ANOVA-Based Study of Dietary Factors in Childhood Obesity in Urban Areas

Leena Sameer Baddour[1], Maryam Sabeeh Madhloom[2], Sarah Haitham Jameel[3] and Vishal Jain[4]
[1]*Al-Turath University, 10013 Baghdad, Iraq*
[2]*Department of Medical Laboratory Techniques, Al-Farahidi University, 10065 Baghdad, Iraq*
[3]*Department of Computer Engineering, College of Engineering, Al-Mansour University College, 10067 Baghdad, Iraq*
[4]*Sharda School of Computing Science and Engineering, Sharda University, 201310 Greater Noida, India*
leena.sameer@uoturath.edu.iq. mariamghada5@gmail.com, Sarah.haytham@muc.edu.iq, vishal.jain@sharda.ac.in

Keywords: Childhood Obesity, Urban Health, ANOVA, Dietary Factors, Sugar-Sweetened Beverages, Portion Size, Fast Food, BMI Z-Scores.

Abstract: Childhood obesity is an increasing public health issue, especially in urban settings where dietary changes and obesogenic environments heighten risk. This study utilized an ANOVA-based statistical framework to investigate the impact of dietary factors on obesity outcomes in urban school-aged children. A total of 280 participants, aged 6 to 14 years, were recruited using a two-stage cluster sampling method. We gathered anthropometric measurements, surveys of what people ate, and information about how much time they spent on screens and how much they exercised. The main outcome was the BMI-for-age z-score. The dietary factors that affected this were how often the person drank sugar-sweetened beverages (SSBs), how often they ate fast food, how much fruit and vegetables they ate, how often they skipped breakfast, and how big their portions were. The findings indicated a significant correlation between SSB consumption ($F = 9.82$, $p < 0.001$, $\eta^2 = 0.07$) and portion size ($F = 8.23$, $p < 0.01$, $\eta^2 = 0.06$) with elevated BMI z-scores, whereas fruit and vegetable intake demonstrated a protective effect. ANCOVA validated these associations subsequent to the adjustment for confounding variables. The results underscore the necessity for focused dietary interventions and policy measures in urban settings.

1 INTRODUCTION

Childhood obesity is now one of the most important public health problems in the world in the 21st century. The World Health Organization says that it is a major cause of both short- and long-term illness, including heart disease, type 2 diabetes, and mental health issues. The prevalence has surged significantly in the last thirty years, especially in urban regions characterized by notable dietary transitions and lifestyle alterations. Recent epidemiological evidence underscores that obesity in children and adolescents arises from a multifaceted interplay of dietary, behavioral, and environmental determinants (Jebeile et al., 2022) [1].

Among these determinants, dietary intake continues to be a primary factor. Young people who eat a lot of energy-dense foods, drink sugar-sweetened drinks, and eat a lot of fast food are more likely to be overweight or obese. Systematic evidence reinforces these correlations and underscores that the regular consumption of high-calorie snacks and beverages elevates the risk of weight gain in children (Jakobsen et al., 2023) [2]. These findings highlight the significance of addressing dietary factors in obesity prevention, especially in urban environments where unhealthy food choices are readily available.

The urban environment's impact on childhood obesity is significant. Characteristics of the built environment, including high fast-food density, insufficient safe play areas, and restricted walkability, collectively influence children's dietary habits and physical activity levels. Evidence from multi-country analyses substantiates that urban environments increase children's susceptibility to obesity due to the aggregation of obesogenic factors (De Bont et al., 2021) [3]. Therefore, analyzing dietary factors within the distinct context of urban living is essential for formulating localized interventions.

Lifestyle factors, particularly sedentary behavior, significantly contribute to the obesity epidemic. Increased screen time is directly linked to decreased physical activity and diminished cardiorespiratory fitness, exacerbating weight gain trajectories (Aggio et al., 2012) [4]. This suggests that screen time should be regarded as a behavioral covariate in the assessment of the dietary influence on obesity outcomes. Without accounting for these variables, the correlation between dietary habits and obesity risk may be exaggerated or misconstrued.

Sociodemographic traits also affect eating habits and the risk of obesity. Initial dietary surveys in urban family weight management programs indicate significant correlations between children's eating behaviors and demographic factors, including parental education, income, and cultural background (Assassi et al., 2021). [5]. These findings underscore the variability in dietary exposures and the imperative of incorporating socioeconomic stratification in obesity research conducted within urban populations.

