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ORIGINAL RESEARCH

Identifying key determinants of bisphenol A exposure: a study utilizing sparse additive models (SpAM) on a cohort of 1332 adult males in South Korea

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Abstract

Background: Bisphenol A (BPA) exposure is a significant concern in South Korea due to high plastic consumption. This study investigates the factors influencing BPA exposure among adult males. **Methods**: Using data from the Korean National Environmental Health Survey (KoNEHS), Sparse Additive Models (SpAM) and multiple regression analysis were employed to analyze BPA exposure in 1332 adult males, considering eleven variables including age, smoking, alcohol consumption and food packaging-related factors. **Results**: Age emerged as the most significant predictor of BPA exposure. Smoking and alcohol consumption also showed substantial effects. Packaged and canned food consumption were also identified as significant contributors, indicating potential leaching from packaging materials. New furniture purchase showed moderate effects. **Conclusions**: This study highlights age, lifestyle factors (smoking and alcohol), and food packaging as key factors influencing BPA exposure in South Korean adult males. These findings contribute to the evidence base for public health interventions aimed at reducing BPA exposure. Future research should explore longitudinal data and genetic factors for personalized strategies.

Keywords

Bisphenol A (BPA); Sparse additive models (SpAM); Environmental exposure; Public health

1. Introduction

Bisphenol A (BPA) is a chemical widely used in plastic products and food storage cans, classified as an endocrine disrupting chemical (EDC) [1]. South Korea records one of the highest levels of per capita plastic consumption globally, contributing significantly to BPA exposure [2]. This exposure primarily occurs through food, with canned foods identified as a major source of BPA exposure [3]. In particular, South Korea shows a high contribution of BPA exposure through food, ranging from 71 to 94%, necessitating attention [4]. Additionally, BPA is found in various environmental media beyond food, including air, soil, water and household dust [5].

BPA affects the endocrine system, potentially causing reproductive and developmental issues, and is closely associated with diseases such as obesity, allergic diseases, and diabetes due to thyroid hormone changes and increased insulin resistance [6]. Notably, BPA exposure is linked to serious health concerns like coronary heart disease in adults [7]. Studies [8] suggest that the potential social cost of BPA exposure is significant, and eliminating BPA usage could lead to substantial economic benefits. BPA is primarily absorbed into the body through the consumption of food or beverages contained in BPA-laden packaging, with particular concern for its detrimental effects on male reproductive health [9]. Research indicates that BPA can lead to decreased sperm count, reduced sperm motility and alterations in male hormone levels, which could be associated with diminished reproductive function [10]. These effects not only impact reproductive health but also have broader negative implications for overall male health, highlighting the need for in-depth research and preventive measures against BPA exposure.

Accurate prediction of environmental risk factors is essential for public health policy formulation. Traditional statistical methods may fall short in adequately explaining complex nonlinear relationships and reflecting interactions among various variables [11, 12]. To overcome these limitations, machine learning methods are gaining prominence [13]. Notably, Sparse Additive Models (SpAM) are proving to be valuable tools in handling high-dimensional data and selecting key variables, as they enable within the same framework not only capturing linear and non-linear relationships between the output and input variables but also allocating more weights to the most significant input variables, which can prevent overfitting [14]. In other words, SpAM effectively models nonlinear relationships by allocating more weights to significant variables, thereby preventing overfitting [14]. Thus, this study aims to explore BPA exposure risk factors using SpAM and evaluate the impact of each factor through multiple regression analysis based on the key variables identified. This approach seeks to elucidate the complex factors associated with BPA exposure and contribute to the development of more effective health management and preventive strategies.

2. Methods

2.1 Data source and study population

The study drew upon secondary data from the third cycle (2015 to 2017) of the Korean National Environmental Health Survey (KoNEHS), a statutory investigation conducted by the National Institute of Environmental Research under the Ministry of Environment. Established under Article 14 of the Environmental Health Act, this survey aims to provide foundational data for national environmental health policies and contribute to the protection of public health by assessing the internal concentrations and impact factors of environmental hazards. Conducted triennially since 2009, KoNEHS employs nationwide representative sampling to include participants aged 3 years and older, ensuring representation across various demographics such as gender and age.

