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Development and implementation of educational and empowerment models to promote healthy and sustainable diets in university students

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Abstract

In recent decades, food systems have been recognized as a major driver of contemporary global challenges, contributing to climate change and the growing incidence of chronic noncommunicable diseases (NCDs) due to the increasingly widespread adoption of so-called Western dietary patterns. Agri-food systems are estimated to be responsible for approximately 30–35% of global greenhouse gas emissions, while unhealthy dietary habits are associated with approximately 11 million deaths annually globally. At the same time, food waste is a systemic problem, with approximately 19% of food available at the consumer level being wasted. Given the projected growth of the world population, which is expected to reach approximately 9.7 billion people by 2050, a radical shift in production is urgently needed, which can be driven by substantial changes in individual consumption patterns. In this context, the promotion of healthy and sustainable diets, characterized by a predominance of plant-based foods, emerges as an urgent priority, requiring integrated approaches that simultaneously address individual, environmental, and systemic determinants.

Among the population groups that can be addressed, young adults, and particularly university students, represent a strategic target. This stage of life is characterized by greater decision-making autonomy and profound changes in eating behavior, often associated with a reduction in diet quality and poor adherence to recommended dietary patterns. These students are both the professionals of tomorrow and can act as change agents themselves. Furthermore, universities offer a unique context for implementing complex interventions, acting as "living labs." Thanks to their intrinsic multidisciplinary expertise, they can implement innovative approaches that address changes in the dietary environment. Furthermore, universities' interest in having healthier students is not only an ethical issue related to the Third Mission, but would represent a win-win approach, as it is well recognized that students with high adherence to healthy dietary patterns tend to perform better academically.

Traditional nutritional interventions are predominantly based on education and increased knowledge, yet they lead to limited effects that are difficult to sustain over time. Theoretical models such as the Behavior Change Wheel (BCW) highlight the need for multilevel approaches to address the primary determinants of behavior (opportunity and motivation) through targeted interventions and, at a higher level, appropriate food policies. In this context, environmental modification strategies such as nudging or digital tools such as mHealth applications represent promising solutions, although they are still poorly integrated with each other and have limited evidence in real-world settings.

Considering these critical issues, the objective of this thesis was to develop, implement, and evaluate empowerment models for promoting healthy and sustainable eating behaviors in university students, combining environmental interventions, digital tools, and a participatory approach in real-world settings. The thesis is structured around four interconnected studies.

The first study evaluated the effectiveness of a multi-component nudging intervention implemented in the university cafeteria on the Parma campus, with the aim of improving food choices and reducing individual waste. The study, conducted over a final sample of 149 days of observation for food choices and 50 days for waste, yielded partially positive results. In terms of choices, no significant effects were observed on the selection of dishes labeled "Healthy and Sustainable", except for white meat-based dishes, the selection of which increased during the intervention. In parallel, the intervention did show a significant food waste reduction, trained by a lower waste of labeled dishes. These results, in line with evidence published in the literature, highlight how changes in the environment often influence single components.

The second study developed and validated FLIC (Food Leftovers In Canteens), an innovative dataset for visually estimating food waste in real-world settings. Data were collected again in the university cafeteria on the Parma campus for 22 days, obtaining RGB images of 401 trays (before and after consumption) using a computer vision system. For these trays, the weight of individual foods served was detected through direct weighing. A pipeline based on the concept of "digital density" was developed, relating pixel area to food mass. The segmentation models achieved high accuracy for complete trays, but lower performance for leftovers, due to the greater visual complexity of trays after the meal. Overall, FLIC demonstrates the feasibility of using computer vision systems for waste estimation in real-world settings, aiming to be an objective and scalable tool.

The third study involved the development of the Uniplate app, an mHealth tool designed through a participatory, multidisciplinary approach. The process was divided into four phases (conceptualization, co-design, development, and testing), involving university students through a focus group and integrating the Taxonomy of Behavioral Change Techniques v1. The app incorporates 21 behavioral change techniques organized into 11 clusters, translated into practical features such as goal tracking, meal planning, a shopping list, a sustainable recipe database, and personalized educational content based on users' psychobehavioral profiles. The Uniplate app was tested in a randomized controlled trial, where participants reported high acceptability and satisfaction.

The fourth study evaluated the effectiveness of the Uniplate app in inducing changes in students' dietary habits through a 12-week randomized controlled clinical trial. The intervention, after six weeks, resulted in a significant increase in the primary outcome, fiber intake, which persisted at follow-up. Secondary outcomes included an increase in vegetable consumption, associated with a corresponding increase in dietary fiber intake. Urinary biomarkers confirmed these findings, showing an increase in metabolites associated with whole grains and other plant-based foods, along with a reduction in those associated with animal products. The intervention group also observed improvements in adherence to the Planetary Health Diet and the Mediterranean Diet, while no significant changes were found for most macronutrients. These results suggest that the app could promote healthier and more sustainable eating patterns, although larger, long-term studies are needed to confirm its long-term effectiveness.

Overall, these findings highlight the complexity of changing dietary behaviors in real-world settings, influenced by individual, social, and environmental factors. From this perspective, universities emerge as ideal context for designing, testing, and implementing integrated models, serving as real-world laboratories for developing scalable and transferable solutions. Overall, this thesis contributes to the advancement of the field by proposing and evaluating a multilevel empowerment model, offering practical and methodological insights for developing effective integrated strategies to promote healthy and sustainable diets in young adults.

Chapter 1 – Introduction

1.1 Transforming food systems in the face of global health and environmental challenges

Food systems worldwide are confronting unprecedented, interconnected pressures stemming from intertwined global health, environmental, and socio-economic crises. The pace of climate change is threatening the stability of planetary boundaries, leading to loss of biodiversity, land degradation, and depletion of freshwater resources [1]. The Sixth Assessment Synthesis Report of the Intergovernmental Panel's on Climate Change (IPCC) estimates that the global surface temperatures have already increased by 1.1°C compared to pre-industrial era, with between 3.3 and 3.6 billion people living in area highly vulnerable to the impact of climate change. Human activities are responsible for the loss of over 75% of land ecosystems and 50% of freshwater ones, while 40% of land suffers from degradation. Moreover, water scarcity caused by climate change is expected to affect 4 billion people for at least a month each year [1]. The global agri-food system is estimated to be responsible for about 30 to 35% of human greenhouse emissions [2], which causes up to 83% deforestation [3], uses 70% of freshwater [4] and is the leading reason for biodiversity loss [5]. These environmental consequences of food systems are determined by multiple stages along the food-chain, among which the land-use changes to livestock farming, food processing, transportation and food waste play a crucial role [6].

These environmental issues are made worse by a growing global population and the higher demand for food, water and land associated with this growth increasing the pressure on the capacity of food systems [7]. The United Nations estimates that the world population reached 8.0 billion in 2022 and is projected to increase to 9.7 billion in 2050 and over 10 billion by 2100 [7]. An increased population implies greater demand for food, water, and land, placing further pressure on the environment and challenging the capacity of food systems to operate sustainably. The risk is not limited to a scenario of food scarcity, where as early as 2024, 2.33 billion people will be food insecure, of whom over 700 million will be suffering from hunger [8]. Malnutrition, in fact, is often defined as a "double burden". Its second component is an imbalance in nutrient intake, leading to over 2 billion adults being overweight, 890 million of whom are obese according to the 2024 State of Food Security and Nutrition in the World report [8]. Furthermore, projections are not reassuring as it is estimated that by 2030, the number of people affected by obesity could exceed 1.2 billion [8]. This component of malnutrition increases the risk of developing noncommunicable diseases (NCDs), such as heart disease, stroke, cancer, diabetes, and chronic respiratory diseases, which are constantly growing globally. According to the Global Burden of Disease 2019 analysis [9], unhealthy dietary patterns are associated to approximately 11 million deaths, representing 74% of all deaths in the world attributed to NCDs, and 255 million disability-adjusted life years (DALYs) worldwide, making unhealthy eating the leading risk factor for the global burden of disease, even exceeding smoking and air pollution [9]. These DALYs reflect both years of life lost due to premature mortality and years lived with disability attributable to diet-related conditions such as cardiovascular diseases, type 2 diabetes, and certain cancers [9].

These health trends are closely linked to the so-called nutrition transition, a global shift toward dietary patterns characterized by high consumption of energy-dense foods, refined grains, added sugars, saturated fats, sodium, and red and processed meats, typical elements of the so-called “Western diet” [10]. This transition is driven by globalization, urban growth and expanding industrial food supply chains, especially in low- and middle-income countries. These eating habits are becoming more common, the average amount of added sugar eaten is often more than 100 g per day, and the average amount of sodium eaten is almost 4 g per day, which is almost twice the WHO recommended limit of 2 g. The average amount of saturated fat eaten is often more than 10% of total energy intake [10, 11, 12]. At the same time, the amount of energy available each day has gone up to more than 3,000 kcal per person in some high-income areas. This has led to more people being overweight, obese, and developing diet-related noncommunicable diseases (NCDs) [9]. These dietary transitions have a disproportionately large effect on the environment, which makes global sustainability problems even worse [13].

The Food and Agriculture Organization of the United Nations and the World Health Organization advocate for diets that are both healthy and sustainable, dietary patterns that support physical and mental wellbeing, remain culturally accepted and affordable and have low environmental impact [14]. Considering this, FAO and WHO have established principles for a healthy and sustainable diet, considering health, environmental impact, and sociocultural aspects [Fig. 1]. In addition, actions needed to make such diets accessible, affordable, safe and desirable have been identified [Fig. 2]. These actions include: (i) promoting diversified and sustainable food production systems; (ii) strengthening local and seasonal food supply chains; (iii) improving food environments to facilitate healthier choices; (iv) implementing fiscal and policy measures that incentivize sustainable and nutritious foods; (v) enhancing food labeling and consumer information; (vi) reducing food loss and waste across the supply chain; (vii) supporting nutrition education and behavior change interventions; and (viii) fostering multisectoral governance and collaboration among stakeholders.

Beyond its environmental impact, food waste represents a neglected component of sustainability of food systems. Globally, one third of the food produced is lost or wasted [59] and more recent studies confirmed those estimations [60]. In collective catering settings, including university canteens, where profit margins are typically low and rely on high meal volumes, there is a strong interest in minimizing such waste. However, this phenomenon persists and is often attributable to structural, organizational, and behavioral factors, such as portioning practices, menu design, time constraints, and students’ choices [61, 62]. University canteens are diverse, sometimes privately managed, sometimes regulated by the universities themselves. Consequently, some of them frequently serve as settings for conducting research. Evidence from these contexts shows that food waste is ubiquitarians and measurable, as measurables are the modifiable factors [62, 63]. This perspective is central to the empirical work developed in this thesis, particularly in Study 1 and Study 2, which explore methods to measure and reduce the food wasted after the consumption, leftovers which will be referred to as “plate waste” in this manuscript, in the university canteen of Parma University.

Figure 1. Guiding principles for sustainable healthy diets. Reproduced from FAO and WHO (2019), Sustainable healthy diets: Guiding principles. [14]

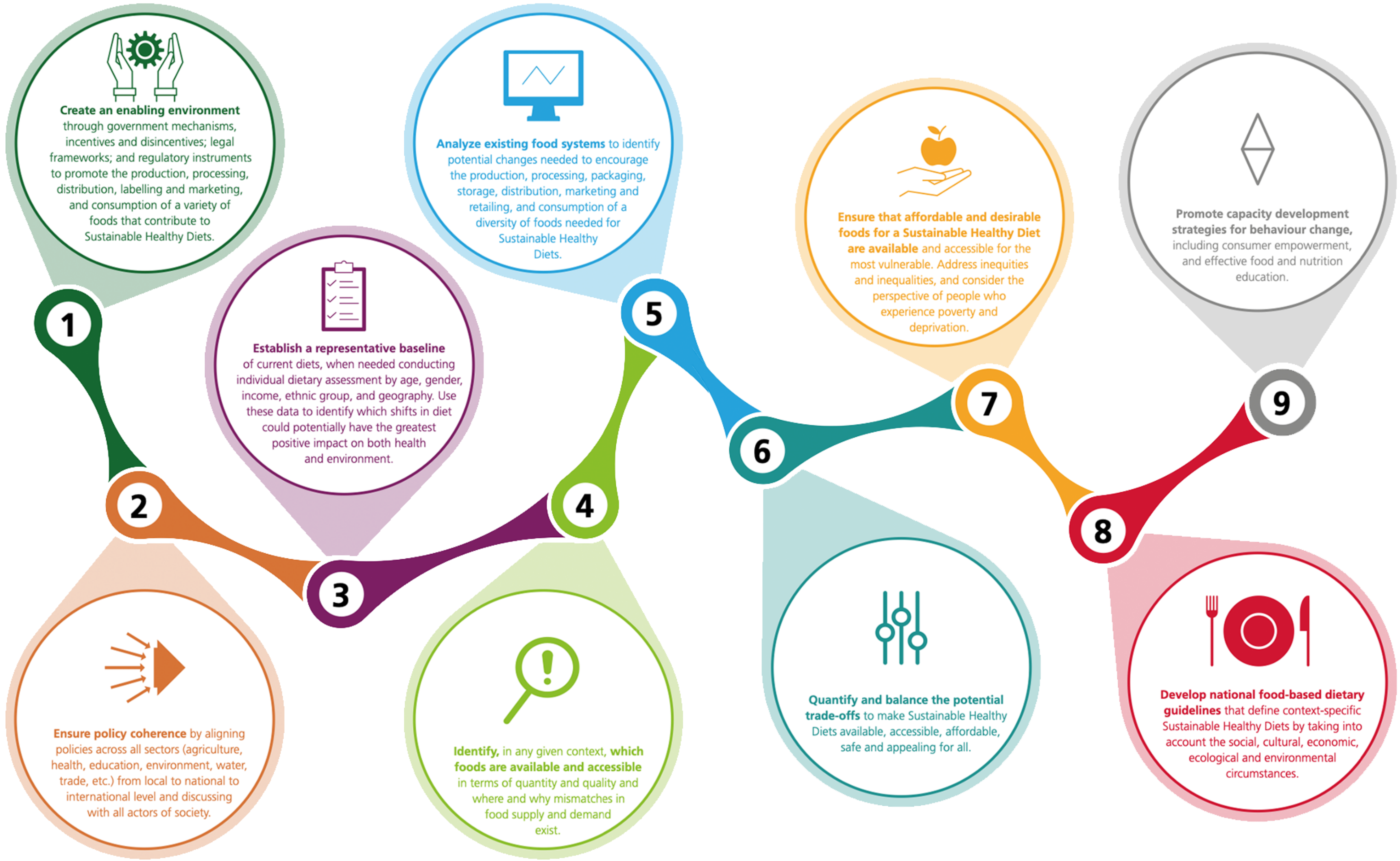

Figure 2. Actions for the implementation of sustainable healthy diets. Reproduced from FAO and WHO (2019), Sustainable healthy diets: Guiding principles. [14]

1.2 Young adults and the university transition: a critical window for shaping lifelong dietary habits

The life period defined as "young adulthood," the transition from adolescence to independence, represents a crucial life stage for defining and consolidating one's eating habits. For many, this age coincides with university, when young people find themselves, often for the first time, eating out, assuming increasing autonomy in their choices, including food choices and lifestyle behavior. This transition is often accompanied by separation from the family environment, increased responsibility in managing financial resources, and greater exposure to independent decision-making. This life stage is often defined by irregular routines and peer influence. Furthermore, young adults are increasingly getting information on nutrition and health on social media, exposing themselves to content of varying quality and misinformation, which can hinder the adoption of eating habits with evidence-based beneficial effects [15, 16, 17].

These contextual and behavioral changes significantly influence dietary patterns, and the literature agrees that there is a tendency to adopt unbalanced dietary patterns, with reduced consumption of fruits and vegetables, a high consumption of convenience foods, and a decline in adherence to the nutritional recommendations provided by the respective national dietary guidelines [18]. Recent evidence from Italian studies shows that adherence to dietary patterns recognized as healthy and sustainable (e.g., the Mediterranean Diet) tends to decline significantly [19]. Only 44% of university students consume at least one serving of fruit a day, while only 22.5% of the sample consumes two servings of vegetables a day [20]. Furthermore, meal regularity is often compromised, with only 8.5% consume five meals a day, as recommended by Italian national guidelines [20, 21]. While this isn't necessarily true for everyone, it's well recognized that this stage of life presents an opportunity for this segment of the population: habits formed in young adults often persist into later stages of life [22].

In Europe, the share of young adults (24-35 years age) with a university degree reached 44.1% in 2024, up from 36.5% in 2015 [23]. The same trend, although less masked than the European average, is also observed in Italy, where it rose from 24% in 2014 to 31.6% in 2024 [23]. Therefore, considering that an increasing number of young people are attending university, these represent a strategic context for nutrition education, capable of influencing both individual food choices and the campus food environment.

In this sense, promoting healthy and sustainable dietary behaviors within universities is not only an ethical responsibility aligned with their third mission, but also a strategic investment. Evidence from the literature clearly indicates that the quality of one's diet influences academic performance [24, 25]. From this perspective, investing in nutritional education, along with redefining food environments, represents a win-win approach.

1.3 Determinants of dietary behavior in university students

Eating behaviors among university students are the result of a complex interaction of multiple factors, as described by socio-ecological models [26, 27]. These factors do not just depend solely on individual choices and willpower but rather emerge from the interaction of multilevel aspects such as individual, interpersonal, environmental and social determinants. [27, 28]. At the individual level, nutritional knowledge, taste preferences, time management, and self-regulation obviously play a crucial role in food choices [28]; however, evidence supports the view that knowledge alone is insufficient to produce lasting behavioral changes, especially in a population segment exposed to multiple constraints and competing stimuli such as young adults [29]. At interpersonal level, determinants such as peers, family, and social norms exert a strong social influence. University students are extremely exposed and sensitive to social influence, particularly from peers since they share mealtimes that contribute to modeling their choices. The phenomenon of replicating food choices of other individuals in your own social context is known as "behavior mimicry" [30, 31].

Economic constraints represent an additional and salient determinant of dietary behavior. If it is true for the general population, this may further affect students' choices: it is common to rely on family financial aid and/or on scholarships at that stage of life. Limited financial resources often restrict access to fresh, nutritious and sustainable food, directing choices toward low-cost and energy dense options. Affordability is explicitly recognized by FAO and WHO [14] as a core principle of sustainable healthy diets yet remains a major barrier for young adults navigating tight budgets. In university settings, the price structure of canteen meals and the availability of subsidized options influence both food selection and food waste practices, adding an important economic layer to the environmental determinants described above.

A further layer of influence in the university context is represented by environmental factors: the availability, accessibility, price, and convenience of food significantly influence dietary choices, favoring the consumption of energy-dense and ready-to-eat foods [32, 28]. Furthermore, specific academic environment factors, such as class schedules, exam periods, and the organization of dining services, limit the ability to make structured and informed choices [28]. Broader factors such as food marketing, exposure to digital media, and cultural norms act at the macro level. The increasing digitalization of the food environment has amplified exposure to food-related content, influencing preferences, perceptions, and behaviors, particularly among young adults [33]

It is important to emphasize that these determinants do not act independently, but interact dynamically with each other. The transition to adulthood in university settings is, in fact, defined by several obstacles that make it an obesogenic environment where it is easy to stumble into suboptimal eating behaviors [34, 28].

1.4 Universities as living laboratories for healthy and sustainable food environments

Higher education institutions are increasingly establishing themselves as ideal "living laboratories" for promoting healthy and sustainable diets. For several years now, various organizations have set out to promote organizational models for health promotion in universities; examples include the World Health Organization's Framework for Health-Promoting Universities [35], along with the 2015 Okanagan Charter [36], or the more recent EU Green Alliance [37]. These initiatives explicitly call on universities to integrate health, sustainability, and well-being into their core missions through evidence-based, systemic approaches. The food environment on campus, including canteens, cafeterias and vending machines, strongly affects what people eat through what's offered, what is extra priced and how it's displayed. Research shows that making targeted modifications can meaningfully affect people's choices, improving both health and environmental outcomes [38]. Interventions such as increasing the offer of plant-based options, introducing clear nutritional labeling, and reorganizing menus have proven effective in guiding choices towards healthier and more sustainable options [39, 38]. In addition to these structural characteristics, universities present further strengths: they integrate research, teaching and practical application, bring together multidisciplinary skills, have advanced digital infrastructures and encourage direct student involvement. These elements make the university context particularly suitable for the design and implementation of complex interventions, capable of acting simultaneously on individual behavior and environmental determinants [40, 41]. However, the review by Ktrarzer et al. (2025) [40] highlights how the available evidence is still heterogeneous and often limited in terms of robustness, with the most promising results observed in multi-component interventions that combine environmental, educational and communication strategies. This evidence is consistent with other systematic reviews, which report moderate but variable effects of interventions on the university food environment and emphasize the importance of integrated and context-specific approaches [42, 43, 44]. Within university food environment, canteens represent the crucial component. The menu structure, portion sizes, pricing, the physical layout and pricing affect the accessibility and desirability of different options. Given that, empirical interventions of this dissertation aim at evaluating different intervention strategies conducted in the canteen of the Campus of the University of Parma. From this perspective, this thesis enhances this potential by designing, implementing and evaluating innovative strategies in a real university context.

1.5 Limitations of traditional nutrition interventions and the need for innovative participatory approaches

Designing educational interventions based on one's personal experiences not only carries the risk of the intervention not being effective, but also of leading to adverse effects. This is why understanding how to effectively promote changes in eating behaviors requires reference to solid theoretical models. Among these, the Behavior Change Wheel (BCW), proposed by Michie et al. (2011) [29], represents one of the most comprehensive and recognized models for designing behavior change interventions. BCW is a synthesis of 19 prior models of behavior change and represents how individual or collective behaviors are determined by multiple factors with multiple levels of influence. It integrates behavioral determinants, intervention functions, and policy levers into a single framework, offering a systemic approach that links behavior analysis to the design of effective strategies.

This framework is structured into three interconnected concentric layers [Figure 3]. At the core there is the COM-B model, which defines the primary determinants of behavior: Capability, defined as the individual's psychological and physical capacity to engage in the activity concerned; Opportunity is the set of factors external to the individual that make a behavior possible; Motivation include those brain process that energize and direct behavior, such as habitual processes, emotional responding ora analytical decision-making.

The second layer includes nine intervention functions that represent paths throw which interventions can influence a behavior on its determinants. Finally, the external layer includes policy categories, the policy levers and regulatory tools that support and enable intervention functions to operate on large-scale settings.

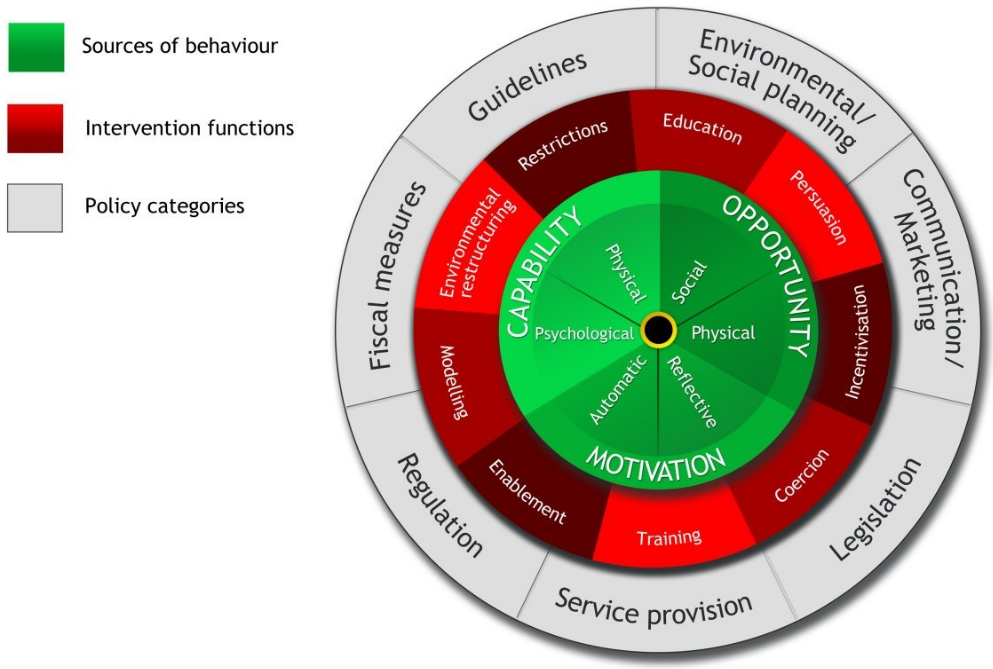

Figure 3. Behavior Change Wheel [29]

Despite the availability of robust theoretical models, traditional nutritional interventions focus on a single component of the behavioral system. Typically, they primarily address capability through the dissemination of information through lectures, the provision of informational materials, or awareness campaigns, resulting in modest results and often short-term improvements [45, 46]. Improving nutritional and health knowledge alone rarely translates into sustained behavioral changes over time, especially among young adults who are exposed to multiple stimuli and influences [45, 47]. According to the BCW logic, interventions that do not address the dimensions of opportunity (e.g., food price, availability and accessibility) and motivation (e.g., social norms, preferences) tend to be ineffective [29], wasting many people's effort and public resources.

Following research published by Michie and colleagues in 2013 [46] settled a milestone for the development of behavioral change interventions. They systematically identified and classified 93 standardized Behavior Changing Techniques (BCTs) that represent the "active components" of interventions, generating a structured taxonomy. Some examples are self-monitoring, setting goals and receiving feedback. However, numerous studies report on how these techniques are frequently used implicitly, unconsciously or singularly, reducing the overall effectiveness of interventions [49, 50].

Further critical issues include a low level of personalization and limited user engagement. Administering a standardized educational intervention without addressing the requests and needs of the sample in question could significantly reduce engagement, especially among university students, who, as digital natives, expect tailored, interactive and engaging experiences. Recent evidence suggests that participatory and co-creation approaches, as opposed to top-down ones, lead to the design of more engaging and effective interventions as they are better aligned with users' needs and preferences and foster greater empower in participants themselves [51, 52].

Overall, these limitations highlight the need to develop innovative, personalized approaches for university students that are theoretically robust and participatory, capable of intervening simultaneously at multiple levels. Effective strategies should therefore integrate intervention functions, as conceptualized within the Behavior Change Wheel (educational, food environment reconstruction), while also providing concrete digital support tools that include explicitly designed and combined behavioral change techniques, leveraging co-creation methodologies to enhance engagement users and empowerment, improve the sustainability of interventions over time. From this perspective, this thesis aims to address these issues through the development and evaluation of targeted, tailored interventions applied in a real university context.

1.6 Empowerment, food literacy and digital intervention co-creation

To promote lasting food behavior changes it is important to go beyond traditional approaches based on knowledge transfer. In this perspective, concepts of food literacy and empowerment have assumed a central role in modern health promotion strategies. Food literacy is defined as the set of knowledge, skills and abilities needed to plan, select, prepare and consume food in a conscious manner and consistent with health and sustainable objectives [53, 54]. At the same time, empowerment refers to the process through which individuals acquire greater control over their own decisions and behaviors, strengthening self-efficacy, autonomy and active participation in change processes [55]. Food literacy and empowerment are then complementary, the former provide practical abilities and critical thinking, while the latter allows them to be translated into sustained behaviors over time.

Fostering food literacy and empowerment on a large scale is challenging, especially in dynamic and complex contexts like universities. In recent years, digital technologies have opened new opportunities due to their widespread reach across a broad population. Interventions delivered through digital tools, including mHealth apps, are enjoying growing success. However, many digital interventions struggle to maintain high levels of engagement over time and lack personalization and relevance to user needs [56]. In response to these critical issues, involving end users in the intervention development process through a co-creation approach has proven to be the most promising approach [57]. Involving the target population has proven to be a solution for addressing needs and preferences, improving acceptability and effectiveness [58]. Integrating food literacy and empowerment in digital tools with a participatory approach appears to be a promising strategy to design effective interventions in university settings.

Despite growing interest in healthy and sustainable diets, several gaps remain in the current literature. Evidence on food waste and its quantification is typically limited to experimental settings. Second, despite the relevance of young adulthood as a critical life stage, few studies adopt comprehensive socio-ecological and behavior change frameworks to analyses students' food practices. Third, digital interventions in this target population often lack grounding, personalization and participatory development and their effectiveness has rarely (or never) been evaluated in real context using objective measures.

This doctoral thesis aims to address these gaps through four interconnected studies. Study 1 examines how multi-component nudging strategies influence food choices and food waste in a university canteen. Study 2 develops and validates FLIC, a novel computer-vision dataset for objective food waste estimation in real settings. Study 3 uses participatory and multidisciplinary methods to design the Uniplate app, integrating behavior-change techniques into a tailored digital tool. Study 4 evaluates the app's effectiveness through a randomized controlled trial, combining dietary assessment with urinary biomarkers. Together, these studies provide an empirical and methodological contributions for designing integrated, context-specific strategies to promote healthier, more sustainable and less wasteful dietary behaviors among university students.

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Chapter 2 – Aim of the Doctoral Thesis

Food systems represent one of the most powerful levers to simultaneously improve human health and environmental sustainability. However, current young adults' dietary patterns are still far from optimal and are influenced by a complex combination of individual, social and environmental determinants. Therefore, in this complex landscape, universities represent an exciting opportunity to promote health and sustainable eating habits, as they enable the integration of educational, social and environmental aspects of nutrition in a single ecosystem. Indeed, given the complexity of eating habits, there is growing need to develop innovative approaches to address issues related to eating habits and food waste in complex settings.

Based on these considerations, the aim of this doctoral thesis is to develop, implement, and evaluate innovative and integrated approaches to promote healthy and sustainable dietary behaviors and habits among university students, combining environmental, technological, and digital strategies within real-world university contexts. To address this objective, the thesis is structured into four interconnected studies.

The first study (entitled "Fostering healthy and sustainable food-related behaviors among university students: a nudging-based intervention study in Italy") investigates the role of the food environment by designing and implementing a multi-component nudging intervention within a university canteen. The aim is to evaluate whether modifications in the choice architecture can promote healthier and more sustainable food choices and reduce plate waste in a real-world setting.

Based on the need for accurate and scalable outcome measurement, the second study (entitled "FLIC: A Real-World Dataset for Visual Estimation of Food Leftovers in Canteens") aims to develop and validate an innovative computer vision system for the automatic recognition and quantification of plate waste in university dining settings. This approach seeks to overcome the limitations of traditional methods and provide objective and reproducible data for evaluating further interventions.

The third study (entitled "Uniplate: a mHealth application developed using a participatory design to support healthy and sustainable dietary behaviors in university students") focuses on the development of a digital educational tool, Uniplate, through a co-creation approach involving university students. The aim is to evaluate the usability and acceptability of a user-centered designed intervention that integrates behavioral change techniques and promotes food literacy, empowerment, and engagement, ensuring alignment with users' needs and daily routines.

The fourth study ("Promoting healthy and sustainable diets in young adults through an educational M-health application: a randomized controlled trial") evaluates the effectiveness of the developed Uniplate app through a randomized controlled trial (RCT), assessing its impact on dietary behaviors. Primary outcome will be the change in dietary fiber intake as a proxy of general health and sustainability indicator. Among others, secondary outcomes will be other nutrients intake, the adherence to the Planetary Health Diet index and to a Mediterranean Diet score.

Taken together, these studies contribute to the development of a comprehensive, multi-level intervention model that integrates environmental modification, objective measurement tools, digital education, and behavioral science. By addressing both food choices and food waste, and by combining real-world experimentation with technological innovation, this thesis aims to generate scalable and evidence-based solutions to support healthier and more sustainable food systems within university contexts.

Chapter 3 – Selected studies

Study 1

Fostering healthy and sustainable food-related behaviors among university students: a nudging-based intervention study in Italy

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This study is currently in preparation for submission to peer-reviewed journals.

Abstract

Background/objectives: The modification of the choice architecture to influence behavior without restricting options has been proven effective in encouraging healthier and more sustainable food choices. However, studies tend to focus on single-component intervention and isolated outcomes. Therefore, this study aimed to promote the consumption of healthy and sustainable meals and reduce plate waste in a university canteen by applying multiple nudging techniques and evaluating their effects during implementation and after removal.

Methods: The experiment has been developed in a canteen at Parma University in Italy, through the collaboration of the catering company. After the baseline phase (April-May 2024, t0), cognitively- and behaviorally oriented nudges, including the use of a logo to mark healthy and sustainable options and multiple educational tools changing the canteen environment, have been applied simultaneously during the intervention phase (October 2024-March 2025, t1). Sales data were collected through a dedicated cash register across time and after a follow-up phase (April-May 2025, t2). In parallel, a direct weighting method was applied to measure plate waste in a subgroup of 51 days during the whole study period.

Results: An increasing trend of daily per capita selection of dishes with logo and protein-based dishes with logo was observed from t0 to t1, while at t2 they significantly decreased (p=0.032 and p=0.027, respectively). For protein-based dishes, the same pattern characterized the selection by offer coefficients, which significantly declined at the follow-up (p=0.010) after slightly increasing during the intervention. Furthermore, white meat-based dishes emerged as more selected at t1 than t0 (p=0.031), with no parallel increase in the relative offer, suggesting a positive effect of the intervention for this protein source category. Among vegetarian protein sources, egg/dairy protein category better performed compared to legumes, which were instead scarcely chosen, with a median selection by offer coefficient constantly below 1. In terms of median waste amount per capita (g), plate waste referred to total dishes, dishes with logo, and side dishes was significantly reduced during the intervention (p=0.040, p=0.006, and p=0.008, respectively).

Conclusions: The study findings show a partial efficacy of the intervention, which, overall, succeeded in decreasing plate waste, without however significantly shifting food choices in the desired direction across time. Results highlight the complexity of consumer behavior, which is not easily modifiable. By acting on the food environment increasing efforts should be made to find affordable and effective strategies to shift dietary habits to accomplish the health and environmental sustainability dimensions.

Keywords: Nudging; University Canteen; Food environment; Food choice; Food waste; Behavioral intervention

3.1.1 Introduction

In the last decades, food systems have been recognized as fundamental lever to face some of the most challenging current global issues, among which climate change, soil degradation and loss, and the growing burden of non-communicable diseases (NCDs) [1]. Current dietary patterns are threatening both human health and environmental issues. It is estimated that poor dietary patterns are linked to 11 million deaths per year, representing 74% of all global deaths caused by NCDs [2], increasing noticeably the pressure on nationals' health systems. From an environmental point of view, the international scientific community agrees to attribute 30 to 35 % of human's greenhouse gasses emission to the global agri-food systems [3]. In this context, international organizations emphasized the urgency of promoting healthy and sustainable diets, defined as nutritionally balanced, economically accessible and fair, as well culturally accepted patterns that support human well-being while maintaining a low environmental impact [4].

Alongside the quality of diet, food waste represents a critical dimension of issues that food systems are confronting with. According to the latest Food Waste Index Report (2024) of the United Nations [5], 1.05 billion tons were wasted in 2022, corresponding to 19% of food available at the consumer level. When considering both food waste and loss along with all the food chain, nearly one third of food produced is not consumed. This inefficiency results in approximately 8-10% global greenhouse emissions [5].

Promoting responsible consumption is therefore crucial for preserving environmental and individual health. Although approximately 60% of waste occurs at the household level, public catering services account for nearly 30% of the total (UNEP, 2024). Considering that in Europe alone, approximately 6 billion meals are served annually in schools, hospitals, company canteens, and universities [6], institutional canteens represent a crucial setting for promoting healthy and sustainable eating habits [7;8]. Indeed, a substantial proportion of meals consumed out-of-home are provided by this sector, where daily eating routines are heavily influenced by menus availability [9;10].

Due to the crucial role of food service, scientific literature increasingly considers collective catering environments as an opportunity for intervention. The tendency is to implement subtle and non-coercive interventions, defined as nudging [11], which aim to influence the architecture of choice with solutions that redefine the decision-making environment to guide behaviors toward healthier and more sustainable choices by preserving individual freedom of choice.

In recent years, an increasing number of studies have explored the application of nudging strategies in collective catering services, including universities canteens. Among these, placement modification, by affecting visibility of certain food options, improved the choice of healthy and sustainable options, including plant-based dishes [12]. Similarly, the use of labels informing about dish environmental sustainability has been tested proving to be effective in female attendees of a university café [13] and in other real-world food environments, including restaurants and retail settings, where sustainability labels have been shown to positively influence consumer choices and perceptions [14; 15].

In addition, the resize and modification of the dish design were associated with the reduction of both food consumption and food waste [16; 17].

Despite these promising results, literature highlighted multiple criticalities. Numerous studies report mild or short-lived effects, with little evidence that behavioral changes persist after the intervention [18; 19]. Furthermore, peer-reviewed literature often reports studies based on single-component interventions and tends to focus on isolated outcomes, such as food choices or food waste, rather than addressing both dimensions simultaneously [20; 21]. This fragmented approach limits a comprehensive understanding of eating behaviors. Furthermore, evidence from real university contexts, particularly in Southern European countries like Italy, is still limited.

Therefore, this study aims to promote the consumption of healthy and sustainable dishes and reduce plate waste in a university canteen in Northern Italy by applying a multi-component nudging intervention and evaluating its effects during its implementation and after its removal.