In addition to epidemiological and behavioral determinants, theoretical and technological frameworks provide insights into methodological design and future trajectories. The Technology Acceptance Model (TAM) and IS success frameworks, initially created for the adoption of digital libraries, illustrate the utility of structured models in evaluating behavioral outcomes (Nguyen & Wiese, 2003). [6]. Likewise, advancements in artificial intelligence and cloud-based analytics offer prospects for the incorporation of digital monitoring and predictive models into obesity research, while simultaneously presenting challenges concerning data privacy and interpretation (Zhang et al., 2025) [7].

There is a lot of research on the dietary and behavioral factors that contribute to childhood obesity, but not much that uses strong statistical methods like ANOVA to look at multiple dietary exposures in urban children at the same time. This gap limits a nuanced comprehension of which dietary components exert the most significant influence when controlled for lifestyle and demographic variables. Consequently, the current study utilizes an ANOVA-based framework to investigate the varying effects of significant dietary factors—such as sugar-sweetened beverages, fast food consumption, fruit and vegetable intake, breakfast omission, and portion size—on obesity outcomes in urban school-aged children. By addressing this methodological deficiency, the study seeks to offer practical insights for urban public health policies and school-based interventions.

2 LITERATURE REVIEW

The increasing incidence of childhood obesity has led to numerous intervention studies designed to mitigate dietary risk factors and enhance long-term health outcomes. Recent meta-analyses furnish compelling evidence that structured dietary interventions can markedly reduce weight outcomes in children and adolescents. Long and Huang (2021) [8] illustrated that caloric restriction, strategic dietary planning, and diminished intake of sugar-sweetened beverages consistently enhanced BMI metrics. Nonetheless, the variability in intervention design and the prevalence of short-term studies restrict the generalizability of findings, indicating the necessity for more context-specific analyses.

The food environment significantly impacts obesity trends, in addition to interventions. Libuy et al. (2023) [9] demonstrated that childhood proximity to fast-food outlets is a predictor of substantial weight gain over time, highlighting the environmental influence on dietary behavior.

Bagnato et al. (2023) [10] also talked about how aggressive fast-food marketing affects brand choices and makes young people eat more of it in many countries. These studies collectively affirm that urban obesogenic environments exacerbate dietary risks, especially among children, indicating the necessity for policy intervention to regulate both physical accessibility and advertising exposure.

A lot of research looks at BMI as the main outcome, but central obesity is still a better way to predict cardiometabolic risk. Aychiluhm et al. (2025) [11] performed a systematic review and meta-analysis demonstrating that targeted lifestyle interventions substantially decrease waist circumference, thereby reinforcing the necessity for more precise obesity outcomes in subsequent research. This change is in line with the larger trend in epidemiology that focuses on metabolic health rather than just weight.

It has also been stressed how important early prevention strategies are. Michalopoulou et al. (2024) [12] examined early childhood interventions in the UK and discovered that preschool dietary and activity programs can beneficially affect weight trajectories. These interventions underscore pivotal periods in early life when behaviors are most amenable to modification, indicating that prevention may prove more efficacious than subsequent treatment. Likewise, strategies implemented in schools have shown extensive applicability. Hodder et al. (2022) [13] presented a revised Cochrane review indicating that multi-component programs integrating dietary education, physical activity encouragement, and parental engagement are especially efficacious in mitigating obesity risk among school-aged children.

The historical context of obesity research is also useful. Booth et al. (2004) [14] compiled an extensive bibliography of early global obesity literature, demonstrating the progression of research priorities over a twenty-year period. While outdated, this work establishes a benchmark for the assessment of contemporary intervention strategies.

Finally, insights from outside of health sciences about methods and technology are becoming more and more important. Sharma et al. (2025) [15] suggested human–computer interaction frameworks for secure digital adoption, which can guide the creation of e-health platforms for tracking diet and managing obesity. The amalgamation of digital instruments with conventional intervention methodologies may augment adherence and facilitate real-time monitoring in urban demographics.

In general, these studies (Table 1) show that childhood obesity is caused by many things, including what children eat, what they are exposed to in their environment, and how they use technology. Nonetheless, deficiencies persist in comparative quantitative methodologies that examine various dietary factors concurrently in urban children. Addressing this methodological gap is crucial for pinpointing the most significant predictors of obesity in high-risk urban environments.