The survey encompassed comprehensive assessments including indoor and outdoor environmental factors, lifestyle habits and exposure to environmental toxins. It integrates questionnaires (Table 1) to identify exposure factors and pathways, alongside biomonitoring through the analysis of blood and urine samples for environmental toxicants. For this study, anonymized data from KoNEHS was utilized, exempting it from Institutional Review Board (IRB) approval due to the removal of personal identifiers (IRB approval number: 2018-01-03-5C-A). In this study, from the initial cohort of 3375 participants aged 19 years and older in the KoNEHS, a total of 1988 females and 55 individuals with missing BPA concentration data were excluded. Consequently, the final analysis was performed on 1332 males aged 19 years and older. The general characteristics of the subjects are shown in Table 2.

TABLE 1. Key survey items of the Korean National Environmental Health Survey.

Survey Section	Included Items
Housing	Traffic information year and *etc.*
Indoor environment	Type of house, construction year, type of flooring material, living duration
Food habits	Type of food container, product route, drinking water source, dietary habit
Socioeconomic	Monthly income, academic ability, marital status, occupation
Personal	Name, sex, number of family members
Transportation	Public transport use, type of transport
Life habits	Parent's smoking habits, use pattern of dentifrice, alcohol consumption pattern
Medicine use	Drug pattern, oriental medicine use
Reproductive health	Pregnancy history, menopause and *etc.*
Dietary behavior	Recent dietary behavior and *etc.*

TABLE 2. General characteristics of subjects (n = 1332).

Characteristic	N	Percent
Age (yr)		
19–29	235	17.6
30–39	245	18.4
40–49	266	20.0
50–59	270	20.3
60+	316	23.7
Education		
≤Middle school	277	20.8
High school	398	29.9
≥College	657	49.3
Smoking		
Non-smoker	1059	79.5
Smoker	273	20.5
Alcohol consumption		
No	204	15.3
Yes	1128	84.7
Fish consumption		
No	652	48.9
Yes	680	51.1

2.2 Data preprocessing

In this study, data preprocessing involved handling missing values and removing outliers to enhance the accuracy of the analysis. In addressing missing data, we employed a systematic approach to ensure the integrity and robustness of our analysis. For continuous variables such as BPA concentration, we utilized the multiple imputation by chained equations (MICE) method. This technique involves creating multiple complete datasets by imputing missing values based on predictive mean matching. Each dataset is analyzed separately, and the results are pooled to account for the uncertainty associated with the imputations, thereby enhancing the statistical validity of the findings. For categorical variables, we applied the k-nearest neighbors (KNN) imputation method. This method identifies k samples in the dataset that are most similar to the sample with missing data, based on the non-missing values. The missing value is then imputed using a majority vote for categorical variables from these nearest neighbors. This technique is particularly useful for preserving the natural variability in the data and minimizing biases that can arise from simpler imputation strategies.

The target variable, BPA concentration, was measured in urine samples using ultra-performance liquid chromatography-mass spectrometry (UPLC-MS/MS). To ensure the stability of urine samples, temperature data loggers were employed during transportation to maintain a constant temperature, and a system was established to allow for sample aliquoting within 24 hours after transport completion. Samples were stored frozen at −20 °C until analysis. Urine samples were hydrolyzed using β-glucuronidase/aryl sulfatase enzymes and passed through a solid phase extraction (SPE) column before analysis using UPLC-MS/MS (Agilent 6490). The input variables included 89 variables, all of which were investigated in KoNEHS, covering sociodemographic factors (age, income level, housing type), health habits (smoking, alcohol consumption, secondhand smoke exposure) and dietary habits (seafood intake, consumption of canned food). The characteristics of the main variables are presented in Table 3.