3.1.2 Methods

3.1.2.1 Study design

The intervention study applied a pre-post study design implemented in the Campus university canteen in Parma (Northern Italy). Canteen selection was based on practical aspects, such as the high attendance by students and logistical feasibility for carrying out the study, besides the collaboration of the catering company. The study took place from March 2024 to May 2025 and included a baseline pre-intervention phase (Apr - May 2024, t0), an intervention phase during which cognitively and behaviorally oriented nudging techniques were simultaneously applied (Oct 2024 - Mar 2025, t1), and a follow-up phase free of nudges (Apr -May 2025, t2). Sales data were collected through a dedicated cash register, while a direct weighting method was applied to measure plate waste across time. A flow chart reporting the study design and activities is depicted in Figure 1.

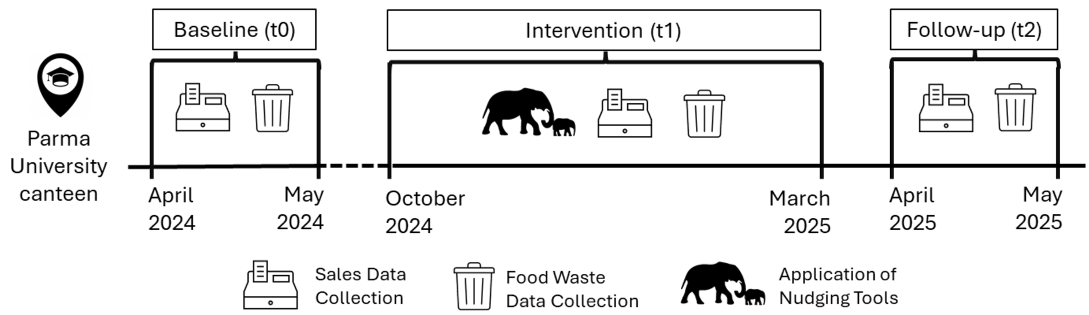

Figure 1. A scheme of study design with data collection activities.

3.1.2.2 Contextual setting

Canteen food offer, which was not modified during the intervention, generally included three options of first courses (i.e., dishes composed mainly of starchy foods, such as pasta, rice and other cereals) and four options of second courses (i.e., dishes mainly composed of protein-based foods, such as meat, fish, eggs, dairy products, legumes). Among both first and second courses, a vegan option was commonly available daily (e.g., plain pasta/rice or pasta/rice with tomato sauce). Canteen attendees were also generally offered side dishes with vegetables, potatoes, or legumes, main course salads, pizza, fruit, bread, and desserts, with the latter composed of yogurt, chocolate pudding, or cakes. Besides the dishes planned to be served, almost every day one or more extra first and/or second dishes were prepared by the canteen staff based on the food surplus not served the day before, contributing to expanding the canteen food offer.

Three price promotions, specifically addressed to students, were applied by default for specific dish combinations: 4.5 euros (a simple first or second course including legumes or eggs or characterized by a simple process of preparation, a side dish, and bread, with the latter included only if a second dish is selected); 5 euros (egg/stuffed pasta or a first course including meat or fish, a side dish, and fruit; a main course salad and fruit; a complete menu composed by a simple first and second dish, a side dish, and fruit); 6 euros (a complete menu where the first or the second course is simple). Alternative combinations of those listed above, as well as beverages (except for water which is free of charge) and desserts were instead paid for as extra by the canteen attendees. Price promotion alternatives were previously specified in the call for tender for the awarding of a concession for catering services at the university canteens in Emilia-Romagna region. The document was drafted by the Regional Authority for the Right to Higher Education (ER.GO), in collaboration with a multidisciplinary team including nutritionists, economists, and psychologists from Parma and Bologna Universities, to incentivize healthy meal selection among university students.

3.1.2.3 Intervention

Multiple nudging techniques were applied to the canteen for the whole intervention period. Among these, a logo, previously co-developed with Parma university students [22], was used daily to mark healthy and sustainable dishes within the list of the canteen menus to indicate recommended dish options. The logo was applied according to the guidelines for promoting sustainable diets at canteens of worksites and universities established during the European LIFE SU-EATABLE project [23]. Briefly, the logo was assigned to main course salads, fruit, and first and second courses compliant with recommendations for a sustainable meal. Specifically, all dishes based on cereals, legumes and vegetables were marked with the logo, alongside poultry, egg, and fish dishes. Dishes were classified exclusively based on the list of the ingredients provided by the cook. Preparation and cooking methods were not considered. This choice was driven by practical constraints: the catering service did not provide standardized or detailed information on cooking procedures, and the preparation methods varied over days and menus. Including these aspects would have introduced inconsistencies and reduced the reliability of the classification. For the latter, it has been decided to not put logos on items with the highest environmental impact (i.e., squid, cuttlefish, and scorpionfish) based on the Peterson et al dataset [24], which collects GHG emissions from production up to distribution. Conversely, logos were not applied to dishes containing beef, lamb, or pork, nor to recipes consisting solely of cheese or those where cheese was paired with meat. Although plain pasta/rice or pasta/rice with tomato sauce could have been labelled with the logo, it was ultimately decided not to mark them to promote more nutritionally balanced food choices. Similarly, side dishes containing potatoes were not marked with logo as it was considered appropriate for occasional consumption and not as substitute for vegetables. Furthermore, the same decision was taken regarding pizza, due to the relatively high content of salt.

Furthermore, the dishes listed in the menus were reordered to first present healthy and sustainable options within first and second course categories. The canteen environment was set up with educational posters reporting information or suggestions about: how to properly compose a healthy and sustainable lunch meal, inspired by the Healthy Eating Plate developed by Harvard T.H. Chan School of Public Health [25] (i); the standard portions of specific food groups (e.g., fruit and vegetables) (ii); recommended consumption frequencies based on Mediterranean food pyramid (iii); strategies to reduce salt, added sugars and saturated fats consumption (iv); the carbon and water footprint associated with different food products (v); how to reduce household food waste (vi); keeping hydrated during the day (vii); ideas for balanced meals across the day (viii); seasonality of fruit and vegetables (ix).

Behind the serving counter, there were instructions on how to properly assemble a tray, with different colors indicating different meal components with peculiar nutritional characteristics. Moreover, colored footprints were stuck to the floor to guide diners in their meal composition, with blue footprints indicating the path to reach the water dispenser. On the table where oil and salt were placed, memes have been added to foster a proper condiment choice and fruit selection, as well as to reduce plate waste and discourage the use of plastic cups if a personal water bottle is available. All the modifications of the canteen environment were decided and implemented by the Human Nutrition Unit of the University of Parma, in agreement with the catering service. Some examples of nudging tools applied to the canteen environment are shown in Figure 2.

Figure 2. A selection of nudging tools applied during the intervention phase, including the logo marking healthy and sustainable dishes, some educational posters designed to increase knowledge about a healthy and balanced diet, as well as raise awareness about food and diet sustainability; adhesive footprints on the floor guiding diners in properly composing their meals.

3.1.2.4 Data collection

In accordance with the cooperation of the catering service and ER.GO, a reprogramming of one of the two cash registers available in the canteen was implemented to allow collection of sales data for each course and dish typology, without causing excessive delay at the till. Therefore, only a subgroup of dishes selected at the canteen during lunch were recorded at baseline (time 0, from April to May 2024), intervention period (time 1, from October 2024 to March 2025), and follow-up (time 2, from April to May 2025). Data was collected automatically by the implemented cash register, where cashiers typed the purchased products, while the only information automatically collected by the default cash register was the number of paying users. The analysis on food choices included only days in which the number of users recorded by the implemented cash register was simultaneously equal to or above the third standard deviation of the mean calculated in reference to the total daily number of canteen users across the whole study period, and above 25% of the total daily number of canteen users.

Through the electronic system only the total number of food choices by typology were collected, preventing the possibility to collect disaggregated information in terms of single meal composition chosen. To properly interpret food choices of first and second course between those with logo and without logo, as well as among different categories of second course distinguished based on the main protein source, three coefficients were calculated. Among these, the “selection coefficient” represents the ratio between the daily number of selected first or second dishes with logo (or by category of main protein source) and the total daily number of selected first or second dishes, respectively. In parallel, the “offer coefficient” is calculated as the ratio between the daily number of offered first or second dishes with logo (or by category of main protein source) and the total daily number of first or second dishes offered by the catering service, respectively. The third coefficient is then calculated as the ratio between the selection and offer coefficient, with a value higher than 1 suggesting a positive effect of nudging in promoting marked or desired food purchases based on the modified choice architecture. On the contrary, a value below 1 suggests the nudge did not shift purchase in the desired direction. Extra second dishes offered and purchased at the canteen were not considered for the calculation of such coefficients. Indeed, although their number was recorded by the cash register, no information about ingredients was available, preventing them from being classified as eligible for the logo or from being categorized according to their main protein source.

Due to feasibility reasons, plate waste data collection was performed over a subgroup of 51 days during the study period. An aggregate selective plate waste method was applied as plate waste (g) was collected from the all the canteen users distinguishing each course typology and each second course protein category in different bins. The weight of the collected food waste was assessed using electronic weighing scales (Laica Electronic kitchen scale KS1050). The percentage of food waste by each course typology was computed out of the total food waste, while food waste of second dish categories was computed out of the food waste of second courses.

Plate waste as total and by course typology as well as by second dish category was divided by the number of canteen users to estimate daily food waste per capita (g). Similarly to the food choice study sample, the analysis on plate waste was set to exclude days of data collection in which the number of canteen users were below the third standard deviation of the mean calculated in reference to the total daily number of canteen users across the entire study period. In addition, to avoid misinterpretations, only days with at least one dish of the first course and one dish of the second course options labelled with logo were considered.

3.1.2.5 Statistical analysis

Data are presented as median interquartile range based on non-normal data distribution explored using the Kolmogorov–Smirnov test. Differences in selection of dishes with logo and in dish selection by course typology reported as number of dishes per capita per day were investigated by applying a non-parametric Kruskal–Wallis test with *p* values for pairwise comparisons adapted based on Bonferroni correction for multiple tests. The same test was applied to compare selection, offer, and selection/offer coefficients across time in reference to first and second dishes with logo as well as second dishes distinguished by main protein source. The same test was used also to compare food waste by course typology and by second dish categories across time both in terms of percentage and as amount of waste per capita (g). The statistical analysis was performed using SPSS 30.0 software (SPSS Inc.), keeping the significance at $p < 0.05$.

3.1.3 Results

3.1.3.1 Study sample

The average number of daily total users was 475 ± 144 across the whole study period (n. total original days = 166), therefore only days (n = 159) with at least 43 users tracked by the implemented cash registered were considered eligible, as above the third standard deviation of the mean calculated in reference to the total daily number of canteen users across the whole study period. Among these, a few days (n = 10) were then excluded as the share of users tracked by the implemented cash register in such days was below 25% of the average number of total canteen users, resulting in a final sample of 149 days. In parallel, the study sample used for plate waste analysis was restricted to 50 days of data collection as one day was excluded due to the absence of options with logo among the first courses. The average number of users and food products (excluding beverages) sold at the canteen on which the analysis of sales data and plate waste was based is reported in Table 1.

Table 1. Average number of users and food products considered for the study.

	Baseline (t0)	Intervention (t1)	Follow-up (t2)	Total
Sales data	(n=16)	(n=106)	(n=27)	(n=149)
Users/day (n)	289 ± 82	422 ± 129	419 ± 39	407 ± 120
Sold products/day (n)	746 ± 240	1120 ± 357	983 ± 257	1055 ± 349
Plate waste data	(n=9)	(n=30)	(n=11)	(n=50)
Users/day (n)	392 ± 58	460 ± 173	557 ± 95	472 ± 152
Sold products/day (n)	725 ± 343	1022 ± 380	1081 ± 103	989 ± 350

3.1.3.2 Impact of multiple nudging strategies on food choice

By comparing users' dish selection in terms of number of selected dishes per capita per day across time (Table 1), the number of total dishes and dishes with logo slightly increased without reaching statistical significance from the pre-intervention to the intervention phase (p=0.678 and p=1.000, respectively). On the contrary, significant reductions were observed moving from the intervention to the follow-up, with the median n. of total selected dishes and dishes with logo decreasing respectively from 2.65 (IR: 2.58-2.77) to 2.55 (IR: 2.41-2.61) ($p < 0.001$) and from 1.43 (IR 1.20-1.64) to 1.30 (IR: 1.15-1.39) ($p = 0.032$). By focusing on food course typology, first dishes followed the same pattern, with a significant decrease ($p < 0.001$) in the post-intervention period, as they declined from a median of 0.73 (IR: 0.70-0.76) in the intervention phase to a median of 0.67 (IR: 0.63-0.70) in the follow-up. On the contrary, the first dishes with logo tended to increase across time, without showing statistically significant differences ($p = 0.542$). In parallel, the choice of second courses and side dishes remained almost stable ($p = 0.507$ and p = 0.155, respectively), although selected second dishes with logo tended to increase in the intervention phase, while significantly decreased in the post-intervention period (median: 0.38, IR: 0.29-0.50 vs. median: 0.29, IR: 0.23-0.40, $p = 0.027$). Fruit tended to decrease across time and reached a significant reduction at the follow-up (median: 0.26, IR: 0.29-0.33) compared to the baseline (median: 0.38, IR: 0.34-0.43, $p < 0.001$) and to the intervention phase (median: 0.36, IR: 0.32-0.39, $p < 0.001$).

Table 2. Daily number of dishes per capita selected at the university canteen during the baseline phase, intervention period, and follow up.

Dishes (n/capita/day)	Baseline (t0) (N=16)	Intervention (t1) (N=106)	Follow-up (t3) (N=27)	*p* value
Total dishes	2.63 (2.44-2.73) ^{a,b}	2.65 (2.58-2.77) ^{a}	2.55 (2.41-2.61) ^{b}	< 0.001
Dishes with logo	1.42 (1.37-1.56) ^{a,b}	1.43 (1.20-1.64) ^{a}	1.30 (1.15-1.39) ^{b}	0.027
First dishes	0.69 (0.62-0.73) ^{a,b}	0.73 (0.70-0.76) ^{a}	0.67 (0.63-0.70) ^{b}	< 0.001
First dishes with logo	0.06 (0.03-0.28)	0.07 (0.04-0.25)	0.21 (0.05-0.25)	0.542
Second dishes	0.69 (0.61-0.72)	0.69 (0.65-0.73)	0.68 (0.61-0.73)	0.507
Second dishes with logo	0.33 (0.16-0.46) ^{a,b}	0.38 (0.29-0.50) ^{a}	0.29 (0.23-0.40) ^{b}	0.022
Side dishes	0.61 (0.54-0.65)	0.63 (0.68-0.71)	0.63 (0.54-0.66)	0.155
Fruit	0.38 (0.34-0.43) ^{a}	0.36 (0.32-0.39) ^{a}	0.26 (0.29-0.33) ^{b}	< 0.001

Note: data are reported as median (IQ). Values referred to total dishes and dishes with logos exclude beverages. Kruskal-Wallis non-parametric test for individual samples. P values for pairwise comparisons are adapted based on Bonferroni correction for multiple tests. Different letters indicate statistically significant different longitudinal values.

First and second dishes sales data were further analyzed by comparing the ratio of selected and offered options with logo out of total selected and offered dishes, respectively (Figure 3). No significant differences across time were detected for the first dishes with logo (Panel A), confirming previous results reported in Table 1. Contrarily to this category, second dishes with logo presented a median value of selection coefficient (Panel B, blue boxplot) above 0.50 at the three time points, reaching a peak of 0.62 (IR: 0.50-0.74) in the intervention period, meaning that, in median, more than half of the second dishes purchased at the canteen had the logo. This finding is particularly meaningful if observed in parallel to the offer coefficient (Panel B, red boxplot) according to which the median number of second dishes offered with logo out of total second dishes is constantly lower, ranging from 0.43 (IR 0.31-0.50) in the pre-intervention phase to 0.50 (IR: 0.43-0.50) in the follow-up, therefore suggesting a positive effect of the applied nudging strategies, although not statistically confirmed. The selection by offer coefficient reflects the discrepancy between the first two coefficients, and it is significantly reduced in the follow-up compared to the intervention period (median: 1.10, IR: 0.90-1.36 *vs*. median: 1.33, IR: 1.20-1.49, $p = 0.010$, respectively).

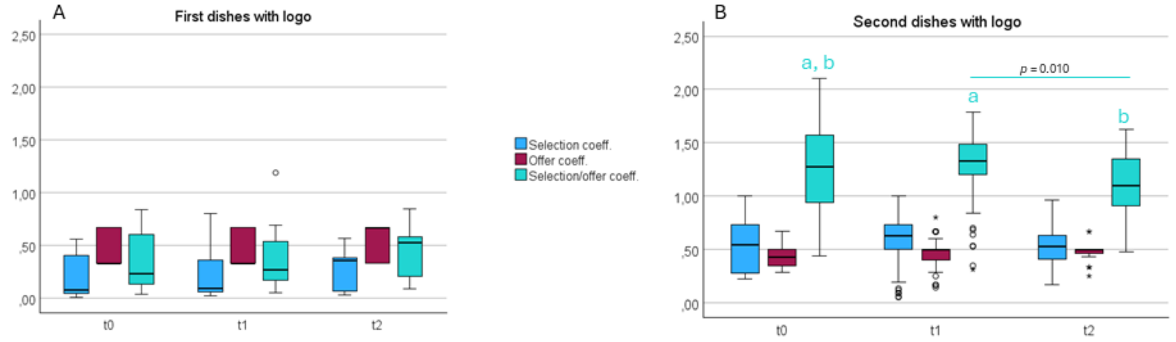

Figure 3. Boxplots reporting selection coefficients (i.e., n. selected dishes with logo/n. total selected dishes), offer coefficients (i.e., n. offered dishes with logo/n. total offered dishes) and the ratio between selection and offer coefficients calculated in reference to first (Panel A) and second courses (Panel B) for baseline phase (t0), intervention period (t1), and follow up (t2). Kruskal-Wallis non-parametric test for individual samples. P values for pairwise comparisons are adapted based on Bonferroni correction for multiple tests. Different letters indicate statistically significant different longitudinal values.

By focusing on different protein-based second dish categories (Figure 4), significant differences in sales data were observed for white meat ($p = 0.009$) and processed meat ($p = 0.005$). Specifically, all the white meat second dishes offered at the canteen were compliant to nutritional and environmental criteria allowing to bear the logo, and their selection coefficient increased from the pre-intervention to the intervention period (median: 0.26, IR: 0.06-0.35 vs. median: 0.34, IR: 0.29-0.42, $p = 0.031$, respectively), while the offer coefficient remained stable (median: 0.17, IR: 0.14-0.23 vs. median: 0.17, IR: 0.14-0.17, $p = 1.000$). Similarly to what observed for all the second dishes with logo, the offer coefficient was constantly lower, with the high discrepancy found during the intervention, as reflected by the selection by offer coefficient, which showed a median of 2.09 (IR: 1.78-2.43). An opposite scenario characterized processed meat, for which the offer coefficient constantly overcame the selection coefficient, which significantly increased in the post-intervention period compared to the baseline phase ($p = 0.004$), with values, however, approaching zero (median: 0.03, IR: 0.01-0.05 vs. median: 0.00, IR: 0.00-0.02, respectively). Such increase is reflected in the significant rise of the selection by offer coefficient by comparing the two time points (median: 0.16, IR 0.05-0.29 vs. median: 0.00, IR: 0.00-0.10, $p = 0.005$), proving the intervention did not affect the choice of processed meat dishes.

The canteen offer of most of the remaining protein categories was instead not stable over time. Indeed, median offer coefficients showed significant increases in the post-intervention period compared to the pre-intervention phase, such as for red meat (respectively 0.17, IR: 0.17-0.17 vs. 0.14, IR: 0.14-0.19, $p = 0.044$), fish (respectively 0.17, IR: 0.17-0.17 vs. 0.14, IR: 0.14-0.17, $p = 0.003$), and plant-based protein sources (legume-based dishes: 0.17, IR: 0.17-0.17 vs. 0.14, IR: 0.14-0.17, $p = 0.004$; egg/dairy-based dishes: 0.17, IR: 0.17-0.17 vs. 0.14, IR: 0.14-0.17, $p = 0.015$), and in a few cases also compared to the intervention phase (egg/dairy-based dishes: 0.17, IR: 0.17-0.17 vs. 0.14, IR: 0.14-0.17, $p = 0.034$; fish-based dishes: 0.17, IR:

0.17-0.17 vs. 0.14, IR: 0.14-0.17, $p = 0.037$). A parallel rise in the selection coefficients was not observed, leading to a reduction, although not significant, in the selection by offer coefficients. Furthermore, among second dishes with vegetarian protein sources, a distinct picture can be observed, with selection by offer coefficients being higher across time for egg or dairy-based dishes (median number > 1) compared to those referred to legumes (median number < 1). Moreover, an opposite trend was observed for white meat and red meat dishes selection by offer coefficients, with the latter decreasing, although not significantly, during the intervention compared to the baseline phase (respectively median: 2.52, IR: 1.64-3.12 vs. median: 2.13, IR: 1.77-2.57, p=0.635). By focusing on the subcategories of dishes with logo, no significant differences were detected for fish, although a decreasing trend in their median selection by offer coefficient over time can be observed (t0: 1.94, IR: 0.97-3.02; t1: 1.41, IR: 1.11-1.66; t2: 1.21, IR: 1.03-1.42, p=0.546). In parallel, for egg/dairy dishes with logo the median offer coefficient significantly raised in the follow-up compared to the intervention period (respectively 0.17, IR: 0.17-0.17 vs. 0.17, IR: 0.14-0.17, p=0.009), similarly to the whole category.

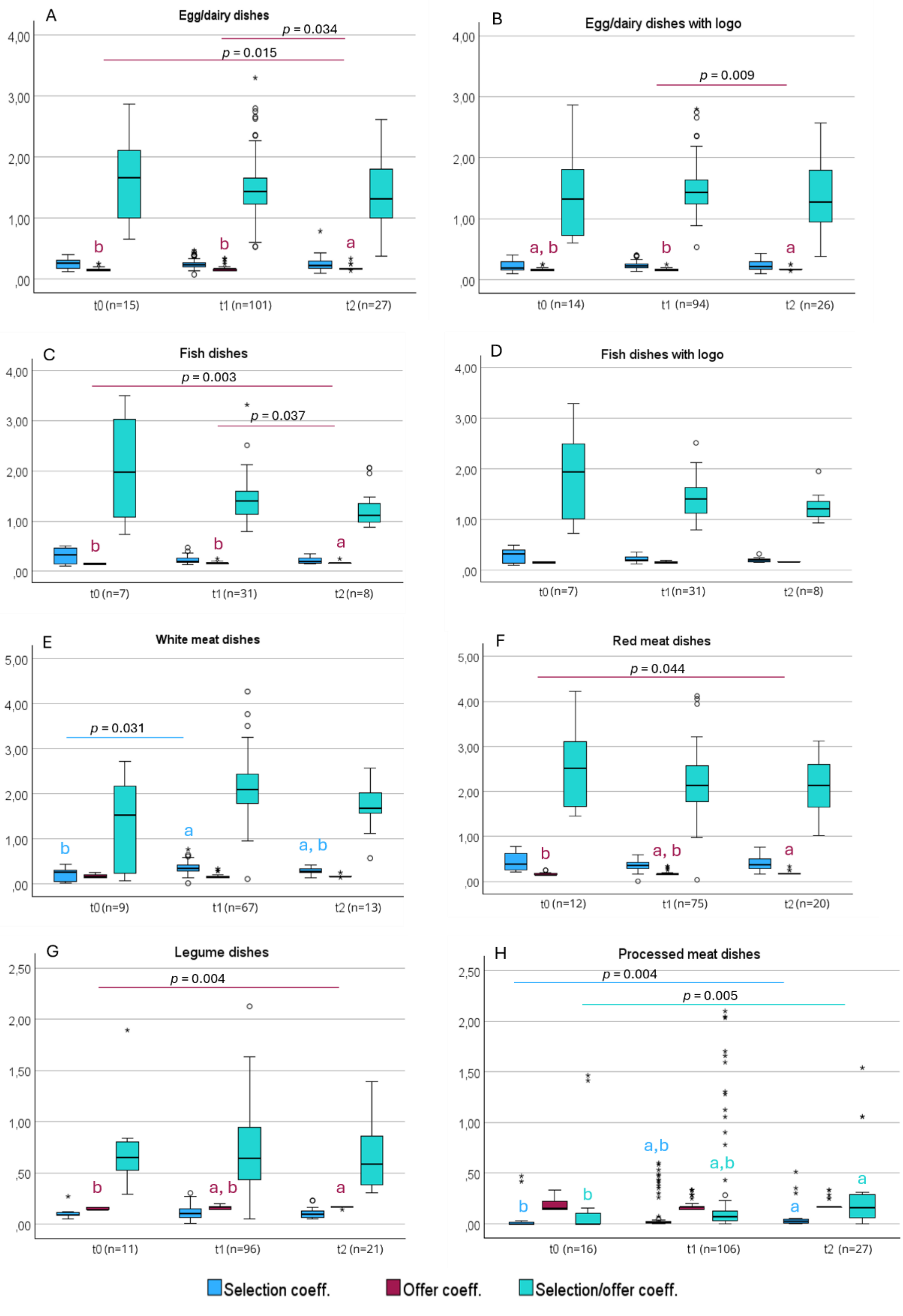

Figure 4. Box-plots reporting selection coefficients (i.e., n. selected second dishes by protein category/n. total selected second dishes), offer coefficients (i.e., n. offered second dishes by protein category/n. total offered second dishes) and the ratio between selection and offer coefficients calculated for baseline phase (t0), intervention period (t1), and follow up (t2). Panel B and D specifically refer to dishes with logo and their selection and offer coefficients are calculated as n. selected (or offered) second dishes with logo within egg/dairy and fish category out of the total n. of selected (or offered) second dishes. Kruskal-Wallis non-parametric test for individual samples. P values for pairwise comparisons are adapted based on Bonferroni correction for multiple tests. Different letters indicate statistically significant different longitudinal values.

3.1.3.3 Impact of multiple nudging strategies on food waste

In terms of composition of food waste (Table 3), the median share of wasted dishes with logo decreased over time from baseline reaching a significant reduction in the follow-up (respectively 59.9, IR: 53.9-66.7, vs. 48.0, IR: 45.2-54.1, p = 0.049). In contrast, no statistical differences were detected for course typologies. However, a decreasing trend across time for the second course and side dish was observed, while first dishes and fruit tended to increase. A mix pattern can be seen for main course salads, which tended to increase in the follow up after a tendency of reduction in the intervention period.

The significant lower median amount of per capita food waste detected during the intervention (20.3, IR: 17.2-22.5) compared to the baseline period (23.7, IR: 21.2-28.8, $p = 0.040$) appeared to be explained by a lower median waste of dishes with logo (respectively 10.0, IR: 8.2-11.9 vs. 14.9, IR: 11.1-18.7, $p = 0.006$), which were wasted at a lower extent also at the follow up from the beginning of the study (respectively 10.3, IR: 7.9-11.9 vs. 14.9, IR: 11.1-18.7, $p = 0.032$). By considering dish course typologies, second courses, fruit, and side dishes decreased over time, with the latter reaching statistical difference ($p = 0.008$) when values in the pre-intervention (median: 5.9 IR: 5.0-7.8) and intervention (median: 4.5, IR: 3.6-5.7) period were compared.

Table 3. Share of food waste and waste per capita by dish type collected at the university canteen during the baseline phase, intervention period, and follow up.

	Baseline (t0) (N=9)	Intervention (t1) (N=30)	Follow-up (t3) (N=11)	*p* value
Food waste (%)				
Dishes with logo	59.9 (53.9-66-7) ^{a}	51.0 (45.4-58.8) ^{a,b}	48.0 (45.2-54.1) ^{b}	0.048
First dishes	24.2 (17.1-27.7)	28.5 (22.4-30.9)	29.1 (26.1-33.1)	0.075
Second dishes	28.2 (20.2-33.3)	24.4 (21.1-31.0)	24.5 (21.8-31.1)	0.983
Side dishes	27.8 (20.2-33.3)	24.0 (18.5-28.4)	24.5 (19.2-26.8)	0.387
Main course salad	0.9 (0.2-5.1)	0.4 (1.1-2.2)	0.8 (0.3-1.9)	0.931
Fruit	6.4 (4.0-12.0)	6.7 (4.6-10.3)	7.5 (5.5-9.4)	0.935
Waste per capita (g)				
Total waste	23.7 (21.2-28.8) ^{a}	20.3 (17.2-22.5) ^{b}	19.6 (17.3-24.2) ^{a,b}	0.045
Dishes with logo	14.9 (11.1-18.7) ^{a}	10.0 (8.2-11.9) ^{b}	10.3 (7.9-11.9) ^{b}	0.007
First dishes	5.5 (3.8-7.5)	5.2 (4.1-7.1)	5.5 (5.3-7.1)	0.617
Second dishes	6.1 (3.9-8.9)	4.6 (3.8-6.3)	4.9 (3.9-6.1)	0.393
Side dishes	5.9 (5.0-7.8) ^{a}	4.5 (3.6-5.7) ^{b}	4.8 (3.5-5.9) ^{a,b}	0.010
Main course salad	0.2 (0.0-1.2)	0.2 (0.1-0.4)	0.2 (0.1-0.4)	0.772
Fruit	1.7 (0.8-2.8)	1.2 (0.8-1.9)	1.4 (1.0-2.0)	0.684

Note: data are reported as median (IQ). Values referred to total waste and dishes with logo excluding beverages. Kruskal-Wallis non-parametric test for individual samples. P values for pairwise comparisons are adapted based on Bonferroni correction for multiple tests. Different letters indicate statistically significant different longitudinal values.

The composition of food waste (%) specifically referred to second course did not significantly change over time (Table 4). However, overall, opposite trends can be observed depending on protein origin: if plant-based second dishes tended to lower, animal-based second dishes tended to increase. In parallel, the amount of food waste per capita showed a significant reduction in legume-based second dishes in the intervention phase compared to the baseline (respectively median: 0.5, IR: 0.2-0.9, vs. median: 1.4, IR: 0.8-1.6, $p = 0.008$).

Table 4. Share of food waste and waste per capita by second dish category collected at the university canteen during the baseline phase, intervention period, and follow up.

Second dish categories	Baseline (t0)	Intervention (t1)	Follow-up (t3)	*p* value
Legumes	(n=8)	(n=7)	(n=8)	
Food waste (%)	19.9 (13.4-30.3)	8.5 (3.2-20.5)	11.0 (7.0-27.0)	0.102
Waste per capita (g)	1.4 (0.8-1.6) ^{a}	0.5 (0.2-0.9) ^{b}	0.5 (0.3-1.2) ^{a,b}	0.011
Eggs or dairies	(n=9)	(n=30)	(n=11)	
Food waste (%)	6.4 (3.1-10.9)	5.0 (3.6-6.8)	3.0 (1.5-7.1)	0.298
Waste per capita (g)	1.3 (0.7-2.5)	0.9 (0.6-1.4)	0.7 (0.3-1.2)	0.217
Fish	(n=4)	(n=15)	(n=6)	
Food waste (%)	30.6 (28.5-36.2)	35.7 (26.9-49.5)	41.7 (18.7-52.0)	0.790
Waste per capita (g)	1.8 (1.1-3.1)	1.9 (1.5-2.0)	1.9 (1.1-2.7)	0.984
White meat	(n=5)	(n=21)	(n=8)	
Food waste (%)	24.9 (8.1-39.0)	27.3 (16.8-42.4)	31.8 (11.5-34.9)	0.727
Waste per capita (g)	1.1 (0.6-2.7)	1.2 (0.7-2.0)	1.7 (0.6-2.1)	0.944
Red meat	(n=6)	(n=24)	(n=7)	
Food waste (%)	23.8 (11.7-34.8)	22.7 (12.3-33.4)	27.0 (15.8-39.2)	0.832
Waste per capita (g)	1.5 (0.9-2.1)	0.6 (1.0-1.8)	1.2 (0.8-2.5)	0.390
Processed meat	(n=4)	(n=24)	(n=10)	
Food waste (%)	10.3 (0.1-23.4)	2.0 (0.2-9.6)	3.5 (2.2-19.3)	0.658
Waste per capita (g)	0.4 (0.0-0.9)	0.2 (0.0-0.3)	0.2 (0.1-0.8)	0.668

Note: data are reported as median (IQ); numbers (n) within brackets reflect the n. of day considered for data collection and depend on the canteen food offer. Kruskal-Wallis non-parametric test for individual samples. P values for pairwise comparisons are adapted based on Bonferroni correction for multiple tests. Different letters indicate statistically significant different longitudinal values.

3.1.4 Discussion

This study analyzed the effect of applying multiple nudging techniques aimed at promoting healthy and sustainable food-related behaviors in a university canteen in the Northern Italy. The intervention was implemented to modify a real-world canteen food environment, without changing the canteen food offer. Results of this study highlight how, in line with existing literature, the intervention didn't determine a significant increase on the selection of healthy and sustainable dishes, confirming how nudging strategies tend to generate moderate and sometimes inconsistent effects, especially in complex contexts [18; 21; 19]. On the contrary, the significant reduction in plate waste observed during the intervention phase is consistent with previous evidence, showing that changes in the food environment can more effectively influence downstream behaviors [20; 21]. Finding referred to plate waste behavior change may suggest that nudges, although designed to affect the purchase decisional moment, may influence subsequent moments, when during the consumption of their meal in the dining hall, students can take the opportunity to further reflect on conveyed messages and more consciously shift their behavior in the virtuous direction trying to limit food waste generation.

A further interpretative element is given by the specific context of the university canteen, where a high number of students, especially freshmen, experience for the first time the responsibility of minding their own meals on a limited budget. The university canteen represents not just a place to go to fill their stomach, but an opportunity to eat a nutritious meal at a standardized price [26; 27]. It allows access to generally expensive dishes (e.g. fish and meat second courses) at a more accessible price. This economic dimension may have affected the efficiency of nudging strategies on their food choices, as price related considerations often overtake decisions based on healthiness and sustainability. Price and convenience are in fact well recognized as determinants of food choices among university students [28; 29].

Moreover, in line with available evidence [18; 21], the attenuation of effects observed in the follow-up phase, when nudges were removed, suggests that the presence of continuous environmental stimulus may be fundamental to maintain behavior changes during time. However, this result needs to be cautiously contextualized, as study design did not allow for the tracking of individuals over time. Therefore, it is not possible to define if the whole same sample of subjects have been exposed to both the intervention and follow-up phase. A possible turnover of the student's population (due to different semesters covered by the study period) may have influenced observed trend, limiting the possibility of assessing the maintenance of behavioral changes at individual level. In this regard, the lack of possibility of tracing the composition of the meal at an individual level represents a methodological limitation. Specifically, the cash register software did not allow the disaggregation of data to individual menus, preventing the analysis of the combination of dishes selected by each user. Additionally, the absence of detailed information on the nutritional and energy intake associated with each meal limits the possibility of fully assessing whether the observed changes translated into meaningful improvements in overall dietary quality.

A key limitation of this study is the absence of a control canteen. Although a second one was initially considered as a potential comparator, the authorization to implement the intervention there was not received. In addition, the two sites differ in structural and operational characteristics: the comparator canteen does not have an on-site kitchen, it relies on the facilities of the previous one. It also serves a markedly different student population in terms of size, flow and fields of study.

Among the strengths of this study, it stands out for its implementation in a highly complex real-world environment, thus increasing the transferability of results. The integrated approach that simultaneously considers both food choices and plate waste aim at filling a gap in literature, where outcomes are usually considered independently [20; 30].

3.1.5 Conclusions

This study contributes to consolidating the evidence on the effectiveness of nudging interventions in public settings, demonstrating how these strategies can effectively reduce food waste if continuously displayed, but are less effective in bringing the same significant changes in food choices.

University canteens can be considered as strategic settings where to promote virtuous healthy and sustainable behaviors, however, to obtain more marked and lasting changes, it is necessary to complement educational strategies with broader and more structured interventions that take into account the economic, social and cultural determinants of food choices.

Future interventions should combine food environmental modifications together with educational, participatory and digital approaches. Given the complexity and multifactorial nature of food behavior, integrated and multidimensional approaches are more effective and allow them to act simultaneously on different levels [31].

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Study 2

FLIC: A Real-World Dataset for Visual Estimation of Food Leftovers in Canteens

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Abstract

Background/objectives: The accurate quantification of food waste in collective catering services represents a crucial challenge for monitoring sustainability and operational optimization. Although computer vision systems for food recognition have been widely explored in recent years, post-consumption analysis has received less attention, especially in real-world settings. This study aims to validate FLIC (Food Leftovers In Canteens), a new dataset designed to support the visual estimation of plate waste and to provide a basic methodology for mass estimation from images.

Methods: Data were collected in the campus canteen at the University of Parma for 22 days, resulting in 401 paired acquisitions of full and leftovers trays. Each sample includes 2D RGB images, pixel-level semantic segmentation masks and physically measured food mass. A standardized acquisition protocol ensured consistent imaging conditions. A baseline estimation pipeline was developed based on the concept of digital density, relating pixel area to food mass. The pipeline integrates automatic food/no-food segmentation (tested across multiple deep learning models) and assisted food classification leveraging the fixed daily menu. Model performance and the relationship between visual features and mass were evaluated through segmentation accuracy and correlation analyses.