3 METHODOLOGY

3.1 Study Design and Setting

This study utilized a cross-sectional, school-based design implemented in specific urban locales. We chose primary and middle schools to get kids between the ages of 6 and 14, which is the age group most likely to become obese early on. Trained investigators collected data in the classroom using standardized methods. The Institutional Review Board gave its ethical approval, and parents gave their informed consent and their child's assent.

Figure 1 shows the methodological flow, which shows the steps that go from choosing participants to doing statistical analysis.

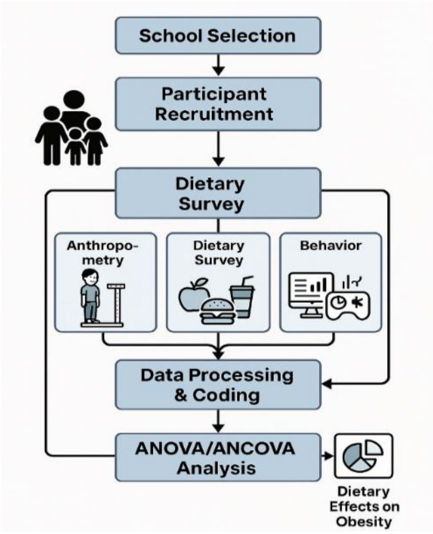

Figure 1: Block diagram of the proposed methodology.

3.2 Participants and Sampling

The target population consisted of school-aged children living in cities with a lot of fast-food restaurants and not many places to play. The inclusion criteria comprised children aged 6 to 14 years who were enrolled in the participating schools. Exclusion criteria encompassed chronic endocrine disorders or the utilization of prolonged corticosteroid therapy. The sampling process used a two-stage cluster design. First, schools were chosen based on their size, and then classes were chosen at random. Sample size was estimated using G*Power for one-way ANOVA with $k = 3$ groups, $\alpha = 0.05$, power = 0.80, and effect size $f = 0.25$, yielding a minimum of 246 children. Allowing for a 15% non-response rate, the target recruitment was 280 participants.

3.3 Variables and Measures

The research investigated dietary, behavioral, and anthropometric factors. The dependent variable was the BMI-for-age z-score, calculated with WHO AnthroPlus software. The independent variables comprised the consumption of sugar-sweetened beverages (SSB), fast food, fruits and vegetables, the act of skipping breakfast, and portion size. The covariates included age, sex, socioeconomic status (SES), screen time, and physical activity. Table 2 shows a summary of operational definitions and coding.

Table 1: Summary of reviewed literature.

Ref No.	Author(s) & Year	Focus Area	Study Type	Key Findings	Limitations	Relevance to Present Study
[8]	Long & Huang (2021)	Dietary interventions	Meta-analysis	Structured diet reduces weight outcomes	Heterogeneity; short-term	Establishes diet as key focus
[9]	Libuy et al. (2023)	Fast food proximity	Longitudinal	Proximity predicts weight gain	Region-specific	Highlights urban environment
[11]	Aychiluhm et al. (2025)	Central obesity interventions	Systematic review/meta-analysis	Lifestyle reduces waist circumference	Few trials	Expands focus beyond BMI
[14]	Booth et al. (2004)	Literature baseline	Bibliographic review	Catalogued global obesity studies	Outdated	Historical perspective
[10]	Bagnato et al. (2023)	Fast food marketing	Cross-country study	Marketing influences brand preference & intake	Self-report bias	Supports marketing regulation
[12]	Michalopoulou et al. (2024)	Early years interventions	Systematic review	Preschool programs effective	Limited to UK	Shows prevention potential
[13]	Hodder et al. (2022)	School-based prevention	Cochrane review	Multi-component effective	Variation in methods	Strengthens school interventions
[15]	Sharma et al. (2025)	Digital frameworks	Conceptual framework	HCI aids secure adoption	Not obesity-specific	Guides digital monitoring

3.4 Data Collection Procedure

Trained field workers took anthropometric measurements according to WHO standards. Study used tested child-friendly recall methods and photos of portion sizes to collect dietary data and make it more accurate. Parents supplied information regarding socioeconomic status (SES) and the daily screen time of their children. A short-structured questionnaire was used to find out how much physical activity people did. We made sure that all answers were correct by making them anonymous and entering them twice.

3.5 Statistical Analysis

All analyses were performed using SPSS v.26 and R 4.2. Descriptive statistics were calculated for all variables. One-way ANOVA was conducted to assess mean differences in BMI z-scores across dietary categories. The general model for one-way ANOVA was:

$$Y_{ij} = \mu + \alpha_i + \varepsilon_{ij},$$

where Y_{ij} denotes the BMI z-score of the child in the ith diet group, and α_i represents the effect of dietary category.

