AI TOOLS IN BABY FOOD SAFETY: CURRENT APPLICATIONS, PARENTAL TRUST AND FUTURE DIRECTIONS

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ABSTRACT

The safety of baby food remains a critical public health challenge as shown by recent findings of heavy metal contamination and historical gaps in regulation. This review examines how artificial intelligence (AI) can enhance detection of contaminants (e.g., lead) and allergens while improving supply chain transparency by using techniques such as, machine learning, hyperspectral imaging, and AI-powered blockchain. This review analyses AI's role in modern baby food production, highlighting real-world applications like Gerber's AI Food Planner and Tiny Human Food AI. However, adoption faces barriers such as, cybersecurity risks in AI-driven systems and regulatory lag. While AI offers transformative potential, this review argue that its success depends on collaborative oversight among manufacturers, policymakers, and parents. The study has analysed 60+ sources to discuss ethical AI applications in baby food production whilst urging stricter standards to align innovation with child health priorities.

KEYWORDS

Baby food, Artificial Intelligence (AI), Food Safety, Blockchain Technology

1. INTRODUCTION

The safety of baby food has become a critical public health issue, especially after a 2021 U.S. Congressional report revealed that 95% of tested baby foods contained dangerous levels of heavy metals**,** including lead, cadmium, and arsenic [1]. Concerns over infant nutrition and food safety are not new; they trace back to the mid-18th century when the Industrial Revolution shifted parental feeding practices. As more parents entered the workforce, demand grew for convenient, nutritionally adequate alternatives to breastfeeding [2].

Baby food is specifically designed to meet the dietary needs of infants (0–3 years), preschoolers (3–6 years), and older children while ensuring safety for their developmental stage [3]. The first commercial baby food emerged when Harold Clapp developed a vegetable puree after his wife fell ill and could not breastfeed [2]. By the 1930s, companies like Gerber mass-produced strained fruits, vegetables, and meat-based baby foods, fueling industry growth [4].

However, as production scaled, it has resulted in an increased number of safety concerns. In the 1960s-1970s, parents started questioning ingredient transparency, nutritional adequacy, and the use of preservatives in baby food [2]. Additionally, Ferguson and Carson's work [5] highlighted pesticide residues in agricultural raw materials for baby food production, raising alarms about long-term health effects on infants. More recently, studies by the Environmental Defense Fund [6] and Hirsch[7] found detectable lead, cadmium, and arsenic in up totwo-thirds of tested baby foods.Chronic exposure to lead, cadmium, and arsenic is linked to neurodevelopmental harm, cancer, and other long-term health risks [8].

In response, manufacturers are turning to artificial intelligence (AI) to enhance safety and quality control. AI techniques like machine learning enablereal-time contaminant detection, while computer vision improves production line inspections. Predictive analytics helps mitigate supply chain risks[9]**.**Tools like Gerber's AI Food Planner and Tiny Human Food AI are already helping parents navigate nutritional needs, yet skepticism persists. Although both manufacturers and parents are trusting AI, ethical concerns such as data privacy and algorithmic bias demand scrutiny.

While existing research explores AI's broad applications in food safety, this review will therefore examine how AI technologies can address persistent safety challenges in baby food production while also evaluating parental trust, ethical risks, and regulatory needs. As AI transforms food safety protocols, balancing innovation with accountability will be key to restoring confidence in infant nutrition.

2. DISCUSSION

Artificial Intelligence (AI) is transforming the food industry through advanced techniques such as, machine learning, deep learning, computer vision and natural language processing. These techniques allow AI tool enhance food safety, quality control, and contamination detection throughout the production process. In baby food manufacturing, AI would play a critical role in minimizing health risks by identifying heavy metals, allergens, chemical and microbial hazards.

2.1. AI Tools in Food Production and Adaptability for Baby Food Production

Artificial Intelligence (AI) leverages techniques such as image analysis and computer vision (CV), natural language processing (NLP), machine learning (ML), deep learning (DL), and neural network cognitive computing. These techniques allow AI to be used in the food industry to help in sorting food quality, accelerating the supply chain management process, protecting food safety, developing new and consumer demanding food products, keeping sanitation of equipment, and improving food production quality [10].

Machine learning (ML) employs training algorithms that allow the computer to learn from a large dataset (training data) and make autonomous decisions without being explicitly programmed to do so [11]. The training data has data of both contaminated and clean samples. The ML learns the patterns of the training data and compares it to the data collected to detect deviations from the threshold in real time [12].