Results: The dataset provides a novel combination of paired visual data and reliable mass collected in real-world conditions. Segmentation models resulted in a high accuracy level of Intersection over Union (IoU) for full trays (92-93%) and reduced performance (70-77% IoU) for leftover trays due to increased visual complexity. A linear relationship was observed between pixel area and mass, with differences depending on the typology of the course, especially for visually heterogeneous dishes. The proposed approach, based on the concept of visual density, allowed reasonable mass estimation, with errors influenced by the category and composition of food. More accurate classification levels produced non-uniform benefits, resulting more relevant for second courses than for first courses.

Conclusions: FLIC represents a new realistic benchmark for the estimation of leftover food in public settings, addressing key limitations of existing datasets. The digital density framework demonstrates the feasibility of mass estimation from images, highlighting at the same time limitations derived from food heterogeneity and post-consumption variability. Future studies should explore nonlinear modelling approaches, integration of volumetric information and automated food classification to improve estimation accuracy and scalability.

Keywords: Food waste, Food Leftovers, Computer vision, Semantic segmentation, Mass estimation, Public dataset

3.2.1 Introduction

In recent years, the increasing focus on health, nutrition, and sustainability has led to the development of numerous systems and applications leveraging computer vision and artificial intelligence for food recognition and analysis [1,2]. These technologies are widely used for identifying food items and estimating key properties such as ingredients, portion size, volume, and mass, with applications ranging from dietary tracking to automated meal payment systems [3,4].

Most of these applications rely on machine learning models that require large, annotated datasets for training. These datasets are typically created through manual labeling by human experts, a time-consuming and resource-intensive process [5,6]. Furthermore, existing food recognition systems are primarily designed for individual users, with image acquisition typically performed via mobile devices. In such settings, users capture images of their dishes before consumption, and the system processes these images to provide nutritional information or facilitate meal tracking [7,8]. However, this approach poses several challenges, including inconsistencies in image quality, variability in user behavior, and the frequent need for manual intervention. In contrast, collective catering environments, such as cafeterias and canteens, present a different set of requirements and opportunities. Fixed-camera systems, where cameras are installed in predefined locations relative to food trays or even integrated with the checkout system, offer a standardized Setup that facilitates automated recognition and analysis. Unlike mobile-based approaches, which suffer from significant variability in intrinsic and extrinsic parameters (e.g., camera calibration, distance, angle, and lighting), fixed setups maintain consistent acquisition geometry and illumination. This enables a much more accurate and repeatable estimation of food quantities. In this work, we deliberately focus on standard 2D RGB image acquisition, as it represents the most scalable and cost-effective sensing modality for large-scale deployment in collective catering environments.

Beyond food recognition, an important goal in collective catering is the estimation of plate waste, a task that must begin with the broader identification of food leftovers. Andrews et al. [9] define food waste (or plate waste) as any uneaten portion of food on a person's plate meal that was intended for consumption but ultimately went uneaten. Aloysius et al. [10] collected several contrasting definitions of what constitutes food leftovers, which range from "prepared but not plated food" to "takeaway leftover food". Here, we define food leftovers based on the diner's leftover interpretation, i.e., the total set of served but uneaten items. This, compared to plate waste, additionally encompasses non-edible fractions (such as bones, peels, and shells) and unrecoverable edible residues like scattered grains or residual sauces. In this sense, the identification of leftovers serves as a foundational step for the broader objective of measuring effective food waste. Initiatives aimed at identifying and quantifying leftovers can provide valuable insights into consumption patterns, helping diners to be more conscious consumers and food caterers to optimize meal offers. At a larger scale, tracking food leftovers at a collective catering level can contribute by highlighting trends, reducing overproduction, and minimizing environmental impact, with positive impacts on natural resources, economic growth, and society. This is particularly relevant when considering the current global food waste scenario.

According to the most recent data [11], approximately 1.05 billion tons of food are wasted globally each year. At the European Union (EU) level, over 59 million tons of food are wasted annually, equal to 20% of the EU region's total food production. Of this, 11% is produced in food services such as restaurants and catering operations. Considering only the Italian scenario, food waste recorded for collective food services was 6% [12]. Given the recent increase in out-of-home meal consumption [13] and the expected growth of the European foodservice market by 2030 [14], the integration of digital tools in food service operations is becoming a sustainable practice for reducing food waste [15], and for reducing its environmental, social and economic impact [11,16].

Despite growing research interest, there is still a lack of reliable, scalable tools for quantifying food mass in collective dining settings. Manual methodologies are labor intensive and subject to observer variability, while many automated systems focus on pre-consumption food recognition, neglecting leftover analysis [17].

The main contributions of this work are summarized as follows:

• We introduce FLIC, a real-world dataset for the estimation of food leftovers in canteens and other collective catering environments, featuring paired full and leftover tray images, pixel-precise semantic annotations, and physically measured food mass ground truth. This explicitly addresses the shortcomings of existing datasets, which only cover part of the aforementioned attributes.

• A reproducible acquisition and annotation protocol based on standard 2D RGB imaging and fixed-camera geometry is reported, designed to enable quantitative and scalable analysis of food leftovers under realistic operational conditions.

• We define a lightweight and interpretable baseline for leftover mass estimation based on the concept of digital density, together with systematic experiments that expose dataset characteristics, sources of variability, and intrinsic challenges of the problem.

In Sections 3.2.2.1 and 3.2.2.2, we provide a detailed overview of existing public datasets related to the analysis of food leftovers and food estimation in order to better contextualize the value of our proposed FLIC dataset. In Section 3.2.2.4, we describe the context for acquisition of the dataset, including the canteen settings, our custom acquisition device, the physical mass acquisition protocol, and the annotation of semantic information. In Section 3.2.2.5, we define our methodology for mass estimation based on the concept of digital density. We also describe how assisted food recognition is used to perform automatic food/no-food segmentation and semi-automatic food classification. In Section 3.2.2.6, we extract an analysis of the collected data, and we present results on food/no-food segmentation and mass estimation.

3.2.2 Material and methods

3.2.2.1 Existing Datasets Related to Leftover and Mass Estimation

We organize existing datasets into two groups: (i) datasets explicitly targeting leftover food and food waste estimation and (ii) datasets providing ground-truth mass (and, in some cases, volume) annotations for food items or complete dishes. Although some level of crosstalk does exist, with certain leftover-oriented datasets also providing food mass data, this categorization highlights the existing structural gap in publicly available resources: datasets focusing on leftovers typically lack reliable physical quantity measurements, while datasets providing mass annotations rarely capture real post-consumption scenarios. A sample of images from the existing datasets is shown in Figure 1. Dataset information is summarized in Table 1, including information on our own FLIC, which is presented in detail in Section 3.2.2.4.

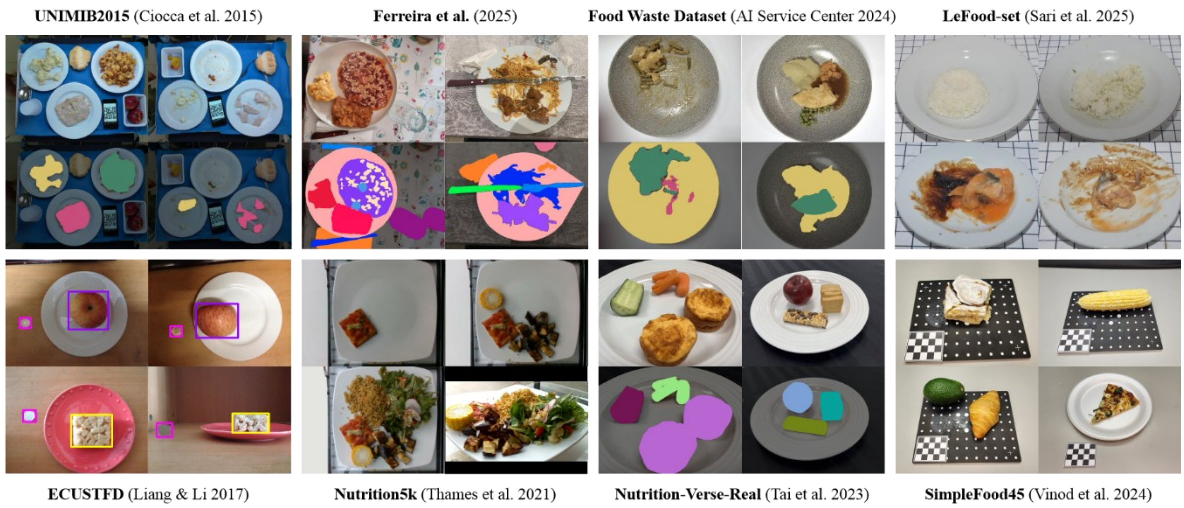

Figure 1. Sample images from existing datasets related to food leftover estimation (**top**) and mass estimation (**bottom**). Datasets focusing on leftovers typically lack reliable physical quantity measurements, while datasets providing mass annotations rarely capture real post-consumption scenarios. Spatial annotations are shown only where available, each dataset with their own color coding.

Table 1. Schematic comparison of datasets related to leftover estimation (first group) and quantitative food analysis (second group), including our proposed FLIC dataset (last row). 'C' identifies the number of semantic classes, if present.

Dataset (year)	Setting/location	Scene/layout	Presentation	Full/leftover	# images/pairs	Spatial annotations	Quantity annotations
UNIMIB 2015 (Ciocca et al. 2015)	University canteen (Italy)	Staged presentation; low realism for leftovers	Trays; multi-item	Both (paired)	1080 images (700 full, 380 leftover)	Polygonal semantic segmentation masks (C=15)	None
Ferreira et al. (2025)	School canteen (Portugal)	Natural canteen views; varied meal progression	Plates; multi-item	Both (unpaired)	175 images	Instance segmentation masks (C=3)	None
Food Waste Dataset (AI Food Service Center 2024)	Food service (Germany)	Natural cafeteria presentation	Plates; multi-item	Leftover only	375 images	Automatic ingredient segmentation masks (C=41)	Plate mass before/after (g); energy (kcal); macronutrients
LeFood-set (Sari et al. 2025)	Hospital cafeteria (Indonesia)	Controlled checkerboard background	Plates; single-item	Both (paired)	524 pairs	None (C=34)	Plate mass before/after (g); leftover score
ECUSTFD (Liang & Li 2017)	Controlled indoor setup (China)	Structured views (top + side)	Plates; single-item	Full only	2978 images	Bounding boxes (C=19)	Item mass (g); volume (mL); item energy (kcal)
Nutrition5k (Thames et al. 2021)	Google cafeterias (USA)	Real cafeteria meals; overhead RGB-D rig	Plates; multi-item	Full only	5000 images; 20k videos; 3500 RGB-D images	None	Ingredient masses (g); macronutrients; dish energy (kcal)
Nutrition-verse-Real (Tai et al. 2023)	Indoor natural scenes (Canada)	Varied smartphone viewpoints; black mat	Plates; multi-item	Full only	889 images	Pixel-precise semantic segmentation masks (C=45)	Ingredient masses (g); dish nutrition
SimpleFood 45 (Vinod et al. 2024)	Controlled environment	Checkerboard reference pattern	Single item	Full only	513 images	None	Item volume (mL); item mass (g); item energy (kcal)
FLIC (this work)	Public canteen (Italy)	Natural messy canteen presentation; top-down capture	Trays; multi-item	Both (paired)	401 pairs (802 images)	Pixel-precise semantic segmentation masks (C=36)	Plate mass before/after (g)

3.2.2.2 Datasets for Food Waste and Leftover Estimation

3.2.2.2.1 UNIMIB2015 (Ciocca et al. 2015 [5])

UNIMIB2015 is one of the earliest datasets explicitly designed for leftover estimation in a canteen setting. It contains images acquired in a university canteen, with different dishes placed on a tray and photographed before and after consumption. The dataset comprises 1080 total images (700 images of full trays and a subset of 380 corresponding leftover trays), with 15 food classes and polygonal annotations of each food region. The arrangement of food on the trays is staged and quite tidy, which reduces realism, especially in leftover images. In addition, some images were obtained by rearranging the same plates seen in other images, changing only their orientation and layout on the tray. A later extension, UNIMIB2016 [6], increased the number of food categories and relaxed the acquisition conditions but only includes full trays and therefore cannot be used for leftover estimation.

3.2.2.2.2 Ferreira et al. 2025 [18]

A more recent dataset focuses on food waste detection in a school canteen environment. It contains 175 real images and an average of 7.2 annotated objects per image, including both food and non-food items. Annotations are provided as pixel-precise semantic masks. Unlike UNIMIB2015, the images are not organized as explicit full-leftover pairs: the collection contains a mixture of plates at different stages of a meal (before, during, and after consumption), typically as close-ups of one or two plates rather than complete trays. This makes the dataset useful for semantic understanding of food waste and for the training of segmentation-based methods, but it is less suited to paired before/after analyses of the same meal.

3.2.2.2.3 Food Waste Dataset (AI Service Center, 2024 [19])

The FoodWaste Dataset released by the AI Service Center (Hasso Plattner Institute) provides images of plates with leftover food, together with rich tabular metadata. The dataset currently includes 375 images (215 trains, 160 test) of meals in institutional foodservice settings, along with detailed ingredient-level nutritional information and per-plate measurements recorded both before and after consumption (mass, calories, macronutrients, and derived waste metrics such as returned quantity and return percentage). An enhanced third-party version [25] also includes segmentation masks automatically generated via YOLO-E [26] and feature embeddings for computer-vision experiments. Some shortcomings of the automated annotation are shown in figure: in the first example, the green beans and chicken are assigned one unique label, whereas some residuals of the chicken’s condiment are marked with a separate label. In the second example, only the chicken is assigned its own label, whereas four other food items are merged into a unique label. This dataset does not provide images of the full plate prior to consumption for each leftover image; instead, the before/after information is purely numeric, as previously described. Consequently, it is well suited for modeling the relation between the visual appearance of leftovers and quantitative waste but less suited for paired visual analysis of the same tray before and after the meal.

3.2.2.2.4 LeFood-Set (Sari et al. 2025 [20])

LeFood-set contains 524 image pairs, each depicting an individual Indonesian dish before and after consumption. The dataset spans 34 food categories and was collected at a hospital in Malang, Indonesia, using a Nikon D3200 DSLR camera. Each sample focuses on a single food item, which may include both solid and liquid components: solid dishes are served on plates, while liquids are provided in bowls. All items are presented on white dishware placed over a wooden placemat featuring a black-and-white checkerboard pattern that serves as a geometric reference for scale. For every image pair, the dataset provides physical mass measurements obtained by weighing the plate or bowl with a digital scale before and after the meal. Several other works describe datasets specifically acquired for food waste or leftover analysis, but to the best of our knowledge, the corresponding data is not publicly downloadable. These include datasets reported by Sari et al. 2021 [27] (about 340 images and 5 classes), Hsieh et al. 2022 [28] (803 images and 16 classes), Rokhva and Teimourpour 2025 [29] (1413 images and 5 classes), and Li et al. 2025 [30] (40 images and no explicit class information).

3.2.2.3 Datasets with Ground-Truth Mass Annotations

In addition to leftover-centric datasets, there is a growing family of datasets that provide ground-truth quantity information for single items or complete dishes—typically based on mass and sometimes with volume and full nutritional breakdown. These datasets are highly relevant to quantitative food intake estimation, even though they usually do not depict leftovers.

3.2.2.3.1 ECUSTFD (Liang and Li, 2017 [21])

The ECUST Food Dataset (ECUSTFD) consists of images of single food items placed on a plate. For each portion, several pairs of images are captured using smartphones, with each pair containing a top view and a side view of the same food. The dataset includes 19 food classes and a total of 2978 images. Annotations include bounding boxes around the food, the mass (measured with an electronic scale), the volume (measured via volume displacement using the drainage method), and the corresponding energy (computed from nutritional tables). ECUSTFD provides a clean, controlled setting with high-quality mass and volume labels but focuses exclusively on isolated items rather than realistic multi-item meals or leftovers.

3.2.2.3.2 Nutrition5k (Thames et al., 2021 [22])

Nutrition5k is a large-scale dataset of approximately 5000 real-world dishes collected in Google cafeterias using a custom scanning rig. For each dish, the dataset provides multiple side-view videos, overhead RGB-D images (when available), a fine-grained list of ingredients, per-ingredient mass, and a complete nutritional breakdown (calories, fat, protein, and carbohydrates). The dishes are assembled incrementally: ingredients are added one at a time, and images and metadata are recorded at each step. This design supports the training of models for dish-level mass and macronutrient estimation, but no segmentation masks or bounding boxes are provided, and the dataset does not include leftovers. The incremental assembly theoretically allows for the construction of synthetic "full vs. partial" states, but these represent artificial constructions rather than real consumption.

3.2.2.3.3 NutritionVerse-Real (Tai et al., 2023 [23])

NutritionVerse-Real is a manually collected dataset targeting dietary intake estimation. It contains 889 images of 251 distinct dishes and 45 unique food types acquired using an iPhone 13 Pro Max from multiple random viewpoints. For each dish, the mass of every ingredient was measured with a food scale, and nutritional values were obtained either from packaging or from the Canada Nutrient File [31]. These per-ingredient values were aggregated to obtain dish-level macronutrients and micronutrients, which is the only information publicly exposed. In addition, the dataset provides manually labeled segmentation masks for a subset of images, combining detailed mass/nutrition labels with dense spatial annotations. As with Nutrition5k, the images depict full dishes rather than leftovers.

3.2.2.3.4 SimpleFood45 (Vinod et al., 2024 [24])

SimpleFood45 is a portion-estimation benchmark of 2D images of real foods captured with a smartphone camera. The dataset contains images of 45 individual food items (grouped into a smaller number of food types) placed on a planar checkerboard pattern that serves as a physical scale reference. For each image, the dataset provides ground-truth volume (mL), mass (g), and energy (kCal), enabling evaluation of single-image volume and energy estimation approaches. SimpleFood45 explicitly targets realistic camera poses and the use of 3D models for portion estimation, but, again, it considers single food items and does not cover leftovers or full multi-item trays.

Konstantakopoulos et al. [32] introduced MedGRFood, a Mediterranean (mainly Greek) food image dataset used for both food recognition and mass estimation studies. To the best of our knowledge, the mass-annotated dataset is not currently available for public download.

Beyond the datasets described above, several works have proposed datasets designed primarily for volume estimation rather than mass. However, these are not publicly released, and we therefore do not consider them in detail here.

The identified limitations of existing datasets motivate the need for a dataset that jointly combines paired full-leftover observations, pixel-level semantic information, and physically measured mass ground truth acquired in a real operational setting, which is the focus of the next section.

3.2.2.4 FLIC Dataset Acquisition

Data collection took place in a canteen of the University of Parma, Italy, located on the scientific disciplines' campus. Every year during the summer season, one part of the dining hall is devoted to the provision of lunch to participants of the summer camp of the broader Giocampus initiative [33], which promotes healthy and sustainable lifestyle among children aged 6–12 in Parma. Meals were offered according to a biweekly rotating menu: each day's lunch consisted of a first course (typically carbohydrate-based dishes such as pasta or rice), a second course (protein-based preparations), and a vegetable side dish. First and second courses were predetermined in advance for the entire rotation, while side dishes changed daily to reflect seasonality. Although every child received the same fixed menu, they had the option to request a reduced portion or to decline any dish altogether.

For dataset acquisition, we collected information on the meal before and after consumption in the form of its physical mass (Section 3.2.2.4.1), and pictures captured using an ad hoc device (Section 3.2.2.4.2). Figure 2 shows the interaction with the user during acquisition: First, the user autonomously composes his/her tray. A QR code specific to that user on that day is then added onto the tray for acquisition through our device, and the individual plates are weighed. After meal consumption, the same acquisition procedure with the same QR code is repeated. QR codes allow for association of the before and after consumption pictures while preserving user anonymity: because the study involved only anonymized photographs and plate-level mass measurements without collecting personal or identifiable data, formal ethical approval was not required.

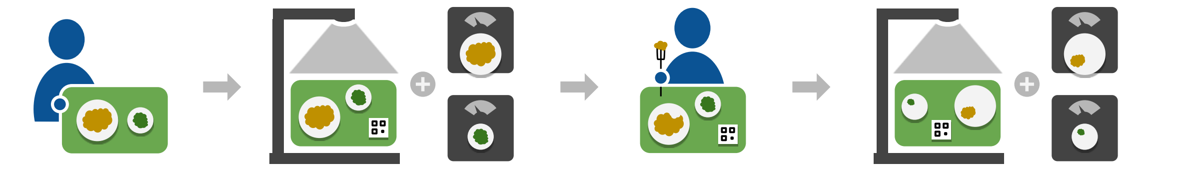

Figure 2. Interaction with the system during dataset acquisition. The user autonomously composes his/her tray. Then, before- and after-consumption information is captured in the form of pictures, and individual plate weighing.

It is worth noting that pictures were shot to frame the whole tray at once, whereas physical mass values were captured per plate: our goal was to design and implement a semi-automatic mass estimation procedure that operates on the whole tray, and the physical mass constitutes our ground-truth reference. Although data were collected in a specific institutional setting, the acquisition protocol and tray-based organization reflect common operational practices in collective catering, making the dataset representative of a broad class of real-world scenarios.

3.2.2.4.1 Physical Mass Acquisition Protocol

All the food mass measurements were carried out by trained researchers using a digital scale calibrated to ±1 g accuracy. Immediately after plating, each compostable plate (tare 10 g or 15 g) carrying the first course, second course, and vegetable side dish was weighed to record the gross served mass. Bread was not weighed before consumption because it was prepackaged in a fixed portion of 50 g. Once diners finished their meals, the same plates were re-weighed under identical conditions. Plate tares were systematically subtracted from each mass annotation by referring to the corresponding plate type.

3.2.2.4.2 Acquisition Device

We developed a custom device to ensure consistent acquisition conditions across all trays and to speed up the overall process. As shown in Figure 3, the device comprises a bottom section where operators place the trays and an L-shaped vertical arm that supports the acquisition camera and lighting system, both of which are oriented downwards. We integrated a camera based on a Sony IMX378 sensor with a resolution of 4056 x 3040 pixels. Images were later subsampled for processing and sharing, as detailed in Section 3.2.2.4.4. We positioned the camera 65 cm above the tray to ensure that each tray fully fits within the field of view. We arranged high-power natural white LEDs around the camera to provide uniform illumination over the tray surface and to reduce shadows caused by ambient light sources, which effectively reduces unknown variability due to uncontrolled illumination conditions. A 7-inch capacitive touchscreen placed in front of the operator provides an intuitive user interface that shows a real-time image preview and offers on-screen controls that allows for the triggering of data acquisition. The lower section of the device houses the electronics required for the camera, LEDs, and display. A Raspberry Pi 5 single-board computer with 8 GB of RAM controls all hardware components, including the LED driver circuitry, while an embedded power supply delivers a regulated 5 V to the system. We built the structure using sealed plastic components to facilitate cleaning and to reduce the risk of damage in the event of food or liquid spills. The proposed acquisition setup relies exclusively on low-cost, off-the-shelf components and is intended as a reference design rather than a specialized sensing solution.

Figure 3. The acquisition device used within the data collection campaign for the FLIC dataset.

The acquisition software was written in Python 3.10.12 and executed directly on the device. The system stores data locally and simultaneously transmits it to a remote database (via Wi-Fi or Ethernet). This architecture ensures data redundancy and supports disaster recovery in case of device failure while still enabling continued operation when the network connection is unavailable or unstable.

3.2.2.4.3 Semantic Annotation

To support our experiments on mass estimation, we defined a ground truth for the semantic annotation of food items on each tray (both full and leftover). This ground truth consists of per-pixel labels that specify the food category associated with each region of the image.

Annotations were created using the Computer Vision Annotation Tool (CVAT) [34], specifically interacting through the Segment Anything Model (SAM) [35]: with minimal user input (often as little as a single click), we obtained a good delineation of a food region, which was then manually refined if necessary, using a brush-like tool.

Beyond binary segmentation, we assigned a semantic label to each food region based on one of the following predefined classes: “first course”, “second course”, “side dish”, “bread”, and “food” (a generic class used when the item was not listed in the daily menu). A complementary “background” class was used to label all non-food regions in the image. Samples of the resulting annotations are shown in Figure 4.

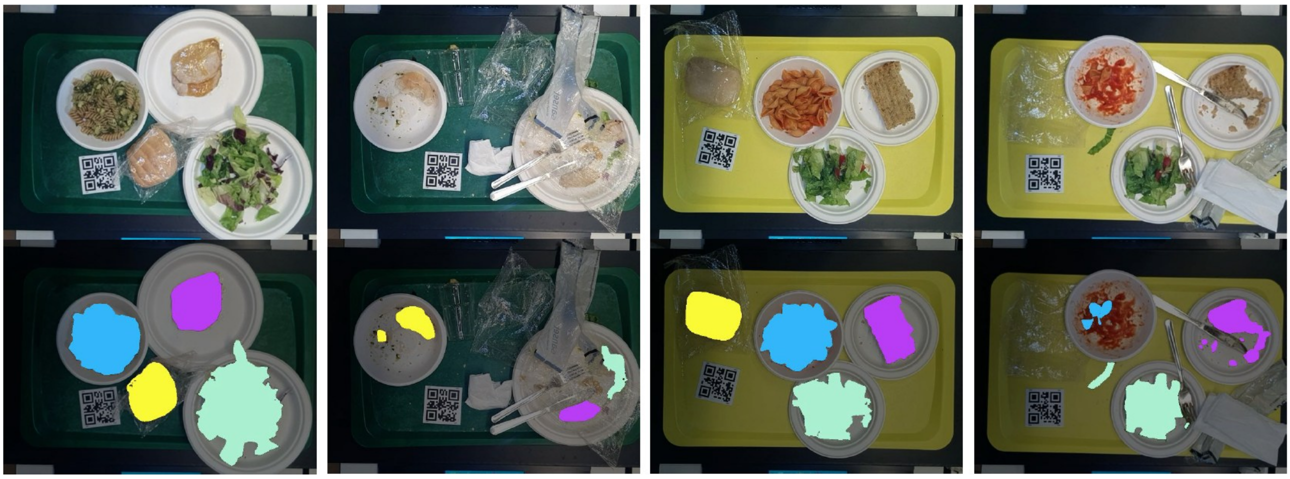

Figure 4. Sample images from the proposed FLIC dataset with corresponding pixel-precise semantic annotations. For the two tray samples (green tray and yellow tray), we show both full and leftover states. Blue segments indicate first course, magenta second course, teal side dish, yellow bread.

We then exploited the known menu structure of the canteen, where each day features, at most, one first course and one second course: this constraint allowed us to further map these general class labels to specific dishes from the corresponding daily menu.

3.2.2.4.4 Resulting FLIC Dataset

The final FLIC dataset was collected over 22 days between June and July 2024. It contains a total of 401 full-tray acquisitions plus the corresponding 401 leftover tray acquisitions. Images in the final dataset have a spatial resolution of 640 ˆ 480 pixels as a result of down sampling the original full-resolution output of the acquisition device.

For each tray, we provide a segmentation mask that identifies food regions with an associated class (first course, second course, side dish, bread, and generic food). As explained in Section 3.2.2.4.3, the first course and second-course classes can be further detailed by referencing the daily menu. This accounts for 17 first courses and 17 second courses plus bread and a generic side dish, for a total of 36 classes. Each plate is also associated with a physically measured mass, following the protocol described in Section 3.2.2.4.1. At the tray level, the average tray mass for full trays is 388.58 g, and the average tray mass per leftover tray is 61.69 g. Concerning individual food items, the average measured mass on full trays is 121.56 g (for a total of 1166 distinct food items), whereas the average mass on leftover trays is 18.54 g per item. Detailed statistics are provided in Section 5.2.3.3.

The final week of acquisitions (5 days, totaling 111 tray pairs) is characterized by trays with the second course and side dish served on the same plate to enable future experimentation on mixed food-dish recognition. This combination of paired visual data, dense semantic annotation, and physically measured mass provides an experimental setup that makes it possible to study food leftover estimation under realistic conditions. The annotated dataset is made available at:

https://drive.google.com/drive/folders/1IGCjr7y-_zsZfHTsL4CyxdkspTp8Uhnt (accessed on 26 May 2026).

3.2.2.4.5 FLIC in the Context of Multimodal Foundation Models

The newly introduced FLIC dataset can also be interpreted in the context of the current shift toward foundation models and Multimodal Large Language Models (MLLMs) [36]. The field of food recognition is increasingly moving away from task-specific supervised models toward these general-purpose architectures, which leverage extensive visual–linguistic pre-training to perform complex semantic reasoning. In the food domain, this allows models to interpret culinary context, identify ingredients through natural language interaction, or evaluate the adequacy of dietary records through domain-specific knowledge [37]. In this evolving landscape, the FLIC dataset may serve as a high-fidelity benchmark for the "physical grounding" of advanced AI. While modern deep learning often prioritizes massiveWeb-crawled collections for pre-training, recent research has demonstrated that self-supervised representations, such as those from DINOv2 [38], can serve as a robust, unified backbone for diverse food-related tasks, including classification and segmentation in few-shot regimes [39]. Furthermore, as MLLMs are increasingly explored for portion and mass estimation through the integration of volumetric reasoning [40], FLIC addresses a critical gap by providing a physically measured mass ground truth paired with visual observations.

3.2.2.5 Methodology for Mass Estimation

This section introduces a simple and interpretable methodology whose primary purpose is to validate and analyze the proposed dataset rather than to define a state-of-the-art mass estimation model.

3.2.2.5.1 Digital density

This section introduces a simple and interpretable methodology whose primary purpose is to validate and analyze the proposed dataset, rather than to define a state-of-the-art mass estimation model.

In order to provide a baseline for food mass estimation in our dataset, we define in the following the concept of "digital density". In physical measurements, "density" (ρ) is a material property that relates the volume (V) of a sample with its mass (M):

$$\underset{[\mathrm{g}]}{M} = \underset{[\mathrm{m}^3]}{V} \cdot \underset{\left[\frac{\mathrm{g}}{\mathrm{m}^3}\right]}{\rho} . \tag{1}$$

In contrast, "*digital* density" (δ) is here defined as relating the apparent area (A) of a food sample, expressed in pixels, with its mass.

$$\underset{[\mathrm{g}]}{M} = \underset{[\mathrm{px}]}{A} \cdot \underset{\left[\frac{\mathrm{g}}{\mathrm{px}}\right]}{\delta} , \tag{2}$$

Where the area (A) is measured under fixed imaging conditions (camera distance, focal length, and angle). The relationship assumed by the digital density formulation is not intended as a physically exhaustive model, but as a controlled approximation that enables systematic analysis of the dataset.

To allow for generality, we cannot assume that two instances of food will have the exact same ratio (δ) of mass over area (even in the case of the same type of food). Therefore, we compute δ by solving an overdetermined system of linear equations defined by a *set* of apparent areas ($\vec{A}$) and corresponding annotated mass values ($\vec{W}$). The solution is obtained by minimizing the least-square error using the Moore–Penrose pseudo-inverse (PInv) [41]:

$$\delta = \mathrm{PInv}(\vec{A}) \cdot \vec{W}. \tag{3}$$

Specializing δ for different food classes is expected to reduce mass estimation errors: to assess the impact of such specialization, we conduct dedicated experiments that require the identification of the individual food classes on each tray. Thanks to the specific setup of our canteen environment, where only one first course and one second course are served each day, this identification can be achieved with minimal operator input. The full procedure is described in Section 3.2.2.5.2, which details the assisted food recognition stage.

The procedure to learn the digital densities is schematized in Figure 5: from a set of several trays, we generate semantically segmented visual maps using assisted food recognition. From these semantic maps, a pixel count of their areas is easily extracted for each food class. Concurrently, we collect physical mass values following the protocol described in Section 3.2.2.4.1. This information is combined, per class, following Equation (3) to compile a table of digital densities.

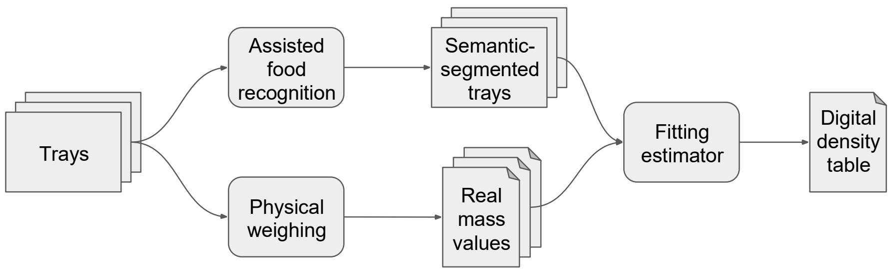

Figure 5: Procedure defined to learn the digital densities, starting from physical weighing and assisted food recognition on full trays.

3.2.2.5.2 Super-Linear Models

Acknowledging the simplification introduced by the linear model of digital density, we take into consideration two additional models of increasing complexity that map the apparent area in pixels to the mass value: a second-degree polynomial and a multilayer perception (MLP). The second-degree polynomial is determined via least-squares optimization under the same constraints as the linear digital density model for mapping 0 pixels to 0 g. Regarding the multilayer perception, we opt for a configuration of 2 processing layers with 5 intermediate neurons each, as determined after preliminary experimentation. The perceptron weights are optimized via gradient backpropagation.

As we show with appropriate ablation studies in Section 3.2.3.4, super-linear models improve estimation performance on specific dishes but result in overall equivalent or worse performance when compared with the digital density approach.

3.2.2.5.3 Assisted Food Recognition

In this section, we delineate the procedure for assisted food recognition employed within this study. As shown in Figure 6, assisted food recognition is achieved in two stages:

1. Food/no-food segmentation:

Given an image of a tray, we automatically return a segmentation mask that identifies, per pixel, whether this represents food or other.

2. Food classification:

The class of each food portion identified in the previous stage is defined at a broad level by manual input (first course, second course, side dish, or bread) and further refined automatically by relying on the daily menu.

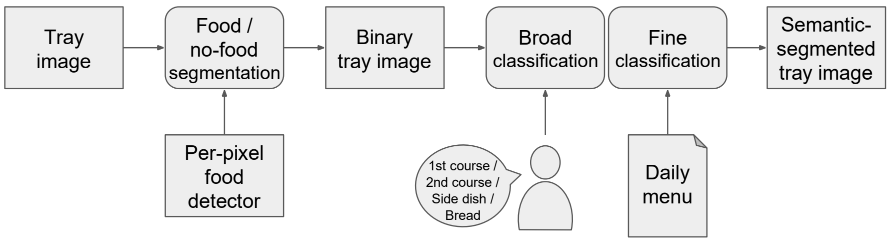

Figure 6: Detailed steps for assisted food recognition, based on automatic food/no-food binary segmentation, manual broad classification of the food classes, and automatic fine-grained classification based on the daily menu.

Details for each stage are provided in the following. The result is a segmentation map of the food-tray image. This procedure is applied to both full trays and leftover trays.

3.2.2.5.4 Food/No-Food Segmentation

At the first stage of assisted food recognition, we are interested in providing an automatic binary segmentation of food vs no-food regions. To this extent, we implement, train, and evaluate different solutions based on deep learning:

• U-Net-like architecture [42]:

As a baseline, we consider a traditional U-Net-like neural architecture where the encoder and decoder are composed of four blocks with skip connections. Each block is structured as two consecutive sequences of convolution–batch-normalization–ReLU layers and is connected to other blocks through a two-dimensional max-pooling layer.

• DABNet [43]:

Based on the Depth-wise Asymmetric Bottleneck module (DAB), DABNet generates a coarse segmentation map directly from a low-dimensional feature map without explicitly relying on a decoder module. In [44], it was shown to exhibit excellent accuracy in food/no-food segmentation while maintaining a moderate computational footprint. This led to the selection of DABNet as a representative for advanced supervised semantic segmentation within this work.

• DINOv2 features [38] combined with FeatUp upsampling [45] (DINOv2+FU):

DINO (self-DIstillation with NO labels) is a self-supervised foundation vision transformer whose features have demonstrated remarkable capability in distinguishing semantic content in open-world scenarios. One significant limitation of DINO, i.e., the low spatial resolution of its features, has been addressed in past [46] with FeatUp, a model-agnostic framework capable of learning an upsampling function specific to a given embedding space. In this work, the 384-dimensional DINOv2 features, upsampled with FeatUp, are eventually mapped to our pixel-wise binary output through a single convolutional head with a kernel size of 1ˆ 1.

• SAM [35] prompted through Grounding DINO [47] (SAM+GDINO):

The Segment Anything Model (SAM) is a general-purpose foundation model for segmentation designed to handle different types of input prompts, including points and bounding boxes. To fully automate its usage and avoid the need for user prompts, we use it in its "Language SAM" configuration [48]. In this setup, the input image is processed with Grounding DINO (DETR with Improved deNoising anchor boxes), an open-world object detector that returns bounding boxes based on an input textual prompt. In this case, the prompt is "food". Of the four approaches, the first three require training to some extent. Namely, U-Net and DABNet were trained from scratch, adhering to a configuration that was consolidated on previous studies for food localization on canteen trays [44] and subsequently tuned to the FLIC dataset after preliminary assessment. This includes 50 epochs of training guided by binary cross-entropy loss, with gradients updated through the Adam optimizer using a fixed learning rate of 0.005 and no weight decay. No data augmentation was found to be beneficial. Experiments were conducted in a two-fold cross-validation setup to ensure fairness. The same configuration was adopted for DINOv2+FU; however, in this case, only the head was tuned to be applied on top of the pre-trained feature extractor. The fourth approach, SAM+GDINO, is the only one completely free from any tuning on our end, and it is selected to test the limits of zero-shot foundation models.

