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Informing food choices with mobile augmented reality: A field experiment on food affordances, functionality, and sustainability

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ABSTRACT

Growing consumer interest in health-conscious and environmentally sustainable practices has underscored the need for innovative tools to support informed decision-making in food consumption. This study explores the potential of mobile Augmented Reality (AR) technology in enhancing consumer awareness of food sustainability, functionality, affordances, and its influence on behavioral change. We conducted a field experiment in a real-world supermarket setting, where participants used a mobile AR application to scan food items and access detailed information on their functional, sustainable, and affordances. The study employed a combination of interviews, questionnaires, and user experience evaluations to assess the system's impact. Results indicate that the mobile AR system received a high usability rating (84.60) and a strong perceived ease of use score (4.42), reflecting a positive user experience. Participants demonstrated a high level of comprehension regarding the information presented, and notably, all expressed an intention to modify their dietary habits based on their interaction with the app. These findings highlight mobile AR's potential to educate consumers and drive positive behavioral shifts toward more sustainable and informed food choices.

1. Introduction

In recent years, growing concerns about personal health and environmental sustainability have driven consumers to seek more informed and responsible food choices (Grunert, 2011; Schumer et al., 2018). However, despite increasing awareness, a significant knowledge gap persists, making it difficult for individuals to translate their intentions into concrete actions (Enriquez & Archila-Godinez., 2022). Consumers often struggle to assess the nutritional, environmental, and economic impact of food products, leading to decisions that may not align with their health and sustainability goals (Ran et al., 2022). Bridging this gap requires innovative solutions that enhance consumer understanding and engagement at the point of purchase.

Recent statistics underline the urgency of real-world interventions addressing food choices and sustainability: for example, dietary risks were responsible for approximately 11 million deaths globally in 2017 (Afshin et al., 2019) and poor diet contributed to 10.6% of all deaths in 2021 according to Institute for Health Metrics and Evaluation.[1] Simultaneously, around one-third of all food produced for human consumption, about 1.3 billion tonnes, is lost or wasted each year (Gustavsson et al., 2011), and recent data indicate that up to 19% of global food production was wasted in 2022 (UNEP, 2024). Taken together, these numbers illustrate the challenges of food-related illnesses and food waste, emphasizing the importance of technological solutions that inform and influence consumer choices.

Recent work leverages AR, integration of digital data with the physical world,[2] facilitating the provision of more engaging and interactive information, which can assist users in making informed decisions about food and dietary choices (Chai et al., 2022). State-of-the-art research focuses mostly on augmenting sensory perception (e.g., Nakano et al., 2021; Ueda et al., 2020), retail food chain applications (e.g., Chiu et al., 2021; Petit et al., 2022), and food education and learning (e.g., Garzón et al., 2020; Juan et al., 2019). However, the current panorama reveals a lack of clear information on the effectiveness of

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[1] Global Burden of Disease Study 2021 (GBD 2021) https://ghdx.healthdata.org/gbd-2021 (Consulted at 2026–04–02)

[2] How AR and VR Are Reshaping The Food Industry? https://www.linkedin.com/pulse/how-ar-vr-reshaping-food-industry-ankit-kapoor/ (Consulted at 2026–04–02)

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augmented reality applications, especially in terms of their interactivity and their influence on user behavior and decisions (Garzón, 2021). Additionally, the research field lacks an analysis of food use beyond mere consumption, such as its functional aspect – food designed to improve overall well-being (Roberfroid, 1999)–, food sustainability – food focused on environmentally friendly production practices and the reduction of food waste (Garnett, 2013)–, and food affordances – a relationship between the food object properties and the user capabilities to determine just how the food could possibly be used (Arciniegas, 2021). Addressing these critical questions will contribute to a comprehensive understanding of the potential of augmented reality to promote positive eating behaviors.

This work explores the potential of mobile AR to improve food choices by providing real-time information on the functionality, sustainability, and affordances of food products, thus facilitating informed decision-making and promoting the development of a healthier and more sustainable food system. We designed and developed a mobile AR app that leverages computer vision and machine learning to scan a food product, identify it, and present to the user critical information in real life settings. We conducted a field experiment in a supermarket to understand whether mobile AR technology can enhance the learning process about the affordances, functionality, and sustainability of food, as well as its impact on the intention to modify behavior and eating habits. Our findings show that users not only demonstrated a willingness to alter their behavior when utilizing the app but also expressed the belief that it would enable them to select products that align with their health and sustainability objectives. Therefore, our results highlight that mobile AR not only increases user engagement and comprehension but also fosters a proactive shift toward healthier and more sustainable eating habits, contributing to the broader goal of developing a more informed and responsible food system, it is important to note that this study measured behavioral intentions rather than long-term behavioral change. To further investigate this potential, this article asks: Can a mobile AR app tested in a real supermarket measurably improve comprehension and intention to change eating behavior?

2. Related work

This section presents essential concepts about AR and its application in the field of nutrition, with a review of relevant studies in this area.

2.1. Augmented reality and nutrition

AR allows the user to see virtual objects superimposed or composited with the real world. Therefore, AR supplements reality rather than completely replacing it (Azuma, 1997). The use of AR in nutrition has advanced significantly with the integration of technologies such as AI, computer vision, and the IoT. In the domain of artificial intelligence and computer vision, research studies have evidenced the capacities and advancements of these technologies in facilitating food recognition (Min et al., 2019; Pouladzadeh et al., 2014). The IoT is a technological framework that facilitates the acquisition of real-time data and its subsequent traceability through the utilization of sensors and interconnected infrastructure (Bouchbout et al. 2025). The integration of these technologies has been demonstrated to enhance the accuracy, scalability, and interactivity of AR-based nutrition systems. Chai et al. (2022) have noted a rise in scientific publications on nutritional AR, highlighting technical challenges such as object recognition in complex environments.

With the technological advances described above, AR applications have increasingly focused on influencing consumer perception and decision-making regarding food. For instance, the study published by Tizhe Liberty et al. (2024) illustrates how AR interfaces can improve visual evaluation of food quality attributes. While such work emphasizes sensory and visual assessment, our study extends this approach by integrating functionality, sustainability, and affordances to influence both comprehension and behavioral intentions. These advances are made possible by the widespread availability of smartphones with high computational capabilities, which support the development of engaging AR applications that deliver fast and accurate information (Abrash, 2021). The seamless integration of AR and mobile platforms has led to innovative solutions that enhance user experience and foster deeper engagement (Alkhamisi & Monowar, 2013). In this study, food recognition is a fundamental aspect of providing users with information related to functional, sustainable, and affordable foods, which will be discussed in more detail in the next section.

2.2. Functional food

According to the FAO, functional food is defined as *"a food that provides a health benefit beyond basic nutrition, demonstrating specific health or medicinal benefits, including the prevention and treatment of disease"*[3]. Functional foods were first regulated and developed in Japan during the 1980s before spreading to Northern Europe and North America; their popularity was influenced by the unique health concerns and consumer cultures present in these regions (Tur & Bibiloni, 2016). Consumer advocacy organizations have been meticulously calling for precise labeling of health claims, as well as careful monitoring and verification of functional foods' claimed health benefits; while companies are aware of these concerns, their main priority remains to ensure the safety of these products (Temple, 2022).