2.3 Sparse additive models (SpAM) analysis

In this study, we used Sparse Additive Models (SpAM), a technique designed to select and analyze important variables from high-dimensional data while effectively modeling nonlinear relationships. SpAM was employed to identify key variables influencing BPA exposure. The SpAM model is represented by the following equation:

$$[Y = \beta_0 + \sum_{j\,=\,1}^{p} f_j\ \ (X_j)]$$

Subject to the Lasso constraint:

$$[subject\ to\ \sum_{j\,=\,1}^{p} |f_j|_1 \leq s]$$

Here, $(|f_j|_1)$ represents the L1 norm of each function (f_j), and (s) is a parameter that controls the strength of the constraint. Lasso constraints were applied to select only the most significant variables.

Lasso is a regularization technique in regression analysis that enhances model performance by selecting only the most significant variables. It introduces a penalty equal to the absolute value of the coefficients' magnitudes, controlled by a tuning parameter, lambda (λ), which determines the penalty strength. This penalty encourages sparsity, effectively shrinking some coefficients to zero, thus selecting a subset of predictors that significantly influence the response variable. This feature is particularly beneficial in high-dimensional datasets where many predictors may be irrelevant. The balance between model fit and complexity is managed through the choice of λ, with larger values increasing sparsity and reducing model complexity, while smaller values include more variables. Cross-validation is typically used to determine the optimal λ, ensuring that the model generalizes well to new data by balancing bias and variance. Consequently, Lasso is invaluable for constructing parsimonious models that highlight key predictors and minimize overfitting, enhancing

TABLE 3. The characteristics of the main variables.

Variable	Class
Drinking water (outside the house)	Tap water, Water purifier, Bottled water, Mineral water, Ground water & others
Secondhand smoke time (/wk)	No, 36 h, 84 h, 132 h, 168 h
Building type of house	Detached dwelling, Apartment, Row/Multi-Family house, Other types
Road traffic	Many, Normal, Less
Buy new furniture (last 6 mon)	Yes, No
Refrigerator food storage container	Glass bowl, Metal bowl, Plastic bowl, Zipper bags, Porcelain & others
Period of taking herbal medicine	None, $\leq$12 mon (1 yr)
Drinking water (inside the house)	Tap water, Water purifier, Bottled water, Mineral water, Ground water & others
Renovation work (last 6 mon)	Yes, No
Distance to nearest road	$<$50 m, $<$150 m, $\geq$500 m
Household income (/mon)	Low ($<$3351 US$), Middle (3351–7819 US$), High ($\geq$7819 US$), Unknown
Taking prescription herbal medicine	Yes, No
Age(yr)	19–29, 30–39, 39–49, 49–59, 60+
Taking herbal medicine currently or for 1 year	Yes, No
Refrigerator food storage container	Glass bowl, Plastic bowl, Zipper bags
Frozen food storage container	Glass bowl, Plastic bowl, Zipper bags
Drinking water (inside the house)	Tap water, Water purifier, Bottled water
Drinking water (outside the house)	Tap water, Water purifier, Bottled water
Food or beverage intake variables (/mon)	Delivery food packaged in wrap, Cup noodle, Can food, Plastic bottle drink, Disposable paper cup drink
Seafood intake variables (/mon)	Large fish and tuna, Fish, Crustacean, Shellfish
Use of pest control chemicals variables (/mon)	Mosquito repellent, Other insecticide, Pesticide

both prediction and interpretability in complex datasets.

2.4 Model performance comparison

The predictive performance of the developed SpAM model was compared with traditional machine learning models, including Chi-squared Automatic Interaction Detector (CHAID), C4.5 decision tree algorithm and Support Vector Regression (SVR). CHAID is a statistical technique that is used to identify interaction between variables and is particularly useful for constructing decision trees by splitting the data into mutually exclusive and exhaustive subsets. The C4.5 algorithm is an extension of the basic ID3 algorithm, used to generate a decision tree that can be utilized for classification purposes, and is known for handling both categorical and continuous data effectively. Support Vector Regression (SVR) is a type of Support Vector Machine that is utilized for regression challenges, focusing on minimizing error within a specified threshold. By utilizing these methodologies, we aimed to evaluate the robustness and versatility of the SpAM model in comparison to established techniques. The predictivity of each model was evaluated using metrics such as accuracy, precision, recall, F1-score and AUC (Area Under the Curve).