ML integrates databases, spectroscopic techniques, imaging (Multispectral, and hyperspectral techniques), and AI-powered sensors to monitor, identify, predict, and prevent chemical and microbiological hazards, adulteration detection, and quality assessment [13]. The main difference between machine learning and deep learn (DL) is that, apart from training data, DL also learns from its mistakes from previous decisions, unlike ML, which mostly requires human intervention for best results [14]. Additionally, deep learning (DL), an innovative approach for analyzing data and pictures, effectively manages to achieve high prediction by handling immense amounts of spectral data to uncover profound features [15].

Hyperspectral and multispectral imaging techniques detect and identify contamination by reading the difference in light absorption of the samples [16]. Hyperspectral imaging has been given much attention as it has shown accuracy in heavy metals detection [17]. It excels in detecting heavy metals at concentrations below 1 mg/kg [18][19]. Due to anthropogenic activities, heavy metals are released into the atmosphere, water, and soil in different forms [20]. These metals are then absorbed by plants grown on contaminated soil or irrigated by contaminated water [21]. In livestock, heavy metals come from supplements of essential elements such as copper (Cu) and zinc (Zn) in animal feed [22].

In computer vision (CV), cameras are used to detect the physical structure of the product. Pictures are obtained at multiple points and analyzed to detect any deformation or external contamination. For instance, Kewpie Corp (Japan) uses Google's TensorFlow AI to analyze 18,000 photos of potatoes per batch, ensuring that the ingredients used for baby food production are safe [23].

IA-powered sensors are being used to detect in real time the presence of chemical residues, heavy metals, and allergens or other contaminants in food production [24]. These sensors help to identify contaminants before they reach the consumers; hence, when they are used in baby food production, they will help to minimize the presence of heavy metals in baby foods to allowable limits.

Minimizing the amount of heavy metals present in baby food products starts with procuring raw materials that are free from contamination. By using AI techniques to analyze the soil before planting, it will help to minimize the presence of heavy metals in plant-based baby food such as baby rice cereals. This can also be complemented by testing ingredients at multiple stages of production. Even though health experts (U.S Center for Disease Control and Prevention and the World Health Organization) have concluded that no level of heavy metals such as lead is deemed safe for infants and toddlers, the USFDA has set 10 parts per billion (ppb) for many products and 20 ppb for baby cereals and vegetables as actionable level of lead [25]. Furthermore, it has also set 100ppb as the actionable level of arsenic in baby rice cereal [26].

Non-distractive methods, such as Fourier Transform Infrared (FTIR) Spectroscopy and Hyperspectral Imaging, are also being used to identify allergy-causing proteins in raw materials by analyzing light absorbance of the samples [27]. Knowing which wavelength band is of interest to the manufacturer can help to detect the presence of allergens in the baby food. Identifying proteins that may cause hypersensitivity of the immune system of infants and toddlers will help manufacturer to properly label the food package, subsequently helping parents to choose products that will not cause allergenic reaction. This technique does not come into contact with the product, hence does not cause contamination.

When AI has detected or predicted that the product will be contaminated or there is an allergycausing protein, by using IoT (Internet of Things) sensors [28][29], ML algorithms optimizes parameter within the production line by using techniques such as High Pressure Processing and predict ideal conditions to maximize pathogen inactivation or neutralize the chemical hazard while preserving the quality of the product [30].

To enhance food traceability and recalls, scientists have integrated artificial intelligence (AI) with blockchain systems, resulting in an AI-powered blockchain that facilitates the capabilities and functions of both technologies [31]. Blockchain achieves traceability and recalls by keeping a complete record of the product from raw material, processing, storage, distribution, and quality control processes up to the consumer [32]. In blockchain technology, data is distributed to several computers/servers so that no entity has authority to change the data. Each transaction is recorded into a block and linked to the previous block. Everyone involved in this network has access to the information at any particular point [33]. This technology ensures that the data is transparent, reliable, and trustworthy. Figure 1.0shows an illustration of AI-powered blockchain technology.

Application of AI in baby food production can help to ensure that the baby foods are free from microbial hazards, heavy metals, and allergens, hence protecting the health of infants and toddlers.