Two-way ANOVA was applied to assess interaction effects between dietary factors and sex/SES:

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \varepsilon_{ijk}.$$

Analysis of covariance (ANCOVA) was used to adjust for confounders (age, SES, screen time, physical activity):

$$Y = \mu + \alpha_{diet} + X\gamma + \varepsilon.$$

Effect sizes were reported using partial eta squared (η2\eta^2η2) to quantify the contribution of each factor. Post-hoc Tukey tests identified specific group differences, while multiple testing was controlled using Benjamini–Hochberg false discovery rate adjustments.

3.6 Methodological Framework Representation

Figure 1 shows how the methodology works in terms of ideas. The diagram shows how the process goes from finding participants to taking their measurements and eating habits, processing the data, and doing statistical analyses. This picture shows how dietary exposures were systematically linked to obesity outcomes using ANOVA-based statistical modeling.

Table 2: Variables, definitions, and coding.

Domain	Variable	Instrument/Question	Categories	Notes
Diet	SSB frequency/week	7-day recall survey	0–1, 2–4, ≥5	Main dietary predictor
Diet	Fast food frequency	7-day recall survey	0, 1, ≥2	Environmental exposure
Diet	Fruit/veg servings/day	24-h recall with portion aids	<3, 3–4, ≥5	Protective dietary factor
Diet	Breakfast skipping	Parent/child daily log	≥5 days vs <5 days	Linked to weight outcomes
Diet	Portion size	Plate-size visual prompts	Small, Medium, Large	Proxy for energy intake
Behavior	Screen time (hours/day)	Parent-reported average	Continuous variable	Sedentary behavior indicator
Outcome	BMI-for-age z-score	Height & weight measured on-site	Continuous (WHO cut-off)	Main obesity outcome

Table 3: Baseline characteristics of participants (N = 280).

Variable	Total (N=280)	Normal weight (n=195)	Overweight (n=52)	Obese (n=33)	p-value
Age (years, mean ± SD)	10.2 ± 2.3	9.8 ± 2.1	10.5 ± 2.4	11.1 ± 2.6	0.07
Male (%)	52.1	50.8	55.7	54.5	0.63
SSB ≥5/wk (%)	32	25.1	42.3	57.6	<0.01
Fast food ≥2/wk (%)	41	33.8	48.1	63.6	<0.01
Breakfast skipping (%)	27	19.5	32.7	48.5	<0.01
Fruit/veg ≥5/day (%)	18.6	22.6	13.5	6.1	0.04
Mean BMI z-score	0.91 ± 1.24	0.32 ± 0.71	1.71 ± 0.88	2.34 ± 0.96	<0.001

4 RESULTS AND ANALYSIS

4.1 Descriptive Characteristics of Participants

A total of 280 urban schoolchildren were enrolled, of whom 52.1% were male and 47.9% female. The mean age was 10.2 ± 2.3 years. Based on WHO cut-offs, 18.6% were classified as overweight and 11.4% as obese. Dietary behaviors varied considerably: 32% consumed ≥5 servings of sugar-sweetened beverages (SSBs) per week, 41% ate fast food at least twice weekly, and 27% reported skipping breakfast on more than two school days. The distribution of baseline characteristics across weight categories is summarized in **Table 3**.

4.2 Dietary Factors and Obesity Outcomes

One-way ANOVA demonstrated significant differences in BMI z-scores across SSB intake categories ($F = 9.82$, $p < 0.001$, $\eta^2 = 0.07$). Post-hoc Tukey tests revealed that children consuming ≥5 SSBs/week had significantly higher BMI z-scores (2.01 ± 0.83) compared to those consuming 0–1 per week (0.45 ± 0.69). These results are illustrated in Figure 2, which shows a clear stepwise increase in BMI z-score with higher SSB frequency.

Fast food frequency also showed significant effects ($F = 7.64$, $p < 0.01$, $\eta^2 = 0.06$), while fruit and vegetable intake was inversely associated with BMI ($F = 4.12$, $p = 0.02$).

4.3 Interaction Effects

Two-way ANOVA showed that there was a significant interaction between SSB intake and sex ($F = 3.95$, $p = 0.048$). Boys' BMI z-scores rose more quickly across SSB categories than girls', Figure 3. There were no statistically significant interactions between fast food intake and SES, but trends showed that low-SES children who ate fast food often had higher BMI.