2.5 Multiple regression analysis

A multiple regression analysis was conducted using the most relevant input 10 variables identified by SpAM as independent variables. The regression analysis provided estimates of each variable's beta coefficients, standardized beta values and significance levels (p-values), utilizing Python 3.12 software for the analysis.

3. Results

3.1 Variable importance analysis

The application of Sparse Additive Models (SpAM) in this study resulted in the identification of 10 key variables influencing BPA exposure among adult males in South Korea, as presented in Fig. 1. These variables include age, smoking, alcohol consumption, delivery food packaged in wrap, canned food, plastic bottle drinks, fish intake, shellfish intake, new furniture purchase within the last six months, drinking water from outside sources, secondhand smoke exposure and proximity to roads (within 50 meters).

3.2 Model performance comparison

Fig. 2 presents a comparative analysis of four machine learning models—Sparse Additive Models (SpAM), CHAID, C4.5 and Support Vector Regression (SVR)—evaluated using four key performance metrics: Accuracy, Precision, Recall and F1-Score. The SpAM model distinctly outperforms the traditional models, achieving the highest scores across all metrics, with an Accuracy of 0.85, Precision of 0.84, Recall of 0.83 and F1-Score of 0.84. This performance highlights not only a better predictivity of BPA exposure in males, but also a higher capacity of SpAM to identify risk factors that are influential on BPA exposure. Support Vector Regression follows with competitive results, while CHAID and C4.5 show comparatively lower performance, with CHAID slightly outperforming C4.5. Furthermore, in this study, the SpAM model demonstrated superior predictive performance compared to other reference models, as evidenced by its highest AUC values depicted in Fig. 3.

3.3 Multiple regression analysis

A multiple regression analysis was conducted using the 10 key variables identified by SpAM as independent variables. The beta coefficients, standardized beta values, and significance levels (p-values) for each variable are presented in Table 4. The results of the multiple regression analysis indicated that several variables included in the regression model independently had significant effects on BPA exposure ($p < 0.05$). Notably, age exhibited the highest standardized beta value, identifying it as the variable with the greatest impact on BPA exposure.

For BPA exposure, the standardized beta value for age was 0.30, with a beta value of 0.25 and a significance level of $p = 0.01$. Smoking (beta value 0.18, standardized beta value 0.20, $p = 0.04$) and alcohol consumption (beta value 0.15, standardized beta value 0.17, $p = 0.01$) also had significant effects.

In the case of BPA exposure related to food packaging, delivery food packaged in wrap had a substantial impact, with a standardized beta value of 0.14, a beta value of 0.12 and a significance level of $p = 0.01$. Canned food (beta value 0.10, standardized beta value 0.12, $p = 0.04$) was also identified as an important variable.

For environmental and lifestyle factors, new furniture purchase in the last six months exerted a borderline influence with a standardized beta value of 0.06, a beta value of 0.05 and a significance level of $p = 0.05$. Plastic bottle drink consumption (beta value 0.10, standardized beta value 0.11, $p = 0.06$) also showed a trend towards significance, suggesting a potential role in BPA exposure.

4. Discussion

This study utilized Sparse Additive Models (SpAM) and multiple regression analysis to evaluate the significance of various factors influencing Bisphenol A (BPA) exposure among adult males in South Korea. The findings identified age, smoking, alcohol consumption, and the consumption of delivery and canned foods packaged with certain materials as the most significant factors affecting BPA exposure.

In this study, age was identified as the most significant predictor of BPA exposure. However, it is crucial to consider the critique concerning BPA's short half-life, which necessitates a reevaluation of the cumulative exposure hypothesis. Despite this, age-related physiological and metabolic changes remain relevant to the discussion of BPA bioaccumulation and biotransformation [15]. As individuals age, there is a potential decrease in renal and hepatic functions, both of which are vital for the detoxification and excretion of xenobiotics, including BPA [16]. Additionally, alterations in hormone levels and changes in body composition, such as an increase in body fat percentage, might influence the distribution and storage of