3.2.2.5.5 Food Classification

At the second stage of assisted food recognition, we consider a user-assisted classification of the food items in order to specialize mass estimation for each class. As a first approximation, in fact, mass estimation could be provided globally at the tray level by relying on a general-purpose digital density obtained with the application of Equation (3) to all food instances indiscriminately. However, it is of interest to quantify the extent to which having food-specific information can lead to a more accurate estimation of mass.

Given the constraints of fixed daily menus, we devise a two-level semi-automatic food classification procedure that involves user interaction to provide reliable identification of the food classes. This allows us to decouple and exclude the error of food recognition from that of food mass estimation.

1. A first level of broad classification is related to identifying each portion of food as belonging to either "first course", "second course", "side dish", or "bread'. For this input, we assume the interaction of our system with a dedicated operator or with the users themselves.

2. A second level of fine classification assigns a specific class to the food items (e.g., tomato pasta, white pasta, etc.). In our case, we rely on the specific constraints of our acquisition setup, where the menu is fixed for any given day; i.e., if the user chooses to eat the first course, that plate can only contain one specific class. Combining the broad classification with the daily menu, it is therefore possible to automatically obtain a fine association of classes related to first and second courses. No details on the side-dish class are available.

If the accuracy gain in mass estimation as obtained by food classification is found to be significant, future developments might involve the use of additional computer vision techniques for the automated recognition of food classes [49].

3.2.3 Results

The methodology described in Section 3.2.2.5 serves as a transparent baseline to investigate the relationship between visual measurements and physical mass within the FLIC dataset. To assess this baseline, we present several experiments in the following. In Section 3.2.3.1, we evaluate different methods for food/no-food binary segmentation. In Section 3.2.3.2, we test the hypothesis of linear correlation between the apparent area in pixels and measured mass in grams. In Section 3.2.3.3, we apply and test our model for mass estimation based on digital densities. In Section 3.2.3.3.4, we report ablation studies for mass estimation based on non-linear predictors and the impact of food/no-food segmentation.

3.2.3.1. Food/No-Food Segmentation

Results for food/no-food binary segmentation are measured in terms of Intersection over Union (IoU):

$$\mathrm{IoU} = \frac{\sum_{i=1}^{N}(\hat{p}_i \wedge p_i)}{\sum_{i=1}^{N}(\hat{p}_i \vee p_i)}, \tag{4}$$

where $\hat{p}_i$ is the predicted set of food pixels and p_i is the ground truth of the i-th image. Two-fold cross validation is used for evaluation, with samples from both full trays and leftover trays used at training and test time.

Results are reported in Table 2: all methods considered for comparison show similar performance on full trays, landing at around 92–93% IoU. However, a significant difference is shown on leftover trays. As a general comment, we can state that leftover trays represent a significantly more challenging scenario than full trays, even for state-of-the-art segmentation models: while more traditional encoder-decoder architectures U-Net and DABNet achieve between 70% and 71%, DINOV2+FeatUp reaches the highest 77.22% IoU, making it the model of choice for our subsequent experiments. SAM+GDINO, which is the only method that does not involve any form of training, also shows competitive performance on full plates but drops significantly in leftover detection.

Table 2. Intersection over union results for food/no-food binary segmentation with different methods.

Method	Training	IoU (Full Trays) ↑	IoU (Leftover Trays) ↑
U-Net-like [42]	Full	92.52%	70.05%
DABNet [43]	Full	93.64%	71.12%
DINOv2+FU [38, 45]	Head only	93.26%	77.22%
SAM+GDINO [35, 47]	None	91.98%	31.77%

Visual examples of binary food/no-food segmentation are provided in Figure 7.
In Section 3.2.3.3.4, we also quantify the impact of imperfect food/no-food segmentation on the downstream task of food mass estimation.

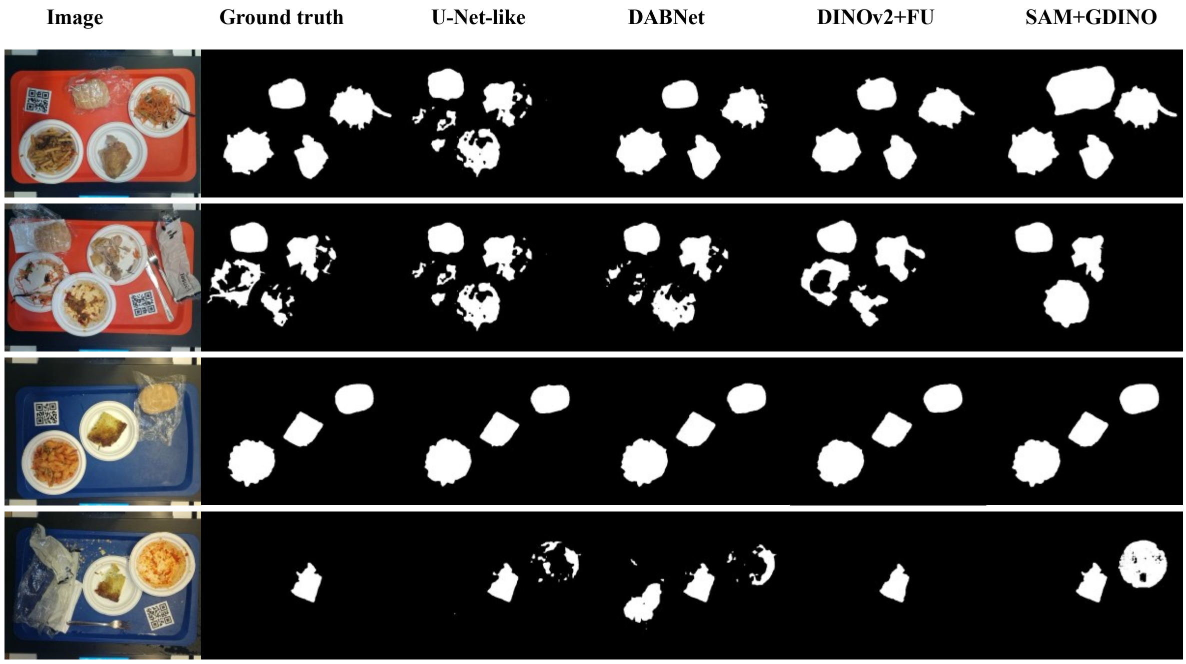

Figure 7. Examples of binary food/no-food segmentation as obtained with different methods on full and leftover trays.

3.2.3.2 Area-to-Mass Linear Correlation Test

Estimating mass values via digital density assumes the existence of a linear relationship between food area in pixels and mass in grams. Here, we test this hypothesis by conducting a correlation analysis of the dataset collected. The results are shown in Figure 8. Every point represents a plate: full-plate observations are reported in blue, and leftovers are reported in orange. Plates with mixed dishes (second course and side dish on the same plate) are excluded from this analysis. The red line represents a purely linear regression with null offset. For the first and second courses (first row) we also report a subset plot of the best and worst correlated classes in Figure 9. For reference, the semi-transparent red line is the same linear regressor from Figure 8, i.e., at the broad level (first course and second course) instead of the fine level. Note the differentranges of the plots.

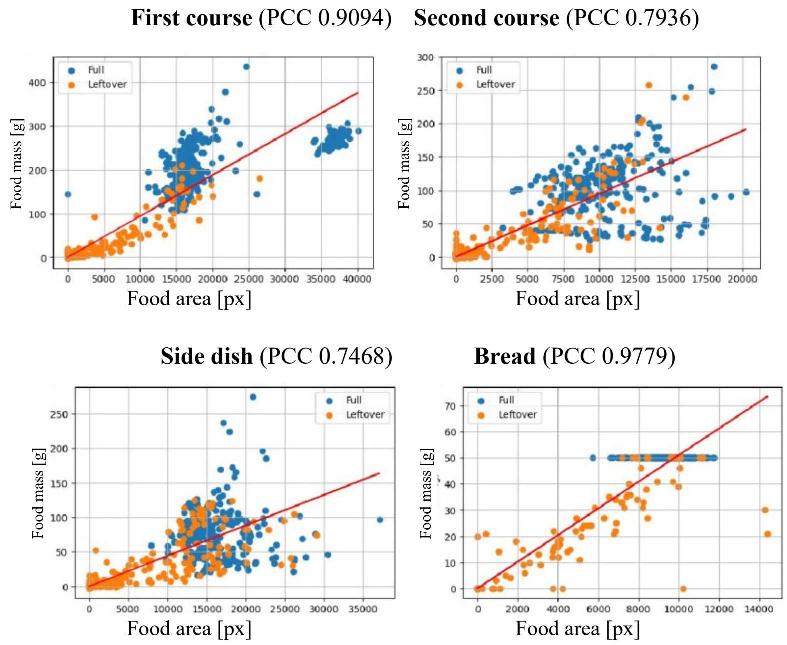

Figure 8. Scatter plots correlating apparent area in pixels and mass in grams,for broad-level classes. Full-tray acquisitions in blue and leftovers in orange. Linear correlations described with a red line and quantified by Pearson Correlation Coefficients (PCCs).

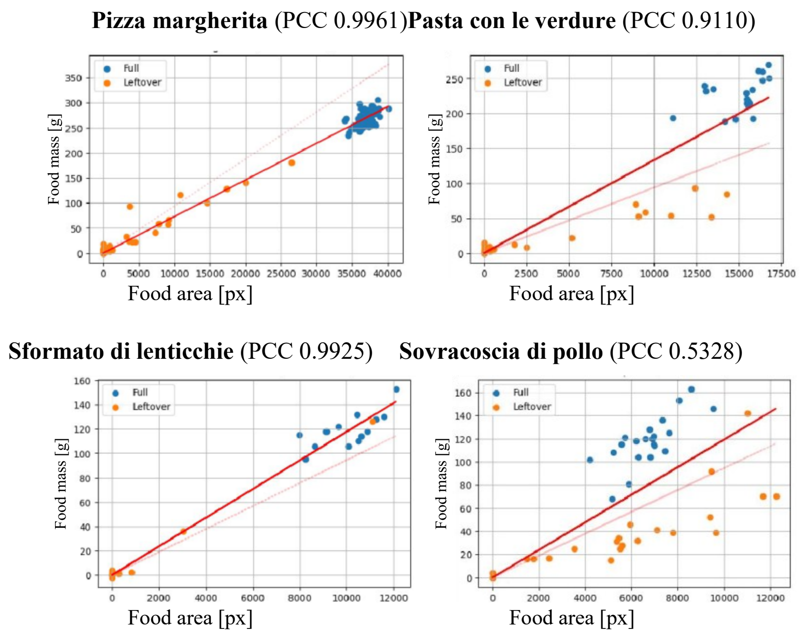

Figure 9. Scatter plots correlating apparent area in pixels and mass in grams for fine-level sample classes. Full-tray acquisitions in blue and leftovers in orange. Linear correlations described with a red line and quantified by Pearson Correlation Coefficients (PCCs).

The first course exhibits a very good Pearson Correlation Coefficient (PCC) of 90.04%. Its plot, however, shows that a non-linear correlation would better fit the great majority of the data and that there is a visible outlier. The outlier is class “Pizza margherita”, which incidentally has the highest correlation among first-course sub-classes (99.61%). The worst correlation is for “Pasta with vegetables”, although still reaching a solid 91.10%. In this case, the non-linearity can be explained by the heterogeneous nature of the meal: the pasta itself and the vegetables have inherently different digital densities, which are not modeled separately in our scenario. The full meal (blue points) is a mix of the two components, while the leftover (orange points) tends to be mostly composed of vegetables, as revealed by visual inspection. This effectively leads to two different linear relationships between full and leftover state for the same meal. Visual examples of the aforementioned classes of interest are provided in Figure 10.

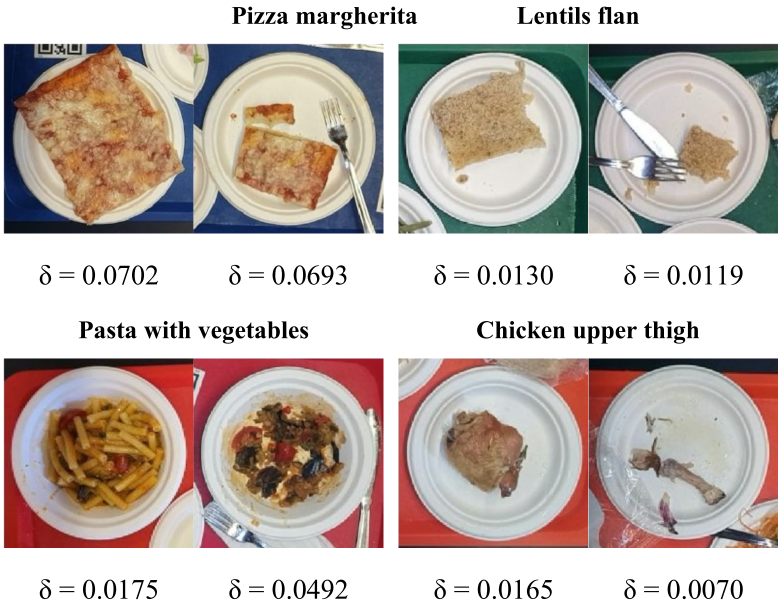

Figure 10. Examples of classes from our FLIC dataset with corresponding digital density values (δ) according to the specific sample shown. The classes of "Pizza margherita" and "Lentil flan" are the most consistent between full and leftover state, whereas "Pasta with vegetables" and "Chicken upper thigh" show significant differences before and after consumption.

The second course exhibits worse linearity overall, with correlation at around 80% and a visibly scattered plot. Within this group, some individual dishes, such as "Lentil flan", do have excellent linear correlation (99.25%). The worst second course is "Chicken upper thigh", at 53.28% correlation. Similarly to "Pasta with vegetables", this is also a case where two components of the dish have inherently different digital densities: the meat and the bone. In this case, however, the bone is mostly invisible on the full plate and mostly visible on the leftover plate. This creates two independent point clouds that cannot be modeled, even with a non-linear correlation. It also suggests that for given food classes, some leftover quantity always be present and should not be counted as waste.

The side-dish class exhibits decent behavior overall, not dissimilar to that of the second-course class, with 74.68% correlation. In this case, however, it is not possible to define food-specific relationships, as the canteen does not provide detailed sub-class labels for side dishes.

Bread shows excellent linear correlation (97.79%). The plot also clearly shows how the full-tray bread information was set to a default of 50 g without actual physical weighing. This analysis highlights the variable level of reliability that can be attributed to linear modeling of the area-to-mass relationship. In the next section, we will quantify how this linear modeling actually impacts the task of mass estimation.

3.2.3.3 Mass Estimation

3.2.3.3.1 Experimental Setup

We learn digital densities by applying Equation (3) to data extracted from full-tray images. We then verify the effectiveness of digital densities for the estimation of mass from leftover tray images. This setup allows us to better observe the distribution of estimation errors, since the leftover trays naturally present a more widespread range of mass values.

Our food recognition pipeline based on binary food/no-food segmentation does not allow us to distinguish mixed dishes (i.e., multiple types of food in close contact within the same plate). Since 111 trays out of 401 contain a second course and a side dish in the same plate, we exclude those specific mixed-dish plates from the mass estimation experiment.

Let $\mathcal{F}$ = {1, 2, . . ., 10} denote the set of possible training-set sizes (i.e., the number of samples) and let R=100 be the number of independent runs for each size. We adhere to the following procedure:

- For each $\mathfrak{F} \mathcal{E} \mathcal{F}$, collect $\mathcal{F}$ random training samples of the class of interest from full-tray images, along with the corresponding measured mass annotation. This emulates a hypothetical "enrollment" phase in the canteen, where few instances of food are individually measured for reference.
- Estimate the digital density, relating area in pixels to mass in grams by application of Equation (3).
- Select all $\mathcal{L}$ food regions that correspond to the class of interest identified on leftover food images.
- Apply the learned digital density to the $\mathcal{L}$ leftover food regions, remapping the food area to estimated leftover mass.
- Compute the Mean Absolute Error (MAE) between the measured leftover mass (m) and estimated leftover mass ($\widehat{m}$):

$$\mathrm{MAE} = \frac{1}{L}\sum_{i=1}^{L}|m_i - \hat{m}_i|. \tag{5}$$

- Repeat the procedure $\mathcal{R}$ times with different random selections of $\mathfrak{F}$ training samples and compute the mean and standard deviation of the resulting MAE values.

In order to assess the impact of classification errors on the final quality estimation results, we consider three levels of food classification in our experiments: no classification (instances from all food classes are considered), broad classification (instances of first course, second course, side dish, and bread are considered separately), and fine classification (instances of all specific first-course and second-course classes are considered separately).

3.2.3.3.2 Experimental Results

In Table 3, we report results for global statistics, i.e., errors computed on all leftover plates (only excluding mixed-dish plates, as in all subsequent experiments). MAE-1 is the error obtained by learning the digital density of just $\mathcal{T}$=1 random training example, as averaged for $\mathcal{R}$=100 runs. MAE-1/full is a relative error provided to gauge the impact of MAE-1 by dividing it for the average mass of a full plate. An alternative option would be to normalize MAE-1 for the average leftover mass. This, however, would lead to numerically unstable and uninformative results, since leftover mass values are often extremely small (especially for the detailed tables presented in the following). The effect of discriminating food classes with specialized digital densities, as indicated by the “Classification” column, is measurable but limited, lowering the relative error by two percentage points.

Table 3. Global statistics for leftover mass estimation. The “Classification” column identifies different specializations of the digital density used in mass estimation. For each, we report both absolute and relative errors.

Course	Classification	N samples	Avg full [g]	Avg leftover [g]	MAE-1 [g]	MAE-1/full
All	No classification Broad classification Fine classification	1166	121.56	18.54	14.30 13.04 11.47	11.76% 10.73% 9.44%

In Table 4, we report a detailed view of the impact of broad classification and fine classification on course-level statistics. Fine classification (i.e., identifying the specific food class) is only available for the first and second courses, since the canteen did not provide detailed information about various side dishes. This experiment shows that fine classification has a significant impact in terms of reducing the error for the second course and virtually no impact (if not a slightly negative impact) on the first course. This can be explained by the relatively uniform nature of first courses in this dataset (different types of pasta) against the heterogeneity of second courses. It should also be noted that several food classes exhibit limited representation in the evaluation set; therefore, performance metrics for these classes should be interpreted with caution due to statistical instability and limited generalization capability.

Table 4. Course-level statistics for leftover mass estimation. The “Classification” column identifies different specializations of the digital density used in mass estimation. For each, we report both absolute and relative errors.

Course	Classification	N samples	Avg full [g]	Avg leftover [g]	MAE-1 [g]	MAE-1/full
First course First course	Broad classification Fine classification	393	207.98	17.59	12.00 12.38	5.77% 5.95%
Second course Second course	Broad classification Fine classification	274	102.31	23.76	20.81 13.60	20.34% 13.29%
Side dish	Broad classification	241	79.12	25.14	16.19	20.46%
Bread	Broad classification	258	50.00	8.29	3.43	6.86%

Figure 11 shows the MAE curves and confidence intervals for the broad classification of “first course”, “second course”, “side dish”, and “bread”. Here, a blue line plots the MAE with the number of training samples varying from $\mathcal{T}$=1 up to $\mathcal{T}$=10. The blue area encodes the standard deviation resulting from $\mathcal{R}$=100 independent runs. The dashed red line is the average mass for leftovers. The average mass for full plates is reported numerically in the figure but not visualized for the sake of compactness. The plot shows how, with more training examples, it is possible to reduce the average MAE. This is visible in the descending blue line. Furthermore, relying on multiple training examples reduces the difference in behavior across runs, since the aleatory of random sample selection has a lesser impact. This is visible in the reducing blue area. In some cases (such as “second course”), the improvement is more apparent than in others (“first course”), a behavior that can also be explained by the more heterogeneous nature of second courses.

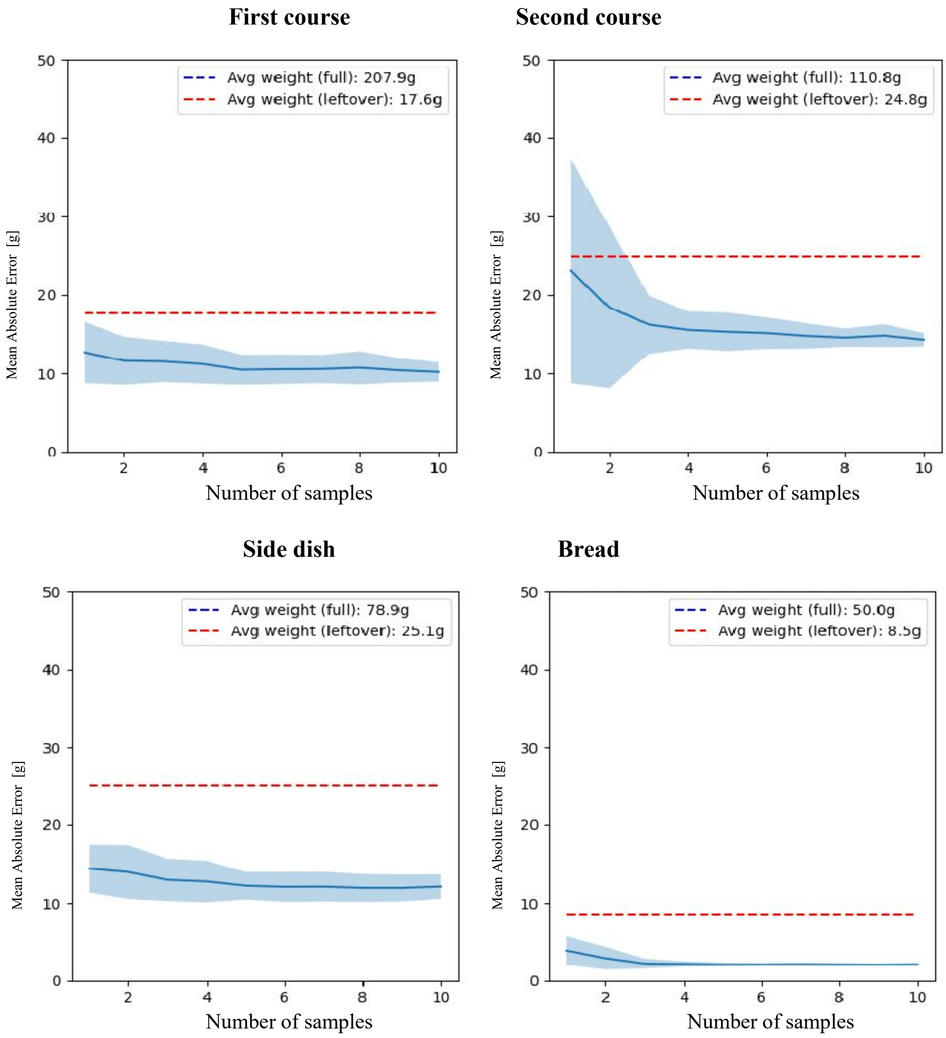

Figure 11. MAE with varying numbers of training samples used to define the digital density. The blue area indicates the standard deviation across multiple runs.

Tables 5 and 6 provide additional details about the error distribution in first courses and second courses, respectively. The impact on mass estimation can be seen to be generally in line with the correlation analysis from Section 3.2.3.2. For example, “Pasta with vegetables” shows the worst absolute and relative MAE-1 values among first courses, and it also shows the least correlation between area and mass. Similarly, “Chicken upper thigh” has the worst MAE-1 for second courses. Other notable examples include the excellent mass estimation for the first course of “Ricotta and spinach tortelli” and for the second course of “Gratin-style plaice fillets”.

Table 5: First course details for leftover mass estimation. For each dish, we report both absolute and relative errors.

First course dish	N samples	Avg full [g]	Avg leftover [g]	MAE-1 [g]	MAE-1/full
Pasta al ragu`	45	195.27	4.51	5.49	2.81%
Pasta integrale pomodoro e basilico	38	227.37	23.71	16.52	7.27%
Pasta integrale alle zucchine	12	177.00	85.33	18.71	10.57%
Pasta con melanzane e pomodorini	15	147.60	15.80	9.06	6.14%
Riso al pomodoro e basilico	14	226.79	27.36	24.48	10.79%
Pizza margherita	71	269.75	20.06	7.76	2.88%
Pasta all'olio evo e parmigiano	16	119.69	2.94	3.24	2.71%
Pasta integrale alle melanzane	12	185.92	17.42	7.82	4.21%
Pasta al pomodoro e tonno	14	176.57	30.71	18.73	10.61%
Tortelloni ricotta e spinaci	10	204.10	3.80	3.52	1.72%
Pasta con le zucchine	11	184.18	6.09	10.21	5.54%
Pasta al pomodoro e basilico	23	193.57	8.30	11.75	6.07%
Riso all'olio evo e parmigiano	22	172.27	22.82	14.97	8.69%
Pasta con le verdure	19	226.68	30.05	33.46	14.76%
Pasta con pomodoro e piselli	23	237.96	11.48	23.34	9.81%
Pasta al pesto	25	184.96	3.96	4.23	2.29%
Pasta fredda tricolore	23	187.61	14.04	13.14	7.00%

Table 6: Second course details for leftover mass estimation. For each dish, we report both absolute and relative errors.

Second course dish	N samples	Avg full [g]	Avg leftover [g]	MAE-1 [g]	MAE-1/full
Frittata con le zucchine	23	135.70	46.57	13.91	10.25%
Tortino di ceci e patate	18	144.06	6.44	2.60	1.80%
Arrosto di maiale	12	94.00	28.33	23.12	24.60%
Seppie gratinate	15	79.73	31.27	10.62	13.32%
Erbazzone	12	206.08	116.67	32.03	15.54%
Prosciutto cotto	46	45.33	5.87	4.38	9.66%
Sformato di lenticchie	14	118.93	12.14	3.12	2.62%
Bocconcini di tacchino al limone	12	116.50	28.92	14.39	12.35%
Frittata di spinaci	11	104.73	8.09	3.46	3.30%
Parmigiano	10	40.00	8.30	33.09	82.73%
Filetti di merluzzo con patate	11	85.55	13.18	7.25	8.47%
Tortino di legumi	22	117.00	23.82	6.95	5.94%
Filetti di platessa gratinati	23	90.43	0.17	0.26	0.29%
Sovracoscia di pollo	21	117.71	39.71	66.20	56.24%
Frittata di bieta e ricotta	22	115.59	25.73	4.81	4.16%
Merluzzo al pomodoro e olive	2	106.00	41.00	8.26	7.79%

3.2.3.3.4 Ablation Studies

In this section, we report ablation studies aimed at quantifying the impact of superlinear models and the impact of food/no-food segmentation errors. Tables 7 and 8 focus on replacing the linear model of digital density with a seconddegree polynomial and a multilayer perception. We report MAE-1 and MAE-10 errors computed with $\mathcal{T}$=1 and $\mathcal{T}$=10 training examples, respectively, based on results averaged from $\mathcal{R}$=100 runs. We also report the MAE differences such that a positive difference indicates an improvement with super-linear models. As can be observed, both for the polynomial and the perceptron approaches, the overall effect on MAE-1 is markedly negative: this is explained by the numerical instability intrinsic in learning more complex models with little data. The overall differences are evened out once more training samples are available (MAE-10), which suggests that more complex models are not, in an average case, more useful than the digital density approach. Specific dishes of interest, as emerged in the previous sections, are also reported to assess the specific positive impact of super-linear modeling (e.g., “Pasta with vegetables” and “Chicken upper thigh” in Table 8).

Table 7. Ablation study that compares the linear model of digital density against a more complex second-degree polynomial (2nd deg). Reported are MAE-1 and MAE-10 errors, together with Differences (Diff.). A positive difference indicates an improvement achieved by the super-linear model.

		MAE-1			**MAE-10**		
Course	**Classification**	**Linear**	**2nd deg**	**Diff.**	**Linear**	**2nd deg**	**Diff.**
All	No classification	14.30	414.85	−400.55	10.99	12.33	−1.34
All	Broad classification	13.04	81.62	−68.58	9.03	11.91	−2.88
All	Fine classification	11.47	14.88	−3.41	9.54	10.16	−0.62
First course	Broad classification	12.00	10.88	+1.12	10.41	14.61	−4.60
First course	Fine classification	12.38	10.37	+2.01	12.02	12.13	−0.11
↳ Pizza margherita		7.76	14.00	−6.24	7.21	9.83	−2.62
↳ Pasta with vegetables		33.46	16.88	+16.58	33.69	37.70	−4.01
Second course	Broad classification	20.81	311.48	−290.67	11.44	14.17	−2.73
Second course	Fine classification	13.60	28.18	−14.58	10.70	11.11	−0.41
↳ Lentil flan		3.12	4.98	−1.86	3.14	3.57	−0.43
↳ Chicken upper thigh		66.20	102.94	−36.74	64.57	58.47	+6.10
Side dish	Broad classification	16.19	18.77	−2.58	12.21	14.81	−2.60
Bread	Broad classification	3.43	3.99	−0.56	2.02	2.69	−0.67

Table 8. Ablation study that compares the linear model of digital density against a more complex multilayer perceptron (MLP). Reported are MAE-1 and MAE-10 errors, together with Differences (Diff.). A positive difference indicates an improvement achieved by the super-linear model.

		MAE-1			MAE-10		
Course	**Classification**	**Linear**	**MLP**	**Diff.**	**Linear**	**MLP**	**Diff.**
All	No classification	14.30	190.96	−176.66	10.99	12.12	−1.13
All	Broad classification	13.04	81.39	−68.35	9.03	10.81	−1.78
All	Fine classification	11.47	90.23	−78.76	8.60	10.47	−1.87
First course	Broad classification	12.00	15.86	−3.86	10.01	11.17	−1.16
First course	Fine classification	12.38	16.05	−3.67	12.02	13.06	−1.04
↳ Pizza margherita		7.76	12.38	−4.62	7.21	9.97	−2.76
↳ Pasta with vegetables		33.46	39.95	−6.49	33.69	32.54	+1.15
Second course	Broad classification	20.81	28.08	−7.27	11.44	13.88	−2.44
Second course	Fine classification	13.60	65.45	−51.85	10.70	13.68	−2.98
↳ Lentil flan		3.12	8.82	−5.70	1.33	3.23	−1.90
↳ Chicken upper thigh		66.20	186.60	−120.40	64.57	60.60	+3.97
Side dish	Broad classification	16.19	303.74	−287.55	12.21	15.00	−2.79
Bread	Broad classification	3.43	30.11	−26.68	2.02	3.10	−1.08

Table 9 focuses on the impact of replacing automated food/no-food segmentation, as obtained via the DINOV2+FeatUp approach presented in Section 3.2.2.5.3, with the human annotations used to train said model. In this context, human annotations are used as a proxy for perfect segmentation. The information is presented following the same scheme as Tables 7 and 8, and here, a positive difference indicates an improvement gained from perfect human segmentation. The results show that, overall, the effect of imperfect segmentation (measured at 93.26% IoU on full trays and 77.22% on leftover trays in Section 3.2.3.1) is negligible on the downstream task of mass estimation. This is explained by the fact that, for each configuration, the digital densities are learned from the corresponding semantic annotation (human or annotated) and, as such, sufficiently compensate for over- and under-segmentations.

Table 9. Ablation study that compares the automated food/no-food segmentation obtained through DINOV2+FeatUp with human-annotated masks. Reported errors are MAE-1 and MAE-10, together with Differences (Diff.). A positive difference indicates an improvement gained from human annotation.

		MAE-1			**MAE-10**		
Course	**Classification**	**Automated**	**Human**	**Diff.**	**Automated**	**Human**	**Diff.**
All	No classification	14.30	14.62	−0.32	10.99	11.18	−0.19
All	Broad classification	13.04	11.61	+1.43	9.03	8.94	+0.10
All	Fine classification	11.47	11.46	+0.01	9.54	9.72	−0.18
First course	Broad classification	12.00	12.50	−0.50	10.01	10.31	−0.30
First course	Fine classification	12.38	12.77	−0.40	12.02	12.47	−0.45
↳ Pizza margherita		7.76	7.21	+0.55	7.21	6.71	+0.50
↳ Pasta with vegetables		33.46	40.87	−7.41	33.69	41.47	−7.78
Second course	Broad classification	20.81	13.98	+6.83	11.44	10.66	+0.78
Second course	Fine classification	13.60	12.97	+0.62	10.70	10.87	−0.17
↳ Lentil flan		3.12	3.34	−0.29	1.33	1.54	−0.21
↳ Chicken upper thigh		66.20	68.66	−2.46	64.57	66.15	−1.58
Side dish	Broad classification	16.19	16.49	−0.30	12.21	12.49	−0.28
Bread	Broad classification	3.43	3.16	+0.27	2.02	1.70	+0.32

3.2.4 Conclusions

This work is primarily intended as a dataset contribution, providing a realistic experimental foundation for studying food leftover estimation rather than proposing a novel estimation model. Specifically, we introduced FLIC: a novel annotated dataset for image-based estimation of food mass in collective catering environments. The dataset includes 401 full and 401 leftover tray images with per-pixel semantic labels and precise physical mass measurements collected in a real-world canteen over 22 days. We defined the concept of digital density to relate image area to food mass and provided baseline results through a lightweight estimation pipeline combining food/no-food segmentation and assisted food recognition. These experiments serve to validate the dataset's applicability and establish an initial benchmark for future research on visual food-waste estimation. While the FLIC dataset provides high-fidelity paired visual and mass annotations, its current scale remains relatively modest. This may affect the statistical stability of some findings and limit its future usage for deep learning methods. Furthermore, its single-site origin and fixed menu may introduce inherent geographic and cultural biases. These constraints reflect the inherent difficulty of acquiring large-scale, culturally diverse data, particularly the significant logistical challenge of manually weighing every individual food item in a high-throughput operational canteen. To mitigate the risk of overfitting and enhance generalization, future efforts will focus on multi-site collection to encompass diverse food compositions, lighting conditions, and tableware types. Furthermore, we intend to explore advanced data augmentation strategies such as the generation of synthetic leftover tray configurations or the use of generative models to simulate the morphological variability and food mixing typically seen in post-consumption scenarios. The proposed digital density model relies on the assumption of a linear relationship between image area in pixels and food mass in grams. While this assumption is supported in several cases by our correlation analysis, it does not hold uniformly across all food types, especially for heterogeneous or multi-component dishes. For this reason, future work will investigate the selective application of non-linear models to mass estimation of specific foods that are found to benefit from increased complexity. Closely related to this limitation is the fact that our current formulation uses only the apparent area as a predictor. A more physically grounded approach would relate food mass to estimated volume rather than projected area, as demonstrated in research utilizing overhead RGB-D sensing [22], voxel-based reconstruction from depth maps [50], or 3D object scaling [24]. Such methods leverage depth estimation or multi-view reconstruction to achieve precise portion quantification, though they typically require specialized hardware or strong 3D priors not available in our standard 2D setup. Our experiments also show that broad and fine food classifications lead to uneven gains in estimation accuracy across courses. Although class-specific modeling does not consistently improve performance, detailed food categorization remains desirable for reporting and monitoring purposes. For this reason, future developments will explore more advanced computer vision methods for automatic food classification, reducing the need for user assistance while preserving class-level reporting. Finally, an open challenge between leftover food mass estimation and true waste estimation is the treatment of non-edible fractions and of edible residues that are practically unrecoverable with standard utensils. Explicit identification of non-waste leftovers will be necessary to more accurately translate visual mass estimates into measures of effective food waste.

3.2.5 Abbreviations

The following abbreviations are used in this manuscript:

- 2D Two-Dimensional 3D Three-Dimensional
- CVAT Computer Vision Annotation Tool
- DABNET Depth-wise Asymmetric Bottleneck Network
- DETR DEtection with TRansformers
- DINO self-DIstillation with NO labels
- DSLR Digital Single-Lens Reflex
- ECUSTFD East China University of Science and Technology Food Dataset
- EU European Union
- FLIC Food Leftovers In Canteens
- FU FeatUp
- GB Giga Bytes
- GDINO Grounding DETR with Improved deNoising anchor boxes
- IoU Intersection over Union
- MAE Mean Absolute Error
- MedGRFood Mediterranean Greek Food
- MLP Multi-Layer Perceptron
- MLLM Multimodal Large Language Model
- QR code Quick Response code
- LED Light Emitting Diode
- PCC Pearson Correlation Coefficient
- RAM Random Access Memory
- RGB Red Green Blue
- RGB-D Red Green Blue and Depth
- SAM Segment Anything Model
- UNIMIB University of Milano-Bicocca
- YOLO You Only Look Once

3.2.6 References

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Study 3

Uniplate: a mHealth application developed using a participatory design to support healthy and sustainable dietary behaviors in university students

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This study is currently in preparation for submission to peer-reviewed journals.

Abstract

Background/objectives: Non communicable diseases (NCDs) and unhealthy dietary patterns represent a growing challenge for public health and sustainability of food systems. In this context, mobile health technologies (mHealth) offer a promising opportunity to promote healthy and sustainable behaviors, especially among young adults. However, many existing applications showed limits in terms of efficacy, quality of content and solid recognized educational models. This study aims to describe the methodological process for the conceptualization and development of *Uniplate*, a mHealth app designed to promote healthy and sustainable eating habits among university students, based on a participatory and multidisciplinary approach.

Methods: The development of the app was conducted following a participatory approach divided into four phases: (i) conceptualization, guided by a targeted literature review and the Behavior Change Technique Taxonomy v1; (ii) co-design through a focus group with university students (n=7); (iii) application development with the contribution of nutritionists, psychologists and computer scientists; (iv) testing in a 12-week randomized controlled trial (RCT) aimed at evaluating the user experience.