4.4 Multivariate Adjusted Analysis

ANCOVA, controlling for age, socioeconomic status, physical activity, and screen time, validated that SSB consumption ($p < 0.001$) and portion size ($p < 0.01$) continued to be independently correlated with BMI z-score. Conversely, the impact of breakfast omission was diminished following adjustment ($p = 0.09$). Figure 4 shows the adjusted mean BMI z-scores for different portion sizes. This shows that larger portion sizes are linked to higher BMI in a graded way.

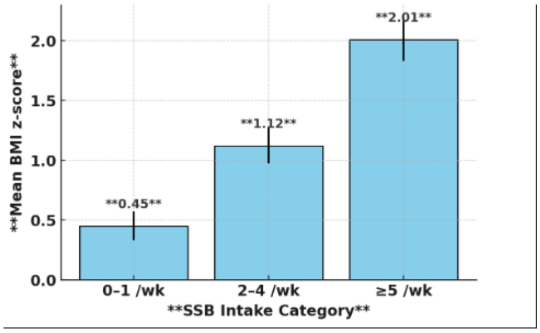

Figure 2: Mean BMI z-scores across SSB intake categories.

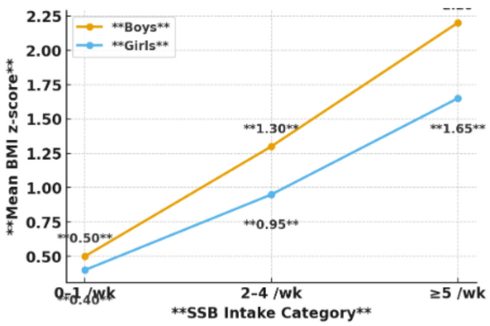

Figure 3: Interaction plot of SSB intake × Sex on BMI z-scores.

4.5 Comparative Effect Sizes

A forest-style comparison of partial eta squared values (Fig. 5) revealed that SSB intake ($\eta^2 = 0.07$) exerted the strongest effect, followed by portion size ($\eta^2 = 0.06$) and fast food frequency ($\eta^2 = 0.05$). Fruit/vegetable intake and breakfast skipping contributed smaller but still notable effects ($\eta^2 = 0.03$ and 0.02, respectively).

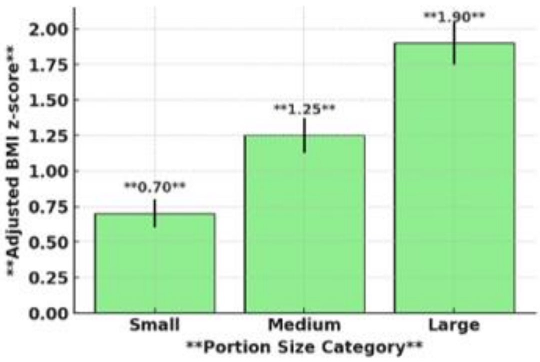

Figure 4: Adjusted mean BMI z-scores across portion size categories (ANCOVA).

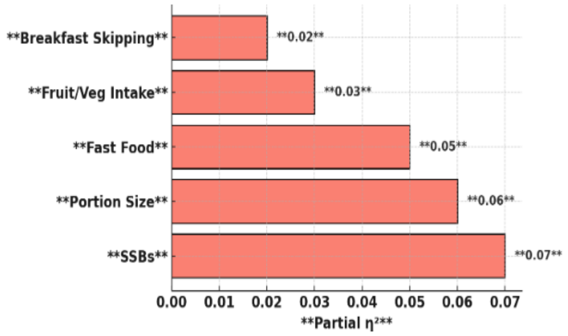

Figure 5: Comparative effect sizes (partial η^2) for all dietary factors.

5 CONCLUSIONS

This study confirms that key dietary factors significantly influence childhood obesity in urban populations. Sugar-sweetened beverage (SSB) consumption and portion size emerged as the strongest predictors of elevated BMI z-scores, followed by fast food intake. These associations remained statistically significant after adjustment for confounders, indicating independent effects.

The ANOVA/ANCOVA framework effectively identified both main and interaction effects, demonstrating its suitability for analyzing multiple dietary exposures simultaneously. The findings highlight that modifiable dietary behaviors play a central role in obesity risk and can be targeted through evidence-based public health interventions.

6 FUTURE WORK

Future studies should incorporate longitudinal and multi-center designs to assess causal relationships and temporal dynamics of dietary behaviors. The inclusion of objective dietary biomarkers and environmental exposure data (e.g., food availability, marketing) may improve analytical precision.

