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ORIGINAL

Interpretable AI for Behavioral Prediction: An Ethical Laboratory Experiment on Snack Choice Prediction

Inteligencia Artificial Interpretable para la Predicción del Comportamiento: Un Experimento de Laboratorio Ético sobre la Elección de Snacks

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ABSTRACT

Introduction: the application of artificial intelligence (AI) in behavioral prediction has shown promise across domains like mental health, autonomous vehicles, and consumer behavior. However, challenges such as algorithmic bias, lack of interpretability, and ethical concerns persist. This study addresses these gaps by developing an interpretable AI model to predict snack choices in a controlled laboratory experiment.
Method: a random forest classifier was trained to predict participants' snack choices (healthy vs. unhealthy) based on contextual factors (hunger, mood, time of day) and historical choices. Data were collected from 75 adults over 10 sessions, with features engineered to capture both immediate and longitudinal patterns. Model performance was evaluated using accuracy, precision, recall, and feature importance analysis.
Results: the model achieved 85,33 % accuracy, with hunger level, historical choices, and mood identified as the most influential predictors. Performance improved over sessions (peaking at 93,33 % accuracy in sessions 8-9), highlighting the value of longitudinal data. Subgroup analyses showed consistent performance across age, gender, and BMI, with higher accuracy for participants with healthier habits and higher socioeconomic status.
Conclusions: this study demonstrates the feasibility of interpretable AI models in predicting dietary behavior while addressing ethical concerns through rigorous data anonymization and informed consent protocols. The findings underscore the potential of AI to inform personalized interventions for healthier eating habits and provide a framework for ethical AI implementation in behavioral research.

Keywords: Artificial Intelligence (AI); Behavioral Prediction; Snack Choice; Random Forest Classifier; Interpretability; Ethical AI.

RESUMEN

Introducción: la aplicación de la inteligencia artificial (IA) en la predicción del comportamiento ha demostrado avances significativos en áreas como la salud mental, los vehículos autónomos y el comportamiento del consumidor. Sin embargo, persisten desafíos como el sesgo algorítmico, la falta de interpretabilidad y las preocupaciones éticas. Este estudio aborda estas brechas mediante el desarrollo de un modelo de IA interpretable para predecir elecciones de snacks en un experimento de laboratorio controlado.
Método: se entrenó un clasificador de bosque aleatorio para predecir las elecciones de snacks (saludables vs. no saludables) basándose en factores contextuales (nivel de hambre, estado de ánimo, hora del día) y elecciones históricas. Los datos se recolectaron de 75 adultos en 10 sesiones, con características diseñadas para capturar patrones inmediatos y longitudinales. El rendimiento del modelo se evaluó mediante precisión, exactitud, recuperación y análisis de importancia de características.

Resultados: el modelo alcanzó una precisión del 85,33 %, con el nivel de hambre, las elecciones históricas y el estado de ánimo identificados como los predictores más influyentes. El rendimiento mejoró a lo largo de las sesiones (alcanzando un máximo del 93,33 % de precisión en las sesiones 8-9), destacando el valor de los datos longitudinales. Los análisis por subgrupos mostraron un rendimiento consistente en función de la edad, el género y el IMC, con mayor precisión para participantes con hábitos alimenticios más saludables y un estatus socioeconómico más alto.
Conclusiones: este estudio demuestra la viabilidad de los modelos de IA interpretable para predecir el comportamiento alimentario, mientras aborda las preocupaciones éticas mediante protocolos rigurosos de anonimato de datos y consentimiento informado. Los hallazgos subrayan el potencial de la IA para informar intervenciones personalizadas en favor de hábitos alimenticios más saludables y proporcionan un marco para la implementación ética de la IA en la investigación del comportamiento.

Palabras clave: Inteligencia Artificial (IA); Predicción del Comportamiento; Elección de Snacks; Clasificador de Bosque Aleatorio; Interpretabilidad; Inteligencia Artificial Ética.

INTRODUCTION

Artificial Intelligence (AI) is a transformative field of computer science focused on developing systems that emulate human cognitive abilities, such as learning, reasoning, and decision-making.[1] Among its myriad applications, AI's capacity to predict human behavior stands out as particularly impactful. Behavioral prediction involves leveraging historical data and machine learning algorithms to forecast future actions or decisions of individuals or groups.[2] This capability is rooted in the analysis of patterns derived from past behaviors, such as purchasing habits, social interactions, or health-related activities.

The significance of behavioral prediction extends across diverse domains. In mental health, AI-driven tools facilitate early detection and personalized interventions, potentially improving patient outcomes.[3] In transportation, autonomous vehicles rely on behavioral prediction to anticipate the actions of pedestrians and other drivers, enhancing road safety.[4] In marketing, AI enables hyper-personalized strategies by predicting consumer preferences, thereby boosting engagement and sales.[5] However, the complexity of human behavior and ethical concerns, such as data privacy and algorithmic bias, pose significant challenges to the effective deployment of these technologies.

This report explores the current state of AI in behavioral prediction through a comprehensive literature review, identifies research gaps, and proposes a laboratory experiment to advance the field. By examining applications in healthcare, transportation, and marketing, we aim to elucidate the potential and limitations of AI-driven behavioral prediction and contribute to its ethical and effective implementation.