Results: The Uniplate app included 21 behavior changing techniques distributed in 11 clusters, translating them into practical features such as goal tracking, meal planning, shopping list, sustainable recipes database and personalized educational contents. Results from RCT highlight a high acceptance and usability with 89% of users reporting high level of satisfaction and 79% declared they would recommend it to others. Daily tips and meal planning functionality emerged as the most appreciated features. However, the perceived impact on eating behaviors was modest, with mean scores close to the central value of the Likert scale (≈3/5).

Conclusions: The *Uniplate* app represents an innovative model of mHealth application based on co-design, scientific evidence and the systemic integration of behavior changing techniques. Results suggest that user engagement and an interdisciplinary approach can improve the acceptability of digital tools for health promotion. Future studies should explore their long-term effectiveness and optimize engagement strategies.

Keywords: mHealth; sustainable diets; healthy diet; behavior change techniques; university students; participatory design

3.3.1 Introduction

According to the latest Global Burden of Disease report [1], non-communicable diseases (NCDs) remain an escalating global health challenge. Specifically, overweight and obesity have emerged as leading risk factors over the last two decades, accounting for 3.71 million deaths and 129 million disability-adjusted life-years (DALYs) in 2021 [2]. Overweight and obesity are multifaceted health risks driven by a convergence of individual and environmental determinants [3]. This includes the shift toward sedentary lifestyles and poor dietary patterns, a transition exacerbated by the rapid urbanization characteristic of the 21st century [4]. At the same time, the growing instability of the global food system underscores the urgency of transitioning toward sustainable dietary patterns to ensuring both human well-being and planetary health while fostering socio-economic resilience [5]. While food systems have been recognized as a primary lever for change, progress toward the Sustainable Development Goal (SDG) targets of 2030 Agenda [6] remains mostly limited. In this context, the Sustainable Development Report 2025 [7] highlights that at the current pace, most sustainability-related targets will not be achieved, and Italy is not excepted from this developmental shortfall. As regards, it is essential to recognize the role of consumer agencies in shaping production patterns. Educating consumers about the multifaceted impacts of their dietary choices is therefore critical to accelerating the transition toward more sustainable food systems [8]. Although the latest trends and research show increasing attention to these issues and growing collective awareness of the environmental and health impact of diets, the debate on how to implement change remains open, and there is a growing need for clear and scientifically sound references and tools. Strategies to improve eating habits and tackling overweight and obesity operate on multiple levels: individual education, clinical support, community interventions, and public policy [9]. All these interventions are synergistic and essential for reaching a larger segment of the population. Because of the possibility of reaching the population in a widespread manner, there has been an increased interest in so-called mobile Health (mHealth) technologies, such as smartphones, tablets, and wearable sensors that facilitate the communication processes and support the tracking and achievement of health goals [10].

The most recent reviews of the literature [11; 12; 13] show encouraging signs regarding the effectiveness of mHealth technologies such as mobile applications in promoting food behavior changes; however, authors highlighted some limitations including the heterogeneity of the outcomes measured, the small number of participants, short intervention periods, and the almost total absence of follow-up phase to evaluate the impact over time. In addition, these studies often involve commercial apps for calorie counting and self-monitoring that show short-term weight loss effects, but their quality and long-term effectiveness remain debated. Other trials were conducted in subjects with physiological conditions or pathologies, or assessed limited number of outcomes such as weight, calories or single nutrient intake. Despite their potential, questions persist regarding the actual effect these applications have on dietary sustainability. They appear to be valuable tools, however, a more comprehensive evaluation, underpinned by standardized indicators, is required to determine their true impact [11]. In addition, health-related disinformation spreads particularly rapidly through online channels and are especially pervasive in the lifestyle domain and among young adults [14], with potentially detrimental effects on their behaviours and an increased long-term risk of noncommunicable diseases [15]. These concerns are further supported by findings from a recent survey conducted by European Food Information Council [16], which indicates that young adults represent one of the EU population groups with the lowest diet quality and limited nutrition knowledge. In response to this scenario, experts have emphasized the pivotal role of educational institutions in promoting evidence-based health communication to counteract the societal and economic costs of disinformation [14]. In line with this perspective, universities represent a particularly strategic setting for implementing innovative strategies to enhance the communication of food and health-related information to young adults, adopting appropriate language and facilitating the translation of knowledge into practice [16]. This is further reinforced by their "third mission," namely their responsibility to bridge academia and society through technology transfer, innovation, and public engagement [17]. At the same time, addressing nutritional issues and eating behaviors among university students is crucial for promoting both health and academic performance. University students represent a priority target group for public health initiatives, as they are particularly vulnerable to developing poor eating habits due to economic constraints, time pressure, and limited nutritional knowledge. Evidence consistently shows that this population tends to consume energy-dense foods, skip meals, and rely on fast-prepared or convenient options, while also engaging in low levels of physical activity and prolonged sedentary behaviors such as computer and television use [18]. In this context, this article describes the methodological stages involved in the development of *Uniplate*, an mHealth application designed to promote healthy and sustainable diets among students at the University of Parma. The paper details the implementation process, emphasizing a transdisciplinary strategy that integrates both top-down and bottom-up approaches. A student-focused methodology was central to the app development, executed through qualitative and quantitative research approaches involving a focus group and a Randomized Control Trial (RCT), respectively. The results of students' feedback on app structure, functionality, content, usability, and satisfaction differently investigated during both research activities were also reported in this paper.

3.3.2 Materials and Methods

The *Uniplate* app was developed within the framework of the ON Foods project (ON Foods - Research and innovation network on food and nutrition Sustainability, Safety and Security –Working ON Foods), a large-scale project funded under the National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.3 - Call for tender No. 341 of 15 March 2022 of Italian Ministry of University and Research funded by the European Union – NextGenerationEU). To provide a clear overview of the methodological framework adopted in the development of the *Uniplate* app, the manuscript reflects the applied process, which followed a participatory design approach structured into four sequential phases from the conceptualization to its testing ensuring that the app was both scientifically grounded and tailored to the needs of its target users.

The workflow is visually represented in Figure 1.

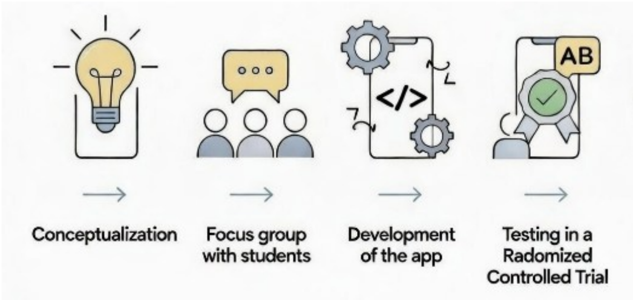


Figure 1. Workflow of the *Uniplate* application development.

3.3.2.1 Conceptualization

The prototype version of the *Uniplate* app was conceptualized by the Human Nutrition Unit at the University of Parma between January and June 2024, with the aim of providing its student community with a practical tool to support healthier and more sustainable eating habits in everyday life. In line with this objective, the conceptualization was informed by a focused search of recent studies in the field to identify the most common features of the existing mHealth applications and their effectiveness in improving eating behaviors. The search was conducted in major scientific databases, including PubMed, Scopus and Web of Science, using the combination of keywords such as “mHealth”, “mobile apps”, “nutrition”, “diet”, “behavior changing techniques”. Priority was given to peer-reviewed articles and literature reviews

within last 10 years. From the outset, the conceptualization was informed by the Behavior Change Technique (BCT) Taxonomy v1 [19], ensuring the association of the most effective features reported in the literature with the corresponding mechanisms of behavior change, thus providing a strong theoretical foundation for subsequent development. Based on the purpose of the *Uniplate* app and the features highlighted in previous studies, the mock-up of the *Uniplate* app was shared with the computer scientists of the AI Lab at the University of Parma to verify its feasibility and evaluate the most suitable technical solutions to its implementation.

3.3.2.2 Focus group with students

As second phase, the app development involved a co-design approach through a focus group session. A convenience sample of Italian university students between 18 and 29 years old were recruited through flyers displayed on university notice boards, emails, and peer to peer recommendations. Individuals not enrolled as students at the University of Parma or attending degree programs taught by the principal investigator of the study were excluded. The entire session lasted approximately 120 min and followed a structured discussion guide developed by the research team in collaboration with a consumer science researcher with expertise in strategies to promote healthy eating among university students (Supplementary Materials S1). While the content of the guide was specifically tailored to the objectives of the study and to the characteristics of the target population, the overall structure of the focus group, the sequencing of activities, and the moderation procedures were informed by established methodological principles for qualitative research and stakeholder engagement. Based on this framework, the focus group was structured in three phases. Two researchers (one moderator and one facilitator) were trained to organize and facilitate the session according to the procedures suggested by Haddaway et al. (2017) [20], ensuring consistency, transparency, and adherence to recognized standards in the conduct of the discussion. The session was recorded and transcribed to enable a thematic analysis. A thematic analysis was conducted following an inductive, data-driven approach. Two researchers independently reviewed the transcripts, generated initial codes, and compared them to ensure consistency. Codes were then grouped into broader themes through iterative discussion and refinement. The resulting themes were subsequently used to inform the iterative development of the app, guiding decisions related to content, functionality, and user-interface design. This ensured that the integration of qualitative insights into the development process followed a systematic and transparent procedure. For each question, the main topics were summarized, and the most interesting feedback has been highlighted. The most widely shared ideas and feedback were used to refine the mock-up. The focus group-related research activity was approved by the local institutional review board (Research Ethics Board, University of Parma, REB 75667) and conducted according to the ethical principles stated in the Declaration of Helsinki. Informed consent was obtained from subjects who voluntarily participated in the focus group. Participants di non received any compensation or incentives for their participation.

3.3.2.2 Development of the app

The content design of the *Uniplate* app was guided by the initial conceptualization and focus group feedback. The app was developed in different sections to include several features based on the most relevant BCTs reported in the literature. The app included modules for daily health tips, plant-forward meal planning, seasonal shopping lists, a sustainable recipe database, and educational content to properly compose a healthy meal, which will be described in detail in the Results sections. The app provides evidence-based content curated by the team of nutritionists according to the most recent dietary recommendations at national [21; 22] and global level [23]. To enhance the user experience, experts from different fields were involved in the development process. A team of psychologists from the Department of Psychology at the University of Milano-Bicocca assisted in tailoring the messaging of the daily health tips to align with the users' psychological profiles. Since the objective was to support students in their decision-making processes for the selection and purchase of healthier and more sustainable products, the informational tips were tailored based on decision-making styles. The latter are generally conceptualized as recurrent patterns of approach to situations that emerge when a decision is required [24]. For the app implementation, the Italian version [25] of the General Decision-Making Style Inventory (GDMSI) developed by Scott and Bruce (1995) [26] was adopted, which assesses a broad range of decision-making orientations. The inventory identifies five distinct styles: rational (decision-making grounded in analytical reasoning and evaluation of evidence), intuitive (decisions guided primarily by feelings and affective impressions), spontaneous (impulsive decisions made in the moment), dependent (a tendency to seek advice and reassurance from others before deciding), and avoidant (a propensity to postpone or delay decisions until the last possible moment). To facilitate profile construction and considering the documented inter-correlation between the intuitive and spontaneous styles [25], these two dimensions were combined into a single profile, resulting in the identification of four distinct decision-making profiles. Each informational tip, whether focused on environmental sustainability or health, was then adapted to align with the specific profile, modulating both communicative style and persuasive cues. For example, in the case of the intuitive/spontaneous profile, emphasis was placed on the sensory qualities and immediate experiential aspects of dishes, whereas for the rational profile greater prominence was given to data concerning environmental impact and preventive health factors. The scoring of the various scales, which was performed automatically within the platform, assigned each user to a specific decision-making profile, thereby linking them to their corresponding set of personalized daily content.

As part of the development team, a chef and a photographer collaborated to prepare and photograph a set of recipes previously defined by an undergraduate student who collaborated on the project. This mixed approach was adopted to ensure both the visual appeal of each dish as well as ease of its preparation. Each recipe was analyzed in terms of nutritional values (i.e., energy and nutrients content) and environmental impacts (i.e., carbon and water footprint) using, respectively, the Food Composition Database for Epidemiological Studies in Italy [27] and a dataset collecting greenhouse gas emissions and water use linked to the production and the subsequent steps of the supply chains of food commodities, up to distributions [28]. All the recipes were one-dish meals and their sustainability was assessed according to the Dietary Reference Values of Nutrients and energy for the Italian adult population [22] and the impact targets according to the guidelines for promoting sustainable diets at canteens of Worksites and Universities developed during the SU-EATABLE LIFE project [29] (i.e., maximum of 1000 g CO_2 eq emitted and 1000 L of water used). Given the different nutritional needs of students and the sensitivity of the target population to the onset of eating disorders, often exacerbated by the increasingly widespread phenomenon of obsessively counting calories and nutrients, ingredients quantities were set based on an average daily intake of 2000 kcal, with users advised to adjust amounts to their hunger while maintaining the same proportions, if they wish. Recipes are proposed as lunches or dinner options within a weekly menu, according to the frequency recommendations for protein sources and starchy foods outline in the Italian food-based guidelines [21]. The app allowed the users to personalize the menu by replacing dishes with nutritionally equivalent alternatives, while maintaining compliance with the dietary guidelines. Breakfast options were also included in the cookbook. Finally, the user interface was designed by the Dinamo s.r.l. following user-centered principles and maintaining continuous collaboration with the development team. Most suitable design solutions were selected to ensure effective interaction and enhance usability and overall user experience. In addition, several infographics were developed to summarize various educational content and thus improve information retention.

The *Uniplate* app is structured using a client-server architecture. The client was written using web technologies such as React with TypeScript, while the server is realized using the PHP language. Both React and PHP are widely supported and used to realize web and mobile applications. Client-server communication uses encrypted messages to protect privacy and integrity of the exchanged data while it is in transit. A React app cannot be deployed as a standalone app on any app store without being encapsulated inside a container. This is why Apache Cordova is also needed to deploy the *Uniplate* app. Cordova is a framework acting like a bridge between a web app and a standalone app providing a wrapping container which allows a web client to work as a mobile app. This container is a platform-independent wrapper that encapsulates the web application in a standalone browser. Therefore, the same web frontend can be distributed to different platforms (i.e. iOS, Android, and Web). Another fundamental element for the development of the app is the Prolog language. In fact, one of the main features of the app is automatic menu generation. When a new menu, or a modification of an existing one, is requested by the client, the server executes the menu recommender and provides the result to the client. Therefore, the menu generator must be correctly optimized to give the answer in a reasonable amount of time. The problem has been thus formalized as a Constraint Satisfaction Problem using the Prolog language with Constraint Logic Programming techniques to improve the generation speed.

Another important aspect of the development of the app is data handling. Most of the content of the app is retrieved from the server every time the app is launched, which reduces the need for app upgrades. In fact, both user data and app content (i.e. educational content, recipes, and tips) are stored in a database which is accessed by server only. Using this approach, it is sufficient to directly modify the contents in the database to consistently update the corresponding information at the next start of the app, without the need for a complete app upgrade. Using the database to store user data has another important advantage: it allows the app to synchronize all the user's progress and preferences among different devices. The architectural model combined with this data handling allows the *Uniplate* app to also be a multi-device app. It is sufficient to login on a different device and user data will be imported from the database.

3.3.2.3 Testing in a Randomized Controlled Trial

Once developed and refined with suggestions coming from students, a group of students took part in a 12-weeks Randomized Controlled Trial (RCT) (registered at ClinicalTrials.gov, number NCT06977802, 24 March 2024) to assess the effectiveness of the *Uniplate* app in promoting healthy and sustainable dietary habits among university students, considering the fiber intake as primary outcome. In this study, the app was used as intervention for 6 weeks and its impact in terms of dietary habits change was assessed both at the end of the intervention (i.e., week 6) and after a follow-up period without the app (i.e., week 12). As a secondary outcome, user app access days were recorded, and user experience (UX) were assessed in the intervention and control groups at different time points. In the intervention group, these outcomes were evaluated at the end of the intervention period (week 6), while in the control group 2 weeks after the end of the follow-up period (week 14), to give them time to try the app once the study was completed. User experience was evaluated using an extensive questionnaire specifically developed for this study. The questionnaire is composed by 74 items grouped into three categories: i) positive and negative UX, ii) lifestyle consequences; iii) *Uniplate* app features. UX and lifestyle consequences were investigated using items adapted from a validated questionnaire on satisfaction with the use of mHealth apps (Melin et al., 2020) using a 5-point Likert scale from "Strongly disagree" to "Strongly agree" for all items. The corresponding scores to the answer options ranged 1 to 5, except for the scale applied to the negative experiences sub-section that was reversed. In addition, a set of ad hoc items tailored to the *Uniplate* app features were administered, including specific questions to assess the liking and frequency of use of specific App sections. The RCT study was approved by the local Ethical

Committee of the Area Vasta Emilia Nord (Prot. no. 25445 of June 13, 2024) and conducted according to the ethical principles stated in the Declaration of Helsinki. Informed consent was obtained from all subjects involved in the study. The RCT results concerning the changes in dietary habits are presented subsequently in the study entitled "Promoting healthy and sustainable diets in young adults through an educational M-health application: a randomized controlled trial" presented in this doctoral thesis (pages 117-126).

3.3.3 Results

3.3.3.1 Conceptualization

Each function of the app was conceived to operationalize specific BCTs from the outset, ensuring alignment between behavioral mechanisms and app functionalities (Table 1). Through systematic mapping using the BCT Taxonomy v1, the final prototype integrates 21 BCTs across 11 clusters, resulting in a broader and more balanced distribution than what is typically reported in existing nutrition apps. The most represented clusters were goals & planning, feedback & monitoring, natural consequences, and reward & threat, reflecting an emphasis on self-regulation, awareness of outcomes, and motivational reinforcement. At the same time, the app incorporates less commonly used but theoretically relevant clusters such as identity, shaping knowledge, comparison of outcomes behavior, antecedents, associations, and repetition & substitution, which are often underrepresented in commercial tools despite their importance for habit formation and long-term adherence. Within the Home section, daily tracking of fruit, vegetables, cereals, water, and breakfast operationalizes BCTs such as self-monitoring of behavior (2.3), feedback on behavior (2.2), and review of behavioral goals (1.5). These techniques support users in observing their dietary patterns, receiving immediate reinforcement, and adjusting their goals over time. The rotating daily tips further embed BCTs related to information about health, social, and environmental consequences (5.1, 5.2, 5.3), enhancing awareness of the broader impact of food choices and strengthening motivation through increased salience of outcomes. In the Eat section, the weekly menu planner is grounded in action planning (1.4) and problem solving (1.2), enabling users to translate intentions into concrete, feasible plans.

Table 1. *Uniplate* app features aligned with the corresponding Behavioral Change Techniques

Uniplate Section	**Linked App Feature**	**Cluster 1**					**Cluster 2**		**Cluster 4**	**Cluster 5**			**Cluster 6**		**Cluster 7**	**Cluster 8**	**Cluster 9**	**Cluster 10**		**Cluster 12**	**Cluster 13**	
		1.1	**1.2**	**1.4**	**1.5**	**1.9**	**2.2**	**2.3**	**4.1**	**5.1**	**5.2**	**5.3**	**6.1**	**6.2**	**7.1**	**8.2**	**9.1**	**10.2**	**10.4**	**12.1**	**13.1**	**13.5**
Login	Profile creation					✓																✓
Home	Goals tracking	✓					✓	✓														
	Daily tips									✓	✓	✓										
Eat	Menu planner		✓	✓												✓	✓					
Buy	Shopping list			✓																		
	Seasonality calendar														✓					✓		
Recipes	Recipes								✓	✓		✓										
	User ratings												✓	✓					✓			
Learn	Educational content								✓	✓		✓					✓					
Profile	Badges						✓											✓	✓			
	Notifications				✓																	
	Personal info management																				✓	

The table includes the following BCTs clusters and their corresponding component techniques: Cluster 1 – Goals and Planning including 1.1 Goal setting (behavior), 1.2 Problem solving, 1.4 Action planning, 1.5, 1.9); Cluster 2 – Feedback and Monitoring including 2.2 Feedback and behavior, 2.3 Self-monitoring of behavior; Cluster 4 – Shaping Knowledge including 4.1 Instruction of how to perform a behavior; Cluster 5 – Natural Consequences including 5.1 Information about health consequences, 5.2 Salience of consequences, 5.3 Information about social and environmental consequences; Cluster 6 – Comparison of Behavior including 6.1 Demonstration of the behavior, 6.2 Social comparison; Cluster 7 – Associations including 7.1 Prompts/cues; Cluster 8 – Repetition and Substitution including 8.2 Behavior substitution; Cluster 9 – Comparison of Outcomes including 9.1 Credible sources; Cluster 10 – Reward and Threat including 10.2 Material reward (behavior), 10.4 Social reward; Cluster 12 – Antecedents including 12.1 Reconstructing the physical behavior; Cluster 13 – Identity including 13.1 Identification of self as role model, 13.5 Identity associated with change behavior.

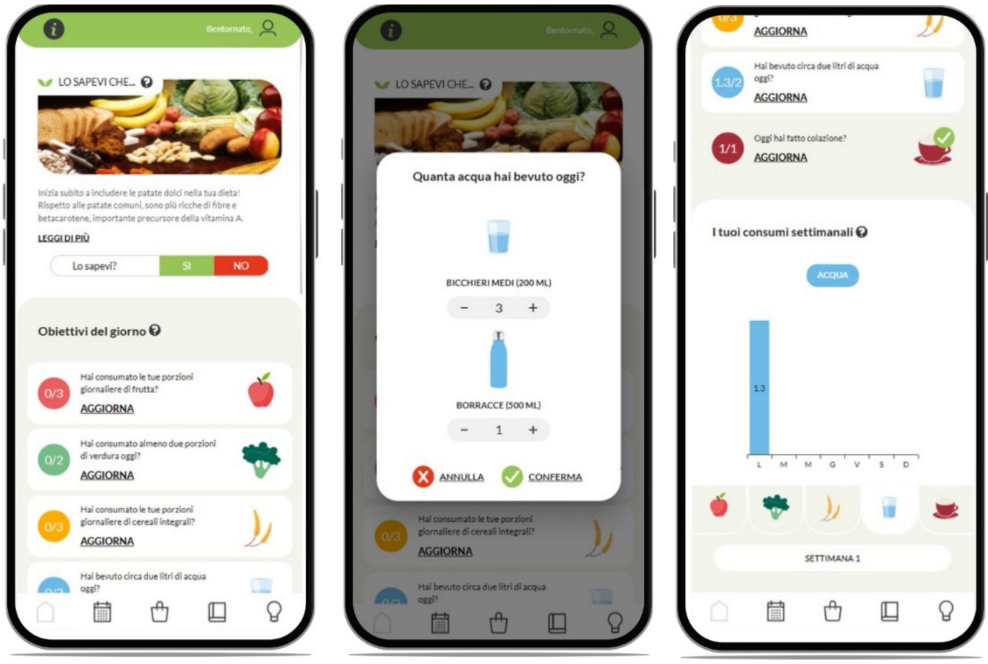
The automatic generation of nutritionally balanced menus also reflects restructuring of the physical environment (12.1), as it modifies the choice architecture by presenting "ready to use" options. The Buy section incorporates associative learning (8.2) and prompts/cues (7.1) through the automatic shopping list and the seasonal food calendar. Within the Recipes section, the recipe library and user rating system embed instruction on how to perform the behavior (4.1), demonstration of the behavior (6.1), and social reward (10.4). The Learn section operationalizes shaping knowledge (5.1) and comparison of outcomes/behavior (6.2) through educational content and personalized Q&A. The presence of credible sources (9.1) both in the home and in in the learn section further strengthens trust and supports informed decision-making. Finally, the Profile section integrates identity-related BCTs such as identification of self as role model (13.1) and identity associated with changed behavior (13.5) through the badge system for goals achieved. Notifications embed commitment (1.9) and prompts/cues (7.1), supporting continuity of engagement and reinforcing the user's evolving self-concept as someone who makes healthier and more sustainable choices.

3.3.3.2 Focus group findings

The focus group involved 7 Italian university students from the University of Parma (mean age 26.4 ± 2.6 years), comprising 3 females and 4 males. Participants socio-demographic data were reported in Supplementary Materials Table S1. Briefly, students had diverse academic backgrounds: life sciences (n=1), food science and technology (n=2), medicine and surgery (n=3), and social disciplines (n=1). Four were out-of-town students, 2 were student-workers, and 6 were always preparing their own meals. All followed an omnivorous diet. Six had deepened their knowledge of nutrition, primarily through university courses or individual study, and three had previously consulted a nutrition professional. Participants consistently reported that fatigue, stress, and low motivation as barriers to adopting healthy and sustainable eating habits, often resulting in impulsive behaviors. Social influences from peers were described as a "contagion" that reduced individual willpower. As one participant noted, *"Fatigue, stress, and little motivation and willingness to do the shopping led to unhealthy choices"* (P1), linking emotional states to dietary behaviors. Another emphasized the informational gap: *"I can say I eat healthy, but it's hard to say if I eat sustainable… there are no labels on sustainability"* (P3). Conversely, facilitating factors were identified in the awareness of the health benefits associated with balance nutrition, and the sense of control in consciously planning meals, by reducing random choices. One participant stated: *"Knowing that a healthy diet has positive effects on health can push one to eat healthy"* (P2). Economic and practical considerations also played a role, such as the connection between affordability and sustainability: *"I have increased the consumption of legumes because they cost less than meat and fish and are ready to consume"* (P1). Students primarily relied on online sources for information on food education and sustainability, but these channels were often viewed as unreliable. As one participant explained, *"On social media there are conflicting information… you have to be careful because there is too much disinformation"* (P2), highlighting the need for structured and credible educational tools. Despite limited prior experience with dietary mHealth technologies, participants demonstrated an openness toward evidence-based digital interventions, outlining precise expectations regarding their design and utility. Participants highlighted the importance of flexible and non-prescriptive suggestions, practical tips on food storage to reduce waste, an integrated recipe book and motivational goalsetting with progress tracking. One participant suggested: *"If there was an app that gives ideas and suggestions without impositions on kcal quantities… it could be useful"* (P2), while another emphasized the motivational role of tracking: *"The app should propose goals that motivate people to change their eating habits. Keeping track… can make one more aware of their diet"* (P4). Feedback on the mockup sections of the app further refined these expectations. For the *Home* section, students proposed the inclusion of brief news items addressing the psychological aspects of eating, weekly goals to limit excessive intake of certain food groups, and integration of physical activity objectives. The *Eat* section elicited no specific suggestions beyond the request for flexibility and avoidance of rigid schemes.

3.3.3.3 Uniplate app features overview

The Home section (Fig. 2) provides daily tips and allows users to give feedback replying to the question "Did you know?" (Fig. 2a). In addition, this section allows users to self-track their daily consumption of selected foods and dietary habits (i.e, Goals of the day) in relation to Italian food-based guidelines (Fig. 2 a-b). Throughout the week, users can monitor their intake of fruit, vegetables, whole grains and derivates, as well as their water intake and breakfast habits (Fig. 2c).



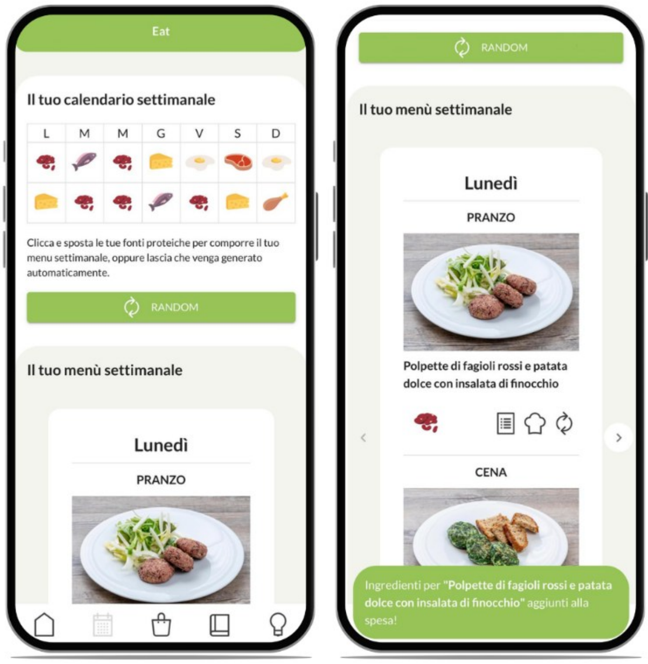
a b c

Figure 2. Home section. (a) Daily tips and goals; (b) Self-tracking; (c) Monitoring.

The Eat section (Figure 3) allows users to plan their weekly menu according to the frequency recommendations for protein sources and starchy foods as outlined in the Italian food-based guidelines. The *Uniplate* app randomly suggests recipes for both lunch and dinner, displaying the associated protein source in a grid (i.e., Your weekly calendar) and allowing users to change the protein source using "Random" or a drag-and-drop features (Fig. 3a). At the bottom of this section, users can view the recipes suggested for each day (i.e., Your weekly menu), access the ingredients and procedure, or replace them with similar alternatives in terms of protein and carbohydrate sources (Fig 3b).

Formalizing menu generation as a Constraint Satisfaction Problem has been chosen for its efficacy in giving a result almost real-time. The tests made after the development of the *Uniplate* app confirmed the expected results, and the App provides the user with a generated menu almost instantly. The menu generation algorithm has two modes of operation: i) complete menu generation for the entire week, this mode is used when an existing generated menu is not available (i.e. the first day of the week the user opens the App), or when the user select the "Random" feature to allocate protein sources differently throughout the week; ii) replacement of a single meal with an existing one, the system facilitates meal replacement through direct manipulation. By performing a drag-and-drop gesture, the user can exchange protein sources between two different days, effectively updating the meal plan. The two different modes share the same core algorithm, which uses a set of logic rules based on consumption frequencies suggested by Italian dietary guidelines [21]. Therefore, it can provide a coherent result when it is used, regardless of the operating mode chosen.

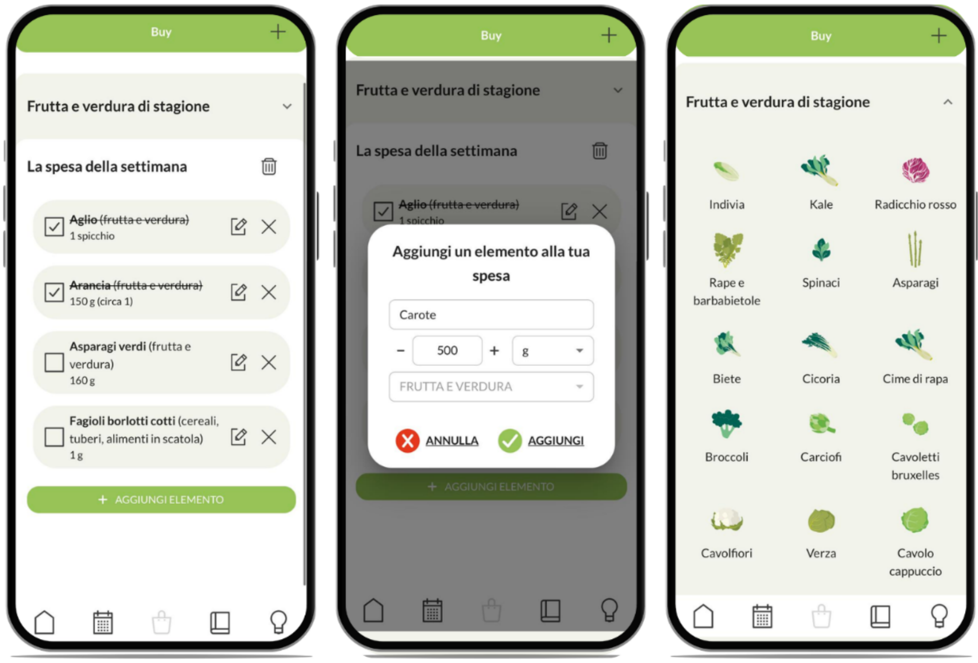
The Eat section includes a "switch button", represented by two arrows which allows the user to change a recipe suggested by the generator. When users do not like a meal in the generated menu, they can replace the corresponding recipe with another one sharing the same protein source of the original meal.



a b

Figure 3. Eat section. (a) Menu generation; (b) Weekly menu.

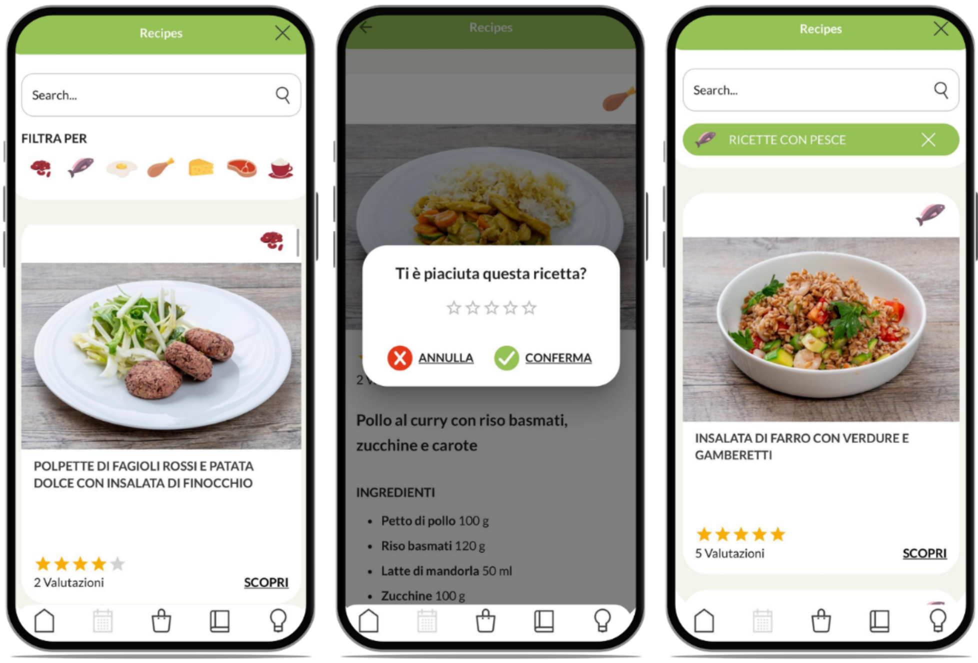
The Buy section (Fig. 4) functions as a grocery list linked to the Eat section. By clicking the list icon, ingredients are automatically added to the Buy section, generating a shopping list (Fig. 4a) that can be also edited by modifying quantities or adding items (Fig. 4b). This section also provides the user with the calendar of seasonal fruits and vegetables (Fig. 4c).



a b c

Figure 4. Buy section. (a) Shopping list; (b) Adding elements; (c) seasonal calendar.

The Recipes section (Fig. 5) gathers all dishes used in menu generation in a cookbook, searchable by name, keywords or using the filters (i.e., protein source or breakfast) (Fig. 5a)~~.~~ Users can also rate recipes on a five-star scale (Fig. 5b) and see the average user rating (Fig. 5c).

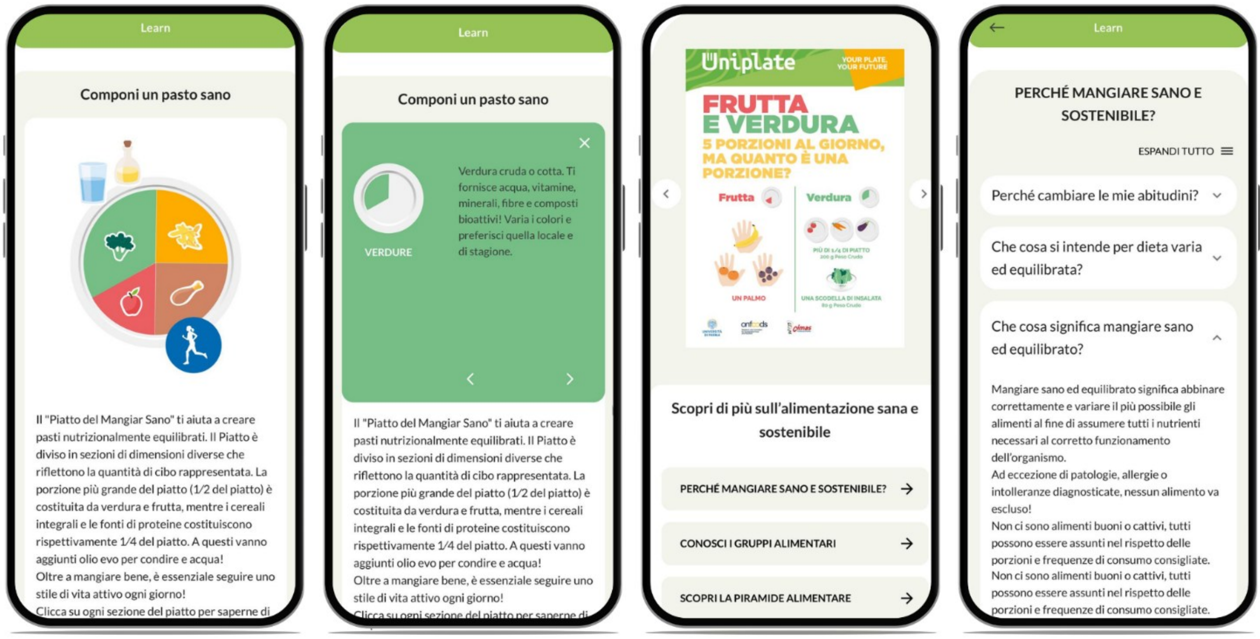


a b c

Figure 5. Recipes section. (a) Cookbook; (b) Recipe rating; (c) average user rating.

