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Intergenerational care and rural childhood obesity in the digital era: Based on screen exposure perspective

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ABSTRACT

Background: Rural Chinese children are experiencing increasing obesity rates, yet studies often neglect the impact of IT and screen media growth on obesity risks in the context of intergenerational care, leading to incomplete strategies for the digital era.

Methods: By comprehensively utilizing the data on rural children aged 6–17 from the China Family Panel Studies (CFPS) and the China Health and Nutrition Survey (CHNS), this study aims to test the logical chain and specific mechanisms regarding "intergenerational care - screen exposure - rural childhood obesity". We employ the Propensity Score Matching (PSM) and Generalized Propensity Score Matching (GPSM) methods to respectively address the self-selection biases associated with inter-generational care and children's screen exposure behaviors.

Results: 1) Intergenerational care significantly increases screen exposure among rural children. 2) Gender bias increases the risk of screen exposure for rural boys under intergenerational care. 3) Children with higher screen exposure levels are more affected by intergenerational care, which further undermines parental supervision. 4) Children's screen exposure leads to increased sedentary time and higher probability of purchasing unhealthy foods, thereby exacerbating obesity. This process is facilitated by enhancing preferences for snacks, fast food, and beverages, and weakening preferences for physical activity. 5) GPSM analysis indicates that children's screen exposure has an inverted "U"-shaped impact on unhealthy dietary preferences and a "U"-shaped impact on activity preferences. It results in a nonlinear positive impact of screen exposure on obesity. This study reveals a positive association between screen exposure and obesity, offering new insights into how intergenerational care in the digital era may elevate obesity prevalence through excessive screen time for rural children.

1. Introduction

The prevalence of childhood overweight and obesity has witnessed a rapid surge in recent years. WHO reports that in 2019, there were 38.2 million overweight or obese children under 5 globally, with Asia representing half the cases.[1] The number of overweight or obese children and adolescents aged 5 to 19 reached over 340 million, rising from 4% in 1975 to over 18% in 2016.[1] As the largest developing country in Asia, China is also grappling with a substantial problem of childhood overweight and obesity (Pan et al., 2021). Remarkably, childhood obesity is not an "urban disease" in China. There are evidences of increasing obesity among rural children. The 2015 China Nutrition and Chronic Diseases Report shows that rural children aged 6 to 17 have higher rates of overweight/obesity than urban children, with a greater disparity than in 2002 data.[2] By 2015, the rate of mild obesity or higher was 24.62% in rural children and 13.58% in urban children.[3] The 2020 China

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[1] We mitigate the impacts of sample loss, attrition due to age cohorts, and the intertemporal stability of obesity on the efficiency of fixed effects models by utilizing mixed cross-sectional data.

[2] The data on intergenerational care was cleaned by excluding anomalous samples where grandparents were reported as deceased but provided intergenerational care. For samples with missing or abnormal BMI values, the average values of age- and gender-matched peers from the same community were used for imputation, and the accuracy of height and weight records was checked. Additionally, samples with missing data on screen exposure and those with extreme exposure times were removed.

[3] 1 nursery school, 2 kindergarten/preschool, 3 elementary school, 4 middle school, and 5 high school/junior high school/technical school/vocational high school. Some of the control variables belong to ordered category variables, which are not continuous variables, but because they only play a control role in this paper, they are treated as continuous variables in the regression.

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Children's Development Report shows that overweight and obesity trends among urban and rural children from 2010 to 2019 were more severe in rural areas. According to studies, after 2005, rural children's BMI growth rate accelerated, with projections suggesting that without intervention, their risk of overweight/obesity could match or surpass urban rates by 2025 in China (Luo et al., 2023). Unhealthy eating patterns and insufficient physical activity are direct causes of childhood obesity. However, it is difficult to explain the more severe trend of obesity among rural children, the underlying complex mechanisms and social issues require further investigation.