However, the integration of digital applications in functional food technology is low. Some functional food technology applications have been identified in this study: Mango, developed by Waltner et al. (2015), aims to prevent cardiovascular diseases by promoting healthy eating habits; it provides real-time information on nutritious foods, using AR technology to link products with dietary recommendations. It uses an algorithm that achieves an accuracy of 80.30% in classifying foods and also proves its effectiveness in providing additional information on nutritional benefits. Another existing application available in the App Store is called Functional Foods.[4] This application, developed by Luiza Reingatch, aims to identify foods with a positive effect on health. It includes 150 functional foods to improve well-being, plus there is a detailed guide to the foods, their nutritional benefits, and how they can prevent diseases. The application shows the importance of the nutrients needed to support the body, mind, and mood. Allowing the user to know their diet and promote well-being, observing eating habits, and learning to nourish the body, organs, and cells.

2.3. Sustainable food

The concept of sustainable food, according to the FAO sustainable food is defined as *"a food system that delivers food security and nutrition for all in such a way that the economic, social and environmental bases to generate food security and nutrition for future generations are not compromised"* (Thakur, 2024). Mass food production has a considerable environmental impact, affecting the entire food system, from processing and packaging to transportation and consumption.[5] This system contributes to climate crises, accounting for approximately one-third of greenhouse gas emissions and 70% of global water use[5]. Implementing sustainable food practices is essential for preserving biodiversity, reducing greenhouse gas emissions, and fostering economic benefits for regions (Thakur, 2024).

[3] Functional Food https://www.fao.org/faoterm/viewentry/en/?entryId=170967 (Consulted at 2026–04–02)

[4] Functional Food Application https://apps.apple.com/us/app/functional-food/id1481788624 (Consulted at 2026–04–02)

[5] Global food systems 'broken', says UN chief, urging transformation in how we produce, consume food. https://news.un.org/en/story/2023/07/1139037 (Consulted at 2026–04–02)

Mobile applications and online platforms are becoming more important for learning about sustainable food practices (Mu et al., 2019). These resources serve two main functions: providing important information about brands' commitment to social and environmental responsibilities, such as Buycott,[6] which allows users to scan barcodes and research brand practices, and addressing specific issues such as food waste. Another application developed by Haas et al. (2022) called MySusCOnf seeks to improve user behavior to reduce food consumption with information resources, techniques to minimize food waste, recipe suggestions, smart shopping recommendations, and kitchen management. The study assessed the app's usability and effectiveness, revealing that users were satisfied with its functionality and content, and viewed it positively as a tool for changing their approach to food waste. Overall, MySusCOnf shows the potential to raise awareness and help users adopt better habits.

2.4. Food affordances

The idea of affordance was first explained in 1977 by J.J. Gibson as the connection between an organism and its environment (Gibson, James, 1977). Donald Arthur Norman, an American researcher, defines affordance as "a relationship between the properties of an object and the capabilities of the agent that determine just how the object could possibly be used" (Sareh & Loudon, 2024). An illustrative example is the use of chopsticks in Japanese restaurants. Expert users can easily handle food items with these chopsticks, whereas inexperienced users may encounter difficulties using them effectively as an eating utensil.[7]

Gaver (1991) defined three types of affordances: perceptible affordances, which are evident from the perceptual characteristics of the object and indicate potential actions, such as a door handle; hidden affordances, which require users to rely on experience or trial and error to discern, such as hidden drop-down menus; and false affordances, which suggest actions that are not possible, such as underlined text that is not a link. Hartson (2003), an expert in human-computer interaction, identified four additional categories: physical, which employs visual cues to indicate actions, such as an "Add to Cart" button; cognitive, which facilitates users' comprehension of options, such as clear labels; sensory, which enables users to perceive environmental cues, such as an audio signal indicating an available upgrade; and functional, which facilitate goal achievement, such as adding an item to the cart after clicking "Add to Cart".

While the classification of affordances proposed by Gaver and Hartson offers a valuable framework, it requires adaptation to different contexts. In the case of food, affordances extend beyond its primary nutritional function. For example, a lemon may afford culinary use, but it may also afford cleaning or disinfecting, which is a well-known popular use. This research aims to examine this concept in greater depth by analyzing the affordances associated with various unconventional uses of food, hence, here we introduce such a concept as *food affordances*.

2.5. Intention to change behavior

The intention to change behavior is a critical component of research on the adoption of new technologies (Venkatesh & Bala, 2008). The Theory of Planned Behavior (TPB) (Ajzen, 1991), argues that the intention to perform a behavior is the closest predictor of actual behavior. As Ajzen (1991) explained, intention depends on three things: emotional response to change, the perceived expectations of others, and the individual's belief in their capacity to effect change. So to achieve real change, individuals must first ensure that people have a strong and clear intention to change.

A study by Mikropoulos et al. (2024) showed that people are more likely to use mobile AR when they find it useful, enjoyable, and easy to use. These factors increased users' intention to adopt AR in an educational setting. Although the study focused on teaching, these same factors are common drivers of technology use across many areas. Therefore, in the context of our work, these findings suggest that AR can similarly support the adoption of healthy eating habits by making high-quality nutritional information more appealing and accessible, increasing people's intention to adopt and maintain healthier eating habits. Other research has examined the impact of AR on consumer perception and behavior concerning food (Fritz et al., 2022). A comparative analysis of dessert purchases was conducted at an international restaurant between two groups of consumers: those who viewed the menu in AR and those who viewed a static digital version. The findings indicated that AR, which superimposes digital data on the physical environment, enhances the desire to purchase and the probability of purchasing products in comparison to static displays. Moreover, it markedly enhances consumer perception and behavior. Similarly, the present study seeks to examine the potential of overlaying images in the real world to facilitate the adoption of healthier eating habits and encourage more beneficial choices among users.

2.6. Research gap

There is a lack of research on food consumer behavior, in particular how information influences food choices for well-being and environmental sustainability. Studies on functional and sustainable foods are limited, and the concept of "food affordance" remains little explored. There is also a lack of clear evidence on whether AR applications are effective in influencing food choices and promoting healthier, more sustainable habits. Key questions remain about the impact of AR on decision-making and long-term behavior change, making this an important area for future research.

Furthermore, current literature has not addressed three key dimensions in an integrated manner: "functionality", "sustainability", and "food affordances". Although some studies have attempted to communicate functional or sustainable attributes through AR, these approaches are often isolated and focused on educational or marketing objectives, without an empirical evaluation of their behavioral effects. To date, there is no conceptual framework that combines these three dimensions to analyze how AR can influence food understanding and behavioral intentions. This multidimensional gap defines the need for and the main contribution of the present study.

3. Methodology

We aim to address the research gap described above by examining the potential of AR technology to enhance dietary habits and food knowledge. Our aim is to answer the following research question: How can mobile AR technology enhance the learning process about the affordances, functionality, and sustainability of food, as well as its impact on the intention to modify behavior and eating habits? We employed a mixed methodology of qualitative and quantitative approaches to assess the impact of AR on knowledge and attitudes towards dietary decisions, with a particular focus on the benefits, sustainability, and other uses of food. The following sections provide a detailed account of the design and development of the mobile application and the user study to validate the app.

3.1. Application design

This section provides an overview of the application's design,

[6] Buycott https://www.buycott.com/ (Consulted at 2026–04–02)

[7] Affordances, signifiers and good food experiences https://medium.com/@avinash.mair/affordances-signifiers-good-food-experiences-ead0f188c1d2 (Consulted at 2026–04–02)

including its architecture, layout, navigation, and development components. The source code and implementation details for the AR prototype and model integration are available in a public repository.[8] The repository includes the Android project files.