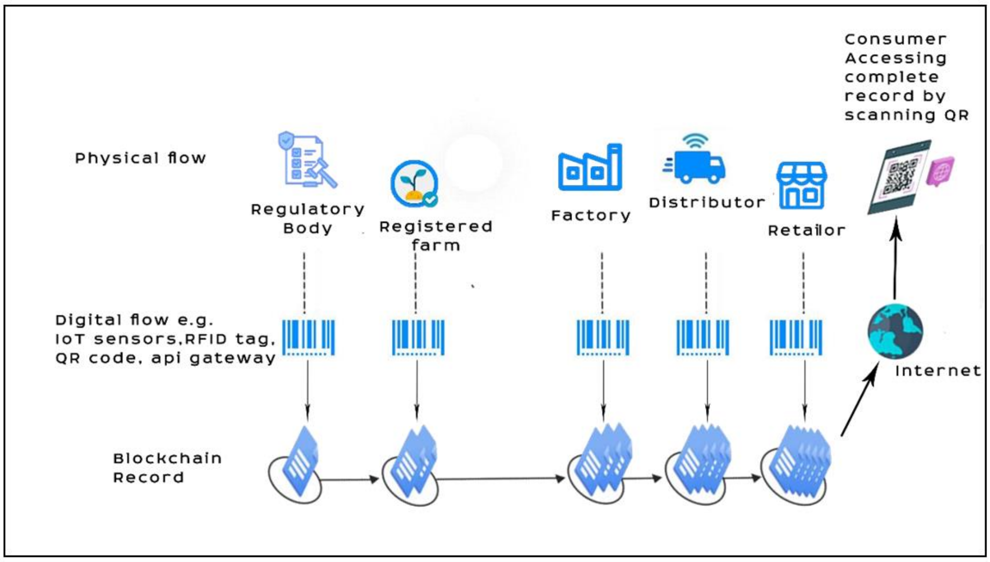

Figure 1.0AI-powered blockchain

2.2. Parental Adoption for AI-Driven Food Choices

As Artificial Intelligence is constantly shaping food production to ensure safety and quality of the food products, baby food manufacturers are giving parents a sense of control over baby food selection and formulation by introducing interactive AI tools.

AI utilizes natural language processing (NLP) technique, which focuses on computational linguistics interpretation. NLP encompasses several areas of textual and audio interpretation [34]. This technique allows the collection and analysis of large volumes of textual data. NLP processes consumer feedback from various platforms, and it helps the manufacturer detect reported safety issues. This ensures quicker resolution to any reported baby food safety issue; hence, consumer trust is maintained [35].

NLP is helping parents to identify manufacturers that are not complying or that are violating regulations in baby food production. NLP examines regulatory documents, inspection reports, and compliance records. When parents have scanned the packaged baby food or typed the name of the manufacturer, the AI tools provide all the details associated with the manufacturer.

Research from the University of Kansas Life Span Institute has shown that parents are trusting AI tools such as chatbots and large language models such as ChatGPT than experts for health care information about their children. Parents have found AI to be more trustworthy, accurate, and reliable [36]. This shows that parents are relying more on AI than dietitians to fulfill the nutritional needs of their infants and toddlers.

Other AI tools, such as the WHO AI tool, are helping parents to report any promoted unhealthy products that are targeting infants and toddlers [37]. Additionally, as manufacturers are now making test results of heavy metals in baby food publicly available, parents are using AI scanners to scan the QR codes on food packages to access these results [38]. Furthermore, AI tools such as

Google's AutoML Vision are helping parents to scan and analyze information on Front of the Package (FOP). These tools analyze information such as nutritional content, allergens, and certification marks of the products and analyze the status of the product [39]. This is helping parents to choose baby foods that are meeting nutritional needs and health status of their infants and toddlers.

2.3. Potential Risks and Safety Implications of AI in Baby Foods

Even though baby food manufacturers and parents are adopting and trusting AI to ensure the safety of baby foods, data security has become a challenge due to continuous cyber threats [40]. By 2025, about 53% of the cyberattacks have been linked to ransomware, and they are targeting AI quality control systems and AI-driven supply chains [41]. The companies with outdated industrial control systems paired with AI tools are prioritized in the attacks due to poor patching. Additionally, as food companies collect and analyze large datasets such as infant nutritional status and health conditions, cyberattacks cause data breaches and unauthorized access; hence, data privacy and security are at risk [42].