Finally, the Learn (Fig. 6) section provides educational content on healthy and sustainable diets using a Q&A

format. The section also includes an interactive healthy plate and several infographics designed to summarize key concepts and enhance information retention through visual presentation.



a **b** **c** **d**

Figure 6. Learn section. (a,b) Interactive Healthy Plate; (c) Infographics; (d) Q&A format.

In addition, the Profile page allows users to view badges achieved during the week, recent notifications, and to edit personal information. Badges were designed as motivational element to encourage user engagement and daily use of the app; each badge is linked to a specific function of the mobile application such as daily goals, recipes, etc.. As an example, one of the app badges is called "Il soldato della salute" and it is unlocked when users complete the all 5-goals of the current day.

Figure 7. Badges

3.3.3.4 User experience

Out of the total sample of 56 participants, 38 students used the app and completed the UX questionnaire, 21 in the intervention group and 17 in the control group. During the period before the questionnaire administration, system logs recorded a median (IQR) of 8 (3–10) days of use, with a median of 1 (1–2) daily accesses. The main UX results are reported below.

Overall, user satisfaction, assessed on a 5-point Likert scale, was high, with 89% of respondents reporting a score greater than 4. Within this group, 19% reported being 'very satisfied' (data not shown). As illustrated in Figure 8, the app received high scores (4 or 5 on the Likert scale) across several dimensions: 87% of users found it intuitive, 79% enjoyable, and 92% self-explanatory. Furthermore, 79% of participants stated they would recommend the app. Regarding the user negative experiences, 76% of respondents did not consider the app time-consuming or boring, and 97% did not perceive it as intrusive.

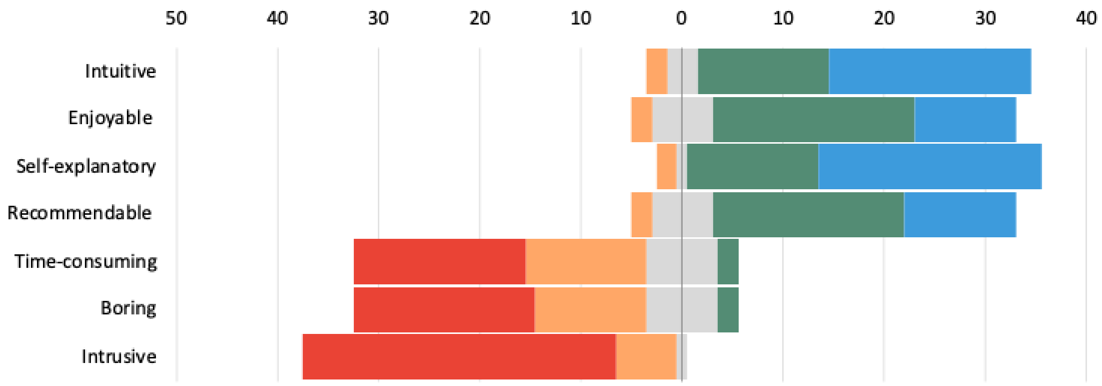


Figure 8. Diverging stacked bar chart showing the distribution (%) of user experience ratings. Percentages are based on a 5-point Likert scale, where colors represent the level of agreement: strongly disagree (red), disagree (orange), neutral (grey), agree (green), and strongly agree (blue).

The impact of the use of the App in terms of lifestyle consequences, assessed through 5-point Likert scale, is shown as mean of the total sample and depicted in Figure 9. The symmetrical geometry of the plot reflects a consistent trend across all the dimensions considered (i.e., motivation, benefit awareness, practical insight, goal-setting support, dietary habits improvement). Although the perceived effectiveness regarding dietary improvement appears slightly higher, the mean score remains close to the midpoint as for the other variables. This suggests that the app had a limited overall impact on modifying user attitudes and behaviors regarding healthy diets, or at least the user perception of such improvements. Findings from the RCT, utilizing a combination of 24-hour dietary recalls, food frequency questionnaires, and urine biomarkers, will elucidate the app's actual efficacy in facilitating dietary behavioral change.

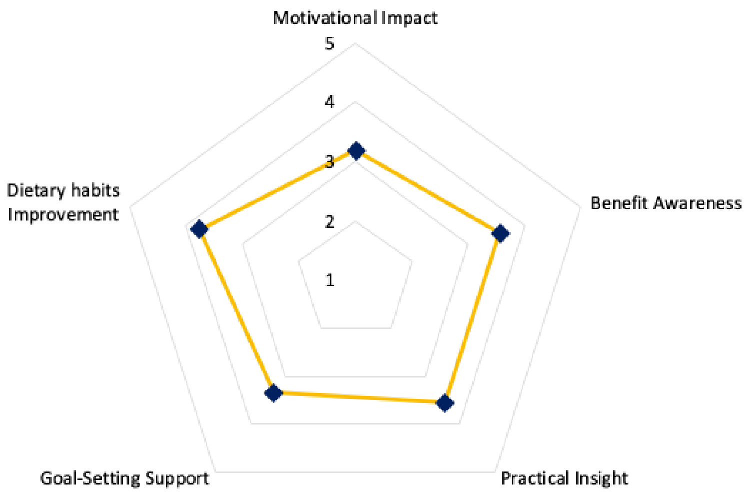


Figure 9. Radar chart showing the lifestyle consequences after the use of the App.

Finally, the association between frequency of use and the perceived liking of different app sections, assessed through 5-point Likert scale, were visualized using a 2x2 matrix (Figure 10).

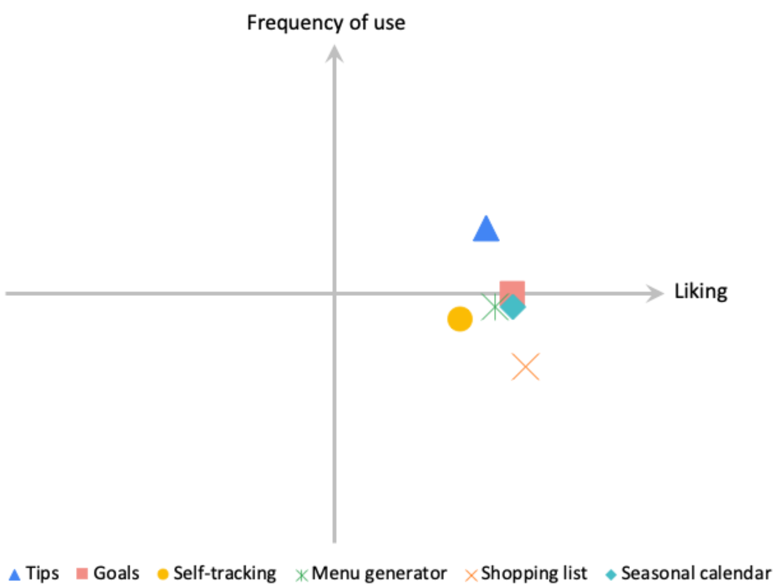


Figure 10. 2x2 matrix reporting the association between the frequency of use (y axis) and the perceived liking (x axis) of different app sections.

As illustrated, 'tips' emerged as the most favored and frequently used feature among students, followed by 'goals', 'seasonal calendar', and the 'menu generator'. Regarding 'self-tracking' and the 'shopping list', despite receiving liking scores similar to other features, a lower frequency of use was reported.

3.3.4 Discussion

The mHealth applications have gathered greater attention as potential tools to promote healthy diets and improve people's lifestyle [30; 31], especially in digital native generations such as university students. However, most mHealth applications face high attrition rates and limited sustained use [32] reducing their long-term efficacy, which combined with persistent misinformation issues, make younger adults (university age) among the EU population segments with the lowest quality diet, and worst nutrition knowledge [16]. To mitigate this problem, human-centered design approaches based on BCTs are recommended [33]. The International Organization for Standardization (ISO) established "*requirements and recommendations for human-center design principles and activities throughout the life cycle of computer-based interactive systems*" [34]. This document outlined main steps to enhance long-term user engagement, including activities to identify both the context of use and user needs to strive for co-design approach over the course of the creation process and the definition of consensus solutions. Furthermore, interdisciplinary collaboration has been shown to enhance and facilitate long-lasting changes in health-related behaviors [35; 36; 37].

In this context, the involvement of a multidisciplinary team, the engagement of students through focus groups, and preliminary RCT testing collectively ensured the creation of a well-designed, user-centered, and evidence-based digital tool. Co-design with students played a central role in shaping the app's structure: participants directly influenced the refinement of features such as personalized daily tips, flexible weekly menu planning, and motivational badges. These design choices were reflected in the pilot data, which showed high usability ratings and no major technical failures during the RCT. In addition, recent literature reviews on nutrition mHealth applications consistently show that majority of available diet related apps are commercial products developed for the mass distribution rather than as research interventions; consequently, BCTs are rarely embedded intentionally during development and are often detected only later by researchers through post-hoc coding of app features. Analyses of commercial diet-tracking apps and lifestyle applications reveal a narrow behavioral profile dominated by self-monitoring, typically implemented through food diaries or calorie tracking logs, and basic goal-setting that usually consists of predefined targets, such as daily calorie limits, weight loss objectives, or step counts, often generated automatically by the app with minimal personalization or behavioral guidance [38; 39; 40]. Within this broader landscape, the development of Uniplate was informed by the recurring limitations highlighted in existing digital dietary tools. Although no single commercial app directly inspired its design, the predominance of calorie-tracking models, limited personalization, and the scarce integration of educational or sustainability-oriented content served as reference points to define the app's conceptual direction and to prioritize features grounded in behavior change theory. More complex mechanisms, such as concrete action planning, identity-related approaches (e.g., seeing oneself as a "healthy eater"), habit-supporting features, habit formation, and explicit educational content and skills training, are rarely integrated by design. In contrast to this retrospective methodology, the development of Uniplate adopted a prospective, theory-informed strategy: the app was intentionally designed to operationalize a broad set of behavior change techniques from the outset, with 21 BCTs mapped across multiple clusters to support self-regulation, planning, identity, and knowledge shaping.

From a technical point of view, featuring a client-server model, a Prolog-based constraint-logic engine for menu generation, and database-driven content management, proved essential for delivering BCTs consistently, enabling real-time personalization and dynamic updates that directly shaped user experience. Compared with existing digital dietary tools, which often rely on calorie-counting and food-logging as their primary interaction model, often emphasizing numerical tracking over learning and decision support. Reviews of diet and weight-loss apps note that many popular tools prioritize food diaries and calorie totals while offering limited educational scaffolding or empowerment strategies for users [30; 41]. By prioritizing knowledge building, practical skills (menu planning and shopping), and confidence-building features (personalized tips and badges) over mere calorie totals, the *Uniplate* app adopts an integrated educational approach that combines evidence-based nutrition content, contextualized sustainability information, and decision-style personalization to foster users' self-empowerment and self-efficacy. By prioritizing knowledge building, practical skills such as menu planning and shopping, and confidence-enhancing features like personalized tips and badges over mere calorie totals, the app aims to shift users from passive tracking to active, informed decision-making. Through actionable menus, seasonality cues, and tailored guidance, Uniplate seeks to address the limitations of calorie-centric apps and promote long-term healthy and sustainable eating habits.

Despite the robustness of the methodology, some limitations must be acknowledged. First, the qualitative phase involved a single focus group with seven participants. Although the initial protocol planned multiple sessions, recruitment proved challenging due to several practical constraints, including the absence of incentives and the voluntary nature of participation. While the resulting sample is adequate for exploratory co design, it inevitably limits the breadth of perspectives captured during the early design phases. Additionally, the limited diversity in academic backgrounds and dietary patterns (e.g., the absence of vegetarian perspectives) may have hindered a comprehensive understanding of the barriers and facilitators to adopting healthy and sustainable food habits. This lack of heterogeneity likely also restricted the scope of feedback available for the refinement of the Uniplate mock-up. Finally, the brief period of use, particularly for the control group (i.e., two weeks), may have been insufficient for the app to be integrated into daily routines. Consequently, while participants expressed high satisfaction with the tool, the study may not have fully captured sustained reflections on long-term dietary changes.

3.3.5 Conclusions and future perspectives

This study outlines the participatory development of Uniplate, an mHealth application that supports healthy and sustainable dietary behaviors among university students. By combining co-design with students, multidisciplinary expertise, and the systematic integration of 21 Behaviour Change Techniques, Uniplate goes beyond calorie-counting tools to offer a comprehensive educational framework grounded in user needs, evidence-based content, and real-time personalization. Pilot testing showed high usability, acceptability, and satisfaction, confirming that end-user involvement throughout the process enhances engagement. The modest perceived impact on lifestyle changes underscores the importance of longer-term evaluation. Practically, the work offers a replicable model for mHealth interventions: structured co-design, transparent BCT reporting, and emphasis on education and skill-building rather than self-monitoring alone. Researchers are encouraged to adopt standardized usability metrics, objective dietary outcomes, and extended follow-up periods. Future refinements will focus on improved navigation, enhanced personalization, and richer educational content based on usage data and feedback.

Supplementary Materials

S1: Focus group script for the development of a mobile app to improve university students' eating habits

Durata da 1,30h a massimo 2h

L'obiettivo generale di questo studio è lo sviluppo di un'applicazione mobile che aiuti gli studenti universitari, attraverso un approccio educativo, nella composizione di pasti sani e sostenibili al fine di promuovere abitudini alimentari più virtuose.

L'obiettivo primario dei focus group è quello di ricavare informazioni sull'usabilità, il gradimento e le eventuali criticità della applicazione mobile proposta, oltre che nuovi spunti di miglioramento dell'interfaccia e dei tools offerti per supportare gli studenti nell'adozione delle abitudini alimentari.

L'obiettivo secondario è quello di indagare le percezioni, l'uso e le riflessioni degli studenti in merito all'interfaccia proposta.

Partecipanti: studenti dell'Università degli Studi di Parma in possesso di uno smartphone e che lo utilizzino regolarmente.

Le sezioni sono numerate (da 0 a 5) mentre i commenti per il moderatore sono riportati in corsivo grigio.

0) <u>ACCOGLIENZA: REGOLE GENERALI</u>

Per prima cosa, il moderatore presenta il collaboratore, e fornisce una breve spiegazione degli obiettivi della ricerca. In secondo luogo, informa i partecipanti che l'intervista di gruppo sarà registrata, che sono liberi di ritirarsi in qualsiasi momento); inoltre, fornisce alcune indicazioni generali (ad esempio, la disponibilità di acqua, di ricorrere a servizi igienici, ecc.).
Il moderatore consegna ai partecipanti il consenso informato, l'informativa per il trattamento di dati e dopo aver ricevuto il loro consenso alla partecipazione allo studio, consegna il questionario sociodemografico affinché sia compilato dai partecipanti stessi (vedi allegato 1).
Successivamente, si ricorda ai partecipanti che alla fine del focus group verranno offerti cibo e bevande come presente per il loro tempo e impegno.

"Rompighiaccio": giro di tavolo con i partecipanti che si presentano (nome, corso di studio frequentato, ecc.).

Buongiorno, benvenuti a questo focus group.

Come anticipato, siamo ricercatori dell'unità di nutrizione umana e stiamo progettando un'app per promuovere diete sane e sostenibili tra gli studenti.

Oggi vorrei parlare con voi di alimentazione sana e sostenibile.

Non è un'intervista individuale ma una discussione di gruppo, è importante che ognuno esprima liberamente la propria opinione.

Prima di tutto vorrei fare un giro di presentazioni. Mentre ci presentiamo vi chiedo intanto di pensare a…

Domanda Rompighiaccio: Qual è la ricetta più buona che abbiate mai cucinato?

In che contesto l'hai preparata? Da solə o in compagnia? A casa in famiglia o da fuorisede?

ALIMENTAZIONE SANA E SOSTENIBILE

1. Cosa significa per voi mangiare sano e sostenibile?

2. Ritenete di mangiare in modo sano?

3. Ritenete di mangiare in modo sostenibile?

4. Ritenete che la vostra alimentazione sia cambiata da quando avete iniziato l'università? In meglio o in peggio?

5. Che fattori hanno contribuito a cambiare la vostra alimentazione?

6. Quali sono i fattori che vi impediscono di mangiare sano e sostenibile?

7. Ci sono invece fattori che vi facilitano mangiare sano e sostenibile?

EDUCAZIONE ALIMENTARE

11. Ritenete di essere sufficientemente informati su cosa definisce un'*alimentazione sana e sostenibile?* Quali sono le principali fonti da cui ottenete le informazioni?

12. Ritenete di dover ricevere più informazioni riguardo a come si caratterizza un'*alimentazione sana e sostenibile?* Nello specifico, quali sono gli argomenti di cui vorreste maggiori informazioni?

13. Conoscete la doppia piramide? *Breve spiegazione della finalità della piramide salute e ambiente*

14. Ora inserite all'interno della doppia piramide (allegato 2) i gruppi alimentari riportati.

Discussione delle risposte

Mostrare lo schema della doppia piramide alimentare (allegato 3)

15. Ci sono aspetti relativi a questa definizione che non conoscevate? Ritenete che il vostro stile alimentare sia più o meno in linea con questo modello?
16. Quali sono gli elementi che rendono il vostro stile alimentare / di vita lontano da questo modello? Quali invece quelli che lo rendono vicino?

COOKING SKILLS

Ora parliamo di cucina.

17. Vi piace cucinare?
18. Ritenete di essere bravi in cucina?
19. Quali sono le difficoltà che riscontri nel cucinare/preparare i pasti?
20. Quali ricette cucini più frequentemente e perché?
21. Quali tipi di cibi trovi più difficili da cucinare?
22. Quando si tratta di prepararvi i pasti li pianificate oppure li improvvisate al momento?
23. Come fate la spesa? La pianificate, seguite uno schema preciso?
24. Quali sono le difficoltà che incontrate nel pianificarvi i pasti e nel fare la spesa?

M-HEALTH

Ora affrontiamo il tema principale di questo focus group.

25. Conoscete il termine m-health? *Spiegazione del termine m-health*

26. Utilizzate o avete utilizzato applicazioni per cambiare le vostre abitudini alimentari?

A chi risponde sì:

27. Perché le avete utilizzate o le utilizzate?

28. Descrivete le applicazioni che avete usato: quali erano/sono le funzionalità utili di tali applicazioni? Quali sono le criticità? Cosa migliorereste?

29. Le trovate o le avete trovate utili per cambiare le vostre abitudini alimentari? Avete ottenuto risultati? Spiegate di che tipo.

30. Perché avete smesso di utilizzarle?

A chi risponde no:

31. Avete mai sentito l'esigenza di cambiare le vostre abitudini alimentari?

32. Avete mai pensato o ritenete utile ricorrere ad un'applicazione a tale scopo? Se sì, perché non l'avete poi scaricata? Se no, perché?

33. Prendereste in considerazione l'idea di scaricare un'app? Perché?

A tutti:

34. Cosa ti spingerebbe a scaricare un'app per migliorare le tue abitudini alimentari?

35. Che funzionalità vorreste che avesse un'applicazione per migliorare le vostre abitudini alimentari?

UNIPR APP

Ora vi mostriamo una proposta di applicazione che abbiamo progettato per voi studenti per migliorare le abitudini alimentari.

Abbiamo pensato ad un'app suddivisa in 5 sezioni:
- Una sezione Home
- Una sezione EAT per aiutare nella composizione dei pasti
- Una sezione BUY per aiutare nella lista della spesa
- Una sezione RECIPES per suggerire ricette
- Una sezione LEARN per fornire contenuti educativi

Ora vi consegneremo delle schede da compilare (allegato 4) .

39. Cosa vorreste ci fosse in ogni sezione?

Discussione delle risposte
Presentazione del mock-up dell'app

40. Qual è la vostra impressione? Descrivetela in una parola.

41. Pensi che potresti utilizzarla nella vita di tutti i giorni? Perché sì e perché no? Che criticità vedete nel suo utilizzo?

42. Cosa non vi piace dell'app? Cosa vi piace e ritenete utile?

43. Cosa cambiereste e cosa aggiungereste dal punto di vista delle funzionalità?

44. Cosa cambiereste e cosa aggiungereste dal punto di vista grafico?

Immaginate di essere in sessione di esami (o in un periodo analogo impegnativo e stressante)

45. Pensate che un'applicazione del genere possa aiutarvi e tornare utile nel comporre i pasti? O pensate che possa solo essere una ulteriore distrazione?

46. Vorresti ricevere delle notifiche sui contenuti educativi che ti ricordino di utilizzare l'app?

<u>DOMANDE FINALI E DEBRIEFING</u>

Siamo ormai al termine di questa discussione.

47. Ci sono argomenti che ritenete importanti in tema di utilizzo di applicazioni per favorire un certo tipo di consumo alimentare, sano e sostenibile, che, secondo voi, non abbiamo toccato? Se sì quali?

Allegato 1. Questionario sociodemografico

1. **Quanti anni hai? ___________**

2. **In quale genere ti identifichi?**
   - Maschio

- Femmina
- Non binario
- Altro

3. Qual è la tua nazionalità?

- Italiana
- Altro (per favore specificare) _______________

4. Qual è la tua area disciplinare di studio?

- Architettura
- Discipline giuridiche
- Discipline umanistiche, sociali e delle imprese culturali
- Ingegneria
- Medicina e chirurgia
- Scienze agrarie
- Scienze degli alimenti
- Scienze della vita o della terra (ad esempio, scienze biologiche, chimiche, ambientali)
- Scienze economiche e aziendali
- Scienze farmaceutiche
- Scienze matematiche, fisiche e informatiche
- Studi politici e internazionali
- Scienze veterinarie
- Altro (per favore specificare) ___________

5. Sei uno studentə fuori-sede?

- Sì
- No

6. Sei uno studentə lavoratore/lavoratrice?

- Sì
- No

7. Ti occupi personalmente di fare la spesa?

- Sempre
- Spesso
- A volte
- Raramente

- Mai

8. **Ti occupi personalmente di preparare i tuoi pasti?**
   - Sempre
   - Spesso
   - A volte
   - Raramente
   - Mai

9. **Soffri di allergie, intolleranze o patologie che limitano le tue scelte alimentari? Se Sì per favore indica che tipo di condizione.**
   - Sì: ____
   - No

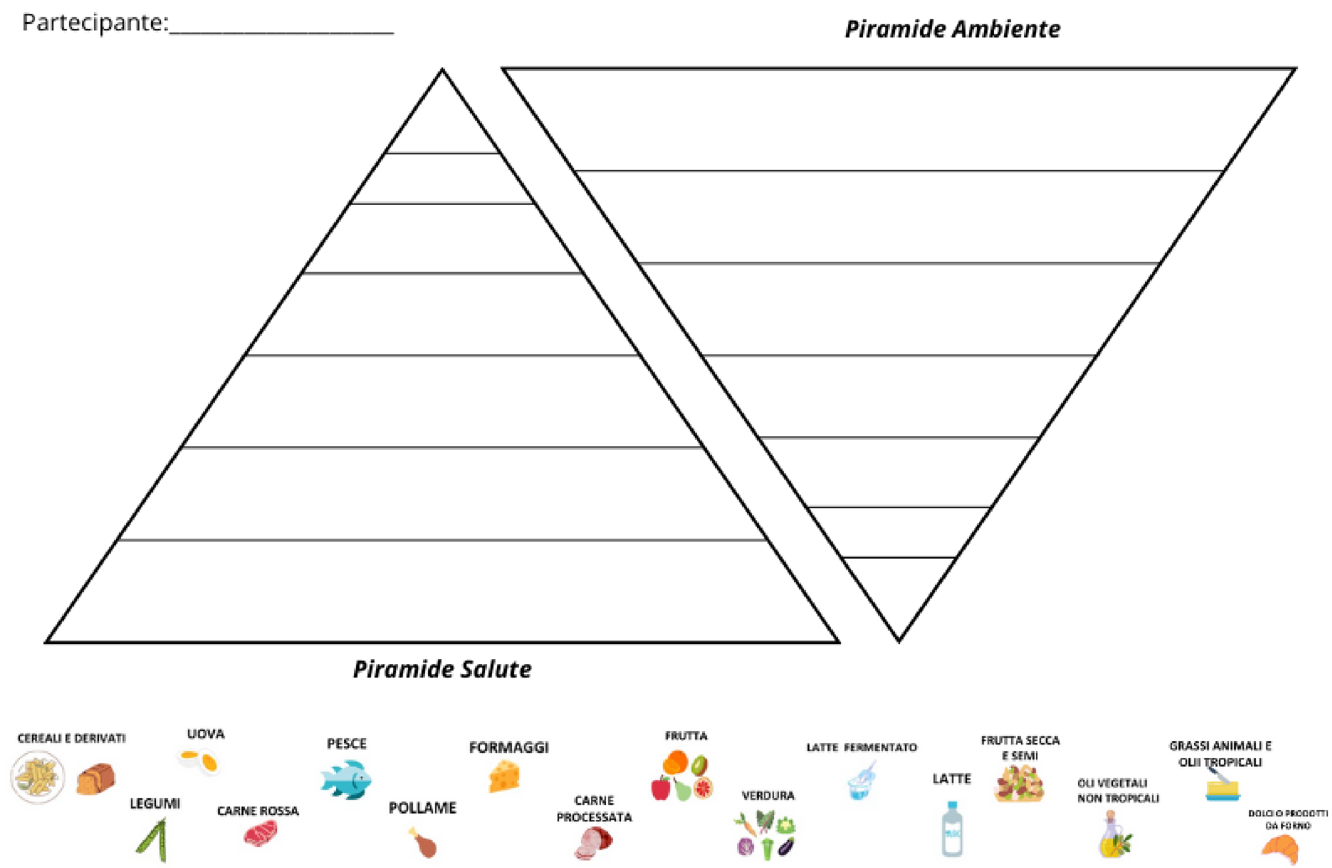
10. **Ti consideri...**
    - Onnivoro (regime alimentare generico, prodotti sia vegetali sia animali sono inclusi).
    - Latto-vegetariano (sono esclusi carne, pollame, pesce e uova; sono inclusi i prodotti lattiero-caseari come latte, formaggio, yogurt e burro).
    - Ovo-vegetariano (carne, pollame, pesce e latticini sono esclusi; le uova sono incluse).
    - Latto-ovo vegetariano (sono esclusi carne, pollame e pesce; sono inclusi i latticini e le uova).
    - Pescetariano (carne, pollame, latticini e uova sono esclusi; il pesce è incluso).
    - Vegano (sono esclusi carne, pollame, pesce, uova e latticini).
    - Flexitariano (dieta a base vegetale con inclusione occasionale di prodotti animali).
    - Altro (specificare) _____________

11. **Nel tuo percorso di vita hai avuto modo di approfondire le tematiche relative alla nutrizione e all'alimentazione sana e sostenibile?**
    - Si
    - No

12. **Se hai risposto "Si" alla precedente domanda, indica come hai approfondito le tematiche della nutrizione e dell'alimentazione sana e sostenibile (puoi indicare più di una risposta).**
    - Approfondimento individuale
    - Corsi di studio universitari
    - Consulenza con professionista della nutrizione
    - Altro (per favore specificare) ___________

13. **Ti sei mai rivolto ad un professionista della nutrizione (dietologo, dietista o biologo nutrizionista)?**
   - Si, mi rivolgo attualmente
   - Si, mi sono rivolta/o precedentemente
   - No

Allegato 2: Scheda Attività Doppia Piramide



Allegato 3: Doppia piramide alimentare

La figura che segue rappresenta la doppia piramide alimentare e ambientale. Sulla piramide di destra i gruppi alimentari sono posizionati in base al loro impatto sul clima che aumenta dal basso verso l'alto. Sulla piramide di sinistra i diversi gruppi alimentari sono posizionati in livelli successivi in base al loro impatto sulla salute cardiovascolare: gli alimenti più protettivi si trovano alla base, al contrario gli alimenti il cui consumo eccessivo si associa ad un aumento del rischio cardiovascolare si trovano nei livelli più alti. Gli alimenti rappresentati sono quelli tipici dell'area mediterranea. Tale piramide si ispira al modello mediterraneo, legato agli stili alimentari tradizionali dei Paesi che si affacciano sul Mar Mediterraneo. La preferenza per gli alimenti locali, stagionali, freschi e minimamente lavorati viene enfatizzata, promuovendo la biodiversità e gli alimenti tradizionali. Questo modello alimentare si basa sul consumo di:

- *numerosi alimenti vegetali (frutta, verdura, pane, altri cereali, patate, legumi);*
- *olio d'oliva come principale fonte di grassi;*
- *prodotti lattiero-caseari (soprattutto yogurt e formaggio);*
- *pesce e pollame in quantità moderate;*
- *fino a quattro uova alla settimana;*
- *una quantità ridotta di carne rossa;*
- *un consumo occasionale di dolci;*
- *una moderata quantità di vino, da consumarsi soprattutto durante i pasti.*

L'immagine vuole dimostrare che agli alimenti che dovremmo consumare con maggiore frequenza si associa tendenzialmente un minor impatto sul clima.

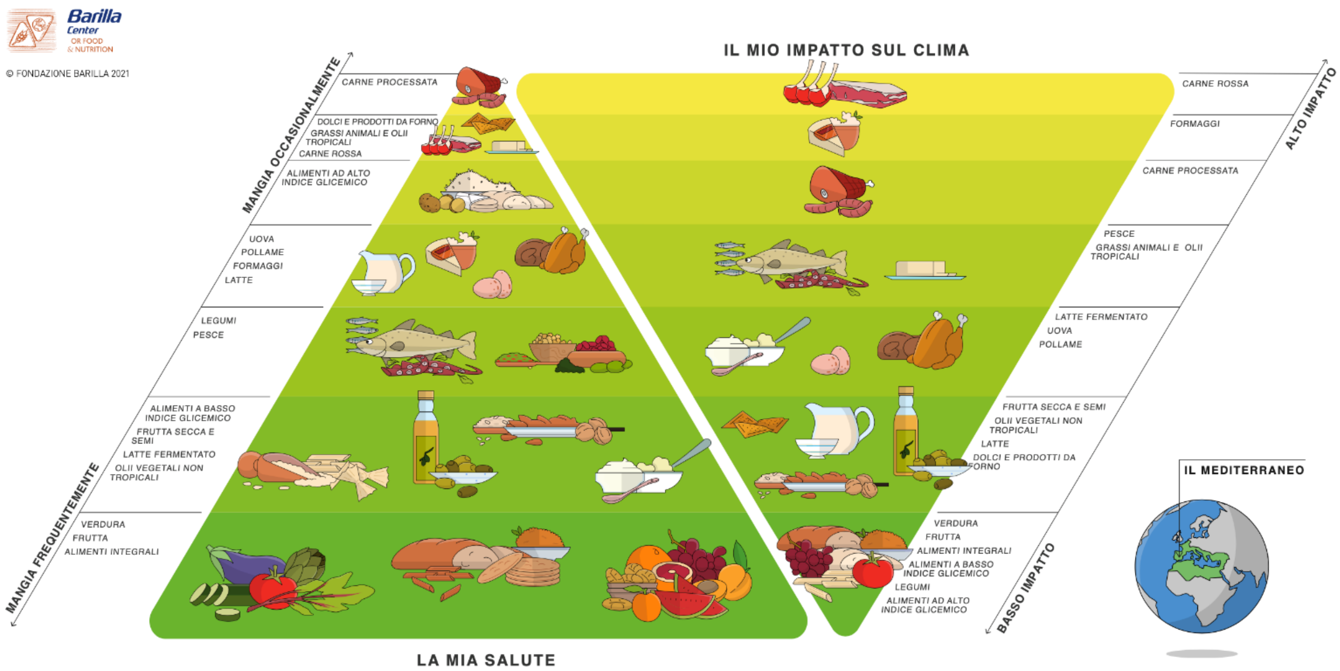


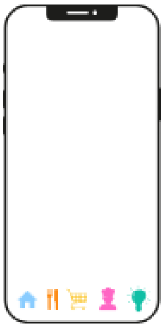
Figura 1: Doppia piramide alimentare e ambientale sviluppata dal Barilla Center for Food and Nutrition nel 2021.

Allegato 3: Scheda Attività m-health

HOME

Partecipante:______________________

COME VORRESTI L'APP ?



SEZIONE EDUCATIVA

SEZIONE PASTI

SEZIONE LISTA SPESA

SEZIONE RICETTE

Table S1. Socio-demographic characteristics of the focus group participants (N = 7). Age is reported as mean ± standard deviation; all other variables are presented as absolute numbers and percentages.

Variable	Value
Age (years ± SD)	26.4 ± 2.6 (range 23–30)
Females (n, %)	3 (42.9)
Nationality	Italian (100%)
Living away from home (n, %)	4 (57.1%)
Working students (n, %)	2 (28.6%)
Grocery shopping autonomy (n, %)	Always: 6 (85.7%); Sometimes: 1 (14.3%)
Meal preparation autonomy (n, %)	Always: 6 (85.7%); Sometimes: 1 (14.3%)
Allergies/intolerances (n, %)	1 (14.3%) - shellfish
Dietary pattern	Omnivorous (100%)
Consultation with a nutrition professional (n, %)	2 previously (28.6%); 5 no (71.4%)
Field of study	Life sciences (n=1); Food science & technology (n=2); Medicine & surgery (n=3); Social sciences (n=1)

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Study 4

Promoting healthy and sustainable diets in young adults through an educational M-health application: a randomized controlled trial

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This study is currently in preparation for submission to peer-reviewed journals.

Abstract

Background/objectives: University years represent a crucial period of life for the development and long-term consolidation of dietary habits. Mobile health (mHealth) applications represent a promising tool to address these critical issues in a population prone to the use of technologies. However, not many apps integrate simultaneously nutritional and environmental aspects and evidence from randomized controlled trials (RCTs) are limited. To evaluate the efficacy of *Uniplate*, a mHealth app designed to promote virtuous food behaviors among university students, with a particular focus on the intake of dietary fiber as a proxy of healthy and sustainable dietary patterns.

Methods: A 12-week parallel group RCT was conducted among university students (n=52) at the University of Parma. Participants in the intervention group (n=22) received access to the app for 6 weeks. A 6-week period of follow-up without exposure to the app followed the intervention. Primary outcome was the change in dietary fiber intake (g/die), assessed through 24h dietary recall. Secondary outcomes included other nutrients intake, food groups consumption, adherence to the Planetary Health Diet (PHD) index and Mediterranean Diet (MD) score, anthropometric parameters and urinary biomarkers.

Results: The intervention group showed a significant increase in fiber intake (+6.2 g/die) at the end of the intervention (p = 0.049). This effect was maintained at follow-up (p = 0.033). This improvement was led by almost doubled consumption of vegetables in the intervention group. Urinary biomarkers confirmed these results highlighting increased levels wholegrain of plant-based food metabolites, alongside a reduction in biomarkers of animal foods. Within-group analysis revealed improvements in PHD index and MD score in the intervention arm. No significant effects were observed for most macronutrients.

Conclusions: The *Uniplate* app demonstrated a positive effect in increasing dietary fiber intake and promoting more plant-oriented dietary patterns, supported by biomarker evidence. These findings highlight the potential of digital technologies as scalable tools, while further studies on larger samples are needed to confirm long-term effectiveness.

Keywords: mHealth; Randomized controlled trial; dietary behavior; Plananetary Healt Diet; University students

3.4.1 Introduction

Non-communicable diseases (NCDs), such as obesity, cardiovascular disease, type 2 diabetes, and certain cancers, continue to be the leading causes of morbidity and mortality globally, with unhealthy eating habits and physical inactivity as primary modifiable risk factors (World Health Organization, 2024). Among beneficial food components, dietary fiber plays a pivotal role in NCD prevention through several mechanisms including improved glycemic control, lipid profiles, satiety, gut microbiota diversity, and reduced inflammation (Threapleton et al., 2013; Reynolds et al., 2019). Recommended intakes typically range from 25–42 g/day, yet actual consumption remains suboptimal in Europe, where average adult intakes generally fall between 15 and 25 g/day (Stephen et al., 2017). Among university students, fiber intake is particularly concerning. Cross-sectional studies from Italy and broader European contexts report persistently low levels, often below 20 g/day, linked to irregular eating patterns and reliance on convenience foods (Seljak et al., 2021; CREA, 2020; Greier et al., 2025; European Commission, 2021).

The university years represent a critical transition period for establishing lifelong dietary habits. Students frequently experience academic stress, time constraints, independent living, and irregular schedules, which contribute to increased consumption of ultra-processed foods, reduced plant-based food intake, and poorer overall diet quality (Ferrara et al., 2022; Franchini et al., 2025). The COVID-19 pandemic exacerbated these issues: longitudinal and cross-sectional data from 2021–2025 show persistent or heterogeneous changes, including increased emotional eating, higher intake of energy-dense snacks and ultra-processed foods, reduced fresh fruits/vegetables, and only partial recovery of healthier patterns years post-lockdown (Bifolco et al., 2024). In Italy, a recent nationwide survey of university students reveals suboptimal adherence to healthy diets, with modifiable factors such as lifestyle, sociodemographic, and sustainable behaviors influencing outcomes (Franchini et al., 2025).