3.1.1. Architecture

The application was developed to investigate users' intentions to modify their dietary habits. The application uses Android Studio and Kotlin and supports Android versions from 5.0 Lollipop through the latest releases. The application integrates TensorFlow Lite[9] for food item detection and Google's ML Kit[10] for barcode identification. Fig. 1 illustrates the architectural design of the application.

The selected tool for object detection was TensorFlow Lite, a lightweight version of TensorFlow designed for running machine learning models optimized to reduce resource consumption and improve efficiency on mobile devices. A pre-trained model would be utilized using the COCO dataset.[11] The model was used as-is, without fine-tuning, to ensure rapid deployment, and it is capable of accurately identifying objects such as bananas, oranges, broccoli, and apples. Furthermore, we use Google's ML Kit to facilitate barcode recognition. This is a cost-free tool for mobile devices that utilizes machine learning to perform detection, segmentation, and scanning. The technology functions effectively, offering speed and accuracy in detection.

The two libraries are utilized for the real-time analysis of images captured by the device's camera to detect and identify specific objects. Once an object is identified, information about its functionality, sustainability, and food affordances is collated and displayed on the screen.

3.1.2. Interaction flow between components

After understanding the application components and layers, it is essential to explain how they interact with each other. The process begins when the user initiates the scan of an object; the UI triggers the camera to capture images or video in real-time. The captured frames are sent to the ImageAnalyzer, which routes them to a dedicated processing layer. This processing layer forwards the frames to the Repository, where inference is performed using the TensorFlow Lite Interpreter or ML Kit APIs to detect and classify the objects in the frames. The detection results, including bounding box coordinates and object labels, are returned to the ViewModel. Finally, the ViewModel updates the UI in real-time, displaying the results as bounding boxes and labels around the detected objects. Fig. 2 illustrates this application flow, spanning the phases of image capture, processing, machine learning inference, and presenting results in the UI, ensuring fast and effective visualization of the data for the user. The following section will provide a detailed account of the user interface of the Android application, which is activated upon the detection of fruits and vegetables.

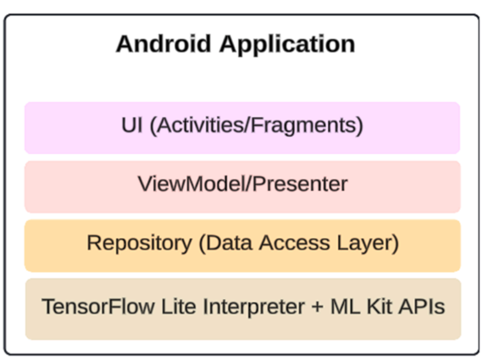


Fig. 1. Application architecture diagram developed in Android Studio using Kotlin.User Interface (UI): responsible for controlling the user interface and user interactions. Additionally, this layer is tasked with initiating model inference operations and displaying the results. View-Model-Presenter (VMP): responsible for the management of application logic and the coordination of interactions between the user interface and the rest of the application. Repository: Provide a clean interface for accessing data. TensorFlow Lite and ML Kit: Perform object and barcode recognition.

3.1.3. User interface

The Android application interface comprises four principal components: a home screen, a display of the device camera, a screen that presents augmented information about the detected object, and a screen that provides detailed information.

The welcome screen (see Fig. 3a) introduces the objective of the application. At this stage, the user is presented with a button labeled "Scan", which initiates the food scanning procedure; once selected, the camera opens and allows the users to scan oranges, bananas, broccoli, and apples along with barcodes. When an object is detected, it gets identified by the system, enclosed by a green box (Figs. 3b and 3c), and its name is displayed. If the scanned object is a food item, then it is explained in the app about its benefits and uses. If it is scanning the barcode, then it provides sustainability-related details about the product, such as origin, classification, cultivation methods, and transportation.

Additionally, upon the detection of the objects (i.e., oranges, bananas, broccoli, apples, and barcodes), three buttons will appear on the screen. These buttons provide the user with information related to food. Specifically: Benefits (orange) provides information regarding the functionality of the foods. The data was sourced from the Functional Foods Component Chart developed by the International Food Information Council (IFIC) Foundation[12]; Uses (blue) provides information about the affordances or other uses of the foods. The information was manually collected from websites using targeted searches with the term "other uses" of the selected food item; and Eco (green) provides information about the sustainability of the foods, specific barcode was used to retrieve information from the OpenFoodFacts[13] database, which includes indicators such as Eco-Score, carbon footprint, packaging type, origin, cultivation methods, transportation, and food processing level. After clicking on one of these buttons, a panel displays essential information about the food, as illustrated in Figs. 3d, 3e and 3f. In this panel, a button with a "+ " icon is provided, which allows the user to access a new screen and view detailed information, as illustrated in Figs. 3g, 3h and 3i. It is crucial to highlight that the buttons (Benefits, Uses, Eco), the green box indicating detection, and the informational content with images are only visible during detection. Nevertheless, the pertinent information panel is consistently accessible, independent of whether the user is performing a scan of the food item. This functionality is designed to facilitate the user's ability to read and learn more details about the scanned object. Upon scanning another item, the panel will promptly disappear.

3.2. User study

We conducted a field experiment where participants used the app with a specific set of products to understand how users consider the information regarding food sustainability, functionality, and affordances and how they evaluate the app's usability.

[8] https://github.com/maribeljaramillo-ops/Food-related-information
[9] https://ai.google.dev/edge/litert (Consulted at 2026–04–02).
[10] https://developers.google.com/ML-kit (Consulted at 2026–04–02).
[11] https://cocodataset.org/ (Consulted at 2026–04–02).
[12] Functional Foods Component Chart. http://www.ific.org/nutrition/functional/index.cfm (Consulted at July 4th, 2025).
[13] https://world.openfoodfacts.org/product (Consulted at 2026–04–02).

