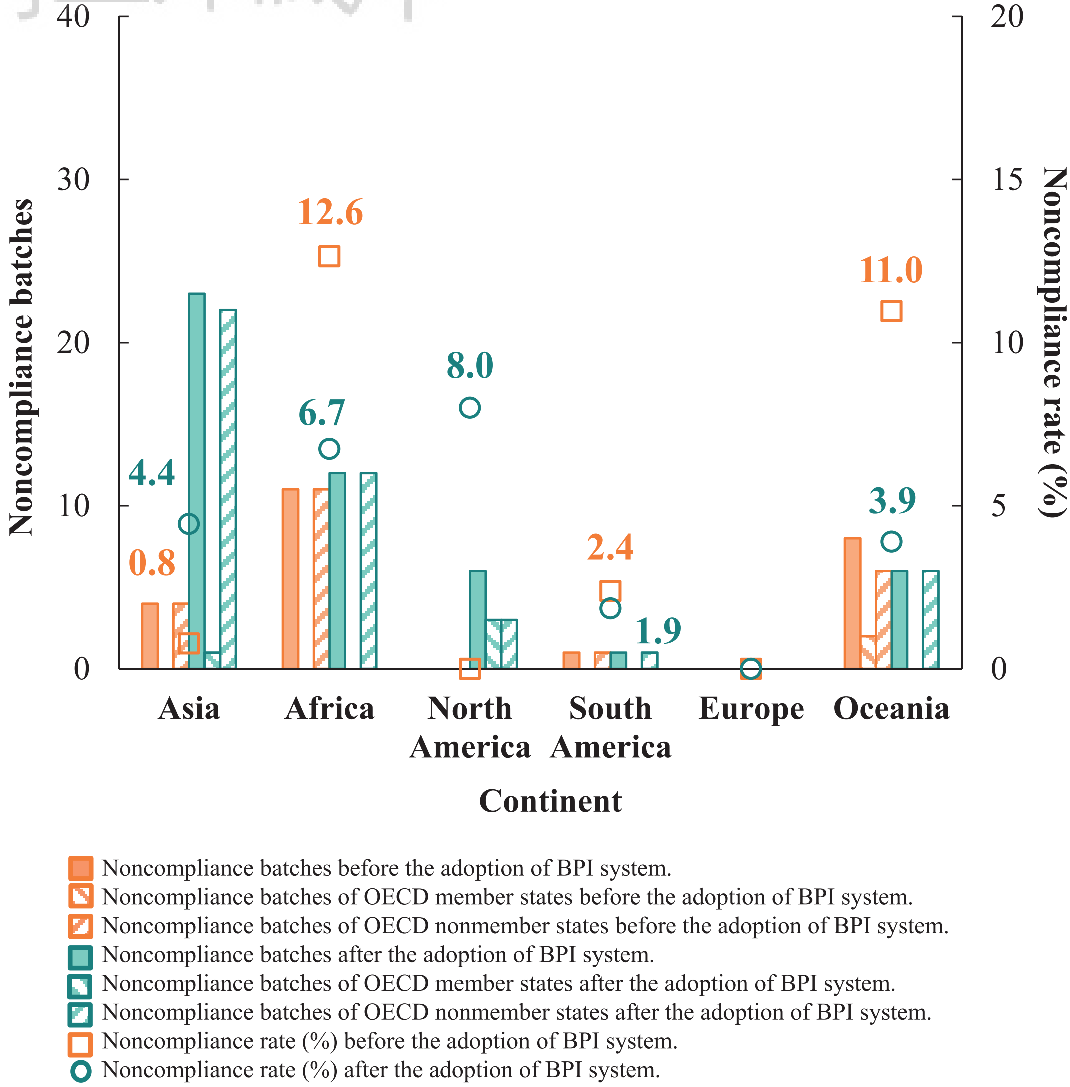

Fig. 7. Noncompliance batches and noncompliance rates at the border by continent. (Source: TFDA's IFI system). BPI: The Border Prediction Intelligent system, IFI: The Import Food Inspection system, and OECD: The Organization for Economic Cooperation and Development. The adoption of the BPI system, the increments in the noncompliance rates were more in Asia (4 batches before and 22 batches after adoption, rates increased to 4.4%) and North America (zero batch before and six batches after adoption, rates increased to 8.0%) compared to those of other continents.