Caregivers in early childhood critically impact children's health outcomes(Skouteris, Hill, Mccabe, Swinburn, & Busija, 2016). Changes in population and family structures have led to the rise of intergenerational care as a family caregiving model worldwide, including in the United States (Dunifon et al., 2018), the United Kingdom (Wheelock & Jones, 2002), Europe (Masfety et al., 2019), Singapore (Low & Goh, 2015), and so on. It is also prevalent in Chinese families, especially in rural areas (Tang et al., 2018; Chen et al., 2011). Given this, recent research increasingly examines childhood obesity through the lens of intergenerational care. Some limited studies propose that there is no significant relationship, and possibly an inverse correlation, between grandparental care and obesity in the children they care for (Pulgarón-Escobar, Patiño-Fernández, Sánchez, Carrillo, & Delamater, 2013; Lindberg et al., 2016). However, the majority of research suggests that grandparental care may contribute to or exacerbate obesity in the children they care for. Within this body of work, some studies offer evidence through descriptive analyses(Moschonis et al., 2010; Zong et al., 2015). Other studies have endeavored to explore the underlying mechanisms of this relationship. Related research can be categorized into two main branches: energy intake and energy expenditure. Regarding energy intake, findings indicate : Some offer unhealthy food to their grandchildren as a means of coddling, rewarding, or appeasing them (Young et al., 2018; Jongenelis & Budden, 2023). Some pressure or encourage children to eat based on biased notions of body image and an excessive focus on food (Jiang et al., 2007; Zhang et al., 2015). In terms of energy expenditure, studies have found that, some limit children's outdoor activities to reduce caregiving risks (He et al., 2018; Li et al., 2015), which lower children's energy expenditure. These findings enhance the evidence for the connection between grandparental care and childhood obesity. However, the current literature has methodological flaws in quantitative assessments, including imprecise definitions of 'intergenerational care' (e.g., conflating living with grandparents with caregiving), oversimplification of empirical validation methods (frequently relying on correlation analysis rather than causal inference), and one-sidedness in theoretical analysis (omitting factors related to intake or expenditure), which prevent a clear understanding of whether intergenerational care truly exacerbates childhood obesity and potential intervention pathways. Simultaneously, the influence of information technology and media growth on childhood obesity has not been thoroughly examined. Despite an association between more screen time and weight gain (Boone, Gordon-Larsen, Adair, & Popkin, 2007), the causal relationship between grandparental care, screen exposure, and obesity remains unexplored, limiting insights into the challenges of intergenerational care in the digital era.

The surge in digital technology and online apps has led to increased concerns about excessive screen exposure for children (Madigan, Browne, Racine, Mori, & Tough, 2019). Screen exposure encompasses a range of activities, including video watching, video gaming, internet browsing, and online social entertainment, facilitated through television, computers, and mobile phones (Slater, 2004). The China Child Development Report (2019) reveals that rural children average 108.18 min daily screen media usage outside school, exceeding the 88.40 min for urban children.[4] There is no evidence indicating that rural children prefer or possess more screens. The positive correlation between intergenerational care and children's sedentary behavior and media use suggests a potential relationship between it and children's screen exposure, which falls under the category of sedentary activities and includes various forms of media (Lu, Shen, Huang, & Corpeleijn, 2022; Elias et al., 2019). Despite limited research on the mechanisms of screen exposure leading to obesity, its link to conditions like obesity and hypertension has been observed (Reid ChassiaKos, Radesky, Christakis, Moreno, & Cross, 2016). Based on the evidence, we infer a potential causal relationship between intergenerational care, screen exposure, and obesity in rural children. Furthermore, given the addictive quality of screens(Lin et al., 2020), the impact of intergenerational care on childhood obesity through screen exposure may vary with different levels of screen time.

The research targets the effects of intergenerational care on rural childhood obesity, particularly concerning screen exposure, using data from the China Family Panel Studies (CFPS) and the China Health and Nutrition Survey (CHNS). Additionally, we examine the impact of intergenerational care on parental supervision. Furthermore, we utilize the law of diminishing marginal utility and Generalized Propensity Score Matching (GPSM) to explore how screen exposure affects dietary and exercise preferences and behaviors.

The study adds new insights into the effects of intergenerational care on rural childhood obesity and extends research on family education and addiction disorders, as well as providing insights into the link between screen exposure and obesity.

2. Intergenerational care, Children's screen time exposure and childhood obesity: what are the mechanisms?

2.1. Intergenerational care and childhood obesity

The introduction notes that a consensus among studies suggests an association between grandparental care and an increased prevalence of childhood obesity. This association is attributed to several factors, including a lack of dietary knowledge and beliefs in healthy eating practices(Tan et al., 2010; Zhang et al., 2015), cognitive biases regarding the perception of a healthy body shape(Jiang et al., 2007), and indulgent parenting behaviors(Martin, Albrechtsons, Macdonald, Aumeerally, & Wong, 2021). Although these conclusions have not been rigorously validated, the literature implies that grandparents may engage in unhealthy child-rearing practices.