Parallel to health concerns, the environmental sustainability of diets has gained urgent attention. Current food systems contribute significantly to greenhouse gas emissions, water use, and biodiversity loss, necessitating a shift toward sustainable models, like the Planetary Health Diet (PHD) proposed by the EAT-Lancet Commission (Willett et al., 2019; Rockström et al., 2025). Adherence to the PHD remains low among young adults in Europe: recent studies across multiple countries, including Italy, report Planetary Health Diet Index (PHDI) scores typically in the 30–60 range (out of 150), with moderate levels in university students (e.g., mean ~55 in some Southern European samples) and higher but still suboptimal adherence in Mediterranean contexts (Grant et al., 2025; Jovanović et al., 2025). Promoting diets that are simultaneously nutritious, health-oriented, and environmentally sustainable is therefore a dual public health priority, particularly among university populations who are often receptive to education and behavior change.

Mobile health (mHealth) applications offer scalable, cost-effective tools for nutrition education and promotion. Recent systematic reviews and randomized controlled trials indicate that smartphone-based interventions can improve dietary behaviors, including increased fruit/vegetable consumption and better overall habits in young adults (Curtin et al., 2025; Seid et al., 2024). However, most of the apps considered are commercial and generally focus on calorie tracking, weight management, or individual nutrient goals, with limited integration of sustainability metrics and sporadic use of tailorization/personalization. Those developed by health professionals are, however, generally limited to specific clinical contexts. Very few randomized controlled trials have simultaneously targeted health related dietary outcomes and environmental sustainability indicators. To date, integrated approaches remain largely limited to study protocols, such as the NutriSOS mHealth randomized controlled trial, which incorporates both nutritional outcomes and environmental footprint metrics but has not yet reported results (LaresMichel et al., 2023). Moreover, to the best of our knowledge, no published mHealth trials have employed objective biomarkers, such as urinary metabolomics or gut microbiota profiling, for outcome validation, with such methods currently limited to protocol-level designs (LaresMichel et al., 2023). In addition, recent systematic reviews indicate that only a minority of mHealth nutrition trials include follow up assessments to evaluate the persistence of intervention effects, highlighting a broader gap in long-term evaluation (Curtin et al., 2025).

To address these gaps, the present randomized controlled trial evaluated the effectiveness of *Uniplate*, a novel, academically developed mobile application designed to promote both healthy and sustainable eating habits among students at the University of Parma, Italy. Informed by focus groups and psycho-behavioral profiling, the app provides tailored educational content, plant-based recipe suggestions, meal planning tools, daily tips, during a 6-week intervention phase, followed by a 6-week follow-up. The primary objective was to assess whether *Uniplate* use leads to a significant increase in daily dietary fiber intake (target difference ≥7 g/day) compared to a no-intervention control group. Secondary objectives included improvements in other nutrients and food groups intake, Planetary Health Diet (PHDI) and Mediterranean Diet (MedScore) adherence, anthropometric parameters, with objective validation through urinary and fecal biomarkers. In parallel, to inform about future possible bottom-up improvements in app functionalities and contents, the app usability and satisfaction have been tested among students.

3.4.2 Methods

3.4.2.1 Study design and setting

This study consisted in a 12-week, parallel-group, randomized controlled trial (RCT) conducted at the University of Parma, Italy. The trial was structured into a 6-week active intervention phase followed by a 6-week follow-up period designed to evaluate the maintenance of dietary changes once the intervention was withdrawn. During the follow up, the intervention group no longer had access to the Uniplate app, while the control group never received the app at any point, as the app itself constituted the experimental treatment. Throughout the follow up period, participants in both groups only completed the scheduled dietary assessment questionnaires, without receiving any prompts, guidance, or access to app functionalities.

The study was designed and reported in accordance with the Declaration of Helsinki, Good Clinical Practice (ICH GCP) guidelines, and the CONSORT 2025 statement. The protocol was prospectively registered on ClinicalTrials.gov (NCT06977802) and approved by the local Ethics Committee (Comitato Etico Area Vasta Emilia Nord, protocol ID SIRER 7369).

3.4.2.2 Participants and recruitment

Healthy university students from 18 to 29 years old were recruited between October 2024 and January 2025 via social media QR codes, posters in university canteens, and university services. Eligibility was confirmed through digital screening and subsequent in-person interviews. Inclusion criteria required Italian nationality and residence, ownership of a smartphone with internet access, and a baseline habitual dietary fiber intake <17.7 g/day (below the Italian national mean), assessed via a validated screening questionnaire (Healey et al., 2016). Participants were excluded if they used nutrition-tracking apps, reported chronic diet-related diseases, were pregnant or lactating, or had used antibiotics, probiotics, or nutritional supplements in the month prior to enrollment. All participants provided written informed consent.

3.4.2.3 Sample size

The sample size was determined based on the primary outcome of daily dietary fiber intake (Noordzij et al., 2010). Calculation parameters assumed a clinically meaningful difference (Δ) of 7 g/day between groups, a value associated with a significantly lower risk of coronary heart disease and cardiovascular diseases in prospective cohort studies (Threapleton et al., 2013), with a standard deviation (σ) of 7.69 g/day (pooled from the CREA SCAI IV study for the 18–29 age bracket, CREA,2020). Setting the significance level at $\alpha = 0.05$ and the statistical power at 90% ($1 - \beta = 0.90$), the required sample size for two independent groups was calculated using the following formula, where z indicates the critical value of the standard normal distribution corresponding to the specified tail probabilities. Accordingly, $z_{1-\alpha/2}$ equals 1.96 and $z_{1-\beta}$ equals 1.28.

$$n = \frac{2 \cdot (z_{1-\alpha/2} + z_{1-\beta})^2 \cdot \sigma^2}{\Delta^2}$$

This calculation yielded a requirement of 26 participants per arm. With an expected 15% dropout rate, the recruitment target was set at 30 participants per group, totaling a sample of 60 subjects.

3.4.2.4 Randomization and intervention

Participants were randomly assigned (1:1) to the intervention or control group using random numbers generated by Microsoft Excel (Microsoft, Redmond, WA). The intervention group utilized the *Uniplate* mobile application, co-designed with students and developed by the Human Nutrition Unit of the Department of Food and Drug with the support of the Artificial Intelligence laboratory (AI-LAB) of the University of Parma. Given the nature of the intervention (use of an app), participants and operators who administered the intervention were not blinded. However, participants were not informed about the study's primary outcome, which helped minimize the risk of behavior-related bias. Furthermore, the researchers who processed biomarkers were unaware of group assignment.

The app featured a tailored educational approach where communication strategies were assigned based on four baseline food-related psycho-behavioral profiles (i.e., Rational, Impulsive, Reflective, or Emotional). These profiles were derived from the Italian validated version of the General Decision-Making Style Inventory (Gambetti et al., 2008), originally developed by Scott and Bruce (1995), and administered within a profiling questionnaire developed by a research team from the Psychology Department at the University of Milano

Bicocca. The app included modules for daily health tips (*Home*), plant-forward meal planning (*Eat*), seasonal shopping lists (*Buy*), a sustainable recipe database (*Recipes*), and educational content on the "Healthy Plate" model (*Learn*). App modules are described in detail in the study n. 3 of the present doctoral thesis (pages 85 - 88). The control group received no intervention.

3.4.2.5 Outcome measures and methods of measurements

The primary outcome was the longitudinal change in total dietary fiber intake (g/day), quantified via interviewer-administered 24-hour dietary recalls at four time points: baseline (T0), 3 weeks (T1), 6 weeks (T2), and 12 weeks (T3). All recalls were conducted in person by trained nutritionists or by trained master students with the nutritionists' supervision, following a standardized multi-step procedure designed to enhance completeness and accuracy. The protocol included an initial quick-list, probing for commonly forgotten foods, specification of time and eating occasion, detailed characterization of each item (ingredients, preparation methods, portion size), and a final review. Nutrient values were derived using the Italian food composition tables for epidemiologic studies provided by Gnagnarella et al., 2022. Food group intakes were computed from the same recalls and expressed as grams per day.

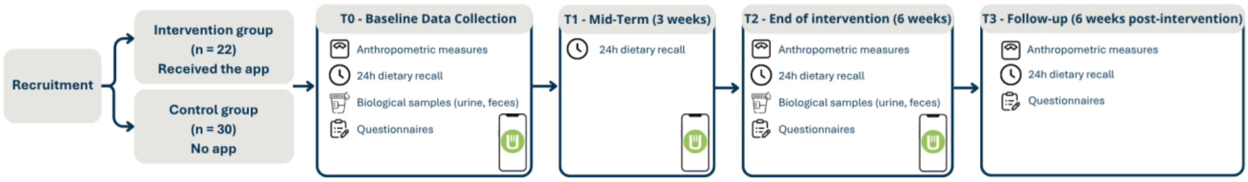

Figure 1. Study design and timeline.

A comprehensive suite of secondary outcomes was analyzed to evaluate broader dietary shifts.

- Nutrient and food group intakes (24h Recall-derived): Estimated at T0, T1, T2, and T3, including total energy, fiber density, carbohydrate fractions, and protein/lipid fractions (animal vs. vegetable). Daily consumption of major food groups was quantified in grams per day.
- Dietary patterns and sustainability (FFQ-derived): Adherence to global sustainable and traditional models was assessed at T0 and T3 only using a semi-quantitative Food Frequency Questionnaire (FFQ) (Zanini et al., 2020). From these data, the Planetary Health Diet Index (PHDI) was calculated to measure alignment with the EAT-Lancet Commission targets (Cacau et al., 2021), and the MedScore index was utilized to assess adherence to the Mediterranean dietary pattern (Zanini et al., 2022).
- Anthropometric measurements: At T0, T2, and T3, various anthropometric parameters were collected, including body weight, height, body mass index (BMI), waist and hip circumferences, and body composition (fat mass, fat-free mass, total body water). Measurements were performed using a calibrated stadiometer for height, while body weight and composition were assessed via vertical bioelectrical impedance analysis (BIA) using a TANITA device (model MC-580M S). Circumferences were measured using a flexible, non-stretchable tape measure following international standardized protocols.
- Dietary biomarkers: Urine samples were collected at T0 and T2 for the quantification of biomarkers to validate dietary intake changes assessed through interview-administered 24-hour recall.

- App usability: At T3, the intervention group completed an adapted version of the mHealth Satisfaction Questionnaire (Melin et al., 2020), a validated instrument assessing usability, perceived usefulness, and overall satisfaction with digital health tools. Additional specific *Uniplate* related items and open-ended questions were included to capture qualitative feedback on user experience. Results specifically referred to App usability have been already presented in the study entitled "Uniplate: a mHealth application developed using a participatory design to support healthy and sustainable dietary behaviors in university students" reported in this doctoral thesis (page 88 - 90).

3.4.2.6 UHPLC-MS/MS analysis of selected food intake biomarkers in urine

A total of 19 urinary biomarkers reflecting the intake of major food groups and overall dietary patterns (plant-based foods, foods of animal origin, meat, and wholegrain cereals) were selected according to the literature and the research group's experience (Jackson et al., 2025; Cuparencu et al., 2024; Clarke et al., 2020) (Table S1 in Supplementary Information). For the analysis of food intake biomarkers, urine samples collected at baseline (T0) and at the end (T2) of the intervention were prepared according to the protocol developed by Brindani and colleagues (Brindani et al., 2017), with minor modifications. Briefly, samples were thawed, vortexed, diluted in 0.1% formic acid acidified water (1:5, v/v), vortexed again, and filtered (0.22 μm nylon filter) prior to analysis by ultra-high performance liquid chromatography coupled with tandem mass spectrometry (UHPLC-MS/MS).

In detail, urine samples were analyzed through an Acquity UPLC™ I-Class Plus system coupled to a Xevo TQ-XS triple quadrupole mass spectrometer (MS) (Waters, Milford, MA, USA) equipped with an electrospray ionization source (ESI). Chromatographic separation was performed using a reversed-phase C18 ACQUITY Premier HSS T3 UPLC column (2.1 x 100 mm, 1.8 μm particle size, Waters) interfaced with a precolumn cartridge (Waters). For UPLC, water (eluent A) and acetonitrile (eluent B), both acidified with 0.01% formic acid, were used as mobile phases. The gradient started with 7% B, maintaining isocratic conditions for 0.5 min, followed by an increase to 15% B at 3 min, 30% B at 7.5 min, 40% B at 8 min, and finally to 95% B over 0.5 min. This 95% B condition was maintained for 1.5 min, before returning to the initial conditions (7% B) in 0.2 min. Isocratic conditions were maintained for 1.3 min to re-equilibrate the column, resulting in a total run time of 11.5 min. The flow rate was set to 0.4 mL/min, the injection volume was 2 μL, and the column temperature was maintained at 40 °C. The MS operated in both positive and negative ionization mode with a desolvation temperature of 600 °C. The source temperature was set to 150 °C, and the source voltage was +1.0 and –2.3 kV, in positive and negative ionization mode respectively. The gas flows were set to 150 L/h for the cone gas, 800 L/h for the desolvation gas and 7.0 bar for the nebulizer. Selected food intake biomarkers were monitored in multiple reaction monitoring (MRM) mode, with up to four molecular transitions used to qualify and quantify the compounds (Table S1 in Supplementary Information). The system was controlled by MassLynx 4.2 software (Waters), and the data was processed using TargetLynx XS 4.1.1.0 software (Waters).

Compound identification was performed by comparison of the retention time with authentic standards and/or

MS/MS fragmentation patterns. Quantification was performed with calibration curves of standards when available. When not available, metabolites were quantified with the most structurally similar compound, *i.e.* the aglycone instead of the conjugated derivative, an isomer, or the most similar compound commercially available (Table SX in Supplementary Information). To obtain a proper estimation of food intake biomarker levels in urine, the obtained concentrations for each biomarker were normalized according to creatinine excretion and expressed as µmol/mmol creatinine.

Urinary creatinine analysis was performed by UHPLC-MS/MS after further dilution (1:5000, v/v) of filtered samples with water 0.1% formic acid. Samples were analysed through Accela UHPLC 1250 apparatus equipped with a Linear Ion Trap Mass Spectrometer (LIT-MS) (LTQ XL, Thermo Fisher Scientific Inc.), fitted with a heated-electrospray ionization source (H-ESI-II). Separation was carried out by means of a XSelect HSS T3 column (50 x 2.1 mm; 2.5 µm particle size; Waters, Ireland) installed with a precolumn cartridge (Phenomenex, CA, USA). Chromatographic separation was performed in an isocratic mode keeping both mobile phase A (acetonitrile containing 0.1% formic acid) and B (water containing 0.1% formic acid) at 50% for 2 min (duration of a single run). The flow rate was set at 0.2 mL/min, the injection volume was 5 µL, and the column was thermostatted at 40°C. The H-ESI-II interface was set to a capillary temperature of 275 °C and the source heater temperature was 200 °C. The sheath gas (N_2) flow rate was set at 40 (arbitrary units) and the auxiliary gas (N_2) flow rate at 5. The source voltage was 5 kV, and the capillary voltage and tube lens voltage were +3 and +45 V, respectively. Ultra-high purity helium gas and a CID equal to 55 were used to obtain MS^2 fragmentation. Creatinine was analyzed with a full MS^2 analysis of the molecular ion with *m/z*=114 in a positive ionization mode, monitoring all the product ions with a *m/z* value between 50 and 130 Da. For identification and quantification, the molecular ion with *m/z*=114 and the product ion with *m/z*=86 were considered. Identification and quantification were performed by comparison with the standard. Chromatograms, mass spectral data and data processing were performed using Xcalibur software 2.1. Creatinine concentration in urine samples was expressed as mmol/L.

3.4.2.8 Statistical Analysis

Analyses adhered to the intention-to-treat (ITT) principle. Continuous variables were summarized as means ± SD, while categorical variable as number (%). Primary and secondary outcomes were analyzed using repeated-measures General Linear Models (RM-GLM) and linear mixed-effects models to assess time × group interactions. Specifically, RM-GLM were conducted both for the active intervention phase (T0 to T2) to evaluate immediate app efficacy, and for the full duration (T0 to T3) to assess long-term maintenance. Models were adjusted for age, sex, baseline BMI, and psycho-behavioral profile. Sphericity violations were addressed using Greenhouse-Geisser or Huynh-Feldt corrections.

For food intake biomarkers, the analyses were performed using a per-protocol (PP) approach. First, the Shapiro-Wilk test was used to assess the normality of distribution of all monitored variables. Then, to identify differences in urinary levels of food intake biomarkers between the groups before the intervention (T0), a non-parametric Mann–Whitney *U* test for non-normally distributed variables was applied. An ANCOVA analysis was performed to evaluate the effect of the intervention (differences at T2) on urinary levels of food intake biomarkers (dependent variable), including the dietary intervention (control or intervention) as a fixed factor and the baseline value (T0) for each variable as covariate. Intra-group differences (within each intervention group) throughout the study (between visits, T0 and T2) were analyzed using the non-parametric Wilcoxon signed-rank test for non-normally distributed variables.

Differences were considered statistically significant for $p < 0.05$. All statistical analyses were performed using IBM SPSS Statistics version 29 (IBM, Chicago, IL, USA).

3.4.3 Results

3.4.3.1 Participant Flow and Baseline Characteristics

A total of 52 participants were randomized and all provided baseline data and were therefore included in the intention-to-treat analysis (22 in the intervention group and 30 in the control group). Missing data at follow-up were handled using a Last Observation Carried Forward (LOCF) approach, whereby each participant's most recent available value was carried forward to replace missing observations, allowing all randomized participants to contribute to the longitudinal analyses. The flow of participants throughout the study is presented in the CONSORT diagram (Figure 2).

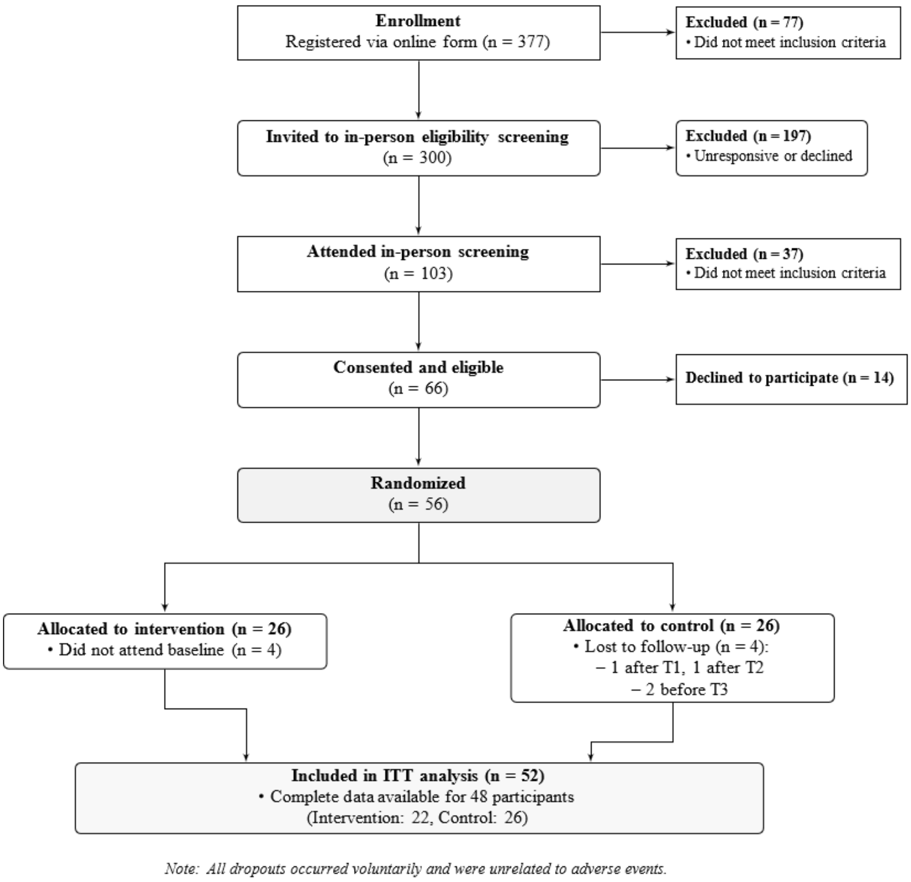

Figure 2. CONSORT flow diagram.

Baseline anthropometric characteristics, summarized in Table 1, indicated that the study arms were well-balanced across nearly all variables. The control and intervention groups are comparable for weight, BMI, waist and hip circumferences, waist-to-hip ratio (WHR), body composition parameters, including fat mass, fat-free mass, and total body water (all $p > 0.05$). A slight but statistically significant difference was noted regarding mean age, with the intervention group being older (21.36 ± 2.63 years) than the control group (20.17 ± 1.62 years; $p = 0.048$). Consequently, age was included as a covariate in all subsequent inferential analyses.

Table 1. Baseline Characteristics of Participants.

Variable	Intervention (n=22)	Control (n=30)	Total (n=52)	p
Age (years)	21.36 (2.63)	20.17 (1.62)	20.67 (2.17)	**0.048***
Females (n, %)	16 (72.73)	19 (63.33)	35 (68.31)	0.476
Height (m)	1.68 (0.07)	1.68 (0.09)	1.68 (0.08)	0.873
Weight (kg)	63.81 (9.29)	65.02 (11.79)	64.67 (10.72)	0.692
BMI (kg/m^2)	22.59 (2.91)	23.07 (3.52)	22.87 (3.26)	0.600
Waist circumference (cm)	67.65 (6.42)	68.96 (9.30)	68.41 (8.09)	0.569
Hip circumference (cm)	92.70 (6.95)	92.64 (7.10)	92.67 (7.00)	0.976
WHR	0.73 (0.05)	0.74 (0.06)	0.74 (0.06)	0.425
Fat mass (%)	23.56 (7.99)	23.32 (8.06)	23.42 (7.95)	0.917
Fat-free mass (%)	76.44 (7.99)	74.98 (8.06)	75.58 (7.95)	0.633
Muscle mass (%)	72.58 (7.61)	72.80 (7.70)	72.71 (7.58)	0.917
Total body water (%)	52.93 (6.31)	54.11 (5.66)	53.61 (5.91)	0.484
Fiber intake (g/day)	17.65 (8.51)	18.19 (10.68)	17.96 (9.73)	0.845

Note: Continues variables are reported as mean (SD), n (%) for categorical variables. Group differences at baseline were assessed using independent samples t-tests for continuous variables and chi-square tests for categorical variables. WHR: waist-to-hip ratio. Statistical significance is indicated as follows: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

3.4.3.2 Dietary Fiber and Nutritional Outcomes

As shown in Table 2, RM-GLM revealed a significant main effect of treatment and a time × treatment interaction on total fiber intake changes at the end of the intervention ($p = 0.011$ and $p = 0.049$, respectively). This pattern persisted beyond the active phase, with the time × treatment effect remaining significant at follow-up ($p = 0.033$). In parallel, the significant main effect of treatment on fiber intake changes between the baseline and the end of intervention is confirmed also when data are expressed per 1000 kcal ($p = 0.039$).

Table 2. Changes in daily intake (Δ g/day) of total dietary fiber and fiber density (g/1000 kcal) between baseline (T0) and subsequent timepoints (T2 and T3) in control and intervention groups.

Outcome	Control	Interv.	F	*p*	η^2_p	Control	Interv.	F	*p*	η^2_p
	Δ T0-T2		RM-GLM (T0-T2)			ΔT0-T3		RM-GLM (T0-T3)		
Dietary fiber (g/day)	-3.18	6.18				-2.01	0.21			
Time			0.212	0.741	0.005			0.774	0.482	0.017
Treatment			7.110	**0.011***	0.134			3.416	0.071	0.69
Time x Treatment			3.505	**0.049***	0.071			3.311	**0.033***	0.067
Fiber density (g/1000kcal/day)	-1.42	0.68				-0.62	0.53			
Time			1.614	0.205	0.034			1.289	0.281	0.027
Treatment			4.526	**0.039***	0.090			3.418	0.071	0.069
Time x Treatment			2.276	0.108	0.047			1.891	0.134	0.039

Note: Mean change scores (Δ T0–T2 and Δ T0–T3) are reported. Differences across time intervals, the treatment and control conditions, and for the time × treatment interaction were assessed using RM-GLM with Bonferroni correction. The F statistic represents the ratio of the variance explained by the model to the residual variance. Effect sizes are reported as partial eta squared (η^2_p). Statistical significance is indicated as follows: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

As shown in Figure 3 (Panel A), in the intervention group, mean fiber intake increased from 17.65 (st. dev: 8.51) g/day at T0 to 19.84 (9.79) g/day at T1, reaching 23.83 (16.22) g/day at T2, corresponding to an overall rise of approximately +6.2 g/day. In contrast, the control group showed a slight downward trajectory, decreasing from 18.19 (10.68) g/day at T0 to 14.97 (6.61) g/day at T1, and stabilizing at 15.31 (6.93) g/day at T2, consistently remaining below baseline levels over the same period.

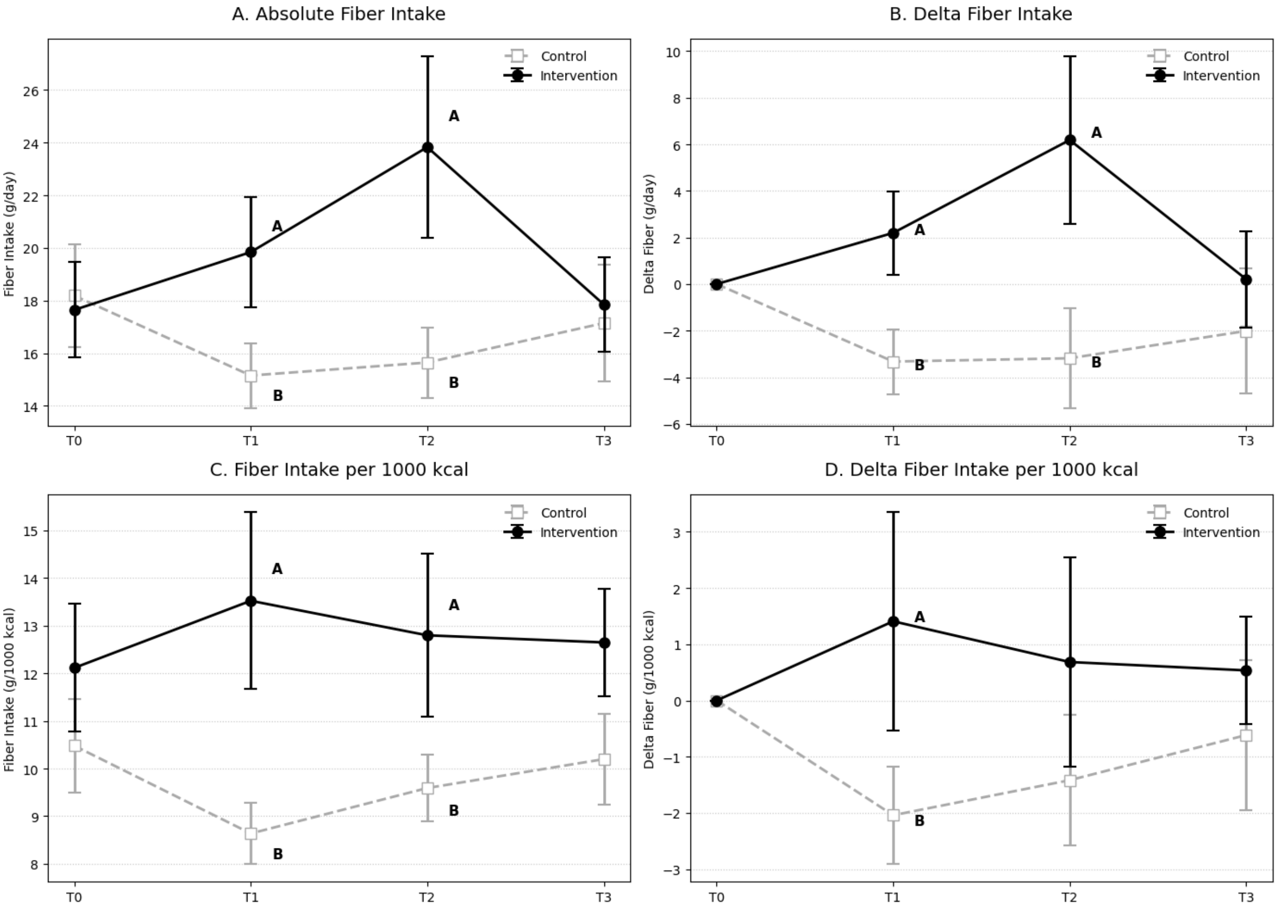

Figure 3. Average total fiber intake levels and average change scores (g/day) in the control and intervention groups across time (Panels A and B, respectively). Intake values normalized per 1000 kcal are shown in Panels C and D.

Note: Error bars represent standard error of the mean (SEM). Different letters indicate statistically significant differences identified through pairwise comparisons between the intervention and control groups at each time point, based on the RM-GLM. In Panel A, the divergence between intervention and control at T1 and T2 corresponds to a significant time × treatment effect ($p = 0.014$ and $p = 0.008$, respectively). In Panel B, the divergence at T1 and T2 reflects a significant time × treatment effect ($p = 0.016$ and $p = 0.033$, respectively). In Panel C, the divergence at T1 and T2 corresponds to a significant time × treatment effect ($p = 0.002$ and $p = 0.031$, respectively). In Panel D, the divergence at T1 corresponds to a significant time × treatment effect ($p = 0.024$).

RM-GLM analyses conducted on the broader set of nutritional outcomes (Table 3) did not reveal significant time × treatment interactions, indicating that the intervention did not produce differential temporal effects between groups for nutrients other than fiber. For energy intake, a significant main effect of time was observed over the full study period (T0–T3, $p = 0.032$), suggesting a general reduction at the follow-up across both groups, but without a significant interaction ($p = 0.749$), implying that this trend was not specifically attributable to the intervention. Similarly, total lipids showed a significant time effect ($p = 0.018$), yet no interaction effect emerged ($p = 0.299$).

Total, animal, and vegetable proteins intake remained statistically stable across timepoints, with no significant effects of treatment or interaction. Vegetable protein approached significance for time × treatment at T0–T2 ($p = 0.058$), but this trend was not sustained at follow up. Although not statistically significant, the direction of the effect is consistent with the increase in fiber intake, hinting a possible shift toward higher consumption of plant-derived foods during the intervention phase. Lipid subtypes followed a similar pattern: animal lipids showed a marginal time effect at T0–T3 ($p = 0.063$), while vegetable lipids approached significance for interaction at T0–T2 ($p = 0.064$), though neither reached conventional thresholds.

Available and soluble carbohydrates did not exhibit significant treatment or interaction effects. Soluble carbohydrates showed a marginal time effect at T0–T2 ($p = 0.066$), but this was not maintained at follow-up ($p = 0.212$). Overall, these results suggest that the intervention impact was specific to fiber intake, with other macronutrients remaining largely unaffected or showing non-specific temporal trends.

Table 3. Daily intake (g/day) of energy and selected macronutrients across timepoints (T0–T3) in control and intervention groups.

Outcome	**Control**				**Intervention**				**T0-T2**			**T0-T3**		
	T0	T1	T2	T3	T0	T1	T2	T3	F	*p*	η^2_p	F	*p*	η^2_p
Energy (kcal/day)	1779.3±140.9	1825.9±109.2	1683.9±123.5	1647.6±114.8	1501.4±89.1	1629.0±123.3	1853.2±138.2	1457.3±123.8						
Time									2.861	0.098	0.059	4.888	**0.032***	0.096
Treatment									0.071	0.791	0.002	0.351	0.556	0.008
Time x Treatment									2.000	0.141	0.042	0.103	0.749	0.002
Total proteins (g/day)	75.9±5.3	75.9±6.0	78.3±6.7	80.6±7.5	59.3±4.4	75.0±8.6	69.0±5.8	62.2±6.1						
Time									0.879	0.343	0.019	0.463	0.500	0.010
Treatment									1.258	0.268	0.027	2.648	0.111	0.054
Time x Treatment									0.631	0.534	0.014	0.286	0.596	0.006
Animal prot. (g/day)	45.9±4.5	47.4±5.9	50.4±5.6	51.9±6.7	34.3±4.5	46.6±8.2	35.1±4.9	36.1±4.9						
Time									1.270	0.266	0.027	0.400	0.530	0.009
Treatment									2.057	0.158	0.043	3.601	0.064	0.073
Time x Treatment									0.828	0.440	0.018	0.965	0.331	0.021
Vegetable prot. (g/day)	29.9±2.6	28.5±2.0	27.8±2.1	28.6±2.8	24.7±1.8	28.3±2.0	33.8±4.3	26.1±2.8						
Time									0.050	0.824	0.010	0.029	0.865	0.001
Treatment									0.293	0.591	0.006	0.079	0.780	0.002
Time x Treatment									3.323	0.058	0.067	0.981	0.327	0.021
Total lipids (g/day)	71.0±6.1	80.5±7.4	66.0±6.6	62.8±5.0	58.9±5.4	62.6±5.9	73.5±6.2	61.8±6.3						
Time									2.107	0.153	0.044	6.075	**0.018***	0.117
Treatment									0.462	0.500	0.010	0.508	0.480	0.011
Time x Treatment									2.422	0.094	0.050	1.103	0.299	0.023
Animal lipids (g/day)	36.5±5.1	38.3±4.5	29.8±4.7	29.9±3.8	25.9±3.0	30.8±5.7	31.9±3.7	27.1±5.1						
Time									1.585	0.214	0.033	3.633	0.063	0.073
Treatment									0.418	0.521	0.009	0.547	0.463	0.012
Time x Treatment									0.844	0.433	0.018	0.559	0.458	0.012
Vegetable lipids (g/day)	34.5±3.1	42.0±4.3	36.2±3.7	32.9±2.8	32.8±4.5	31.9±3.1	41.6±5.0	34.8±4.3						
Time									0.546	0.464	0.012	1.988	0.165	0.041
Treatment									0.110	0.742	0.002	0.076	0.784	0.002
Time x Treatment									2.854	0.064	0.058	0.487	0.489	0.010
Available CHO (g/day)	211.1±21.7	204.1±15.0	198.1±14.8	189.4±16.2	184.2±12.6	184.8±14.9	229.4±23.4	161.8±16.3						
Time									1.756	0.192	0.037	2.726	0.106	0.056
Treatment									0.027	0.870	0.001	0.038	0.847	0.001
Time x Treatment									1.714	0.186	0.036	0.002	0.969	0.000
Soluble CHO (g/day)	68.9±9.1	56.0±6.0	60.8±8.9	55.4±5.7	61.6±5.9	54.2±5.9	71.8±6.7	59±7						
Time									3.552	0.066	0.072	2.560	0.212	0.034
Treatment									0.036	0.849	0.001	0.020	0.824	0.001

Time x Treatment	0.678	0.510	0.015	0.303	0.585	0.007

Note: Values are expressed as mean (± SEM). Differences between baseline and follow-up timepoints (T0–T2 and T0–T3), between groups, and for the time × group interaction were assessed using RM-GLM with Bonferroni correction. The F statistic represents the ratio of the variance explained by the model to the residual variance. Effect sizes are reported as partial eta squared (η^2_p). Statistical significance is indicated as follows: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

3.4.3.3 Changes in dietary composition and food group consumption

Total plant-based and total animal-based foods, derived respectively from the sum of all plant-origin and animal-origin food groups (Table 4), showed no significant time × treatment interactions, yet their temporal patterns offer additional context for interpreting dietary shifts. For total plant-based foods, the intervention group started with lower intake at baseline (212.3 ± 33.0 g/day) compared with the control group (260.2 ± 31.5 g/day), but displayed a steady increase during the active phase (250.6 ± 35.6 g/day at T1; 252.2 ± 35.2 g/day at T2), maintaining similar levels at follow-up (246.4 ± 35.2 g/day). In contrast, the control group showed only modest fluctuations over time (289.4 ± 33.4 g/day at T1; 293.5 ± 34.8 g/day at T2; 318.3 ± 41.1 g/day at T3). Although the interaction was not significant ($p = 0.104$), the intervention group's trajectory is directionally consistent with the broader plant-forward shift observed for vegetables and fiber. Total animal-based foods did not follow a coherent pattern in either group, with both arms showing substantial fluctuations across timepoints. Baseline values were comparable (593.9 ± 60.8 g/day in the control group; 577.7 ± 55.9 g/day in the intervention group), but subsequent changes lacked a systematic direction, and no significant interactions emerged ($p = 0.772$ for T0–T2; $p = 0.505$ for T0–T3), indicating that animal-derived food intake was not meaningfully influenced by the intervention.

Patterns in specific food-group consumption broadly mirrored those observed for nutrients, with most categories showing no differential change between groups over time. Across both the active phase and the follow-up, cereals, fruit, red and white meat, fish, eggs, dairy products, oils, fats, and water intake did not exhibit significant time × treatment interactions, indicating that their relative consumption evolved similarly in both groups. In contrast, vegetable intake showed a clear and sustained divergence. At baseline, the two groups were comparable (187.0 ± 36.4 g/day in the control group vs. 141.0 ± 33.6 g/day in the intervention group), but by the end of the intervention the intervention group had nearly doubled its intake (250.8 ± 41.0 g/day), while the control group showed only a modest change (166.2 ± 24.8 g/day). This divergence was statistically significant during the intervention ($p = 0.017$) and at follow-up ($p = 0.015$), when the intervention group further increased to 269.1 ± 42.2 g/day compared with 167.8 ± 20.5 g/day in the control arm. This pattern aligns with the rise in fiber intake and suggests a coherent shift toward plant-forward eating. Legumes displayed a different temporal profile, with no group differences during the active phase ($p = 0.660$), but a significant interaction emerging at follow-up ($p = 0.035$), indicating that changes in legume consumption unfolded later in the study.