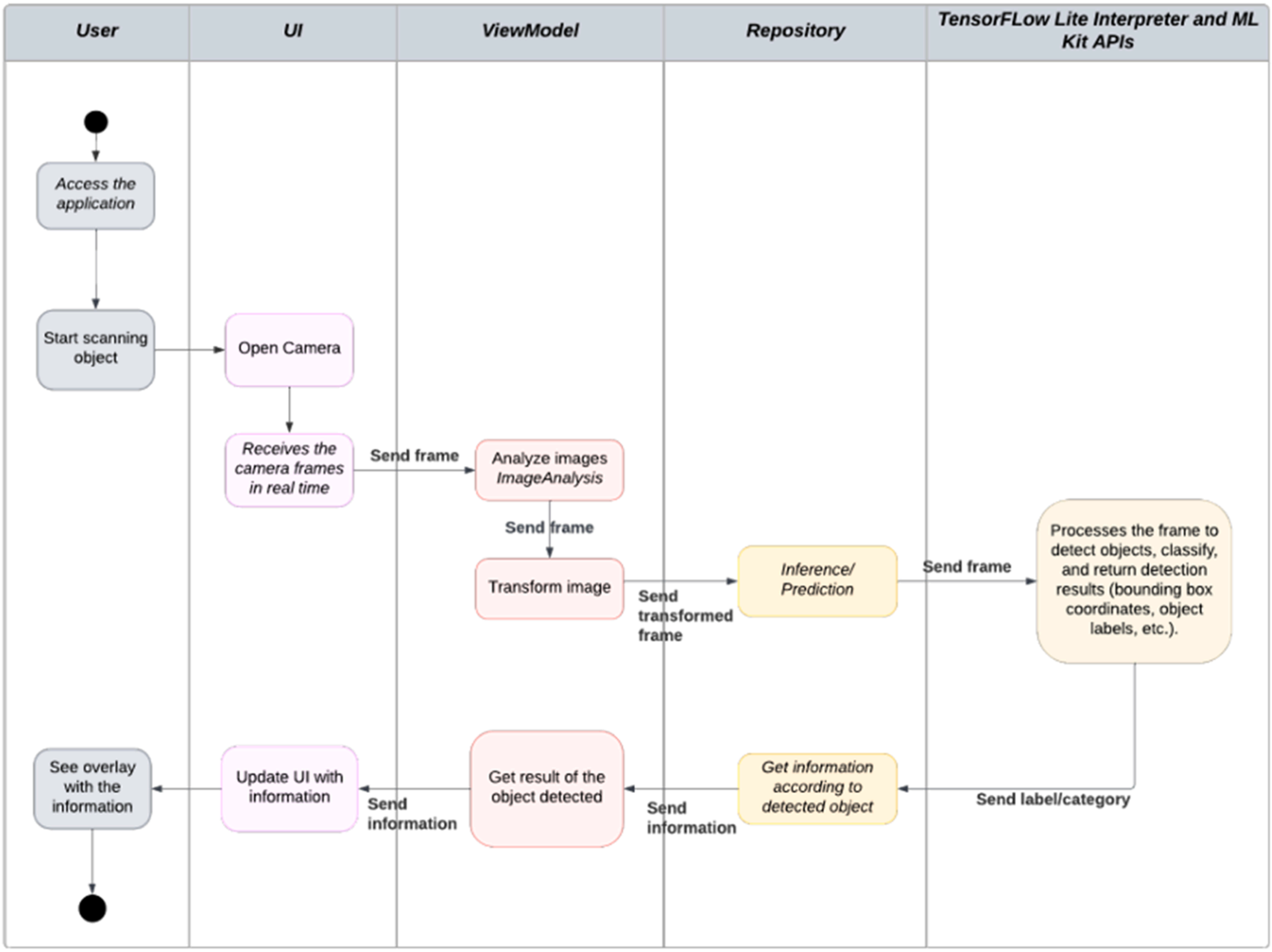


Fig. 2. Interaction flow between components.

3.2.1. Tasks

The tasks for this study were conducted in a real supermarket, allowing observation of participants' behavior for about 45 min. Shoppers interacted with augmented reality information on food functionality, sustainability, and affordances, assessing how AR technology influences consumer decision-making in a natural environment. The app provides data on fruits and vegetables, focusing on functionality, sustainability, and affordances (other uses of food). We used the following tasks:

- Task A: Scan a banana to get functionality information. The researcher instructs the participant to scan a banana using the augmented reality application. Once recognized, the participant reads the information and answers three questions during the process: Which parts of the body benefit from consuming bananas? Which vitamin does the banana contain? Why do bananas help lower blood pressure?
- Task B: Scan two barcodes on the product to get sustainability information. The participants scan two orange product barcodes to compare and retrieve sustainability information. Once the review of the information for the two barcodes is finished, the participant starts to answer the following questions: Which of the two foods was local? What was the Eco-score of the scanned objects? Which of the two barcodes shows a more sustainable product?
- Task C: Scan a broccoli and get affordance information. Participants learned about alternative uses of the food. Participants scanned broccoli to learn about its applications and answered: How is broccoli used in art? What recipe was mentioned? How can it be used for makeup?

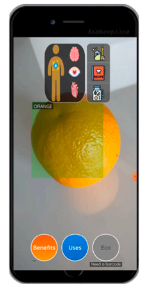
Each participant completed the three tasks in a random order to avoid bias. Each task prompted users to use the application to scan a specific product and then find specific pieces of information. Participants had no time limit to complete the task. Each task concluded when the participants verbally confirmed that they had completed the activity. Also during the experiment, participants were invited to follow a think-aloud protocol for active participation, ensuring that they provided additional reflections on the information acquired after each task.

3.3. Metrics

This study measured the impact of AR information on users' intention to change eating habits through the following variables:

- Perceived usability: The post-experiment SUS questionnaire (Brooke, 1996) was utilized to assess the perceived usability of the app, with measurements taken of ease of interaction and user experience when accessing food-related information via augmented reality.
- Perceived ease of use: The post-experiment TAM questionnaire (Venkatesh & Bala, 2008) assessed users' perceived ease of use of the AR system, providing insights into its acceptance.
- User satisfaction: A post-experiment questionnaire was administered. This metric assesses how valuable and satisfactory users find

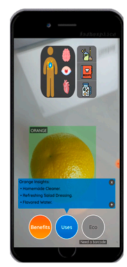
(a) Initial Screen. Initial interface presented to the user when starting the application. It features the application logo and a “Scan” button to activate the camera and facilitate the scanning of fruits and vegetables.



(b) Fruit Object detection. An orange has been detected highlighted with a green square. Information is shown that it is good for improving the immune system, the brain, the eyes and the heart, and about the affordances, with which the food can be used to prepare a recipe, a refreshing drink, and for cleaning.

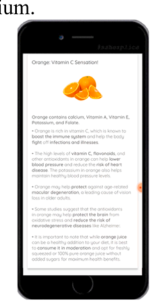
(c) Barcode object detection. The system detects a barcode to deliver sustainability information. It determined that the barcode corresponds to an orange; this product has a classification E, non-sustainable product, recyclable packaging and is not a local product.

(d) Functional food information. The selection of the Benefits option (orange) prompts the appearance of an orange menu, which presents a summary of the benefits associated with the detected food. It includes information about the components: Vitamin A, Potassium, and Calcium.

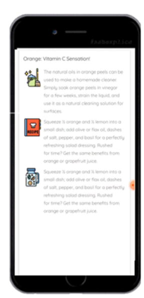


(e) Affordance food information. The user can select the Uses button (blue), which displays food affordance information, such as that the orange can be used to make a homemade cleaner, a refreshing drink, and a salad dressing.

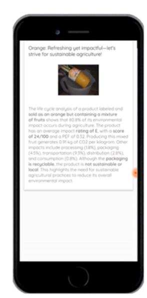
(f) Sustainable food information. Selecting the green ECO button brings up the sustainability information menu, showing the rating, if the product is sustainable and organic, and if the packaging is recyclable.



(g) Detail functional food information. This screen displays detailed product information showing functional power supply and components.



(h) Detail Affordance food information. Present more precise information regarding food preparation, cleaning, recipes, and other uses of food.



(i) Detail Sustainable food information. This screen shows sustainability information. It displays the amount of carbon dioxide (CO2) and information that affects product qualification (e.g., transportation, distribution, processing, packaging, and consumption).