2.2. Intergenerational care and children's screen exposure

Research on children's screen exposure primarily focuses on parents, with less attention given to the role of grandparents. Some studies note that certain parents are permissive with children's mobile device use, using screen time as a reward(Chiong & Shuler, 2010). Others show that some parents use interventions like supervision and time limits to restrict screen time (Nikken & Schols, 2015). While there's no direct evidence linking intergenerational care with increased screen time, differences in parental interventions could be related to their understanding of screen risks, parenting styles, and children's screen exposure (Decker et al., 2014). In rural China, grandparents typically have a more relaxed parenting style and often lack awareness of the potential harms of screen exposure. China's research indicates that intergenerational care may enhance children's online socialization (Hu & Ning, 2020), though the relationship with overall screen exposure is unclear since

[4] 0 illiterate, 1 elementary school graduate, 2 junior high school graduate, 3 high school graduate, 4 junior college/vocational school, 5 college/university, 6 master and above.

online socialization is only a fraction of potential screen time activities. Based on these literature, we suggest that the parenting practices of rural Chinese grandparents may contribute to an increased risk of children's screen exposure.

2.3. Children's screen exposure and obesity

The discourse on children's screen exposure and its profound impact on mental health issues, such as cognitive abilities, social-emotional skills, emotional regulation, and executive functions, has been extensive(Wan, Fitch-Bunce, Heron, & Lester, 2021; O'Toole & Kannass, 2021). In contrast, the discussion on the relationship between screen exposure and obesity is relatively superficial, primarily relying on correlational analyses to suggest a positive association between the two (Boone, Gordon-Larsen, Adair, & Popkin, 2007; Furthner et al., 2018). Regarding the underlying mechanisms, although some literature has elucidated possible mechanisms involving eating behaviors and energy expenditure(Robinson et al., 2017), these are mostly based on small-sample medical studies that fall short of providing causal explanations and empirical validation. Upon further review of the pertinent literature, it has been observed that some studies indicate a non-linear association between screen time and health outcomes, such as all-cause mortality and mental health(Foster et al., 2020; Przybylski & Weinstein, 2017). However, research on the non-linear association between children's screen exposure and obesity is limited, with a paucity of insights into the mechanisms driving such relationships.

Turning to the focus of our study, we have developed a theoretical analytical framework that examines the relationship between intergenerational care, screen exposure, and rural childhood obesity, as illustrated in Fig. 1.

Firstly, intergenerational care presents challenges in limiting rural children's screen exposure. In accordance with Social Learning Theory, observational learning and self-regulation play a crucial role in the formation of behavior (Bandura & Walters, 1963). Tolerant older adults who reduce their intervention in childrearing may serve as models for such behavior, leading children to learn lenient attitudes towards screen exposure. Concurrently, grandparents with lower authority may have a weakened role as models, which could affect their effectiveness in transmitting behavioral norms and self-control. So elderly individuals often struggle to enforce strict parenting practices and discourage inappropriate screen usage due to indulgence and a lack of authority. Secondly, intergenerational care often overlooks preventing rural children's access to screens. Risk Perception Theory suggests that individuals' cognition and evaluation of risks are influenced by their direct and indirect experiences with risk events, their understanding and interpretation of risk information (Slovic, 1987), limited education and inadequate information access among rural elderly individuals contribute to a lack of awareness regarding the health risks of excessive screen exposure in children. In fact, some elderly individuals perceive screen usage as a reward for good behavior (Pearson, Salmon, Crawford, Campbell, & Timperio, 2011). Thirdly, intergenerational care contributes to the increase in rural children's screen exposure. The demanding nature of child care may place a significant strain on elderly caregivers, negatively impacting their health(Komonpaisarn & Loichinger, 2019). Increased screen time leads to children's increased sedentariness, making intergenerational care less physically demanding for elderly caregivers. Thus, in line with the Theory of Rational Behavior, older individuals might be inclined to indulge in their children's screen exposure while providing care, resulting in reduced caregiving costs per unit of care time. In addition, coordinating outdoor leisure activities between the elderly and children can be challenging due to generational differences and varying physical abilities. In accordance with Protection Motivation Theory (Milne et al., 2000), elderly caregivers often choose to reduce outdoor exercise time for themselves and the children to fulfill caregiving responsibilities while minimizing elderly care risks in China (He et al., 2018). This shift towards indoor activities provides children with more opportunities to spend time on screens.

Hypothesis 1. Intergenerational care increases screen exposure for rural children.

Screen exposure, such as watching TV, using cell phones, and using computers, often requires a fixed position and posture. This can result in increased sedentary time and reduced energy expenditure for rural children. Moreover, screen exposure contributes to the issue of childhood obesity in rural areas through two main mechanisms.