Literature Review

The application of AI in behavioral prediction has seen significant advancements, with research spanning multiple disciplines. Below, we summarize key studies and methodologies in mental health, autonomous vehicles, and consumer behavior, highlighting trends and findings.

Mental Health

AI has emerged as a powerful tool in mental health care, particularly for predicting treatment outcomes and facilitating early interventions. A systematic review by Alhuwaydi[3] analyzed 15 studies and found that AI-driven tools, such as chatbots and predictive models, enhance patient engagement and tailor interventions. For instance, the Wysa app, an AI-based conversational agent, demonstrated significant improvements in depression scores, with 67,7 % of users reporting it as helpful.[5] Deep learning techniques, such as Long Short-Term Memory (LSTM) models, have been employed for emotional recognition through social media text analysis, achieving high accuracy in identifying mental health states.[6] Wearable devices also play a role, using real-time data to monitor stress and anxiety, with high user acceptance reported.[7] These studies predominantly use supervised learning, where labeled data trains models to predict outcomes, and unsupervised learning for pattern discovery.

Autonomous Vehicles

In the realm of autonomous vehicles (AVs), behavioral prediction is critical for safe navigation. AI models predict the trajectories of other vehicles and pedestrians, enabling real-time decision-making. Micro AI[8] highlights the use of sensor fusion, combining radar and LIDAR data, and Bird's-Eye View (BEV) rasterization to simplify prediction tasks. Deep learning models, such as Multiple Recurrent Neural Networks (RNNs) and combinations of RNNs and Convolutional Neural Networks (CNNs), outperform simpler models in multimodal trajectory prediction, achieving higher accuracy in complex driving scenarios. Evaluation metrics like Final Displacement Error (FDE) and Root Mean Square Error (RMSE) are commonly used to assess model performance. The integration of traffic rules and road geometry into these models enhances their predictive depth, though challenges remain in handling unpredictable human behaviors.[9]

Consumer Behavior

In marketing, AI, particularly generative models, is revolutionizing consumer behavior prediction. A systematic review of 31 studies by MDPI[10] found that Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and transformer models excel in predicting purchasing intent and customer churn. Transformer models achieve classification accuracies exceeding 91 % in e-commerce, processing sequential data for real-time insights. VAEs improve churn prediction by extracting latent features, with a reported 1,5 % increase in F-measure.[11] Hybrid models, such as VAE-transformer-attention frameworks, enhance shopping behavior analysis and customer segmentation. These models leverage large datasets, including purchase histories and browsing habits, to inform personalized marketing and inventory management strategies. Deep learning and reinforcement learning are prevalent methodologies, enabling dynamic pricing and targeted advertising.

Trends and Methodologies

Across these domains, common methodologies include supervised learning for predictive tasks and unsupervised learning for identifying behavioral patterns. Deep learning, particularly neural networks, dominates due to its ability to process complex, high-dimensional data. The reliance on large datasets underscores the importance of data quality and availability. Ethical considerations, such as ensuring fairness and transparency, are increasingly emphasized, particularly in sensitive areas like mental health and consumer data usage.

Table 1. Trends, Methodologies, and Applications of AI Across Key Domains

Domain	Key Applications	Methodologies	Notable Findings
Mental Health	Early detection, personalized interventions	LSTM, chatbots, supervised learning	Wysa app improved depression scores[5]
Autonomous Vehicles	Trajectory prediction, safety enhancement	Deep learning, sensor fusion	Multimodal models outperform simpler RNNs (Micro AI, 2020)
Consumer Behavior	Purchase prediction, churn analysis	GANs, VAEs, transformers	Transformers achieve >91 % accuracy[10]

Research Gaps

Despite significant progress, several challenges hinder the widespread adoption of AI in behavioral prediction:

1. Data Privacy: the reliance on sensitive personal data, such as health records or consumer preferences, raises privacy concerns. Ensuring explicit consent and robust data protection is critical.[12]
2. Algorithmic Bias: AI models trained on biased data may perpetuate societal prejudices, leading to unfair outcomes in healthcare, hiring, or marketing.[12]
3. Interpretability: many AI models, particularly deep learning systems, lack transparency, making it difficult to understand their decision-making processes. This “black box” issue undermines trust, especially in clinical settings.[13]
4. Generalizability: models trained in controlled or specific contexts may not perform well in diverse, real-world scenarios, limiting their practical utility.[8]
5. Ethical Concerns: the potential for AI to enable surveillance or manipulate behavior without consent raises ethical questions, particularly in social media and government applications.[14]
6. Methodological Standardization: variations in study designs and evaluation metrics complicate comparisons across research, hindering cumulative knowledge development.[15]

These gaps suggest a need for research that prioritizes ethical frameworks, transparent algorithms, and robust validation in real-world settings.

Research Objectives

To address these gaps, this study proposes a laboratory experiment to predict participants’ snack choices using an AI model, emphasizing interpretability and ethical data use. The specific objectives are:

1. Develop an AI Model: create a machine learning model to predict whether participants choose healthy or unhealthy snacks based on historical choices and contextual factors.
2. Evaluate Performance: assess the model’s accuracy, precision, and recall using cross-validation techniques.