An in-depth investigation of internal organ product sampling noncompliance at the border revealed that, prior to the adoption of the BPI system, the noncompliance rate of large fish internal organ product sampling was 17.1% (six noncompliant batches of 35 sampled batches), while all three batches of medium fish tested were complaint. With the BPI system, the noncompliance rate for large fish internal organ product was 24.4% (10 noncompliant batches of 41 sampled batches), and that for medium fish was 8.3% (one noncompliant batch of 12 sampled batches). The noncompliance rate of large and medium fish internal organ product increased, indicating that the BPI identified internal organ product as a high-risk surveillance target. For the postmarket, no noncompliance batches of internal organ product were identified before or after adoption of the BPI system (one sampled before and 13 sampled after adoption of the system). These results indicate that most of the noncompliant products were intercepted at the border.

3.3.3. Region

To reveal the relevance of national economic development in terms of the food safety management of fish products, the OECD was used as a classification indicator, including member and nonmember states in the analysis. In the analysis of the OECD and seven continents, no statistically

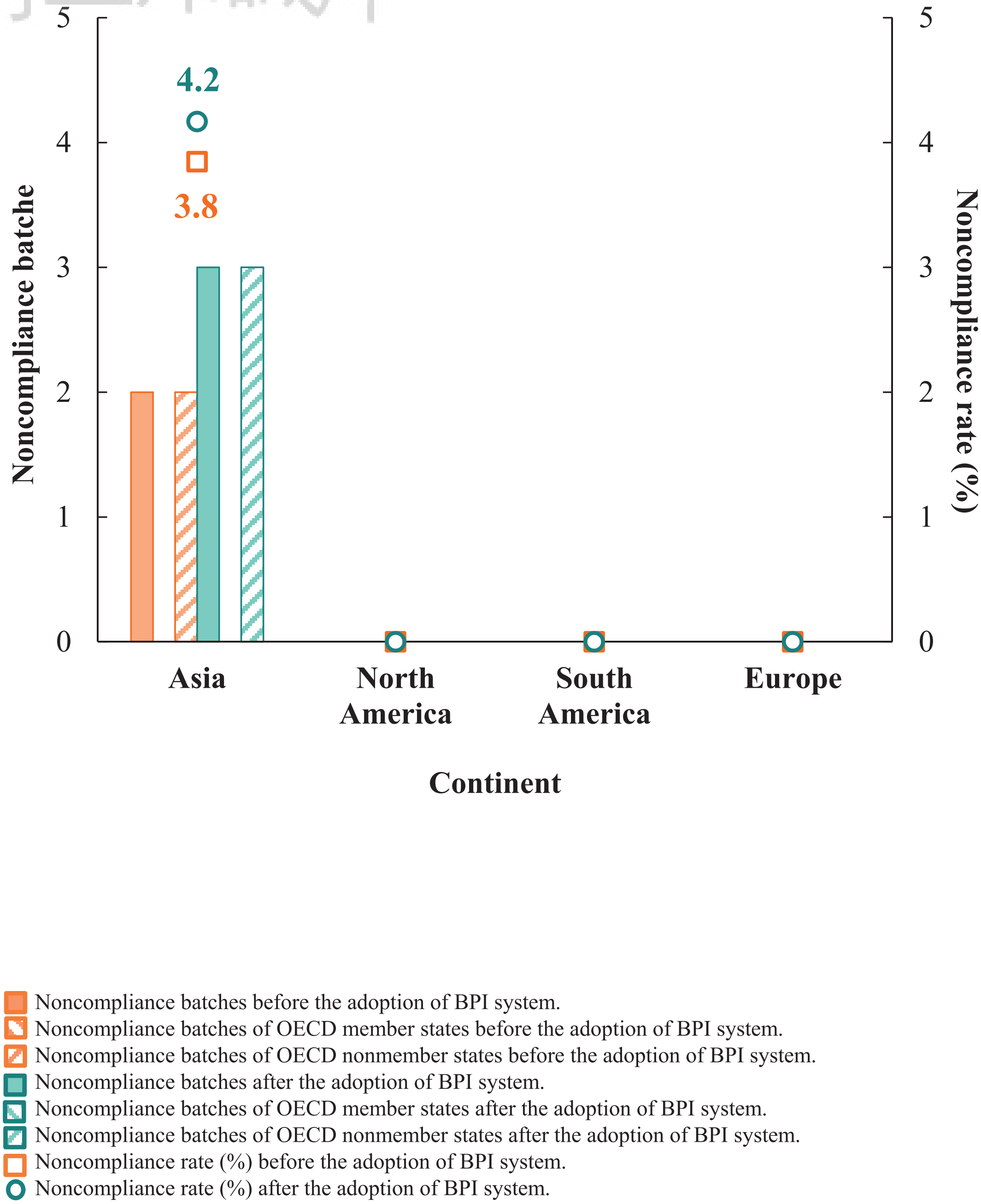

Fig. 8. Noncompliance batches and noncompliance rates in the postmarked by continent. (Source: TFDA's PMD system). BPI: The Border Prediction Intelligent system, PMD: The Product Management Distribution system, and OECD: The Organization for Economic Cooperation and Development. The adoption of the BPI system in the postmarket data, the increments in the noncompliance rate were more in Asia (two batches before and three batches after adoption, rates increased to 4.2%) compared to those of other continents. There were samples from North America, South America, and Europe, but there were no noncompliance batches.

significant differences were observed, indicating that the noncompliance rate was not influenced by whether a country was an OECD member state. The main reason was, for most captured fish products, the country of origin was based on the nationality of the fishing vessel.