Firstly, increased screen time exposes children to unhealthy food advertisements, which reinforce unhealthy dietary preferences and behaviors. Children's programs frequently feature advertisements for snacks, drinks, and desserts that are high in oil, fat, salt, and sugar (Kelly et al., 2019; De Jans, Van de Sompel, Hudders, & Cauberghe, 2019). Continuous exposure to these advertisements reinforces children's preferences for unhealthy foods, leading to increased purchase and consumption, thereby exacerbating the problem of obesity (Russell et al., 2019). Purchasing advertised foods, children can raise their peer status by embracing and exhibiting the cultural symbols within these food advertisements(Schor & Ford, 2007). This not only boosts the food's consumption utility but also gives it social value(Roberts & Pettigrew, 2013), reinforcing a preference for unhealthy foods among children. Secondly, screen exposure satisfies the immediate entertainment needs of rural children through audio-visual content, yet it concurrently reduces their time for exercise and encourages unhealthy dietary habits. This, in turn, diminishes children's preferences for outdoor activities and their involvement in physical activities (Felix et al., 2020). Furthermore, rural areas in China often lack outdoor equipment and sports programs, further restricting opportunities for children to engage in outdoor activities that offer immediate gratification.

Hypothesis 2. Rural children's screen exposure increases sedentary behavior and indoor time, directly contributing to obesity. Furthermore, it indirectly fosters obesity by decreasing outdoor activities and promoting the consumption of unhealthy advertised foods.

3. Methods

3.1. Study setting

To what extent does intergenerational care contribute to increased screen exposure among rural children? Are the effects of intergenerational care consistent across children with varying levels of screen exposure? Does intergenerational care reduce parental supervision? Specifically, how does screen exposure contribute to childhood obesity? Is the relationship between child screen exposure and obesity solely linear? Regrettably, these crucial questions remain largely unaddressed in existing research, which has largely overlooked the potential significant correlation between frequent screen media usage among rural children, the prevalence of intergenerational care in rural areas, and the higher rates of obesity observed among rural children.

We utilize China Family Panel Studies (CFPS) and China Health and Nutrition Survey (CHNS) to answer the above questions comprehensively. The former data for hypothesis 1 and the latter one for hypothesis 2. The reasons are as follows.

Firstly, evaluating intergenerational care is complex due to the collection time and questionnaire design of the CHNS data. The CHNS survey determines intergenerational care based on three questions: "Was the child cared for by someone outside the household last week?", "Was the care provided at the paternal grandparents' home last week?", and "Was the care provided at the maternal grandparents' home last week?".[5] Crucially, the CHNS data collection is concentrated in the

[5] 1 this village council 2 another village council 3 another village/town 4 none, the same code definition for the village recreation site situation.

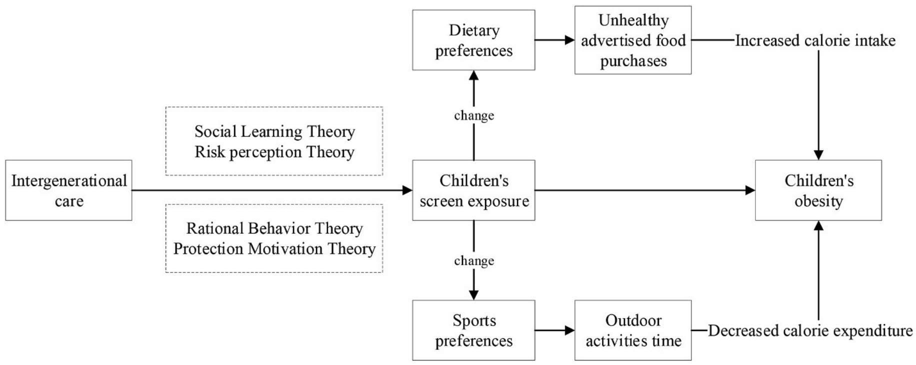

Fig. 1. Theoretical analysis framework.

second half of the year, coinciding with the return of migrant workers to China. This timing may introduce non-random measurement errors. While respondents may report children being cared for at grandparents' homes, such responses denote only the location of care and do not ipso facto indicate grandparental involvement. In contrast, the CFPS identifies intergenerational care by posing questions such as "Who is the primary caregiver for children during the day in general?" and "Who is the primary caregiver for children at night in general?".[6] To ensure methodological rigor, the first step is to use CFPS data to verify whether screen exposure is a mechanism variable of intergenerational care leading to childhood obesity.

Secondly, both datasets include screen exposure information, but only CHNS collects data on two specific mechanism variables in hypothesis 2: "Outdoor activities time" and "Unhealthy advertised food purchases". Having confirmed the chain of "intergenerational care - > screen exposure - > childhood obesity" via CFPS data, we employed CHNS data to conduct a thorough analysis of the direct and indirect mechanisms by which screen exposure contributes to childhood obesity.