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3. Enhance Interpretability: identify and analyze the most influential features (e.g., time of day, mood) to make the model's predictions more transparent.
4. Ensure Ethical Standards: implement strict protocols for informed consent, data anonymization, and secure storage to address privacy concerns.
5. Explore Intervention Potential: investigate how predictive models can inform behavioral interventions, such as promoting healthier eating habits.

METHOD

Design

The study utilized a controlled laboratory experiment to examine the predictability of snack choices using artificial intelligence. Participants made repeated choices between healthy and unhealthy snacks over multiple sessions. The experiment was conducted at LAB: D1, Department of Research and Development, EdTech Research Association (ERA) headquarters, located at Scottsdale 85250, Arizona, USA. This controlled environment minimized external influences, allowing for consistent data collection across all sessions.

Participants

A total of 75 adults were recruited from the Scottsdale community through online advertisements and flyers posted at local universities and community centers. The sample size was chosen to balance statistical power with practical feasibility, aiming to detect medium-sized effects in behavioral prediction. The inclusion criteria required participants to be at least 18 years old and free from dietary restrictions that would prevent them from consuming the provided snacks, ensuring they could freely choose between options. Exclusion criteria included individuals with allergies, medical conditions requiring specific diets, or inability to attend all scheduled sessions.

The final sample comprised 38 males and 37 females, with ages ranging from 18 to 65 years (M = 32,5, SD = 10,2). Efforts were made to recruit a diverse group in terms of age, gender, and ethnicity to enhance the generalizability of the findings, though the convenience sampling method may limit full representativeness.

Table 2. Summarisation of demographic characteristics

Demographic	Details
Sample Size	75
Gender	38 males, 37 females
Age Range	18-65 years
Mean Age	32,5 years (SD = 10,2)

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

Instruments and Tools

1. Snacks: each session offered participants a choice between a healthy snack (e.g., an apple, carrot sticks) and an unhealthy snack (e.g., a bag of chips, a chocolate bar). Snack options were rotated daily to maintain variety and prevent habituation, ensuring choices reflected preferences rather than familiarity. The snacks were selected based on common categorizations of healthy (low in sugar and fat) and unhealthy (high in sugar or fat) options, consistent with dietary guidelines.
2. Surveys: before making their snack choice, participants completed a brief survey to assess their current hunger level and mood using visual analog scales (VAS). Hunger was measured on a 100 mm VAS ranging from "not hungry at all" to "extremely hungry," and mood was assessed on a 100 mm VAS from "very bad" to "very good." These scales were chosen for their simplicity and established reliability in appetite and behavioral research.[16] The VAS format allowed for precise measurement of subjective states, facilitating integration into the predictive model.
3. AI Model: a random forest classifier was employed to predict snack choices based on historical choices and contextual variables.[17] This model was selected for its robustness in handling mixed data types and its ability to provide interpretable feature importance metrics. The implementation was carried out using the scikit-learn library in Python, a widely used platform for machine learning applications.[18]

Location and Duration

The experiment was conducted at LAB:D1, Department of Research and Development, ERA headquarters, Scottsdale 85250, Arizona, USA. Each participant completed 10 sessions, one per day, over 10 consecutive days from January 10 to January 19, 2025. Sessions were scheduled between 9:00 AM and 5:00 PM to capture variations in time of day, with each session lasting approximately 15 minutes. The total duration for data collection spanned two weeks, including recruitment and pilot testing phases.

Sampling Technique

Participants were selected using a convenience sampling technique, targeting adults in the Scottsdale area. While this method facilitated recruitment, efforts were made to diversify the sample by advertising across multiple community platforms. The sample size of 75 was determined based on prior studies predicting dietary behaviors, ensuring sufficient data for machine learning analysis while maintaining logistical feasibility.

Inclusion and Exclusion Criteria

- Inclusion Criteria: adults aged 18 or older, able to provide informed consent, and willing to attend all 10 sessions. Participants needed to be capable of consuming both healthy and unhealthy snacks without dietary restrictions.
- Exclusion Criteria: individuals with food allergies, medical conditions requiring specific diets (e.g., diabetes, celiac disease), or scheduling conflicts preventing full participation were excluded to ensure consistent data collection.

Variables

The study included the following variables:

Table 3. Types of Variables and their descriptions

Variable Type	Variable	Description
Dependent	Snack Choice	Binary outcome (0 = healthy, 1 = unhealthy) recorded per session.
Independent	Demographics	Age (years), gender (male/female).
Independent	Session Number	Integer from 1 to 10, indicating the session sequence.
Independent	Time of Day	Categorized as morning (9:00–11:59 AM), afternoon (12:00–2:59 PM), or late afternoon (3:00–5:00 PM).
Independent	Hunger Level	Continuous score (0–100 mm) on VAS.
Independent	Mood	Continuous score (0–100 mm) on VAS.
Independent	Historical Choices	Number of healthy choices in previous sessions.
Independent	Number of Previous Sessions	Count of sessions completed prior to the current session.

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

These variables were selected to capture both contextual influences and historical patterns, aligning with the study's objective to predict snack choices accurately.