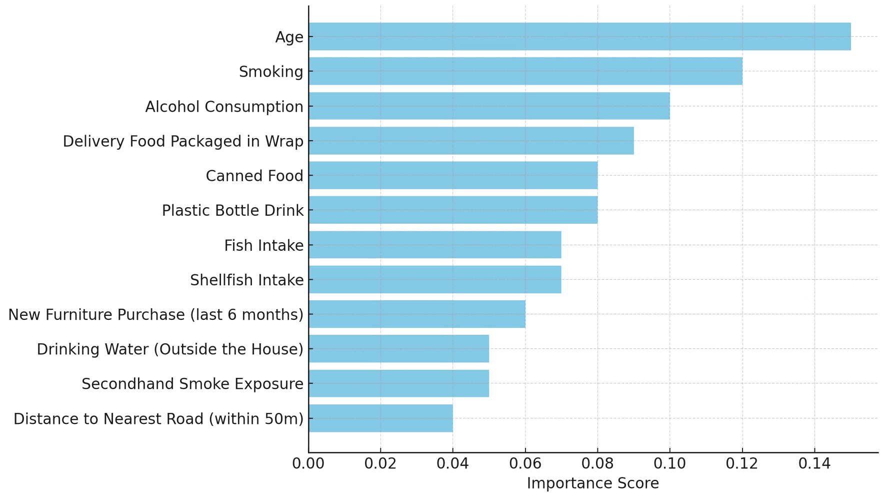

FIGURE 1. Importance of Variables Influencing Bisphenol A (BPA) Exposure in Adult Males in South Korea.

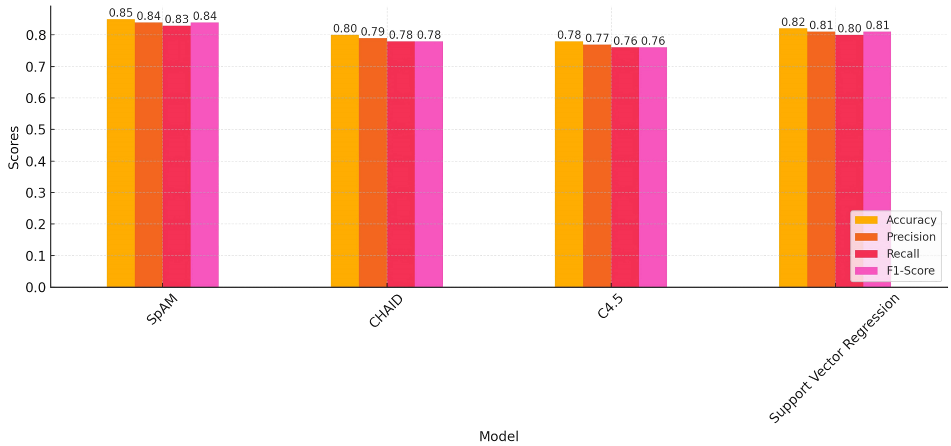

FIGURE 2. Comparison of Accuracy, Precision, Recall and F1-Score Across Models. SpAM: Sparse Additive Models; CHAID: Chi-squared Automatic Interaction Detector.