3.2. Study sample

CFPS is a nationally representative longitudinal survey of households in China, designed and implemented by the Institute of Social Science Survey (ISSS) at Peking University. Its aim is to reveal changes in Chinese society, economy, demography, education, health, and other areas. The CFPS conducted its initial baseline survey in 2010, subsequently completing four waves of comprehensive follow-up surveys in 2012, 2014, 2016, and 2018. These surveys utilized a multistage probability-proportional-to-size (PPS) sampling approach. The survey covered 25 provinces, cities, and autonomous regions across China, excluding Qinghai, Inner Mongolia, Tibet, Xinjiang, Ningxia, Hainan, Hong Kong, Macao, and Taiwan.

CHNS is an collaborative project between the Caroline Population Center at the University of North Carolina and the National Institute of Nutrition and Food Safety at the Chinese Center for Disease Control and Prevention. It utilizes a multistage random cluster sampling technique, stratified by income and weighted. This survey has been carried out in 1989, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015. The main survey encompasses nine provinces: Guangxi, Guizhou, Heilongjiang, Henan, Hubei, Jiangsu, Liaoning, and Shandong.[7] Restricted by the unavailability of community variable indicators in the CHNS dataset post-2011 and the absence of permission to access subsequent data, our analysis is confined to data through 2011. Although the data is relatively outdated, it will not affect the research conclusions. Given China's media equipment development, the increase in screen accessibility for rural children in 2023 versus 2011, the worsening aging problem in rural areas, the diversification of video food advertising, and the better development of the snack processing industry, the conclusions from the CHNS data remain robust, if not strengthened, by these contextual factors.

In view of these considerations, we have employed three-stage mixed cross-sectional data from CFPS for the years 2014, 2016, and 2018, as well as CHNS for the years 2006, 2009, and 2011.[1] The study primarily focuses on children aged 6–17 residing in rural areas. Following the exclusion of outliers and missing values,[2] the CFPS dataset includes 3224 samples, and the CHNS dataset contains 1990 samples.

3.3. Data collection

3.3.1. Explained variable

"Childhood obesity" was defined as 1 for obesity children and 0 otherwise. Zero values serve as the reference group in regression; this applies to other binary variables elsewhere. Given children's ongoing growth and development, applying adult obesity standards is not suitable. We use Chinese Health Commission's screening standards for overweight and obesity in school-aged children and adolescents (WS/T 586–2018) , the standard divides the BMI into intervals based on the gender and age of children.[8] Both Hypothesis 1 and Hypothesis 2 in the study focus on childhood obesity as the dependent variable.

3.3.2. Explanatory variable

3.3.2.1. Intergenerational care. The CFPS survey queries the primary caregiver's identity during both day and night, posing the questions "Who is the primary caregiver during the day?" and "Who is the primary caregiver during the night?" to ascertain caregivers. The response answers include "grandparents, father, mother, daycare/kindergarten, self-care, babysitter, and others". We specifically examine the comparison between intergenerational care and parental care, thus excluding the remaining four caregiving arrangements. If the child was primarily cared for by grandparents during the day or at night, we assigned a value of 1 to the "Intergenerational care"; otherwise, the value was 0.

3.3.2.2. Child screen exposure. For hypothesis 1, the variable "Child Screen Exposure" was utilized to quantify child screen time. The inquiry was structured as: "How many hours per week do children spend watching TV, movies, and other video content via various platforms during regular weeks, excluding holidays?". It is crucial to note, that the CFPS data might underestimate the impact of intergenerational care on rural children's screen exposure for several reasons. Firstly, in 2014, the Internet penetration rate in rural China was 28.8%, which rose to 38.4% by 2018.[9] However, the CFPS does not explicitly account for internet-related screen exposure activities, which could result in an underestimation of the recorded screen exposure. Secondly, children's screen

[6] 0 rarely, 1 less often, 2 sometimes, 3 often, 4 usually.
[7] 1 disliked it very much, 2 didn't like it much, 3 neutral, 4 liked it somewhat, 5 liked it a lot.

activities are not always supervised, which may further contribute to discrepancies in reported screen exposure. Lastly, children's actual screen exposure levels may be higher during holiday periods. Notwithstanding these possible underestimations, they are not anticipated to substantially affect the study's foundational conclusions.