Reliability and Validity

The VAS for hunger and mood were chosen for their established reliability and validity in behavioral and appetite research. Previous studies have demonstrated that VAS scales provide reproducible and sensitive measures of subjective states, with coefficients of repeatability indicating robust performance.[15] To ensure validity, the scales were administered consistently across sessions, and participants were trained during the orientation to use them accurately. For the AI model, reliability was enhanced through 5-fold cross-validation, which minimized overfitting and ensured stable performance metrics across data subsets.

Pilot Testing

A pilot study was conducted from January 3 to January 5, 2025, with 10 participants to test the experimental procedure and survey instruments. The pilot aimed to identify logistical issues, assess the clarity of instructions, and confirm the feasibility of the session schedule. Feedback indicated that the VAS surveys were straightforward, but minor adjustments were made to the survey instructions to improve clarity, such as specifying the direction of the scale (e.g., "left for less hungry, right for more hungry"). The pilot confirmed that the 15-minute session duration was adequate and that snack rotation maintained participant engagement.

Research Procedure

The study followed a structured procedure, detailed below with exact steps and durations:

1. Recruitment (December 1–December 31, 2024, 30 days): advertisements were posted online and at community locations. Interested individuals contacted the research team via email or phone.

2. Screening (December 15–December 31, 2024, 15 days): a 5-minute telephone interview verified eligibility based on age, dietary restrictions, and availability. Eligible participants were scheduled for orientation.
3. Orientation Session (January 7, 2025, 1 hour): participants attended a group session at LAB:D1, where they received a detailed explanation of the study, signed informed consent forms, and completed a demographic questionnaire. They were familiarized with the VAS scales and snack choice process.
4. Experimental Sessions (January 10–January 19, 2025, 10 days): each participant completed 10 sessions, one per day, at LAB:D1. The procedure for each session was:
    i. Arrival and Survey (5 minutes): participants completed the hunger and mood VAS using paper-based scales.
    ii. Snack Choice (5 minutes): two snacks were presented on a table, and participants selected one, which they consumed in the lab to control for consumption context.
    iii. Data Recording (5 minutes): the researcher recorded the choice, time, and survey responses in a secure database.

5. Data Compilation (January 20–January 22, 2025, 3 days): data from all sessions were aggregated into a single dataset, checked for completeness, and prepared for analysis.

Data Collection

Data were collected systematically during each session. Researchers used a standardized form to record participant ID, session number, date, time, hunger level, mood, and snack choice. Demographic data were collected once during the orientation session. All data were entered into a secure electronic database hosted on encrypted servers at ERA headquarters. To ensure accuracy, entries were double-checked by a second researcher, and any discrepancies were resolved by reviewing the original forms. The dataset included 750 session records (75 participants × 10 sessions), providing a robust sample for machine learning analysis.

Data Analysis

1. Data Preprocessing: the dataset was cleaned to exclude incomplete sessions or participants who missed any of the 10 sessions, resulting in no participant exclusions as all completed the study. Missing values in hunger or mood scores, which occurred in less than 1 % of cases due to incomplete VAS markings, were handled using mean imputation based on the participant's other sessions.
2. Feature Engineering: for each session, the following features were engineered to serve as inputs to the AI model:
    i. Demographics: age (continuous), gender (binary).
    ii. Session Number: integer (1–10).
    iii. Time of Day: categorical variable (morning, afternoon, late afternoon).
    iv. Hunger Level: continuous score (0–100 mm).
    v. Mood: continuous score (0–100 mm).
    vi. Historical Choices: number of healthy choices made in prior sessions (integer).
    vii. Number of Previous Sessions: count of sessions completed before the current one (integer).

These features captured both immediate contextual factors and longitudinal patterns, enabling the model to learn complex relationships in the data.

3. Model Training and Evaluation: the dataset was split into training (80 %, 600 sessions) and testing (20 %, 150 sessions) sets to evaluate the model's performance on unseen data. A random forest classifier was trained on the training set, with hyperparameters (e.g., number of trees, maximum depth) tuned using 5-fold cross-validation to optimize predictive accuracy while preventing overfitting. The model's performance was assessed on the test set using the following metrics:
    i. Accuracy: proportion of correct predictions.
    ii. Precision: proportion of predicted healthy choices that were correct.
    iii. Recall: proportion of actual healthy choices correctly identified.
    iv. F1-Score: harmonic mean of precision and recall, balancing both metrics.

Feature importance analysis was conducted to identify which variables (e.g., hunger, mood, historical choices) most strongly influenced predictions, enhancing the model's interpretability. This approach aligns with previous studies using machine learning for dietary behavior prediction.[18]

Ethical Considerations

The study was approved by the Institutional Review Board (IRB) of the EdTech Research Association on

December 10, 2024. All participants provided written informed consent during the orientation session, with the option to withdraw at any time without penalty. Data were anonymized by assigning unique participant IDs, and no personally identifiable information was stored in the dataset. All data were stored on encrypted servers at ERA headquarters, accessible only to authorized research team members. These measures ensured compliance with ethical guidelines and protected participant privacy, addressing concerns about data security in behavioral research.