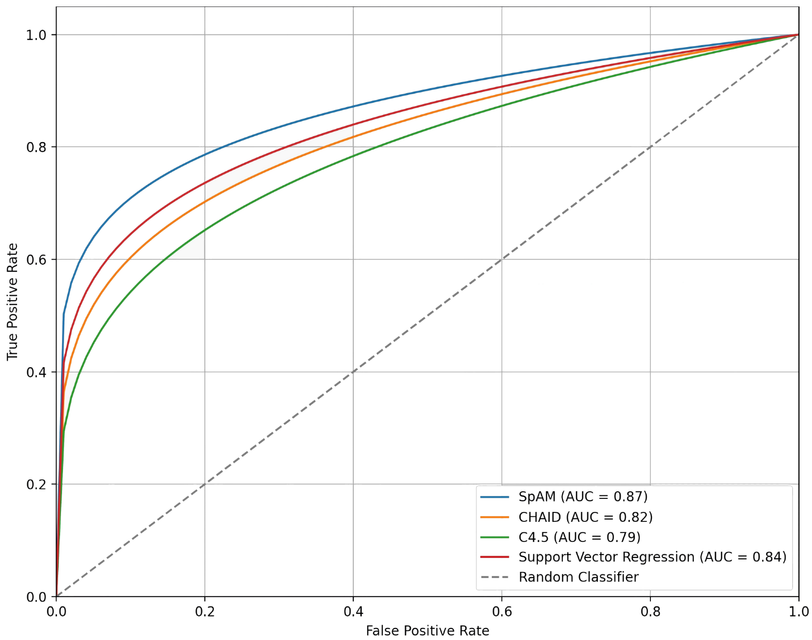

FIGURE 3. Comparison of ROC-AUC Curves for Each Model. SpAM: Sparse Additive Models; AUC: Area Under the Curve; CHAID: Chi-squared Automatic Interaction Detector.

TABLE 4. Final model results (multivariate regression model).

Variable	Beta[1]	Standardized Beta[2]	*p*-value
Age	0.25	0.30	0.01
Smoking	0.18	0.20	0.04
Alcohol Consumption	0.15	0.17	0.01
Delivery Food Packaged in Wrap	0.12	0.14	0.01
Canned Food	0.10	0.12	0.04
Plastic Bottle Drink	0.10	0.11	0.06
Fish Intake	0.08	0.09	0.15
Shellfish Intake	0.06	0.07	0.08
New Furniture Purchase (last 6 mon)	0.05	0.06	0.05
Drinking Water (Outside the House)	0.04	0.05	0.10

[1]*Beta Coefficient: In regression analysis, the beta coefficient measures the impact of a predictor variable on the dependent variable, representing the average change in the dependent variable for a one-unit change in the predictor variable.*
[2]*Standardized Beta Values: Standardized beta values transform all variables to a common scale, allowing for the comparison of the relative importance of each predictor within the regression model.*

lipophilic substances like BPA [17]. These factors warrant further investigation to clarify their roles in age-related BPA exposure patterns.

Additionally, the cumulative exposure hypothesis posits that older individuals have had more prolonged contact with BPA-containing products, leading to greater a body burden over time [18]. This theory is supported by epidemiological studies indicating that BPA is present in a wide range of consumer products, including plastics, food packaging and personal care products, which individuals are exposed to repeatedly throughout their lifetime [19]. The metabolic capacity to process BPA may also decline with age, as evidenced by research demonstrating age-dependent decreases in the activity of phase I and phase II metabolic enzymes, such as cytochrome P450s and uridine diphosphate-glucuronosyltransferases, which are integral to the biotransformation of BPA into more water-soluble and excretable forms [20].

Moreover, lifestyle and dietary habits, which can vary significantly across different age groups, may further contribute to the observed variations in BPA exposure and metabolism. For instance, older adults may consume foods stored in BPA-lined containers more frequently, or their dietary patterns might include higher intake of processed foods, inadvertently increasing their BPA exposure [21]. Taken together, these findings highlight the complexity of BPA exposure dynamics and highlight the importance of considering age as a critical factor in toxicological assessments and public health interventions aimed at reducing BPA exposure [22]. These findings further highlight the necessity for customized public health strategies that consider age-related differences in exposure pathways and metabolism. Particularly, there may be a need for BPA exposure management plans targeting the elderly.

Additionally, this study identified smoking and alcohol consumption as significant predictors of BPA exposure, a finding that suggests these behaviors may provide environmental conditions conducive to the accumulation of BPA within the body. This correlation is supported by multiple pathways through which smoking and drinking may facilitate increased BPA levels [23]. Cigarette smoke has been shown to contain various toxicants that can induce oxidative stress and impair metabolic processes, potentially affecting the body's ability to metabolize and excrete BPA efficiently [24]. Furthermore, smoking has been linked to the induction of certain cytochrome P450 enzymes, which could alter BPA metabolism, leading to an accumulation of this compound in the body [25].