After adoption of the BPI system, the noncompliance rate for Asia (4 batches before and 22 batches after adoption) and North America (zero batch before and six batches after adoption) increased (Fig. 7). The countries of origin for the postmarket with noncompliance batches were both in Asia (two batches before and three batches after adoption) (Fig. 8). Increases in the rate and number of noncompliance batches were observed for countries in Asia, which suggests that the BPI system may be more accurate in terms of identifying noncompliance regions.

In addition, prior to the adoption of the BPI system, the reasons for noncompliance were 19 batches of heavy metals and 5 batches of veterinary drugs at the border. The causes for the noncompliance in the postmarket included one batch each of heavy metals and veterinary drugs. After adoption of the BPI system, the causes of noncompliance at the border were excessive heavy metals (37 batches) and veterinary drugs (11 batches), while the causes of noncompliance at the postmarket included excessive heavy metals (one batch) and veterinary drugs (two batches). These results show that heavy metals were the primary reason for noncompliance of frozen fish products (Table 8).

The postmarket inspection results are closely related to the effectiveness of the border risk management processes. Strengthening the application of postmarket inspection results will improve the overall effectiveness of the border risk management. Currently, the border system has not fully integrated the postmarket inspection information; hence, its noncompliance products feedback to the border should go through manual reporting. To combine the useful information on noncompliance products corresponding to the postmarket and border in a timely and dynamic manner, it is necessary to feedback the postmarket inspection results to the border.

3.4. Sensitivity analysis

The imported food products generally has slack or peak seasons depending on the food types and categories, especially in the imported frozen fish products of fish species and the demand of consumers. Thus, clear differences are present in this regard between different seasons (e.g., bluefin tuna annual production season is from April to June and demand for mullet roe is high on traditional festivals). Therefore, to eliminate selection bias due to different seasons or durations and ensure that the comparison between the groups remained the same in different conditions, same analysis periods of 320 d were used in different conditions. Notably, the BPI system has only been adopted at the border for one year. Thus, to avoid limitations in terms of the data interval and ensure that the same statistical results are obtained for a long period of time, the original comparison interval was used representatively. Sensitivity analysis was conducted using different groups of time interval to investigate and confirm the stability of the results and assess whether the different time intervals affect the original results or deviate from the original results.

The results shown in Table 9 demonstrate that the compliance and noncompliance rates were similar for the three groups (no statistically significant differences), i.e., before the adoption of the BPI system (analysis period group of IFI), sensitivity analysis I (IFI I), and sensitivity analysis II (IFI II). The pre-BPI groups considered in this study show the actual distribution trend prior to the adoption of the BPI system.

3.5. Limitations

The BPI system employs ensemble learning prediction models constructed using multiple different machine learning algorithms, and the factors and data required for modeling frequently change with different considerations, e.g., the external environment and government policies. Furthermore, the data change over time; thus, the model's ability to obtain accurate predictions may decrease. According to historical border inspection application data, the number of noncompliance batches accounts for a small proportion of the total number of inspection applications, and modeling based on these data can easily result in prediction bias [2].

To solve these problems, the current BPI system utilizes an automatic modeling mode, where the system updates information each week based on the actual inspection applications at the border, and a

Table 8. Inspected items in noncompliance batches.

		Inspected items		Number of noncompliance batches
		Heavy metals	Veterinary drugs	
Border	IFI[a]	19	5	24
	BPI[b]	37	11	48
Postmarket	IFI[a]	1	1	2
	BPI[b]	1	2	3

(Source: TFDA's IFI system and PMD[c] system).
The major causes of noncompliance were heavy metals, and some batches were due to veterinary drugs.
[a] The Import Food Inspection system.
[b] The Border Prediction Intelligent system.
[c] The Product Management Distribution system.

Table 9. Sensitivity analysis of frozen fish products.