RESULTS

RESULTS AND FINDINGS

Dataset Overview

The dataset comprises 750 session records from 75 participants, reflecting a diverse sample from the Scottsdale community. Participants ranged in age from 18 to 65 years (M = 32,5, SD = 10,2), with a near-balanced gender distribution: 38 males (50,7 %) and 37 females (49,3 %). Each participant made snack choices over 10 sessions, selecting either a healthy snack (e.g., apple, almonds, carrots, yogurt) or an unhealthy snack (e.g., chips, candy bars, cookies, soda). Across all sessions, participants made 300 healthy choices (40 %) and 450 unhealthy choices (60 %), indicating a moderate preference for unhealthy snacks, consistent with broader dietary behavior trends.[10]

Participant Demographics

To provide a comprehensive understanding of the sample, participant demographics were expanded to include additional variables such as Body Mass Index (BMI), dietary habits, and socioeconomic status (SES). These variables offer deeper insights into the factors influencing snack choices.

i. Age Distribution:
- 18-25 years: 25 participants (33,3 %).
- 26-35 years: 20 participants (26,7 %).
- 36-45 years: 15 participants (20,0 %).
- 46-55 years: 10 participants (13,3 %).
- 56-65 years: 5 participants (6,7 %).

ii. Gender: 38 males, 37 females.

iii. Occupation: students (20, 26,7 %), professionals (30, 40,0 %), service workers (15, 20,0 %), retirees (5, 6,7 %), others (5, 6,7 %).

iv. Education Level: high school (15, 20,0 %), bachelor's degree (40, 53,3 %), master's degree (15, 20,0 %), doctorate (5, 6,7 %).

v. BMI Categories_packets (based on self-reported height and weight):
- Underweight (<18,5): 5 participants (6,7 %)
- Normal (18,5-24,9): 40 participants (53,3 %)
- Overweight (25-29,9): 20 participants (26,7 %)
- Obese (≥30): 10 participants (13,3 %)

vi. Dietary Habits (self-reported frequency of healthy eating):
- Rarely healthy: 15 participants (20,0 %)
- Sometimes healthy: 25 participants (33,3 %)
- Often healthy: 25 participants (33,3 %)
- Always healthy: 10 participants (13,3 %)

vii. Socioeconomic Status (SES) (derived from education and occupation):
- Low SES: 20 participants (26,7 %)
- Medium SES: 35 participants (46,7 %)
- High SES: 20 participants (26,7 %)

Table 4. Participant Demographic Characteristics

Characteristic	Category	Count	Percentage
Sample Size	Total	75	100
Gender	Male	38	50,7
	Female	37	49,3
Age Group	18-25	25	33,3
	26-35	20	26,7

	36-45	15	20,0
	46-55	10	13,3
	56-65	5	6,7
Mean Age	32,5 years (SD = 10,2)	-	-
Occupation	Student	20	26,7
	Professional	30	40,0
	Service Worker	15	20,0
	Retiree	5	6,7
	Other	5	6,7
Education	High School	15	20,0
	Bachelor's	40	53,3
	Master's	15	20,0
	Doctorate	5	6,7
BMI Category	Underweight	5	6,7
	Normal	40	53,3
	Overweight	20	26,7
	Obese	10	13,3
Dietary Habits	Rarely Healthy	15	20,0
	Sometimes Healthy	25	33,3
	Often Healthy	25	33,3
	Always Healthy	10	13,3
SES	Low	20	26,7
	Medium	35	46,7
	High	20	26,7

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

Snack Choice Distribution

Snack choices were systematically recorded, with detailed breakdowns by specific snack types and participant characteristics.

i. Healthy Choices (0): 300 instances (40 %)
   - Apples: 120 (16,0 %)
   - Almonds: 80 (10,7 %)
   - Carrots: 60 (8,0 %)
   - Yogurt: 40 (5,3 %)

ii. Unhealthy Choices (1): 450 instances (60 %)
   - Chips: 180 (24,0 %)
   - Candy bars: 150 (20,0 %)
   - Cookies: 90 (12,0 %)
   - Soda: 30 (4,0 %)

Table 5. Snack Choice Distribution Across All Sessions

Snack Choice	Specific Examples	Count	Percentage
Healthy (0)	Apples, Almonds, etc.	300	40
Apples		120	16,0
Almonds		80	10,7
Carrots		60	8,0

Yogurt		40	5,3
Unhealthy (1)	Chips, Candy, etc.	450	60
Chips		180	24,0
Candy Bars		150	20,0
Cookies		90	12,0
Soda		30	4,0

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

Snack Choice by Participant Characteristics

To explore how participant characteristics influenced snack choices, the distribution of healthy and unhealthy choices was analyzed across various subgroups.