Fig. 3. Application user interface. During real-time scanning, the application recognizes objects and presents information using augmented reality. (a–c) Real-time scanning screens. (d–f) Summary information panels for functional nutrition, affordances, and sustainability.Fig. 3: (Continued). At any time during the process, the user can access summary or detailed information. Detailed information screens for functional nutrition (g), affordances (h), and sustainability (i).

the augmented reality system for delivering food-related information.
- Information quality perception: A post-experiment questionnaire assessed users' perceptions of the reliability, accuracy, and overall quality of the AR food information, focusing on its credibility and trustworthiness.
- Comprehension of Information: This metric analyzes participants' understanding of food functionality, sustainability, and affordance-related information when using the augmented reality app. Real-time questions during tasks (3.2.1) assessed information retention by questioning product benefits, sustainability comparisons, and food uses, allowing for testing the effectiveness of the augmented reality system in transferring unambiguous concepts.
- Interaction Time: We tracked the task completion time, in seconds, to measure user engagement.

Besides the quantitative metrics, we analyzed qualitative content through open-coded thematic analysis to understand the intention to change eating habits. In particular, we conducted semi-structured interviews both before and after the experiment. The pre-experiment interview focused on the participants' perceptions of their current diet, sustainability awareness, openness to new foods, and the role of technology concerning food information. The post-experiment interview examined any changes in habits, the effects or impacts of AR information, and confidence in making informed food choices. Questionnaires and scoring procedures are provided in the Supplementary Material.

3.4. Participants

The sample for this study consisted of 25 participants, of which 10 (40%) were male and 15 (60%) were female, with an age range of 15–71 years (44 ± 13.74 years). Participants were selected voluntarily in supermarkets. The recruitment process was conducted through an on-site convenience sampling approach. Individuals entering the supermarket were approached by the researcher and invited to participate voluntarily. There were no predefined selection criteria beyond willingness to engage with the prototype. As the application under investigation was not available to the public, all participants utilised an Android device that had been provided by the researcher. Despite the limitations imposed by convenience sampling and the modest sample size, which compromise external validity, this strategy is deemed appropriate for an exploratory field experiment. Since it enables testing with real supermarket customers in the environment where food-related decisions naturally occur. This decision aligns with the study's objectives of evaluating usability, comprehension, and behavioural intentions rather than estimating population-level effects, thereby supporting ecological validity.

3.5. Procedure

Prior to participation, individuals provided written consent, which encompasses the collection of voice recordings, data usage, age, and gender. After consent, the researcher explained the purpose of the study and provided the participants with an Android device containing the pre-installed AR application, since the application was not publicly available for download at the time. The procedure started with a preliminary interview that explored dietary habits, sustainability awareness, and experience with food-related technology. Subsequently, we provided a five-minute tutorial to each participant on the use of the AR app, encompassing food and barcode scanning to access information on functionality, sustainability, and affordances.

During the experiment, participants verbalized their thoughts (thinking-out-loud method) while completing three tasks (3.2.1), arranged in Latin Squares. After completing the tasks, we conducted a post-experiment interview to explore potential dietary habit changes. Participants then filled out a questionnaire evaluating the clarity, usefulness, accuracy, and ease of use of the AR system. Finally, we thanked participants for their time.

4. Results

We analyzed data through means, standard deviations, and 95% confidence intervals for quantitative data, while qualitative data is subjected to thematic analysis involving coding, theme categorization, review, and the creation of a narrative report with participant quotations.

4.1. Pre-interview

The interviews and open-ended responses were analyzed using open coding and thematic clustering. A single researcher performed the coding, identifying recurring words and similar messages among the participants. From this, a small set of categories (codebook) was created to group common themes such as sustainability, technology use, and nutritional knowledge, among others. The percentage of participants who mentioned each theme was calculated based on the presence or absence of each code in their responses. This approach allowed us to identify general patterns in eating habits and perceptions of sustainability. Table 1 presents a sample of the codes used during the pre-interview analysis. It includes brief descriptions and representative quotes to illustrate how themes were identified.

The preliminary interview findings reveal different eating habits and divergent views regarding sustainability. Some participants (33%) understand sustainability and the health benefits of food, whereas 67% show little interest or do not know at all. Approximately 83% do not use any form of technology to aid their decisions about food apart from recipes, and 67% rarely try new recipes. Participants were not very interested in food affordances but took functionality and sustainability into great consideration, and 67% of participants prioritize cost and practicality over other factors.

In terms of satisfaction, half of the participants expressed dissatisfaction with their eating habits, citing a lack of knowledge or difficulty in making dietary changes. Conversely, the other half have achieved a balanced diet but desire to improve aspects such as increasing fruit and vegetable variety or consuming organic products. Likewise, participants mentioned that they acquire knowledge about the benefits of foods

Table 1
Thematic Analysis of Pre-Interview Responses.

Code	Description	Example Quote
SUST_IMPORTANT	Explicit mention of sustainability as a food choice factor.	"We live in a small town and mostly buy local products."
SUST_OCCASIONAL	Considers sustainability occasionally, but faces barriers (price, lack of info).	"Sometimes I buy organic foods, but they are often more expensive."
SUST_NOT_IMPORT	Does not consider sustainability when choosing food.	"We check the expiration date and packaging."
TECH_NO_USE	Does not use technology to support food decisions (except for recipes).	"I don't use apps, just look up recipes sometimes."
RARELY_RECIPES	Rarely tries new recipes.	"I always cook the same things."
COST_PRIORITY	Prioritizes price and practicality when choosing food.	"The most important thing for me is that it's cheap and easy to prepare."
SATISFIED	Feels satisfied with current diet but wants to improve (e.g., more vegetables).	"I eat well, but I'd like to include more vegetables."
DISSATISFIED	Feels dissatisfied with current eating habits.	"I want to change, but I don't know how."
KNOWLEDGE_GAP	Expresses lack of nutritional knowledge.	"I consume supplements because I don't know the benefits of foods."

through medical recommendations, suggestions from other users, or social media. Users said: "I consume supplements because I do not know the benefits of foods", "I know that proteins are important for the organism", and "I do not have much knowledge, I would like to learn more".

Regarding sustainability, 33% of participants consider it an important factor when choosing food, while 50% do so occasionally, although they report difficulty accessing clear information on the topic. On the other hand, 17% do not consider sustainability in their purchasing decisions. Some comments that reflect users' support for sustainability include: "We live in a small town and mostly buy local products." In contrast, others said, "We check the expiration date and packaging," and "Sometimes I buy organic foods, but they are often more expensive."

4.2. Perceived usability, ease of use, satisfaction and information quality perception

The results of the system usability evaluation, as measured by the SUS, indicate a high level of usability perception among the participants, with an average score of 84.60 ± 10.62, 95% CI $[80.21; 88.99]$. A comparison of this score with the study on the usability of augmented reality applications on mobile devices (Dutta et al., 2021), reports a SUS score of 85.95, indicating that it falls within the high range.

The PEOU analysis of the AR system indicates a predominantly positive perception, with an average PEOU score of 4.42 ± 0.85, 95% CI $[4.07; 4.77]$ on a scale of 1–5. The results indicate that users find the system fairly straightforward to use, with the majority reporting a positive experience and no significant difficulties. A comparison of these results with those of the study by Campos et al. (2024), in which participants were divided into two groups, namely nutritionists and patients, revealed that the patients reported an average PEOU of 4.38, which is similar to that observed in this study.

A questionnaire was employed to assess user satisfaction and the quality of the information provided by the AR application, utilizing a scale of 1–5. The results demonstrated that the mean overall user satisfaction was 4.312 ± 0.763, 95% CI $[3.99; 4.62]$, while the mean quality of information was 4.26 ± 0.83, 95% CI $[3.91; 4.60]$. These values indicate a markedly favorable assessment of the AR system by the participants in terms of their overall experience and the quality of the information provided.