Table 4. Mean (± SEM) daily intake (g/day) of selected food groups across timepoints (T0 to T3) in control and intervention groups.

Outcome	Control				Intervention				T0-T2			T0-T3		
	T0	T1	T2	T3	T0	T1	T2	T3	F	*p*	η^2_p	F	*p*	η^2_p
Total plant-based food (g/day)	260.2±1.5	289.4±33.4	293.5± 4.8	318.3±41.1	212.3±33.0	250.6±35.6	252.2±35.2	246.4±35.2						
Time									0.062	0.805	0.001	0.763	0.387	0.016
Treatment									3.262	0.077	0.066	4.289	**0.044***	0.085
Time x Treatment									2.756	0.104	0.057	2.109	0.153	0.044
Total animal-based food (g/day)	593.9±60.8	481.4±27.6	538.9±42.8	503.4±38.0	577.7±55.9	591.0±55.1	717.7±76.9	647.3±74.5						
Time									1.746	0.193	0.037	0.881	0.353	0.019
Treatment									0.773	0.384	0.017	1.526	0.223	0.032
Time x Treatment									0.085	0.772	0.002	0.451	0.505	0.010
Cereals (g/day)	270.7±31.2	237.6±24.2	227.8±21.1	217.3±27.7	231.4±36.9	241.4±33.8	256.7±43.4	156.9±24.2						
Time									0.190	0.665	0.004	2.277	0.138	0.047
Treatment									0.231	0.633	0.005	0.026	0.874	0.001
Time x Treatment									0.516	0.476	0.011	0.356	0.554	0.008
Fruit (g/day)	116.8±26.4	81.2±17.9	112.3±25.7	76.9±18.4	146.8±29.6	157.0±27.3	142.1±31.5	190.8±47.2						
Time									0.072	0.790	0.002	0.157	0.694	0.003
Treatment									2.165	0.148	0.045	4.877	**0.032***	0.096
Time x Treatment									0.207	0.651	0.004	1.013	0.320	0.022
Vegetables (g/day)	187.0±36.4	137.4±19.4	166.2±24.8	167.8±20.5	141.0±33.6	154.9±24.4	250.8±41.0	269.1±42.2						
Time									1.074	0.306	0.023	0.027	0.871	0.001
Treatment									0.398	0.531	0.009	1.903	0.174	0.040
Time x Treatment									6.144	**0.017***	0.118	6.385	**0.015***	0.122
Legumes (g/day)	11.6±5.7	15.2±7.4	20.2±9.1	31.6±10.4	50.9±17.6	25.6±13.0	48.3±20.1	14.2±6.2						
Time									0.024	0.877	0.001	0.001	0.972	0.000
Treatment									10.709	**0.002****	0.189	6506	**0.014***	0.124
Time x Treatment									0.196	0.660	0.004	4.745	**0.035***	0.094
Red meat (g/day)	83.5±23.2	69.3±16.3	107.8±33.6	81.3±22.5	29.9±7.8	71.4±27.3	53.0±20.6	38.9±16.9						
Time									0.011	0.918	0.000	0.267	0.608	0.006
Treatment									1.900	0.175	0.040	2.592	0.114	0.053
Time x Treatment									0.002	0.968	0.000	0.208	0.651	0.005
White meat (g/day)	48.0±14.4	53.2±16.7	56.7±15.5	56.5±16.2	43.6±14.2	52.5±24.2	20.5±11.7	40.7±14.2						
Time									1.441	0.236	0.030	0.706	0.405	0.015
Treatment									0.793	0.378	0.017	0.662	0.420	0.014
Time x Treatment									1.437	0.237	0.030	0.183	0.671	0.004
Fish (g/day)	21.3±13.1	17.8±7.0	21.4±8.4	38.9±20.3	16.1±5.7	23.1±8.4	2.4±2.4	30.6±12.2						
Time									0.181	0.672	0.004	0.344	0.560	0.007
Treatment									0.541	0.466	0.012	0.344	0.560	0.007

Time x Treatment									1.852	0.180	0.039	0.278	0.600	0.006
Eggs (g/day)	12.2±9.6	10.2±2.9	21.2±9.9	32.3±10.3	18.6±7.0	231±9.3	45.9±11.8	21.2±10.5						
Time									1.407	0.242	0.030	0.444	0.508	0.010
Treatment									4.876	**0.032***	0.096	0.785	0.380	0.017
Time x Treatment									1.546	0.220	0.033	0.529	0.471	0.011
Milk and yogurt (g/day)	106.5±22.5	112.5±22.6	90.5±21.3	116.8±20.9	86.6±24.3	97.5±21.9	118.2±29.5	130.0±23.1						
Time									3.876	0.055	0.078	2.401	0.128	0.050
Treatment									0.001	0.974	0.000	0.016	0.899	0.000
Time x Treatment									0.757	0.389	0.016	0.707	0.936	0.000
Cheese (g/day)	38.1±9.1	53.8±10.6	41.4±11.6	27.9±8.2	35.6±10.0	35.0±8.0	37.8±8.9	17.8±5.2						
Time									0.218	0.643	0.005	0.004	0.953	0.000
Treatment									0.373	0.544	0.008	0.728	0.389	0.016
Time x Treatment									0.000	0.989	0.000	0.129	0.721	0.003
Vegetable oils (g/day)	13.7±2.2	17.4±3.8	15.7±2.4	10.5±1.2	15.7±2.9	15.7±2.3	21.7±3.5	19.7±4.0						
Time									0.689	0.411	0.015	2.025	0.161	0.042
Treatment									0.607	0.440	0.013	2.151	0.149	0.045
Time x Treatment									0.266	0.608	0.006	2.294	0.137	0.048
Animal fats (g/day)	7.7±2.9	10.0±4.6	3.5±1.2	5.5±3.1	3.4±1.1	5.0±2.2	6.8±2.2	13.5±9.2						
Time									0.082	0.776	0.002	1.302	0.260	0.028
Treatment									0.516	0.476	0.011	0.034	0.855	0.001
Time x Treatment									2.119	0.152	0.044	2.349	0.132	0.049
Water (g/day)	1537.4±102.5	1616.1±128.3	1492.3±110.6	1479.8±121.1	1417.2±148.5	1598.7±127.1	1504.5±152.5	1389.8±123.9						
Time									0.539	0.467	0.012	1.014	0.319	0.022
Treatment									0.004	0.952	0.000	0.012	0.915	0.000
Time x Treatment									0.179	0.674	0.004	0.050	0.824	0.001

Note: Values are expressed as mean (± SEM). Differences across timepoints (T0–T2 and T0–T3). Differences between baseline and follow-up timepoints (T0–T2 and T0–T3), between groups, and for the time × group interaction were assessed using RM-GLM with Bonferroni correction. The F statistic represents the ratio of the variance explained by the model to the residual variance. Effect sizes are reported as partial eta squared (η^2_p). Statistical significance is indicated as follows: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

3.4.3.4 Diet Quality Scores

Longterm diet quality, assessed via FFQ at T3, showed numerically greater improvements in the intervention group compared to the control group, although the overall RM-GLM effects did not reach statistical significance. As shown in Table 5, the Planetary Health Diet Index (PHDI) increased by +10.12 points (from 62.23 to 72.35) in the intervention group versus +3.25 (from 64.19 to 67.44) in the control group (RM-GLM p = 0.203), while the Mediterranean Diet (MD) Score increased by +2.41 points (from 11.00 to 13.41) in the intervention arm compared to +0.74 (from 11.21 to 11.95) in the control arm (RM-GLM p = 0.202). However, longitudinal pairwise comparisons indicated a significant within group improvement from T0 to T3 in the intervention group for both MD and PHD scores (p = 0.009 for both outcomes), consistent with the pattern shown in Figure 4.

Table 5. Changes in Mediterranean Diet (MD) score and Planetary Health Diet (PHD) index between baseline (T0) and follow up (T3) in control and intervention groups.

Outcome	Control	Interv.	F	p	η^2_p
	RM-GLM (T0-T3)				
MD score (0-25)	+0.74	+2.41			
Time			0.528	0.471	0.011
Treatment			1.678	0.202	0.035
Time x Treatment			1.678	0.202	0.035
PHD score (0-150)	+3.25	+10.12			
Time			2.917	0.094	0.060
Treatment			1.670	0.203	0.035
Time x Treatment			1.670	0.203	0.035

Note. Mean change scores (Δ T0–T3) are reported. Effects of time, treatment, and the time × treatment interaction were evaluated using RM-GLM with Bonferroni correction. Effect sizes are expressed as partial eta squared (η^2_p).

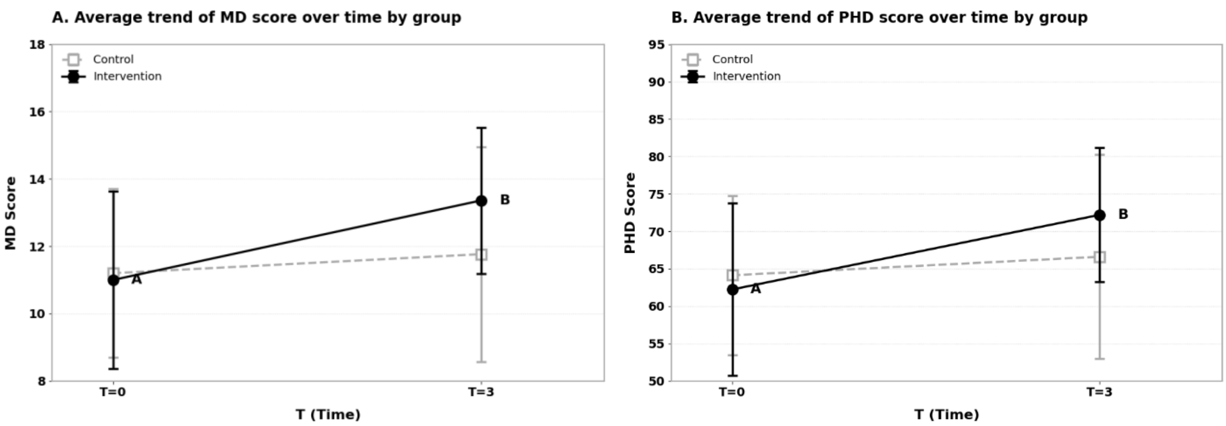

Figure 4. Average Mediterranean Diet (MD) score (Panel A) and Planetary Health Diet (PHD) score (Panel B) at baseline (T0) and at the 12-week follow-up (T3) in control and intervention groups.

Note: Error bars represent standard error of the mean (SEM). Different letters (A, B) for the intervention group indicate a statistically significant change from baseline (T0) to the 12-week follow-up (T3), based on longitudinal pairwise comparisons (p = 0.009 for both MD and PHD scores). No significant within-group change was observed in the control group. Differences between groups, across time, and for the Time × Group interaction were evaluated using generalized linear models for repeated measures with Bonferroni correction.

3.4.3.5 Changes in urinary food intake biomarkers

A total of 19 urinary biomarkers reflecting the intake of major food groups and overall dietary patterns (plant-based foods, foods of animal origin, meat, and wholegrain cereals) were identified and quantified in urine samples collected from study participants. Baseline concentrations were largely comparable between control and intervention groups, with minor non-significant differences observed for biomarkers of wholegrain cereal intake (3-(3′,5′-dihydroxyphenyl) propanoic acid and 3,5-dihydroxybenzoic acid), and the biomarker of meat intake (creatine).

By the end of the intervention (T2), the levels of biomarkers of wholegrain cereal intake (3-(3′,5′-dihydroxyphenyl) propanoic acid, 3,5-dihydroxybenzoic acid, and enterolactone-glucuronide) were significantly increased in the intervention group and exceeded those observed in controls. In parallel, 3-*N*-methyl-*L*-histidine, an intake biomarker of foods of animal origin (Cho et al., 2016; Kubomura et al., 2009; Cuparencu et al., 2019), was significantly reduced in the intervention group compared with controls. Notably, trimethylamine-*N*-oxide (TMAO), the other biomarker selected to reflect animal-derived food consumption, did not change as a result of the intervention. No significant between-group differences were detected for intake biomarkers of plant-based food, although a consistent upward trend was observed in the intervention arm. No temporal changes were detected in the control group for any of the food intake biomarkers considered. In contrast, the intervention group exhibited significant within-group increases in a few biomarkers of intake of plant-based foods (2-isopropylmalic acid and hippuric acid), as well as in intake biomarkers of wholegrain cereals (3-(3′,5′-dihydroxyphenyl)propanoic acid and 3,5-dihydroxybenzoic acid), alongside a significant reduction in a biomarker of intake of animal-derived foods (3-*N*-methyl-*L*-histidine).

3.4.4 Discussion

The present randomized controlled trial demonstrates that a tailored mHealth educational intervention delivered through the Uniplate app can effectively shift dietary behaviour among university students toward higher fiber intake and more plant-forward patterns. The statistically significant treatment effect and time × treatment interaction for total dietary fiber intake confirm the primary hypothesis and correspond to a mean increase of approximately +6.2 g/day in the intervention arm, which is close to the minimum desired threshold (+7 g), while the control group showed a decline.

Among the food-group outcomes, the most striking and sustained change was observed for vegetable intake, which exhibited a clear and statistically significant time × treatment interaction both at the end of the intervention and at 12-week follow-up. In the intervention group, daily vegetable consumption nearly doubled from 141.0 ± 33.6 g at baseline to 250.8 ± 41.0 g at T2 and further to 269.1 ± 42.2 g at T3, whereas the control group remained essentially stable (166–168 g/day). This targeted increase in vegetables coupled with directional (though non-significant) rises in total plant-based foods directly contributed to the fiber gains and represents a highly desirable shift. The pattern is consistent with the app’s core educational content centered on the “Healthy Plate” model and plant-forward recipes.

Objective urinary biomarkers provided independent corroboration of these food-group shifts: the intervention arm showed significant increases in wholegrain-cereal metabolites (3-(3′,5′-dihydroxyphenyl)propanoic acid, 3,5-dihydroxybenzoic acid, enterolactone-glucuronide) and selected plant-food markers (2-isopropylmalic acid, hippuric acid), together with a reduction in the animal-origin marker 3-N-methyl-L-histidine, while no temporal changes occurred in controls. TMAO remained unaffected, in line with the modest overall reduction in animal foods observed by interviewer-administered 24-hour dietary recalls.

In parallel, urinary biomarkers revealed qualitative improvements in cereal choices that were not detectable in the aggregated dietary data. Specifically, metabolites associated with wholegrain intake increased significantly in the intervention group, suggesting a shift toward higher-quality, fiber-rich cereal products. This signal did not emerge in the food-group analysis because refined and wholegrain cereals were combined into a single category, preventing detection of within-group substitutions. A more granular disaggregation of the 24-hour recall data, distinguishing wholegrain products, refined grains, could be derived from the existing dataset and would likely clarify these patterns. Nonetheless, the biomarker profile strongly supports the interpretation that the intervention promoted an improvement in the type, not only the amount, of cereal-derived fiber consumed.

For composite diet-quality indices, between-group differences in the change of the Planetary Health Diet Index (PHDI) and Mediterranean Diet Score (MedScore) did not reach statistical significance, yet pairwise longitudinal comparisons revealed clear within-intervention improvements, underscoring meaningful individual-level movement toward EAT-Lancet and Mediterranean targets. The lack of between-group statistical significant differences on these secondary outcomes is consistent with modest effect sizes typical of digital nutrition trials and with the inherent day-to-day variability of single 24-hour recalls (Curtin et al., 2025).

The 10-point rise in PHDI in the intervention group is particularly noteworthy when contextualized within the broader European literature. Cross-sectional studies in university and young adult populations generally report moderate adherence to the Planetary Health Diet, with mean PHDI type values (0–150 scale) clustering between 30 and 60. For example, Croatian university students scored 55.5 on an adapted PHDI specifically developed for that study (Jovanović et al., 2025), whereas Turkish young adults scored 59.9 ± 14.2 using the original PHDI developed by Cacau et al. (2021) (Mortaş et al., 2024). Importantly, the recent PLAN’EAT multicounty mapping across 11 European nations (Grant et al., 2025) did not use the PHDI developed by Cacau et al. (2021); instead, it employed alternative but conceptually comparable indices (EATLancet, WISH, WISH 2.0). Despite methodological differences, PLAN’EAT similarly documented low overall adherence (mean EATLancet score 18.1/42; mean WISH/WISH 2.0 scores 43.7/130–150), with Italy achieving the highest national values (EATLancet 22/42; WISH 68.6/130). This pattern confirms that Southern European populations, including an Italian sample, start from a relatively more plantforward baseline while still falling well below optimal sustainability targets. Within this landscape, the intervention induced a 10-point PHDI increase, which represents a health and environmentally relevant improvement, effectively moving participants closer to the upper adherence levels observed in their national context and aligning with broader European trends toward sustainable dietary transitions.

This study has several methodological strengths. It is among the first European university-based RCTs to evaluate a psycho-behaviorally personalized mHealth tool that simultaneously targets health-related dietary outcomes and environmental sustainability indicators, with objective urinary metabolomic validation and a dedicated follow-up phase to assess maintenance. The app's co-design with students and its integration of four validated psycho-behavioural profiles represent an innovative approach rarely implemented in commercial or research-grade nutrition apps. The inclusion of urinary biomarkers addresses a critical gap identified in recent systematic reviews.

Important limitations must nevertheless be acknowledged. Although the protocol was powered for 60 participants (30 per arm after allowing for 15 % dropout), only 52 students were ultimately randomized (22 intervention, 30 control). Recruitment was particularly challenging, primarily because of the invasive nature of the biomarker protocol (repeated urine sampling and in-person 24-hour recalls), which deterred participation and contributed to the unbalanced groups. The reduced sample size limited statistical power. While between-group significance was achieved for the primary fiber outcome, vegetable intake, and legumes at follow-up, the inability to reach the planned sample size prevented detection of longitudinal significance in some individual-arm comparisons, including fiber intake. In addition, the single 24-hour recall per time point introduces within-person variability; future studies should incorporate multiple non-consecutive recalls to improve precision. A further limit concerns the baseline fibre intake as criterion for the enrollment. Because only students with fibre intake below the Italian national average were included, the findings reflect the response of a nutritionally at-risk subgroup rather than the wider university population. This restricts the external validity of the results, and future trials should assess the intervention in more heterogeneous samples to determine whether similar improvements occur across different baseline dietary profiles.

Despite these constraints, the observed changes remain directionally consistent with the app's educational focus. The net fiber increase occurred despite a later decline in legume intake in the intervention arm, suggesting that gains from vegetables and wholegrains are more than compensated for any compensatory reduction in other fiber sources.

3.4.5 Conclusions

The present study provides proof-of-concept that a short, academically developed, personalized mHealth intervention can produce sustained, objectively supported improvements in fiber intake, vegetable consumption and overall alignment with healthy and sustainable dietary patterns among young adults. The Uniplate app therefore represents a scalable, low-cost tool with dual public-health and planetary-health relevance. Confirmatory evidence is now required from larger, adequately powered trials that extend follow-up beyond 12 weeks, implement repeated dietary assessments, embed environmental-impact metrics as prespecified outcomes, and ensure balanced recruitment. Future versions of Uniplate could further leverage user-satisfaction data (already reported separately) to refine engagement features and maximise long-term adherence. Taken together, the present findings advance the limited evidence base for integrated nutrition–sustainability mHealth interventions and highlight the feasibility of behaviourally tailored digital tools in university settings.

Supplementary Information (SI):

S1.1 Materials

All chemicals and solvents used for the food intake biomarker analysis were of analytical grade. UHPLC-grade solvents and reagents were purchased from Carlo Erba Reagents srl (Cornaredo, Milan, Italy). Hippuric acid, trigonelline, 2-isopropylmalic acid, trimethylamine-*N*-oxide, creatine, enterodiol, and 3-(3′,5′-dihydroxyphenyl)propanoic acid were purchased from Sigma-Aldrich (St. Louis, MO, USA). 3-(4′-Hydroxyphenyl)propanoic acid-3′-sulfate, 3′-hydroxyhippuric acid, dopamine-3-sulfate, 3-hydroxyurolithin-8-glucuronide (Urolithin A-8-glucuronide) and 3-*N*-methyl-*L*-histidine were purchased from Toronto Research Chemicals (Toronto, ON, Canada). 4′-Hydroxyhippuric acid was purchased from Bachem Ltd. (St Helens, UK). 3,5-Dihydroxybenzoic acid was purchased from Santa Cruz Biotechnology Inc. (Dallas, TX, USA). 5-(3′-Hydroxyphenyl)-γ-valerolactone-4′-sulfate and 5-(5′-hydroxyphenyl)-γ-valerolactone-3′-glucuronide were synthesized in house using the synthetic strategy previously outlined by Brindani and colleagues for phase II conjugates [1].

Supplementary Table S1. Chromatographic and spectrometric properties of the monitored food intake biomarkers. RT, retention time; ES, electrospray ionization mode; CV, cone voltage; CE, collision energy; STD, standard use for the quantification. Compounds in the table are order by corresponding food group, and by RT.

Table S1. Chromatographic and spectrometric properties of the monitored food intake biomarkers. RT, retention time; ES, electrospray ionization mode; CV, cone voltage; CE, collision energy; STD, standard use for the quantification. Compounds in the table are order by corresponding food group, and by RT.

Compound	**RT (min)**	**ES +/-**	**Parent ion $[M]^+$ / $[M-H]^-$ (*m/z*)**	**CV (V)**	**Quantifier**		**Qualifier(s)**		**STD** (in bold those reference compounds used to quantify the corresponding metabolite)	**Corresponding food group**
					Product ion (*m/z*)	**CE (V)**	**Product ion (*m/z*)**	**CE (V)**		
Trigonelline	0.64	ES+	138	10	95	20	78	20	**Trigonelline**	PLANT-BASED FOODS
Dopamine-3-sulfate	1.16	ES-	232	40	152	18	122, 80	32, 18	**Dopamine-3-sulfate**	PLANT-BASED FOODS
4′-Hydroxyhippuric acid	2.19	ES-	194	8	150	12	93	18	**4′-Hydroxyhippuric acid**	PLANT-BASED FOODS
5-(5′-Hydroxyphenyl)-γ-valerolactone-3′-glucuronide	2.54	ES-	383	20	191	20	163, 113	20, 20	**5-(5′-Hydroxyphenyl)-γ-valerolactone-3′-glucuronide**	PLANT-BASED FOODS
3′-Hydroxyhippuric acid	2.56	ES-	194	8	93	18	150	12	**3′-Hydroxyhippuric acid**	PLANT-BASED FOODS
2-Isopropylmalic acid	2.97	ES-	175	6	157	14	115, 85	14, 12	**2-Isopropylmalic acid**	PLANT-BASED

									FOODS
5-(3′-Hydroxyphenyl)-γ-valerolactone-4′-glucuronide	3.48	ES-	383	20	207	20	113, 163	20, 20	5-(5′-Hydroxyphenyl)-γ-valerolactone-3′-glucuronide	PLANT-BASED FOODS
Hippuric acid	3.64	ES-	178	6	134	12	77	18	**Hippuric acid**	PLANT-BASED FOODS
5-(4′-Hydroxyphenyl)-γ-valerolactone-3′-glucuronide	3.83	ES-	383	20	207	20	113, 163	20, 20	5-(5′-Hydroxyphenyl)-γ-valerolactone-3′-glucuronide	PLANT-BASED FOODS
5-(3′-Hydroxyphenyl)-γ-valerolactone-4′-sulfate	4.19	ES-	287	26	207	20	163	28	**5-(3′-Hydroxyphenyl)-γ-valerolactone-4′-sulfate**	PLANT-BASED FOODS
5-(4′-Hydroxyphenyl)-γ-valerolactone-3′-sulfate	4.36	ES-	287	26	207	20	163	28	5-(3′-Hydroxyphenyl)-γ-valerolactone-4′-sulfate	PLANT-BASED FOODS
8/3-Hydroxyurolithin-3/8-glucuronide (Urolithin A-glucuronide)	4.88	ES-	403	32	227	28	198, 171, 113	60, 50, 14	3-Hydroxyurolithin-8-glucuronide (Urolithin A-8-glucuronide)	PLANT-BASED FOODS
3-(4′-Hydroxyphenyl)propanoic acid-3′-sulfate	5.09	ES-	261	96	181	20	137	25	**3-(4′-Hydroxyphenyl)propanoic acid-3′-sulfate**	PLANT-BASED FOODS
3-*N*-Methyl-*L*-histidine	0.53	ES+	170	18	153	14	126, 109	14, 14	**3-*N*-Methyl-*L*-histidine**	FOOD OF ANIMAL

									ORIGIN
Trimethylamine-*N*-oxide	0.58	ES+	76	14	59	8	57, 42	74, 56	**Trimethylamine-*N*-oxide**	FOOD OF ANIMAL ORIGIN
Creatine	0.61	ES+	132	20	90	20	44, 43	20, 20	**Creatine**	MEAT
3,5-Dihydroxybenzoic acid	2.19	ES-	153	12	109	12	65	14	**3,5-Dihydroxybenzoic acid**	WHOLEGRAIN CEREALS
3-(3′,5′-Dihydroxyphenyl)propanoic acid	3.11	ES-	181	2	137	10	119, 95	14, 16	**3-(3′,5′-Dihydroxyphenyl)propanoic acid**	WHOLEGRAIN CEREALS
Enterolactone-glucuronide	7.50	ES-	473	20	113	20	297	20	Enterodiol	WHOLEGRAIN CEREALS
Enterodiol	8.34	ES-	301	20	253	20	106	20	-	-

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Chapter 4 – Discussion

The present thesis, entitled *“Development and Implementation of Educational and Empowerment Models to Promote Healthy and Sustainable Diets in University Students”,* emphasizes importance of developing integrated, innovative and evidence-based approaches to promote healthy and sustainable behaviors in university settings. Scientific literature widely recognizes that dietary behavior is determined by a complex interaction of individual, social and environmental factors, as described by socio-ecological models [1, 2]. Specifically, the university context represents a highly complex environment, characterized by decision-making autonomy, time constraints and a strong social influence that often leads to suboptimal food choices [2, 3].

In this scenario, in literature it is well demonstrated how non-integrated and single component interventions generally lead to insufficient results on determining lasting behavioral change, highlighting the need for multi-level and theory-driven strategies that target the sources of behavior simultaneously (capability, opportunity and motivation) [1]. Moreover, the interest towards the integration of digital tools and participatory approaches is raising, as it is considered as promising in increasing engagement and the efficacy of interventions, especially in a digital native population such as university students [4].

Based on this evidence, this thesis aimed to contribute to the development and evaluation of integrated approaches, combining environmental, technological innovation and educational strategies in real-world contexts.

In the first study, the role of food environment was investigated through the implementation of a multi-component nudging intervention in Parma's campus university canteen, including a large number of users in a real-life context of collective catering. This intervention was variably articulated and included multiple modifications of choice architecture trying to target all the sources of behavior [1]. Specifically, menu reordering targeted opportunity, the application of logos and educational posters acted on users' motivation, while informative posters intended to shape capability. Overall, the intervention showed a more pronounced effect on the reduction of food waste with significant changes in plate waste, while its impact on food choices was limited. These findings are consistent with literature evidence that indicates how nudging interventions lead to modest effects, typically limited to specific outcomes [5, 6].

In the second study, an innovative computer vision system for the recognition and quantification of food waste was developed and tested. It was applied in Parma's campus university canteen on a significant number of trays before and after consumption (n = 401). This system demonstrates good accuracy in both food recognition and quantity estimation. Regarding recognition, better accuracy was observed for full trays (Intersection over Union 92-93%) compared to those after consumption (IoU 70-77%) due to their greater visual complexity. Traditional methods for estimating food waste are often based on visual estimates or direct weighing; this contribution addresses one of the main methodological gaps highlighted in the literature, namely the need for more objective and scalable tools [7].

In the third study, the development of the Uniplate app through a co-creation process allowed us to obtain high levels of usability and acceptability, confirming the importance of participatory strategies to better address behavior change purposes and user’s needs. This result is aligned with the literature, highlighting that a multidisciplinary approach combined with the active participation of final users contributes to a better engagement for digital interventions [8]. This is further supported by the findings of the present study, which showed high levels of user satisfaction (approximately 89%) and a strong willingness to recommend the app (around 79%). The deliberated integration of specific Behavior Change Techniques (BCTs) represented a key strength of the study. In contrast to many mHealth nutrition applications where BCTs are identified post-hoc, the Uniplate app was explicitly designed to include a broad set of techniques from early stages of development [4]. This approach has allowed us to move beyond a logic based exclusively on self-monitoring and goal setting, as in most apps available on the stores, integrating instead elements such as action planning, knowledge development, and behavioral support strategies, with the aim of strengthening users' self-efficacy and promoting a more informed decision-making process.

Lastly, in the fourth study the efficacy of the Uniplate app in changing dietary behaviors was evaluated in a randomized controlled trial. Results highlighted positive results on primary and secondary outcomes. Specifically, a significant increase in fiber intake, driven by the increased intake of vegetables, was observed in the intervention group (approximately +6.2 g/day), compared to a decrease in the control group, confirming the study's main hypothesis. This finding was consistent with the app’s educational focus, which centers on plant-forward eating patterns and the “Healthy Plate” framework proposed by Harvard University [9]. The use of urinary markers for the objective validation of the observed changes represented a key an innovative element that helps fill a gap in the literature and strengthening the reliability of the findings.
These results suggest that personalized and theory-based digital interventions can effectively affect dietary behaviors, however their overall impact remains moderate. However, the relatively limited sample size, due to the complexity of the protocol and the need to collect biological samples, was a limit and may have affected results. Therefore, further research on larger cohorts is needed to further investigate the effect of the Uniplate app.

Overall, the four studies confirm that university students' eating behavior is the result of a complex set of determinants and that no single intervention can substantially impact students' eating habits. Instead, they demonstrate that an integrated approach involving environmental, technological, educational, and innovative monitoring interventions is necessary to impact university students' eating habits.

In this sense, this thesis contributes to the design of a multilevel model applicable to a real-world context, where the integration of environment, technology, and behavior represents a real lever for promoting sustainable change over time and supporting the transition toward healthier and more sustainable food systems within universities.

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Chapter 5 – Overall Conclusion

The present doctoral thesis, entitled *"Development and Implementation of Educational and Empowerment Models to Promote Healthy and Sustainable Diets in University Students"*, addresses the understanding and promotion of dietary behavior change in university settings.

It can be underlined that the findings of the current research project, which is based on four interrelated studies, support the evidence that university students' dietary behaviors are shaped by the interaction of individual, social, and environmental factors. Such complexity requires interventions which, to be effective, need to target the key determinants of dietary behavior: capability, opportunity, and motivation, in accordance with the COM-B model of the Behavior Change Wheel.

From an environmental perspective, the first study demonstrated that a multi-component nudging intervention in a real university canteen can effectively influence food waste reduction (significant reductions in total waste, logo-marked waste, and per capita side dishes have been observe during the intervention phase), although the impact on food choices was more limited and non-persistent.

The second study filled an important methodological gap by developing and validating the FLIC dataset and its related computer vision pipeline. Conventional methods of estimating food waste, such as visual estimation and weighing, are time-consuming, subjected to human errors, and difficult to scale up. The FLIC method, relying on pairs of images of full and residual trays, semantic segmentation, and digital density modeling, resulted in high accuracy for both full (IoU 92-93%) and residual trays (IoU 70-77%). This technique promises to be objective and scalable for monitoring and evaluating interventions.

The third and fourth studies focused on the Uniplate mHealth app, developed through a participatory co-creation process with university students and based on 21 evidence-based behavior change techniques. This user-centered approach yielded exceptional usability, acceptability, and engagement rates, reinforcing the effectiveness of multidisciplinary and multidisciplinary approaches in digital interventions. Importantly, the randomized controlled trial also showed significant effects of the app in changing certain dietary habits, such as an increase in dietary fiber intake of +6.2 g/day, mainly due to almost doubling vegetable consumption. These effects were also shown to be maintained at 12-week follow-up. Urinary biomarkers objectively correlated with these findings showed an increase in whole grain and plant-based metabolites and a decrease in animal-based metabolites. A slight improvement in Planetary Health Diet index and Mediterranean Diet score was also found in the intervention group.

In conclusion, these findings reinforce the idea that an intervention targeting individual determinants, although theoretically sound and highly engaging, may not be enough to induce significant and long-lasting behavioral changes without parallel changes in the individual environment. In this sense, this thesis contributes to building a multilevel intervention model applicable in real-world scenarios in universities, in which the integration of these aspects is considered a key factor in promoting long-term and sustainable behavioral changes in dietary habits and facilitating the transition towards healthy and sustainable food systems.

Chapter 6 – Future Perspectives

Based on these findings, several future perspectives can be outlined.
First, further studies should investigate the effectiveness of fully integrated interventions that simultaneously address all elements of the COM-B model of behavior. This is because the combination of different types of interventions, such as digital and environmental interventions could be more effective and lead to more lasting behavioral outcomes.
Second, further research should include larger and more diverse populations of university students, not only from a single academia, to allow result generalization for the target population. From this perspective, the relatively small sample size of the RCT study, partially due to the need to collect biological samples, highlights the need for large-scale multicenter studies that can confirm the findings of the present research or even achieve better results.
Third, the integration of objective measurement tools should be further expanded. For instance, the computer vision system could be integrated by default in the university canteen to enable scalable, real-time waste quantification. This would represent a significant step forward in improving the accuracy of waste quantification, minimizing reliance on manually collected data and enabling objective, real-time quantification of any further interventions. It would also enable menu optimization, allowing for less frequent serving of the most discarded dishes in favor of new recipes.
Furthermore, given the demonstrated satisfaction and potential of the Uniplate app, future research could extend the duration of exposure and include longer follow-up periods, as habit formation processes require extended time. Although the Uniplate app has already received substantial improvements after being tested in the RCT, it has the potential to incorporate further enhancements, such as the addition of indicators of the environmental impact of recipes, gamification elements, or the promotion of a student community, which could suggest new recipes and tips.

In summary, this thesis provides evidence demonstrating how significant and lasting changes in eating behavior can be achieved through the strategic integration of objective measurement tools, participatory educational approaches, and behavioral science. Universities represent "living laboratories," an ideal environment for designing and testing public health interventions. The challenge (and opportunity) now lies in the ability to scale up and make these models sustainable to maximize their impact on the general population.

About the author

WORK EXPERIENCE

Gen 2023 – Present **Ph.D. Student**

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June 2025 – Sept 2025 **Visiting Researcher**

- Dept. of Food and Drug, University of Parma, Parma, Italy
- Department of Pediatrics, University of California Los Angeles (UCLA)
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Apr 2022 – June 2022 **Pre-graduate intern**

- Dept. of Food and Drug, University of Parma, Parma, Italy
- Project: Nutritional status assessment throughout anthropometric measurements and food questionnaires in a rural context of Tanzania
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OTHER EXPERIENCES

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- Thesis co-supervisor for Bachelor and Master students

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- Member of the SINU Giocani group (Italian Society of Human Nutrition)

2023-2025

- Newsletter editor for Spoke 7 - OnFoods

PUBBLICATION

- Piccoli, F., Callegaro, D., Marelli, D., Buzzelli, M., Franchini, C., Stella, L., Bianco, S., Ciocca, G., Schettini, R., & Scazzina, F. FLIC: A Real-World Dataset for Visual Estimation of Food Leftovers in Canteens, Applied Sciences, Volume 16, Issue 11, 2026, Article 5465. MDPI. https://www.mdpi.com/2076-3417/16/11/5465

ORAL COMMUNICATIONS

May 10th, 2023

- Title of the presentation: *"La mensa del futuro tra sogno e realtà: parola agli studenti"*
  Aperitivi della conoscenza (University of Parma, Italy)

May 22nd, 2023

- Title of the presentation: *"Case study 8: OnFoods Project"*
  Food City Design Seasonal School (University of Parma, Italy).

Sep 11th, 2025

- Title of the presentation: *"The University of Parma's Approach to Healthy and Sustainable Food Practices"*
  A Research-Infused Lunch Series on Shaping Tomorrow's Food Practices (University of California Los Angeles UCLA, Los Angeles)

POSTER COMMUNICATIONS

Jun 8th, 2023

- Title: *"Assessment of the nutritional status, eating habits, and lifestyle of children enrolled in elementary schools in Parma: a prospective study"*
  XLIII SINU National Congress 2023

Jun 6th, 2024

- Title: *"Participatory design of solutions towards sustainable University canteens: an online cross-sectional survey"*
  XLIV SINU National Congress 2024

May 28th, 2024

- Title: *"Can a mobile health app promote healthy and sustainable eating among university students? Preliminary*

findings from a Randomized Controlled Trial"
XLV SINU National Congress 2025

Sep 14th, 2023

- Title: *"Evaluation, development and implementation of a mobile application as an educational and empowerment tool to promote healthy and sustainable diets in university students"*
  27° Workshop on the developments in the Italian Phd research on Food Science, Technology and Biotechnology

Sep 19th, 2023

- Title: "*Development and implementation of educational and empowerment models to promote healthy and sustainable diets in university students"*
  28° Workshop on the developments in the Italian Phd research on Food Science, Technology and Biotechnology

Sep 10th, 2023

- Title: "*Assessment of students' nutritional status and canteen menus in two schools in Tanzania"*
  16th European Public Health Conference 2023