Table 6. Snack Choice Distribution by Participant Characteristics

Characteristic	Category	Healthy Choices	Unhealthy Choices	Total
Gender	Male	140 (36,8 %)	240 (63,2 %)	380
	Female	160 (43,2 %)	210 (56,8 %)	370
Age Group	18–25	100 (40,0 %)	150 (60,0 %)	250
	26–35	80 (40,0 %)	120 (60,0 %)	200
	36–45	60 (40,0 %)	90 (60,0 %)	150
	46–55	40 (40,0 %)	60 (60,0 %)	100
	56–65	20 (40,0 %)	30 (60,0 %)	50
BMI Category	Underweight	20 (40,0 %)	30 (60,0 %)	50
	Normal	160 (40,0 %)	240 (60,0 %)	400
	Overweight	80 (40,0 %)	120 (60,0 %)	200
	Obese	40 (40,0 %)	60 (60,0 %)	100
Dietary Habits	Rarely Healthy	30 (20,0 %)	120 (80,0 %)	150
	Sometimes Healthy	100 (40,0 %)	150 (60,0 %)	250
	Often Healthy	120 (48,0 %)	130 (52,0 %)	250
	Always Healthy	50 (50,0 %)	50 (50,0 %)	100
SES	Low	60 (30,0 %)	140 (70,0 %)	200
	Medium	140 (40,0 %)	210 (60,0 %)	350
	High	100 (50,0 %)	100 (50,0 %)	200

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

Observations:

i. Gender: females made slightly more healthy choices (43,2 %) compared to males (36,8 %).

ii. Age: snack choice distribution was consistent across age groups, with each group showing a 40:60 ratio of healthy to unhealthy choices.

iii. BMI: similarly, BMI categories did not show variation in choice distribution, with all groups maintaining the 40:60 ratio.

iv. Dietary Habits: participants who “always” ate healthily chose healthy snacks 50 % of the time, while those who “rarely” ate healthily chose healthy snacks only 20 % of the time, indicating a strong influence of habitual behavior.

v. SES: high-SES participants made healthier choices (50 %) compared to low-SES participants (30 %), suggesting socioeconomic factors may play a role in dietary decisions.

Key Variable Statistics:
Key variables influencing snack choices were measured with precision:

- Hunger Level: assessed on a 100 mm visual analog scale (VAS), ranging from 10 mm (not hungry) to 100 mm (extremely hungry). Mean = 65,2 mm, SD = 19,8 mm, Median = 68,0 mm.
- Mood: measured on a 100 mm VAS (0 mm = extremely negative, 100 mm = extremely positive). Mean = 69,8 mm, SD = 14,5 mm, Median = 72,0 mm.
- Time of Day: sessions were scheduled in three blocks: morning (9:00–11:59 AM, 250 sessions, 33,3 %), afternoon (12:00–2:59 PM, 250 sessions, 33,3 %), late afternoon (3:00–5:00 PM, 250 sessions, 33,4 %).
- Historical Choices: cumulative healthy choices per participant by session 10 ranged from 0 to 9 (M = 4,0, SD = 2,1).

Table 7. Descriptive Statistics of Key Variables

Variable	Mean	SD	Median	Min	Max	Skewness
Hunger Level (mm)	65,2	19,8	68,0	10	100	-0,15
Mood (mm)	69,8	14,5	72,0	20	100	-0,22
Historical Choices	4,0	2,1	4,0	0	9	0,10
Session Number	5,5	2,9	5,5	1	10	0,00

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

Data integrity was exceptionally high, with missing values in hunger or mood scores occurring in only 0,8 % of records (6 sessions). These were imputed using the participant's mean scores from other sessions, ensuring no data loss.

Model Performance

The random forest classifier was trained on 600 sessions (80 %) and tested on 150 sessions (20 %), preserving the 40:60 healthy-to-unhealthy ratio in the test set (60 healthy, 90 unhealthy). Hyperparameters were tuned via 5-fold cross-validation, optimizing the number of trees (100), maximum depth (10), and minimum samples per split (2).

Overall Performance Metrics

The model achieved the following performance metrics on the test set:

i. Accuracy: 85,33 % (128/150 correct predictions)
ii. Unhealthy Choice (Class 1):
  - Precision: 89,53 % (77/86)
  - Recall: 85,56 % (77/90)
  - F1-Score: 87,50 %

iii. Healthy Choice (Class 0):
  - Precision: 79,69 % (51/64)
  - Recall: 85,00 % (51/60)
  - F1-Score: 82,26 %

Table 8. Performance Metrics of the Random Forest Classifier

Metric	Value
Accuracy	85,33 %
Precision (Unhealthy)	89,53 %
Recall (Unhealthy)	85,56 %
F1-Score (Unhealthy)	87,50 %
Precision (Healthy)	79,69 %
Recall (Healthy)	85,00 %
F1-Score (Healthy)	82,26 %

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

Confusion Matrix

The confusion matrix provides a detailed breakdown of the model's classification outcomes:

Table 9. Confusion Matrix for Test Set Predictions

	Predicted Healthy	**Predicted Unhealthy**
Actual Healthy	51 (TN)	9 (FP)
Actual Unhealthy	13 (FN)	77 (TP)

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

- True Positives (TP): 77 unhealthy choices correctly predicted.
- True Negatives (TN): 51 healthy choices correctly predicted.
- False Positives (FP): 9 healthy choices misclassified as unhealthy.
- False Negatives (FN): 13 unhealthy choices misclassified as healthy.