To gain a deeper understanding of how different user groups perceive the system, a comparative analysis by gender was conducted. Table 2 presents the gender-disaggregated scores for the metrics of perceived usability, perceived ease of use, user satisfaction, and information quality.

Both women and men show similar perceived usability scores (83.17 and 86.75, respectively). However, women have a lower standard deviation (7.99 vs. 13.90), suggesting a more consistent perception within this group. This difference may be related to women's traditional assumption of greater responsibilities in culinary and personal care, which could translate into greater familiarity with food-related applications.

Table 2
Gender Comparison of Usability (SUS), Perceived Ease of Use (PEOU), Satisfaction, and Information Quality Perception.

Metric	Female			Male		
	Mean	SD	95% CI	Mean	SD	95% CI
Perceived Usability (SUS)	83.17	7.99	[78.74; 87.59]	86.75	13.90	[76.81; 96.69]
Perceived Ease of Use (PEOU)	4.52	0.36	[4.29; 4.75]	4.50	1.14	[3.77; 5.23]
User Satisfaction	4.49	0.33	[4.30; 4.67]	4.04	1.11	[3.24; 4.83]
Information Quality Perception	4.55	0.42	[4.31; 4.78]	3.82	1.09	[3.03; 4.61]

Similarities were also found between the two groups regarding perceived ease of use (4.52 for women and 4.50 for men). However, men's responses were more dispersed, with a wider confidence interval (3.77–5.23) compared to women's (4.29–4.75), indicating greater accuracy and consistency in women's responses.

Regarding user satisfaction, women reported a more positive and consistent experience (4.49), while men expressed lower satisfaction (4.04). Similar results are evident in the perceived quality of the information provided by the system. Women obtained a higher score (4.55) and gave more consistent responses. In contrast, men showed a lower perception (3.82) and greater variability in their responses.

We run Shapiro-Wilk tests to determine the normality of the collected data. Results showed that all data has a non-normal distribution ($p < .001$). Therefore, we continued our analysis by analyzing with nonparametric tests whether age or gender had any significant effect in the self-reported measures. Mann–Whitney U tests indicated no significant differences between genders in perceived usability (Mdn males = 14.80, Mdn females = 11.80, U = 57.00, p = .306), usefulness (Mdn males = 14.50, Mdn females = 12.00, U = 60.00, p = .401), and satisfaction (Mdn males = 11.15, Mdn females = 14.23, U = 56.50, p = .292). In contrast, we found that gender led to significant differences in quality assessment, with males providing lower grades (Mdn = 9.15) than females (Mdn = 15.57), U = 36.50, p = .029. Next, we examined whether age affected the collected measures through Spearman rank-tests with a Bonferroni correction ($\alpha = 0.05/4 = 0.0125$). Results show that age did not affect how individuals reported their perceived usability ($r = -.419, p = .037$), usefulness ($r = -.474$, $p = .017$), satisfaction ($r = -.184, p = .379$), or quality ($r = -.026$, $p = .904$). Overall, nonparametric analyses revealed that gender influenced quality assessments (with females providing higher ratings than males) while no significant gender or age effects were observed for perceived usability, usefulness, or satisfaction.

4.3. Comprehension of information and interaction time

An analysis of the participants' comprehension of the information presented revealed that 65.33% of their responses were accurate, indicating a high level of understanding of the material among the majority of the participants. However, 20% of the responses were partially correct, indicating that some concepts were incompletely understood. Furthermore, 14.67% of the responses were incorrect, indicating deficiencies in understanding.

To understand the assessment of participants' information comprehension, their verbal responses to real-time questions displayed during augmented reality interaction tasks were evaluated. Each response was manually coded into one of three categories: correct, partially correct, or incorrect. A response was classified as correct when all expected items were mentioned. For example, for the question "What parts of the body benefit from eating bananas?", the correct answer was "muscles, digestive system, brain, and kidneys". Participants who recalled all four items were classified as correct. A response was classified as partially correct when only some of the expected information was mentioned. For the same question, a participant who mentioned only "muscles" or "digestive system" was coded as partially correct. Similarly, for the question "What was the ecological score of the scanned objects?", the correct answers were "Score B and D". Participants who recalled only one of the two correct answers were classified as partially correct. A response was classified as incorrect when it contained irrelevant information or no relevant information.

The total number of responses in each category was summed and divided by the total number of responses to calculate the percentage of correct, partially correct, and incorrect answers. The 20% recorded as "partially correct" corresponds to the proportion of responses that contained partially accurate information. This three-level coding approach allows for a more detailed understanding of how participants retained and expressed the information presented by the augmented reality system.

Concerning the average time taken by participants to complete the tasks, it was observed that the longest average time recorded for Task B was 198.80 ± 8.31, 95% CI [181.66; 215.94]. This was because participants were required to scan and compare two products. In contrast, Task A with an average completion time of 105.28 ± 5.33, 95% CI [94.28; 116.28], and Task C with an average completion time of 125.00 ± 7.60, 95% CI [109.31; 140.69]. Tasks A and C involved only scanning one product and were completed in less time.

We proceeded by analysing whether age, gender, or the task affected the collected metrics. Data are mean ± standard error, unless otherwise stated. First, we run Shapiro-Wilk tests to determine the normality of the collected data. Results showed that all data has a non-normal distribution ($p < .001$), except for the task completion time collected for Tasks A ($p = .355$), B ($p = .127$), and C ($p = .407$). Therefore, we continued our analysis by analysing with nonparametric tests whether age or gender, or task type had any significant effect in the self-reported measures and task accuracy. Mann–Whitney U tests indicated no significant differences between genders in perceived usability (Mdn males $= 14.80$, Mdn females $= 11.80$, $U = 57.00$, $p = .306$, $r = .205$), usefulness (Mdn males $= 14.50$, Mdn females $= 12.00$, $U = 60.00$, $p = .401$, $r = .168$), and satisfaction (Mdn males $= 11.15$, Mdn females $= 14.23$, $U = 56.50$, $p = .292$, $r = .211$). In contrast, we found that gender led to significant differences in quality assessment, with males providing lower grades (Mdn $= 9.15$) than females (Mdn $= 15.57$), $U = 36.50$, $p = .029$, $r = .436$. Next, we examined whether age affected the collected measures through Spearman rank-tests with a Bonferroni correction ($\alpha = 0.05/4 = 0.0125$). Results show that age did not affect how individuals reported their perceived usability ($r = -.419, p = .037$), usefulness ($r = -.474, p = .017$), satisfaction ($r = -.184, p = .379$), or quality ($r = -.026, p = .904$).

We continued with a Brunner–Langer nonparametric mixed ANOVA to examine the effect of gender (between-subjects factor) and task (within-subjects factor) on accuracy. We found a significant main effect of task, $F(1.86, 15.04) = 33.61$, $p < .001$, suggesting that accuracy differed across tasks. There was no significant main effect of gender, $F(1, 15.04) = 0.54$, $p = .462$, nor a significant gender by task interaction, $F(1.86, 15.04) = 0.29$, $p = .731$. Relative Treatment Effects (RTEs) indicated that accuracy increased across tasks, with mean RTEs of 0.301, 0.430, and 0.779 for Tasks A, B, and C, respectively. Across genders, mean RTEs were 0.519 for males and 0.487 for females.