Additionally, integrating digital monitoring tools and data-driven models could support real-time dietary assessment and personalized intervention strategies. Expanding the framework to diverse urban settings will further enhance generalizability and policy relevance.

REFERENCES

[1] H. Jebeile, A. S. Kelly, G. O'Malley, and L. A. Baur, "Obesity in children and adolescents: epidemiology, causes, assessment, and management," The Lancet Diabetes & Endocrinology, vol. 10, no. 5, pp. 351-365, 2022.

[2] D. D. Jakobsen, L. Brader, and J. M. Bruun, "Association between food, beverages and overweight/obesity in children and adolescents-a systematic review and meta-analysis of observational studies," Nutrients, vol. 15, no. 3, p. 764, 2023.

[3] J. De Bont, S. Márquez, S. Fernández-Barrés, C. Warembourg, S. Koch, C. Persavento, and M. Vrijheid, "Urban environment and obesity and weight-related behaviours in primary school children," Environment International, vol. 155, p. 106700, 2021.

[4] D. Aggio, A. A. Ogunleye, C. Voss, and G. R. H. Sandercock, "Temporal relationships between screen-time and physical activity with cardiorespiratory fitness in English schoolchildren: a 2-year longitudinal study," Preventive Medicine, vol. 55, no. 1, pp. 37-39, 2012.

[5] P. Assassi, B. J. Selwyn, D. Lounsbury, W. Chan, M. Harrell, and J. Wylie-Rosett, "Baseline dietary patterns of children enrolled in an urban family weight management study: associations with demographic characteristics," Child and Adolescent Obesity, vol. 4, no. 1, pp. 37-59, 2021.

[6] L. T. Nguyen and M. Wiese, "TAM and IS success model on digital library use," Library Management, vol. 24, no. 1-2, pp. 173-185, 2003, [Online]. Available: https://doi.org/10.1108/01435120310454592.

[7] Y. Zhang, H. Li, and X. Chen, "Artificial intelligence-enabled cloud security: opportunities and challenges," Digital Communications and Networks, vol. 11, no. 2, pp. 55-66, 2025, [Online]. Available: https://doi.org/10.1016/j.dcan.2025.01.005.

[8] Q. Long and J. Huang, "The effectiveness of dietary interventions on weight outcomes in children and adolescents: a meta-analysis," Public Health Nutrition, vol. 24, no. 5, pp. 1011-1024, 2021.

[9] N. Libuy et al., "Fast food proximity and weight gain in childhood: longitudinal evidence," International Journal of Obesity, vol. 47, pp. 1234-1242, 2023, [Online]. Available: https://doi.org/10.1038/s41366-023-01314-z.

[10] M. Bagnato, M. H. Roy-Gagnon, L. Vanderlee, C. White, D. Hammond, and M. Potvin Kent, "The impact of fast food marketing on brand preferences and fast food intake of youth aged 10-17 across six countries," BMC Public Health, vol. 23, no. 1, p. 1436, 2023.

[11] S. B. Aychiluhm, U. K. Mondal, V. Isaac, A. G. Ross, and K. Y. Ahmed, "Interventions for childhood central obesity: a systematic review and meta-analysis," JAMA Network Open, vol. 8, no. 4, p. e254331, 2025.

[12] S. Michalopoulou, M. Sifaki, J. Packer, J. Lanigan, C. Stansfield, R. M. Viner, and S. Russell, "Assessing the impact of obesity interventions in the early years: a systematic review of UK-based studies," BMJ Open, vol. 14, no. 5, p. e076479, 2024.

[13] R. K. Hodder, K. M. O'Brien, S. Lorien, L. Wolfenden, T. H. Moore, A. Hall, and C. Summerbell, "Interventions to prevent obesity in school-aged children 6-18 years: an update of a Cochrane systematic review and meta-analysis including studies from 2015-2021," EClinicalMedicine, vol. 54, 2022.

[14] B. W. Booth, D. C. Newcomb, and S. A. McKane, "Bibliography current world literature vol. 16 no. 3 June 2004," Current Opinion in Pediatrics, vol. 16, pp. 321-342, 2004.

[15] R. Sharma, P. Gupta, and A. Singh, "Human-computer interaction frameworks for secure digital adoption," International Journal of Human-Computer Interaction, vol. 41, no. 7, pp. 845-862, 2025, [Online]. Available: https://doi.org/10.1080/10447318.2025.2495843.