Some of the companies that have been compromised with cyberattacks include; JBS Foods in 2021. The company's AI-driven quality assurance systems were encrypted, forcing the company to shut down its production plants in Australia and U.S [41]. Another case was also witnessed at Campbell Soup in 2023. The company's AI-based production scheduling and quality control systems were compromised after a cyber intrusion [43].

AI can give inaccurate and biased information, which might compromise public health [44]. Some AI specialists, such as Naval Ravikant, have highlighted that AI does not know anything and it does not have consciousness; it only provides data that it has memorized (training data) or sourced from various platforms. This shows that AI may give wrong information without considering the harm it will cause to public health; hence, parents and manufacturers have to be conscious before completely trusting the AI tools.

AI in food safety relies on the quality of the data that has been fed into the system. When the data is unreliable or incorrect, it may overestimate or underestimate the risk [45]. Additionally, [46] demonstrated that while AI techniques such as rear-infrared hyperspectral imaging are capable of detecting contamination as low as 0.01%, these techniques are only accurate on concentrations between 0.1% and 10%. Some studies, such as [47] and [48], have also shown that AI tools may give false positive and false negative errors, which limits the accuracy of the results.

AI tools used in food production are sophisticated and are evolving faster than experts in other fields can understand them. For instance, AI has Black Box algorithms whose function is to make decisions, and these decisions cannot be questioned by human beings [49]. Because most of the food safety professionals, such as food scientists, are not computer specialists, it is hard to validate or challenge AI food safety reports. Additionally, AI can create and manipulate data and present it as real, resulting in decisions that will affect public health [45].

2.4. Current Regulations Landscape, Gaps and Future Directions

Despite promising revolutionization of the food industry by AI, it still lacks regulatory guardrails [50]. With the increase in AI applications by both manufacturers, consumers, and regulatory bodies, countries are coming up with laws that will guide the adoption of AI in various sectors. However, these laws are not directly targeting the baby food industry. Furthermore, the regulations do not highlight who is responsible between the AI tool developer and the manufacturer in case of a safety issue caused by AI.

In the USA, a task force (Bipartisan House Task Force) was elected to come up with recommendations that will protect consumers from AI risks. This task force recommended that there is a need for specific sector policies within federal agencies. These agencies will use their expertise to help with the safety assessment of the AI risks [51]. Additionally, the California AI Data Training Transparency Act is set to be effective from January 2026. This Act requires AI developers to publicize training data on their website [52]. This change will prevent the developers from using biased data; hence the AI tools will be reliable and trustworthy.

In Europe, the European Union has put into action the European Artificial Intelligence Act (AI Act). This act aims at fostering responsible AI development and deployment in the EU [53]. This act protects citizens from AI risks related to health, safety, and fundamental rights. This act ensures that the AI tools that are being developed and deployed are safe, effective, and ethical, as they have to comply with large regulatory requirements.

Fostering the EU AI Act will require the AI tools to undergo extensive risk assessment. The AI developers have to explain the decision-making process and how the algorithm works. To pass through these strict regulations, it will require time and resources; hence, it will slow down the AI innovations but it will guarantee that the AI tools are reliable and trustworthy. The regulatory bodies should put in place guidelines for assessing and monitoring compliance and actions addressing those that are not complying. In most of the countries, regulatory framework guiding the development and deployment of AI is not yet put in place; hence there is need for establishment of international regulations to ensure that only AI tools deemed safe, reliable and trustworthy can be adopted.

3. CONCLUSIONS

AI has improved food safety from procurement to the distribution of finished products. The successful application of the AI tools by most of the food manufacturers without causing contamination shows that the AI can be positively incorporated into baby food production lines to protect the product from microbiological, chemical, and physical hazards. Additionally, AI will help to facilitate traceability of the ingredients and the finished products. AI will enhance recalls when a food safety issue has occurred. This will help in protecting the infants and toddlers from products that could have caused adverse health consequences. To harness the power of AI in ensuring food safety, regulatory bodies, manufacturers, and parents must collaborate to ensure that the AI tools are safe, transparent, and accountable. Developers of AI tools should put measures that will ensure that these AI programs are secure and working to achieve the intended goals set by the manufacturers, parents and regulatory bodies.

DECLARATION

I, Benson Ali, declare that this review represents my own work and that it has never been presented elsewhere. All sources of information have been rightly acknowledged. No generative AI has been used to help in writing this review. This review has not been funded to promote any brand, instead it has been written to enhance understanding of AI applications in baby food production.

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