Finally, we examined whether gender (between-subjects factor) and task (within-subjects factor) affected task completion time, considering age as a covariate, through a two-way mixed ANCOVA. There was homogeneity of variances ($p > .05$) and covariances ($p > .001$), as assessed by Levene's test of homogeneity of variances and Box's M test, respectively. Mauchly's test of sphericity indicated that the assumption of sphericity was met for the two-way interaction, $\chi^2 = 2.282$, $p = .320$. Age was evaluated at 44.00 in the model. There was no statistically significant interaction between gender and task type on task completion time, $F(2, 44) = 1.245$, $p = .298$, partial $\eta^2 = .054$. For females, we found that they were statistically significantly faster in Tasks A (88.588 ± 12.861 s, $p < .001$) and C (62.107 ± 11.162 seconds, $p < .001$) compared to Task B. Females were also statistically significantly faster in Task A (26.481 ± 9.719 seconds, $p = .037$) than in Task C. Males showed a similar trend with statistically significantly faster task completion times in Tasks A (100.918 ± 15.959 seconds, $p < .001$) and C (91.340 ± 13.850 seconds, $p < .001$) compared to Task B.

Next, we examined main effects from gender and task type. The main effect of task type showed a statistically significant difference in mean task completion time, $F(2, 44) = 9.851$, $p < .001$, partial $\eta^2 = .309$. Participants were statistically significantly faster in Tasks A (94.753 ± 9.922 seconds, $p < .001$) and C (76.723 ± 8.611 seconds, $p < .001$) compared to Task B. We also found a statistically significant effect of age on task completion time, $F(1,22) = 7.240, p = .013$, partial $\eta^2 = .248$ In contrast, gender did not produce measurable main effects, $F(1, 22) = 3.500$, $p = .075$, partial $\eta^2 = .137$.

4.4. Post-interview

Following the AR app interaction, participants completed a semi-structured interview designed to explore their experiences, perceptions, and intentions regarding food choices. Thematic analysis of these responses revealed key patterns related to usability, knowledge acquisition, sustainability awareness, and behavioral intentions (Table 3). Insights were derived through open coding, and representative quotes were used to illustrate each theme. This analysis helped contextualize the app's impact and identify areas for improvement in future iterations.

The semi-structured interview post-experiment revealed that 66% of participants intended to change their diets with the help of the app, with one user noting, "I would make dietary changes if the food aligns with my preferences and budget." Participants reported gaining new knowledge, with comments like, "I liked learning about benefits and sustainability more than affordances," and "I find it interesting to learn about other uses of food, though I'm unsure if I'd use it." Participants particularly valued the information on the functional benefits of foods, with examples such as the brain-health benefits of bananas or the creative uses of broccoli, although some expressed doubts about whether they would apply this knowledge in practice. However, they considered it important to know these features as part of comprehensive learning.

Most participants (66%) valued sustainability, especially local foods, and found ECO-Score information irrelevant. While 55% trusted the

Table 3
Thematic Analysis of Post-Interview Responses.

Theme	Description	Example Quote
USABILITY_ADAPTATION	Adaptation to the app.	"The app was easy to use, from the first interaction I knew how to navigate and find the information I needed."
SCANNING_EXPERIENCE	Challenges with product scanning.	"Scanning was interesting, but sometimes I had to focus carefully to avoid jumping elements on screen."
INTENTION_CHANGE_DIET	Willingness to change their eating habits after using the app.	"I would change my diet as long as the food aligns with my preferences and budget."
KNOWLEDGE_ACQUISITION	Gaining new insights.	"I didn't know the benefits of bananas. It was very educational."
SUSTAINABILITY_AWARENESS	Considered sustainability important.	"I liked learning which brands are more sustainable."
FUNCT_AFFOR_SUSTAI	Learning about food benefits (functionality), sustainability or affordances.	I liked learning about sustainability more than affordances."
REAL-TIME_COMPARISON	Participants valued the ability to compare products instantly while scanning.	"I liked being able to compare benefits and see which product was more sustainable."
TRUST_INFORMATION	Trusted the app's content.	How accurate is this information if it depends on third parties?"
DESIGN_FEEDBACK	Users suggested improvements.	It should be adapted for people with disabilities."

app's information, doubts about sustainability arose due to third-party data sources. They were also willing to buy sustainable products if the app showed they were reasonably priced. A majority (66.6%) preferred learning about food benefits, followed by sustainability, and less about alternative uses. Users commented, "I learned more about sustainability" and "I didn't know the benefits of bananas." Overall, the app proved an effective educational tool, encouraging users to reflect on their food choices and intention to change. Improving data sources and presentation can increase trust.

To provide a concise overview of how each research question was addressed and answered, Table 4 summarizes the mapping between the study's research questions, the corresponding metrics or instruments used, and the key findings derived from the data analysis.

5. Discussion

The findings highlight opportunities to optimize educational initiatives on sustainability, nutritional benefits, and food uses (Table 4). The low use of technology for food learning suggests potential for accessible, practical interventions. Notably, 50% of participants expressed dissatisfaction with their eating habits emphasizes the need for better knowledge and implementation of healthier diets. Receptivity to food benefits and dietary improvement indicates interventions could be effective. Though interest in new recipes is low, focusing on sustainability and functionality may drive significant changes in eating habits.

The high score on the SUS indicates that the app is in the upper range of usability in comparison to other augmented reality applications, as confirmed by the study referenced in Dutta et al. (2021). This outcome affirms the effectiveness of its intuitive and inclusive design, which appears to meet diverse user needs. However, while users generally rated usability and information quality favorably, persistent challenges remain. As noted by Olsson and Salo (2011), factors such as technical issues, usage frequency, and content relevance can detract from overall satisfaction. Our findings echo this concern, particularly in relation to object identification difficulties. Addressing these technical limitations is crucial to sustaining engagement and enhancing the user experience.

Although most participants demonstrated a solid comprehension of the app content, the presence of partially correct and incorrect responses indicates areas of confusion. It is crucial to identify and prioritize these weaknesses, providing additional training that clarifies incomplete concepts and reduces future errors, to enhance overall understanding but also contribute to greater accuracy in participant performance. The longer completion time for Task B, which involved comparing two products, reflects its complexity. It suggests the experiment design could be simplified to reduce cognitive load or that more time and support should be provided to participants for more efficient task completion. Addressing these issues could improve user experience and process efficiency.

Table 4
Mapping of Research Questions, Metrics, and Key Findings.

Research Question	Metrics / Instruments	Key Findings
How can mobile AR enhance users' comprehension of food affordances, functionality, and sustainability?	Comprehension test (real-time questions during tasks); classification of responses (correct, partially correct, incorrect).	Participants showed high comprehension (65.33% correct, 20% partially correct), indicating that AR visualizations effectively conveyed functional and sustainable information.
Does AR-based information influence users' intention to modify their eating habits?	Post-experiment behavioral intention scale (TAM-based items).	76% of participants reported increased intention to make healthier or more sustainable food choices after the AR experience.
How do users perceive the usability and ease of use of the AR application?	System Usability Scale (SUS) and Perceived Ease of Use (PEOU).	High usability (SUS $= 84.60 \pm 10.62$) and strong ease of use (PEOU $= 4.42 \pm 0.85$) suggest the interface design was intuitive and accessible.
What is the overall satisfaction of users when interacting with AR-based food information?	Custom satisfaction questionnaire.	Average satisfaction $= 4.312 \pm 0.763$, showing users found the AR approach engaging and informative.