For hypothesis 2, "Child Screen Exposure" is measured by the CHNS, which calculates the average daily hours children devote to sedentary activities during weekdays and weekends separately. To comprehensively represent the screen exposure aspect of sedentary activities, we assigned a weighted mean to "Child Screen Exposure" based on the duration of activities highly associated with screen exposure. These activities encompass watching TV, videos, movies, or streaming TV programs online or on smartphones, playing video games, browsing the internet, chatting online, and playing computer games. It is crucial to mention that CHNS data offers a more comprehensive measurement of screen exposure compared to CFPS data, incorporating variables for video games and internet socializing during the calculation of screen exposure. Nonetheless, this incorporation does not cause any directional bias in the baseline survey results.

3.3.2.3. Mechanism variables. The mechanism variables in this study are "Outdoor activities time" and "Unhealthy advertised food purchases". The former is a continuous variable, with the CHNS data recording the frequency and duration of an individual's engagement in physical activities. This information is then used to calculate a child's total weekly outdoor time. The latter is a binary variable, with the CHNS data examining the frequency of children purchasing food or drinks advertised on TV, both independently and with their parents. The frequency is categorized as "<1 time/month, 1–3 times/month, 1–2 times/week, 3–4 times/week, ≥5 times/week". For analysis, we combined the two sources of purchase and selected the highest frequency between self-purchase and parental purchase. If the frequency is "<1 time/month, 1–3 times/month", the variable "Unhealthy advertised food purchases" is assigned a value of 0; otherwise, it is assigned a value of 1.

3.3.3. Covariates variable

For hypothesis 1, in addition to the main variables of interest, control variables were included in model 1 and 2 based on previous research. Control variables included child-specific characteristics (gender, education), household attributes (average parental education, parental residence, weight status, annual income, sibling count, food expenditure), and fixed effects for province and year to adjust for regional and temporal variation. For model 3, control variables encompassed child attributes (gender, education) and household factors (education expenditure, annual income, parental education, screen exposure, residence status, sibling count), with province and year fixed effects included. Descriptive statistics of the variables are presented in Table 1.

For hypothesis 2, Additional control variables were incorporated from prior research, covering community, family, and individual child characteristics. Community variables included supermarkets, fast food restaurants, and leisure activity sites. Family characteristics were represented by parents' weight status, education, income, and sibling count. Individual child attributes included gender, education, and walking time to school. Province and year fixed effects were also controlled for. Descriptive statistics for all variables are presented in Table 2.

Table 1
hypothesis 1 variable statistics.

Variables	Variable definition and assignment	Mean	SD	Min	Max
Explained variables					
Childhood obesity	1 = yes, 0 = no	0.17	0.38	0.00	1.00
Core explanatory variables					
Intergenerational care	Existence of intergenerational care, 1 = yes, 0 = no	0.40	0.49	0.00	1.00
Mechanism Variables					
Child screen exposure	Child's weekly hours of screen exposure, hours/week	11.35	9.35	0.00	70.00
Other Variables					
Child gender	Gender, 1 = Male, 0 = Female	0.54	0.50	0.00	1.00
Physical commuting time to school	One-way road physical travel time to school, hours	0.16	0.20	0.00	2.00
Child education level	School-age, code 1~5[3]	3.01	0.39	1.00	5.00
Child education expenses	Log annual household education expenditure, Yuan/per year	6.23	1.96	0.00	10.31
Number of siblings	Number of siblings aged 18 and under	2.00	1.06	1.00	8.00
Average education level of parents	Average years of parental education, years	5.83	3.94	0.00	16.00
Annual household income	Log annual net household income, yuan/year	10.16	1.48	0.00	13.60
Father screen exposure	Weekly screen exposure hours, hours/week	6.72	8.05	0.00	56.00
Mother screen exposure	Weekly screen exposure hours, hours/week	7.16	8.49	0.00	70.00
Father residence situation	Months at home, months/year	5.66	4.58	0.00	12.00
Mother residence situation	Months at home, months/year	6.51	5.09	0.00	12.00
Household food expenditure	Log annual household food expenditure, Yuan/per year	9.05	1.57	0.00	11.88
Parental weight status	Average parental BMI, kg/m^2	23.05	2.48	16.16	35.16