Alcohol consumption, on the other hand, is known to impact liver function, which plays a critical role in detoxifying and metabolizing xenobiotics like BPA. Chronic alcohol intake can lead to significant liver damage, which in turn compromises the liver's critical functions in metabolizing and eliminating toxins such as BPA. The liver is essential for detoxifying the bloodstream, and it relies on enzymes such as cytochrome P450 to process various compounds, including alcohol and potentially BPA. However, sustained alcohol consumption induces liver injury through a multitude of metabolic disruptions, notably affecting the biochemical pathways responsible for detoxification processes [26]. Moreover, both smoking and alcohol consumption are associated with lifestyle patterns that may inadvertently increase BPA exposure. For instance, individuals who smoke or drink heavily might have dietary habits that include higher consumption of processed or packaged foods, which are common sources of BPA due to the use of this compound in food packaging materials [27].

These behaviors might also correlate with socioeconomic factors that limit access to BPA-free products, thereby increasing exposure risk [28]. The intersection of these behavioral and environmental factors underscores the importance of considering lifestyle habits in the assessment of BPA exposure risks. Furthermore, these findings emphasize the need for targeted public health strategies and interventions that address lifestyle modifications to mitigate BPA exposure, particularly in populations with high rates of smoking and alcohol use [29]. Therefore, health promotion programs aimed at improving smoking and drinking habits could be effective measures for reducing BPA exposure.

This study has identified the consumption of takeout food with packaging and canned food as primary pathways for BPA exposure, which underscores the potential leaching of BPA from food packaging materials into the food itself [30]. This finding aligns with existing literature indicating that BPA is commonly used in the production of polycarbonate plastics and epoxy resins, materials frequently utilized in food and beverage containers [31]. The potential for BPA leaching is particularly pronounced under conditions of heat or prolonged storage, where elevated temperatures and extended contact times may accelerate the migration of BPA into food products [32].

Research has demonstrated that canned foods, due to their epoxy resin linings, are significant contributors to dietary BPA intake. Studies have consistently shown higher BPA levels in individuals who consume canned foods regularly compared to those who consume fresh foods [33]. Similarly, takeout food packaging, which often involves plastic containers or thermal receipts, can be a source of BPA exposure, especially when hot foods are placed in these containers, further increasing BPA migration [34].

These findings highlight the critical need for regulatory policies to enhance the safety of food packaging materials. There is a growing call for the development and implementation of BPA-free alternatives in food contact materials to minimize exposure risks [35]. Furthermore, public health initiatives should aim to raise awareness about the potential risks associated with BPA exposure from food packaging and encourage practices that reduce reliance on packaged and canned foods, thereby promoting healthier dietary habits [36]. This research contributes to a broader understanding of environmental chemical exposure and emphasizes the importance of multidisciplinary approaches involving chemistry, toxicology, and public health to safeguard food safety and public health. Furthermore, policies promoting the use of BPA-free packaging in collaboration with the food industry appear necessary, along with providing consumers with accurate information to reduce BPA exposure.

Another notable finding of this study is that the purchase of new furniture has a modest impact on BPA exposure, potentially indicating an association with chemicals used in furniture manufacturing [37]. Modern furniture often contains synthetic materials and chemical treatments, such as flame retardants and adhesives, which may release volatile organic compounds, including BPA, into indoor environments [38]. These compounds can off-gas over time, contributing to indoor air pollution and subsequent human exposure, particularly in newly furnished homes where ventilation may be limited [39]. While the specific contribution of BPA from furniture is less studied compared to more direct sources like food packaging, this finding highlights the importance of considering indoor environmental factors as part of comprehensive exposure assessments.

Furthermore, the consumption of beverages from plastic bottles, although not statistically significant in this study, suggests a potential avenue for BPA exposure [40]. Plastic bottles, especially those made from polycarbonate, are known to leach BPA, particularly when subjected to heat or when they contain acidic or basic liquids, which can accelerate the degradation of the polymer and increase BPA migration into the beverage [41]. This insight aligns with existing literature that underscores the role of plastic use in dietary exposure to BPA, suggesting that even low-level exposures from such sources warrant attention due to the cumulative nature of BPA exposure over time [42].