		Compliance		Noncompliance		P value
		N	%	N	%	
Border	IFI[a]	774	97.0	24	3.0	0.068
	BPI[b]	976	95.3	48	4.7	
	IFI I[c]	1116	97.6	28	2.4	0.005
	BPI[b]	976	95.3	48	4.7	
	IFI II[d]	1005	97.4	27	2.6	0.012
	BPI[b]	976	95.3	48	4.7	
Postmarket	IFI[a]	95	97.9	2	2.1	0.890
	BPI[b]	162	98.1	3	1.9	
	IFI I[c]	131	97.0	4	3.0	0.513
	BPI[b]	162	98.2	3	1.8	
	IFI II[d]	110	98.2	2	1.8	0.984
	BPI[b]	162	98.2	3	1.8	

(Source: TFDA's IFI system and PMD[e] system).
SPSS was employed with the Chi-squared test to analyze the sensitivity analysis. The results demonstrate that the compliance and noncompliance rates were similar for the three groups (with no statistically significant differences) before the adoption of the BPI system (sensitivity analyses I (IFI I), and II (IFI II)).
[a] The Import Food Inspection system.
[b] The Border Prediction Intelligent system.
[c] IFI I: Sensitivity analysis periods from January 1, 2019 to April 14, 2020.
[d] IFI II: Sensitivity analysis periods from January 1, 2019 to February 28, 2020.
[e] The Product Management Distribution system.

major system update is implemented each year. Here, regular update method is employed to capture the latest noncompliance occurrences and improve the efficiency of remodeling. For example, the BPI system will be adjusted on a rolling basis using historical border inspection data and open domestic and international data to implement effective adjustments for handling the “data drift” or “concept drift” problems, thereby preventing model failure.

Note that all batches in the analysis interval were considered; however, only approximately one year of data was collected after the adoption of the BPI system. Changes to the BPI system over time will be modeled automatically. The number of samples in the postmarket was too small to perform statistical analysis, while that of noncompliance batches was even smaller. Although the BPI system can identify the major influencing factors of frozen fish products, the border system has not yet fully integrated with the postmarket inspection information. To timely and dynamically grasp information with regard to noncompliance products on both sides, providing feedback to the border on the results obtained during postmarket inspections is essential. Take the large yellow croaker for example. There was noncompliance at the postmarket but noncompliance was not detected at the border. Thus, it may take a long time to continuously monitor noncompliance batches at the border and postmarket to evaluate the effectiveness of the corresponding AI applications more accurately and to adjust and establish an effective real-time bilateral feedback mechanism.

For future research and analysis, the postmarket feedback mechanism is recommended to be systematically and completely established, supplemented by data collection over a long period and comparison sets between different complete years. The border and postmarket inspection data have category databases. Therefore, a standardized and programmed analysis module should be built to enable simultaneous conversion and comparison of information from these two databases. Subsequently, real-time analysis and BPI observation can be effectively performed. Additionally, the operation mechanism (two-way feedback mechanism) is adjusted in real-time when the BPI's ability to obtain accurate predictions decreases to ensure and maintain the effectiveness of border management. This study only explored imported frozen fish products as the analysis subjects; thus, the application of BPI to other product categories will be considered in the future. Incorporating this experience of the adoption of BPI system to frozen fish products as a reference, timely and appropriate analysis and control based on the situation of border, imported batches will be more beneficial to improving the sampling mechanism and border management.

4. Conclusions

The characteristics and information of imported food are highly complex and affected by international economic, socio-cultural, and environmental factors. Moreover, rapid changes in science and technology have enabled the development of novel foods and the characteristics and styles of imported foods can promote sustainable development. In border management, AI performs monitoring, analysis, and calculations of border data and can quickly and accurately derive strategies and prediction models from complex big data. Using the valuable information generated by AI, decision makers can provide improved solutions to complex problems. Accordingly, AI applications have become a major trend in the future international development.

In this study, after the adoption of the BPI system at the border, the inspection noncompliance rate of frozen fish products increased while that of postmarket sampling decreased. Although no statistically significant differences were observed, the trends indicate that the application of AI methods can improve the effectiveness of border management process, in line with the purpose of using the BPI system for risk management. These trends indicate that, in terms of risk management, compared with the original IFI random sampling, the BPI system can enhance the effectiveness of interception of noncompliant products at the border, thereby preventing the entrance of such products to the postmarket.

In the analysis of major influencing factors at the border, the noncompliance rate of internal organ product of large and medium fish was statistically significant. Furthermore, the noncompliance rate was also statistically significant for the body type of fish species as small fish. The results showed the BPI system can identify the major factors influencing frozen fish products. In this study, the data collected after the adoption of the BPI risk management system at the border only spanned for approximately one year, and the number of postmarket samples was very small. Thus, the correlation between the border and postmarket should be monitored continuously, and real-time information should be shared bidirectionally to realize effective interception of noncompliance products at the border and postmarket.

Conflicts of interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with this work.

Acknowledgments

The data for this work come from the system database of the TFDA and the conceptual diagram of border management related to AI applications provided by the Decision Support Center, TFDA.

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