3.4. Data analysis

3.4.1. Benchmark regression model

For hypothesis 1, To investigate the impact of intergenerational care on screen exposure and obesity among rural children, we developed three models. Model 1 examined the relationship between intergenerational care (as the main explanatory variable) and childhood obesity (as the dependent variable). Model 2 expanded on Model 1, incorporating both intergenerational care and child screen exposure as primary explanatory variables while keeping childhood obesity the dependent variable. Model 3 separately investigated the relationship between intergenerational care (as the independent variable) and child screen exposure (as the dependent variable).Table. 3

$$\text{Probit}(Ofat_{it}=1)=\alpha_0+\alpha_1 C_{it}+\alpha_k Z_{it}+\varepsilon_{it} \tag{1}$$

$$\text{Probit}(Ofat_{it}=1)=\alpha_0+\alpha_1 C_{it}+\alpha_2 T_{it}+\alpha_k Z_{it}+\gamma_{it} \tag{2}$$

$$T_{it}=\beta_0+\beta_1 C_{it}+\beta_k X_{it}+\mu_{it} \tag{3}$$

In the equation, i and t denote the i_{th} respondent and the t_{th} year, respectively. *Ofat* represents "Childhood obesity", C represents "Intergenerational care", T represents "Child screen exposure", and Z and X represent the control set. α and β are parameters to be estimated, while ε, γ, and μ are random error terms.Table. 4

For hypothesis 2, to examine the relationship between child screen exposure and childhood obesity, we designated "Child screen exposure" as the primary explanatory variable and "Childhood obesity" as the dependent variable. Furthermore, we incorporated "Outdoor activities time" and "Unhealthy advertised food purchase" as intermediate variables in model 4 to 7. The models were designed to elucidate the underlying mechanism of the impact of child screen exposure on childhood obesity.Table. 5

Table 2
Hypothesis 2 variable statistics.

Variables	Variable definition and assignment	Mean	SD	Min	Max
Explained variables					
Childhood obesity	Whether obese, 1 = yes, 0 = no	0.05	0.21	0.00	1.00
Core explanatory variables					
Child screen exposure	Screen exposure hours, hours/day	2.15	1.42	0.00	9.75
Mechanism Variables					
Unhealthy advertised food purchase	Frequency of children buying advertised unhealthy foods, 1 = often purchases, 0 = almost no purchases	0.48	0.50	0.00	1.00
Outdoor activities time	Children's weekly Outdoor activities time, hours/week	0.93	2.33	0.00	28.12
Other Variables					
Child physical commuting time to school	Physical travel time per day to school, hours/day	0.08	0.21	0.00	3.00
Child educational attainment	Years of education, years	5.77	2.88	0.00	15.00
Child gender	1 = Male, 0 = Female	0.56	0.50	0.00	1.00
Number of siblings	Number of siblings aged 18 and under	1.56	0.70	1.00	5.00
Annual household income	Log of total annual household income, Yuan/year	8.25	0.94	6.91	11.51
Parental weight status	Average parental BMI, kg/m^2	23.22	2.53	16.72	41.22
Parental education level	Highest level of parental education, code 0~6[4]	1.95	1.02	0.00	5.50
Parents working outside the home	at least one parent works outside the home, 1 = yes, 0 = no	0.16	0.36	0.00	1.00
Village supermarket situation	The nearest supermarket to our village, code 1~4[5]	2.79	1.07	1.00	4.00
Village fast food restaurant situation	fast food restaurants near the village, 1 = yes, 0 = no	0.20	0.40	0.00	1.00
Village recreation site situation	The closest recreation site to our village, code 1~4	2.58	1.19	1.00	4.00
Number of village Internet cafes	Numbers	1.63	3.45	0.00	30.00
Child room TV	Availability of TV in the room, 1 = yes, 0 = no	0.13	0.34	0.00	1.00
Home TV Restrictions	Constraint on the frequency of children's television viewing time, code 0 to 4[6]	1.97	1.24	0.00	4.00
Child fast food preferences	Preference level, code 1~5[7]	3.33	1.19	1.00	5.00
Child snack preferences		3.51	1.09	1.00	5.00
Child beverage preferences		3.75	0.94	1.00	5.00
Child fruit preference		4.18	0.80	1.00	5.00
Child vegetable preference		3.86	0.91	1.00	5.00
Child sports preferences		3.71	1.10	1.00	5.00

Table 3
Intergenerational care and obesity in rural children.

Variables	(1) Childhood obesity	(2) Childhood obesity
Intergenerational care	0.050*** (11.771)	0.048*** (11.193)
Child screen exposure		0.001*** (4.299)
Child gender	0.021** (2.516)	0.020** (2.324)
Child education level	−0.143*** (−12.118)	−0.141*** (−12.291)
Number of siblings	0.016*** (5.155)	0.016*** (5.248)
Physical commuting time to school	0.003 (0.053)	0.003 (0.064)
Average education level of parents	−0.006*** (−5.247)	−0.006*** (−5.417)
Parental weight status	0.010*** (5.103)	0.009*** (5.283)
Household food expenditure	−0.002 (−0.252)	−0.002 (−0.251)
Annual household income	−0.005** (−2.455)	−0.006** (−2.519)
Father residence situation	−0.001 (−0.314)	−0.001 (−0.336)
Mother residence situation	−0.001 (−0.295)	−0.001 (−0.292)
Time effect	Control	Control
Regional effect	Control	Control
Log-likelihood function value	−1388.276	−1386.876
adjusted R2	0.068	0.069
N	3224	3224

Note: (a) *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; (b) z-values under robust standard errors are in parentheses.