Analyses revealed several significant effects on the collected measures. Gender influenced quality assessment, with females providing higher ratings than males. Task type had a significant impact on both accuracy and task completion time, with accuracy improving across tasks and participants completing Tasks A and C faster than Task B. Additionally, age significantly affected task completion time, indicating that older participants took longer to complete the tasks. No other main effects or interactions, including those involving gender, were significant, suggesting that performance differences were primarily driven by task characteristics and participant age rather than gender.

When interpreting these results, certain methodological limitations must be considered. The small sample size ($n = 25$) and the limited set of food products included in the experiment restrict the generalizability of the findings. Furthermore, the study was conducted in a public supermarket, where participation may have been influenced by the novelty of the technology—that is, by increased attention or motivation stemming from being observed. These factors suggest that the results should be understood as exploratory, although they offer valuable information about the initial receptiveness and educational potential of the application.

The AR app positively influenced users' intention to change eating habits, though this was influenced by personal preferences and economic constraints, highlighting the need for personalized information. Users showed strong interest in the functionality and sustainability of food, but less in alternative uses. Concerns about the reliability of sustainability information emphasize the need for better data transparency. Some participants asked how they could be certain that a product was truly organic or whether producers might self-report sustainability values without external verification. These concerns highlight the importance of transparency in the communication of environmental information and reveal a broader issue of trust in sustainability claims. The feedback underscores the need for systems that not only present sustainability indicators but also make their underlying data sources and validation processes visible to users. Overall, the app sparked interest in improving habits and provided valuable insights, but the accuracy of sustainability data remains a concern. Users expressed doubts about the veracity of certain labels, such as the classification of a food as organic, questioning the origin of this information. In particular, they wondered whether the data came directly from the farmer, the supply chain, or external sources, which underscores the need to clearly specify the origin of each piece of data. These concerns highlight the importance of having validated, traceable, and certified sources that support transparency and build trust. Despite these limitations, the application proved to be an effective educational tool, capable of fostering critical thinking and promoting a desire for change among users. It is essential to clarify that the study focused on measuring behavioral intentions rather than observing long-term changes in actual behavior. To determine whether these intentions lead to sustained shifts in food purchasing or consumption patterns, future research should incorporate longitudinal approaches that track behavior over time.

Taken together, this study offers several notable strengths that enhance its relevance and applicability. First, the ecological validity of conducting the intervention in a real supermarket setting ensures that user behaviors and responses reflect authentic decision-making contexts. Second, the mixed-method design, combining quantitative usability metrics with qualitative insights, provides a comprehensive understanding of user experience and behavioral impact. Third, the app has an innovative three-pillar AR content structure (functionality, sustainability, and affordances) represents a novel approach to food education, integrating practical, environmental, and perceptual dimensions. The high SUS score (84.60 ± 10.62) and strong perceived ease of use (4.42 ± 0.85) further validate the robustness of the design, indicating that the system is both intuitive and effective in engaging users.

6. Limitations and future work

The system has limitations affecting its usability and effectiveness. The app can scan only four food types, limiting its utility. Users have requested support for processed foods and barcoded products in addition to fruits and vegetables. Regarding the user interface, issues have been identified that negatively impact the experience. During the scanning process, augmented information sometimes flickers, and buttons for additional information do not always work as expected. This type of glitch reduces efficiency and user satisfaction. Users have indicated that the images are sometimes not clear enough, making it difficult to interpret the associated text and recognize the scanned object. Additionally, the app lacks font size adjustments and zoom options, making it difficult for visually impaired users to navigate, further limiting accessibility. Future versions of the system could address these issues by incorporating clearer and more consistent iconography aligned with current design standards, as well as automatic lighting, focus, and exposure adjustments to improve image quality. Higher-resolution processing modes could also be enabled on devices that support them. In addition, the integration of accessibility features such as adjustable text size, high-contrast visual themes, screen-reader compatibility, and alternative input methods (e.g., voice interaction or text-to-speech) would help ensure that the application accommodates users with diverse abilities and device capabilities.

The participants also emphasized the importance of data validity and expressed concerns regarding the reliability of the sustainability information provided by the app. In order to address the previous concerns, we recommend that future versions of the software rely on certified sustainability databases, verified eco-labels, or trusted third-party institutions responsible for validating organic and environmental data (e.g., production origin, certification status, and direct links to verification records). This would assist users in evaluating the reliability of the information and increasing confidence in the sustainability indicators displayed by the application.

Future work will focus on addressing current issues related to expanding the number of foods that can be scanned and improving the stability and accessibility of the user interface to provide a better, more inclusive, and reliable experience. Additionally, the incorporation of targeted searches facilitates the identification of dietary options that align with specific health considerations. To illustrate this process, consider a user who has selected a health issue they wish to address. In response, the app will then propose a selection of the most pertinent foods. Finally, the user also recommended that the app include the creation of personalized profiles, which would allow for the customization of each user's information based on their specific health goals.

To ensure that the proposed improvements are inclusive and supported by robust evidence, it is crucial to acknowledge the study's methodological limitations. Although participants ranged in age from 15 to 71, the sample size was limited and unevenly distributed in terms of age and gender, preventing reliable subgroup analyses. This limitation underscores the need for future research to incorporate larger and more balanced samples to more rigorously explore how variables such as age and gender influence the understanding of food through augmented reality and the intention to modify eating habits. While gender differences were observed in the quality assessment, this finding should be interpreted with caution, as the study was not specifically designed to analyze gender-related variations. Future research should address this issue more thoroughly, considering mediating variables such as prior experience, familiarity with the content, and gender-related perceptions.

Although gender differences emerged in the quality assessment measure, this effect should be interpreted with caution. The present study was not specifically designed to examine gender-related differences, and the observed effect may be influenced by contextual or sample-specific factors. Future research should explore this finding in more detail by including larger and more balanced samples, examining potential mediating variables such as prior experience or domain familiarity, and considering how gender-related perceptions might interact with other individual differences to shape quality judgments.

Furthermore, it was found that both the type of task and the participants' age significantly influenced performance, suggesting that beyond gender, task characteristics and individual differences can have a relevant impact on outcomes. Therefore, it is recommended that future studies analyze how the complexity, order, and cognitive demands of tasks interact with factors such as age, experience, and other demographic or cognitive aspects to better understand their effect on both subjective assessments and objective measures of performance. This approach would allow for the development of interventions better tailored to the needs of different user profiles, thus optimizing the educational and transformative potential of augmented reality applications.

7. Conclusions

Our study suggests that AR application has a positive impact on users' intention to modify their eating habits and on their knowledge about food. Users significantly value sustainability and show interest in the benefits of food, suggesting significant opportunities to optimize the content and features of the app to better suit their needs and preferences. In addition, moderate interest in learning about other uses of food suggests that this functionality could be enhanced to capture more attention and provide valuable information on how to make better use of food in daily life. Our findings highlight the need for educational resources that not only inform about the benefits, sustainability and other uses of food, but also provide practical and accessible solutions that can be integrated into daily routines and improve eating habits.

CRediT authorship contribution statement

Maribel Jaramillo Zapata: Writing – review & editing, Writing – original draft. **Daniel Simões Lopes:** Writing – review & editing, Supervision. **Tomás Alves:** Writing – review & editing, Supervision.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve his English writing and grammar. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.foohum.2026.101159.

Data availability

Research data is accessible upon reasonable request by contacting the corresponding author.

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