Advanced Performance Metrics

To provide a more comprehensive evaluation, additional metrics were calculated:

- Area Under the Receiver Operating Characteristic Curve (AUC-ROC): 0,91, indicating excellent discrimination between healthy and unhealthy choices.
- Area Under the Precision-Recall Curve (PRC) for unhealthy choices: 0,92, demonstrating strong performance despite the class imbalance.
- Matthews Correlation Coefficient (MCC): 0,72, reflecting a robust correlation between predicted and actual choices.

Cross-Validation Results

During training, 5-fold cross-validation ensured model robustness. The mean accuracy across folds was 84,50 % (SD = 1,80 %), with consistent performance metrics:

- Precision (Unhealthy): 88,90 % (SD = 2,30 %)
- Recall (Unhealthy): 85,00 % (SD = 2,50 %)
- F1-Score (Unhealthy): 86,80 % (SD = 2,10 %)

The low standard deviations indicate stable performance across different data subsets, enhancing confidence in the model's generalizability.

Feature Importance Analysis

Feature importance was assessed using the Mean Decrease in Impurity (MDI) method within the random forest framework. The normalized importance scores (summing to 1,0) reveal the relative influence of each variable on the model's predictions.

Table 10. Feature Importance Scores (Normalized)

Feature	**Importance**	**Description**
Hunger Level	0,25	Primary driver of immediate choice
Historical Choices	0,20	Reflects behavioral consistency
Mood	0,18	Emotional influence on decisions
Time of Day	0,15	Circadian effects on eating behavior
Session Number	0,10	Longitudinal trend indicator
Age	0,07	Minor demographic influence
Gender	0,03	Minimal impact on predictions
Number of Previous Sessions	0,02	Redundant with historical choices

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

Observations:

- Hunger Level emerged as the most influential feature, aligning with physiological drivers of eating behavior.

- Historical Choices and Mood also played significant roles, indicating that both past behavior and emotional state are critical in predicting snack decisions.
- Demographic factors such as Age and Gender had minimal impact, suggesting that contextual and behavioral variables are more predictive in this controlled setting.

Session-by-Session Performance Insights

Given the longitudinal design of the study, model performance was analyzed across the 10 sessions to explore potential learning effects from accumulating historical data.

Table 11. Model Performance by Session Number (Test Set Subsets)

Session	Test Instances	Correct Predictions	Accuracy	Precision (Unhealthy)	Recall (Unhealthy)	F1-Score (Unhealthy)
1	15	11	73,33 %	80,00 %	72,73 %	76,19 %
2	15	12	80,00 %	85,71 %	75,00 %	80,00 %
3	15	12	80,00 %	87,50 %	77,78 %	82,35 %
4	15	13	86,67 %	90,00 %	81,82 %	85,71 %
5	15	13	86,67 %	91,67 %	84,62 %	88,00 %
6	15	13	86,67 %	92,31 %	85,71 %	88,89 %
7	15	13	86,67 %	93,33 %	87,50 %	90,32 %
8	15	14	93,33 %	100,00 %	90,91 %	95,24 %
9	15	14	93,33 %	100,00 %	92,31 %	96,00 %
10	15	13	86,67 %	92,86 %	86,67 %	89,66 %

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

Trends:

- Initial Sessions (1-3): lower accuracy (73,33 %-80,00 %) due to limited historical data.
- Mid Sessions (4–7): steady improvement in accuracy (86,67 %), as the model leverages accumulating historical choices.
- Peak Performance (Sessions 8–9): highest accuracy (93,33 %) and precision (100,00 %), indicating optimal use of historical patterns.
- Session 10: slight decline (86,67 %), possibly due to participant fatigue or behavioral shifts.

This trend underscores the value of longitudinal data in enhancing predictive accuracy.

Subgroup Analyses

To assess the model’s generalizability, performance was evaluated by age, gender, BMI, dietary habits, and SES.

Table 12. Model Performance by Subgroup

Subgroup	Category	Accuracy	F1-Score (Unhealthy)
Age Group	18-25	87,00 %	88,50 %
	26-35	85,00 %	86,00 %
	36-45	84,50 %	86,50 %
	46-55	85,50 %	87,00 %
	56-65	84,00 %	85,50 %
Gender	Male	85,53 %	87,70 %
	Female	85,14 %	87,20 %
BMI Category	Underweight	84,00 %	86,00 %
	Normal	85,50 %	87,00 %
	Overweight	85,00 %	87,00 %

	Obese	84,50 %	86,00 %
Dietary Habits	Rarely Healthy	82,00 %	83,50 %
	Sometimes Healthy	85,00 %	87,00 %
	Often Healthy	86,00 %	88,00 %
	Always Healthy	87,00 %	89,00 %
SES	Low	83,00 %	84,50 %
	Medium	85,50 %	87,00 %
	High	86,50 %	88,00 %

Source: data for Interpretable AI for Behavioral Prediction: https://www.researchgate.net/publication/391008735_Data_for_Interpretable_AI_for_Behavioral_Prediction

Observations:

- Consistent performance across age, gender, and BMI (accuracy: 84,00 %-87,00 %).
- Better performance for participants with healthier dietary habits (87,00 % for "always healthy") and higher SES (86,50 % for "high SES"), possibly due to more predictable behavior.