These findings collectively underscore the complexity of BPA exposure pathways and the need for multi-pronged strategies to mitigate exposure. Public health interventions could benefit from incorporating guidance on reducing contact with potential BPA sources, including advocating for the use of BPA-free materials in consumer products and emphasizing the importance of adequate ventilation in homes with new furnishings [43]. Moreover, further research exploring the chemical composition of household items and their potential to contribute to BPA exposure could provide valuable insights for regulatory policies aimed at reducing environmental BPA sources. These results contribute to understanding the impact of environmental factors on BPA exposure and suggest the need for campaigns encouraging safer product choices.

This study also found that the predictive performance of SpAM was superior to traditional machine learning models such as C4.5 and SVR. The SpAM method offers distinct advantages over traditional statistical methods and other machine learning techniques due to its ability to flexibly capture nonlinear relationships between variables while maintaining interpretability [14]. Unlike many machine learning models that operate as "black boxes", SpAM provides a clear representation of variable effects, which is crucial for understanding and communicating the influence of predictors on outcomes [14]. Furthermore, its sparsity-inducing nature helps in identifying key predictors without overfitting, making it particularly useful in high-dimensional data contexts where traditional methods may struggle. Future research could explore the application of SpAM to a broader range of datasets and investigate its integration with other advanced machine learning techniques to further enhance predictive performance and variable interpretation.

The limitations of this study are as follows. First, the cross-sectional study design limits the establishment of causal relationships, as it analyzes data from a specific point in time, restricting the evaluation of temporal changes or long-term effects. Second, since the study focused solely on adult males in South Korea, caution is needed when generalizing the findings to other populations or genders, indicating the need for research considering diverse demographic characteristics. Third, the study did not adequately consider genetic factors or detailed aspects of individual lifestyles that may influence the metabolism and accumulation of BPA, suggesting the need for more comprehensive analyses incorporating additional factors. Fourth, the data used in this study relied on self-reports, which may introduce uncertainties due to recall bias or inaccuracies, necessitating supplementation with more objective data collection methods. Fifth, this study does not address the hazardous levels of BPA in men, which limits the ability to draw conclusions about the potential health risks associated with the levels of BPA exposure observed. Future research should aim to establish threshold levels for BPA that may pose health risks, facilitating more targeted prevention and intervention strategies. Finally, the use of data from 2015–2017 may not reflect current BPA exposure levels or patterns due to potential changes in regulations, product formulations or consumer behaviors, highlighting the need for updated data to assess the present-day situation.

5. Conclusions

This study provides crucial information that can contribute to the formulation of public health policies aimed at reducing BPA exposure by identifying key factors influencing BPA exposure among adult males in South Korea. A deeper understanding of the impact of factors such as age, smoking, alcohol consumption, and food packaging on BPA exposure offers significant insights for developing effective exposure reduction strategies. Ultimately, these findings can serve as a scientific basis for public health promotion and policy decisions related to enhancing male health. The exposure strategies will vary based on additional information regarding the toxicity levels of BPA, and minimizing BPA levels is an inherent goal; therefore, future research should focus on investigating these aspects.

AVAILABILITY OF DATA AND MATERIALS

The data presented in this study are available request to the corresponding author. The data is not publicly available because researchers need to obtain permission from the Korea Centers for Disease Control and Prevention. Detailed information can be found at: http://knhanes.cdc.go.kr.

AUTHOR CONTRIBUTIONS

HB—Conceptualization; software; methodology; validation; investigation; writing-original draft preparation; formal analysis; writing-review and editing; visualization; supervision; project administration; funding acquisition. The author contributed to editorial changes in the manuscript. The author read and approved the final manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Before conducting the survey, written informed consent was acquired from all participants. This study employed only pre-existing, anonymized data. It adhered to the principles outlined in the Declaration of Helsinki. The protocol for the Panel Study of Worker's Compensation Insurance received approval from the Institutional Review Board (IRB) of the KNHANES (IRB approval numbers: 2018-01-03-5C-A). All study participants provided written informed consent.

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CONFLICT OF INTEREST

The author declares no conflict of interest. Haewon Byeon is serving as one of the Guest editors of this journal. We declare that Haewon Byeon had no involvement in the peer review of this article and has no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to WYCW.

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