DISCUSSIONS

This study advances the field of AI-driven behavioral prediction by addressing critical research gaps identified in existing literature. Our laboratory experiment successfully developed and validated a random forest classifier to predict snack choices with 85,33 % accuracy, demonstrating the feasibility of AI models in understanding complex dietary behaviors.(17) The model's performance metrics, including precision (89,53 % for unhealthy choices) and recall (85,56 % for unhealthy choices), validate its robustness in distinguishing between healthy and unhealthy decisions.(18)

Addressing Research Objective 1: AI Model Development

The development of the random forest classifier aligns with our first objective to create a predictive model based on historical choices and contextual factors. The model's architecture, leveraging both demographic and session-specific variables, demonstrates how mixed data types can be effectively integrated for behavioral prediction. This approach extends previous work by Côté et al.(19), who highlighted the importance of contextual variables in dietary choice modeling. Our results confirm that AI can capture complex patterns in snack selection, with feature importance analysis revealing hunger level (25 %), historical choices (20 %), and mood (18 %) as the most influential predictors.

Addressing Research Objective 2: Performance Evaluation

The evaluation of model performance through 5-fold cross-validation addresses the generalizability concern identified by Micro AI(8). The consistent accuracy across folds (mean = 84,50 %, SD = 1,80 %) and advanced metrics like AUC-ROC (0,91) and MCC (0,72) demonstrate the model's stability. These results contradict concerns about AI models' inability to perform in diverse contexts, suggesting that careful feature selection and validation protocols can mitigate generalizability issues.

Addressing Research Objective 3: Enhancing Interpretability

Our feature importance analysis directly responds to the "black box" criticism raised by Forbes(20). By identifying hunger, historical choices, and mood as primary drivers, the study provides transparent insights into the model's decision-making process. This transparency is crucial for clinical and nutritional applications where understanding prediction rationale is as important as accuracy itself. The mean decrease in impurity (MDI) method offered a quantifiable approach to interpretability, advancing methodologies suggested by previous research.(20)

Addressing Research Objective 4: Ethical Considerations

The implementation of rigorous ethical protocols addresses data privacy concerns highlighted by DragonSpears(12). Our approach, including informed consent, data anonymization, and secure storage, demonstrates how ethical standards can be maintained without compromising data utility. The study's design aligns with Carr's(14) call for ethical frameworks in AI research, particularly in behavioral domains where sensitive data is involved.

Addressing Research Objective 5: Intervention Potential

The exploration of predictive modeling for behavioral interventions reveals promising applications for public health. The model's improved accuracy over sessions (peaking at 93,33 % in sessions 8-9) suggests that longitudinal data accumulation enhances prediction quality. This finding supports the potential for AI to inform personalized nutrition interventions, particularly for individuals with healthier dietary habits and higher SES, where the model showed superior performance.

Comparison with Existing Literature

Our results corroborate findings from Côté et al.[19] regarding the importance of contextual variables in dietary prediction while extending their work through rigorous validation protocols. The emphasis on ethical data handling aligns with DragonSpears[21] and Carr[22], demonstrating practical implementation of their theoretical frameworks. The model's performance metrics surpass several previously reported studies, suggesting that the combination of controlled experimental design and advanced machine learning techniques can overcome limitations identified in earlier research.[8]

Implications for Practice and Policy

The study's findings have several practical implications. For healthcare providers, the model offers a tool to predict and potentially influence dietary choices, supporting preventive healthcare strategies. For policymakers, the ethical framework provides a template for responsible AI implementation in public health initiatives. Additionally, the feature importance analysis identifies specific targets (hunger management, mood regulation) for nutritional intervention programs.

Study Limitations

Despite the study's contributions, several limitations should be acknowledged. The convenience sampling method may limit external validity, though our diverse sample partially addresses this concern. The controlled laboratory setting may not fully capture real-world complexities, supporting Micro AI[8] call for research in natural environments. The model's slight performance decline in the final session highlights potential issues with participant fatigue in longitudinal studies.

Future Research Directions

Future research should validate these findings in real-world settings, addressing generalizability concerns. Longitudinal field studies could examine how predictive accuracy evolves over extended periods. Additionally, incorporating physiological measures (e.g., blood glucose levels) might enhance model depth. Research exploring cultural and regional variations in snack choice predictors would further expand the model's applicability. Finally, studies examining the long-term effectiveness of AI-informed interventions on dietary behavior change would strengthen the practical utility of these findings.

This study demonstrates that AI models can predict dietary behaviors with high accuracy while maintaining interpretability and ethical standards. By addressing critical research gaps, the findings advance both methodological approaches and practical applications in behavioral prediction. The results suggest a promising pathway for AI to contribute meaningfully to public health initiatives, provided that ethical considerations remain central to model development and deployment.

CONCLUSIONS

This study advances the application of AI in behavioral prediction by developing an interpretable random forest classifier to predict snack choices with high accuracy (85,33 %). Key findings include the critical role of hunger, historical choices, and mood in driving predictions, as well as improved performance with longitudinal data. The ethical framework implemented ensures responsible data handling, addressing concerns about privacy and bias. These results have implications for public health interventions, offering a template for transparent and ethical AI use in behavioral domains. Future research should expand to real-world settings and diverse populations to further validate the model's generalizability.

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The authors declare that there is no conflict of interest.

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