Table 4
Rural children's screen exposure and intergenerational care.

Variables	(1) Child screen exposure	(2) Older adult screen exposure
Intergenerational care	1.509*** (4.101)	3.730*** (12.510)
Control variables	Control	Control
Time effect	Control	Control
Regional effect	Control	Control
Constant term	16.809*** (6.414)	0.515 (0.150)
F-statistic	14.470	13.503
R2	0.139	0.110
N	3224	3224

Note: (a) *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; (b) t-values under robust standard errors are in parentheses.

Table 5
Gender heterogeneity result.

Variables	(1) Boy	(2) Girl
Intergenerational care	1.032** (2.187)	0.763 (1.598)
Control variables	Control	Control
Time effect	Control	Control
Regional effect	Control	Control
Constant term	22.101*** (5.470)	18.198*** (5.587)
R2	0.121	0.125
F-statistic	7.791	7.352
N	1748	1476

Note: (a) *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; (b) t-values under robust standard errors are in parentheses.

$$\text{Probit}(Ofat_{it} = 1) = \delta_0 + \delta_1 T_{it} + \delta_k Z_{it} + \nu_{it} \tag{4}$$

$$\text{Probit}(Buy_{it} = 1) = \lambda_0 + \lambda_1 T_{it} + \lambda_k Z_{it} + \varphi_{it} \tag{5}$$

$$Spo_{it} = \eta_0 + \eta_1 T_{it} + \eta_k Z_{it} + \varsigma_{it} \tag{6}$$

$$\text{Probit}(Ofat_{it} = 1) = \theta_0 + \theta_1 T_{it} + \theta_2 Buy_{it} + \theta_3 Spo_{it} + \theta_k Z_{it} + \tau_{it} \tag{7}$$

Buy represents "Unhealthy advertised food purchases", *Spo* represents "Outdoor activities time", and *Z* represents the control variables of the aforementioned models. δ, λ, η, and θ are parameters to be estimated, while ν, φ, ς, and τ are random error terms.

3.4.2. Robustness check

For hypothesis 1, we employed the following methods to test the results, see Appendix 1.

(1) Tobit model. Due to a left-censored and constrained dependent variable with no screen exposure, OLS regression may not yield valid results. Hence, model 3 was re-estimated with the Tobit model (see Table A1 cols. 1).
(2) Joint fixed effects. Although we controlled for regional and time fixed effects, potential oversight of region-specific variables over time could bias the results. To account for regional trend effects, following existing research (Guimarães & Portugal, 2010), we replaced the fixed effects in model 3 with a combined region-year fixed effect. This was done through two strategies: province-year fixed effects and county-year fixed effects (see Table A1 cols. 2–3).
(3) PSM method. Intergenerational care is affected by children's age, health, income, parenting time, and grandchild quantity and gender, implicating selection bias. We addressed this with Propensity Score Matching (PSM) to obtain matched samples. In Chinese culture, after marriage, most women reside with their husbands(ZHANG, 2003), typically resulting in paternal grandparents providing intergenerational care. Consequently, age and health of paternal grandparents served as proxies for grandparental care, with controls for child's gender, sibship size, income, and residency. PSM identified these as covariates, with intergenerational care as the treatment, using a kernel matching method and a 0.05 bandwidth. Tobit regression was used for model 3 estimation on the matched sample, as shown in Table A1 cols. 4 and Table A2.

For hypothesis 2, We use the following methods to verify the robustness, see Appendix 2.

(1) Explained variable substitution. We have expanded the definition of childhood obesity to include overweight and obesity, and have re-estimated the impact of screen exposure on it, see Table A3 (cols. 1–2).
(2) Joint fixed effects. For the same reasons as those mentioned in hypothesis 1 for robustness testing, we revised the model by replacing district and time fixed effects with province-year fixed effects, see Table A3 (cols. 3–4).
(3) GPSM. Consistent with intergenerational care behaviors, children's screen exposure may be subject to self-selection bias. We adopted the Generalized Propensity Score Matching (GPSM) method (Hirano & Imbens, 2004), to address the limitations of traditional PSM only for binary treatments. To standardize comparisons, drawing on existing research (Guardabascio & Ventura, 2014), children's screen exposure was normalized by dividing by its maximum value, adopting the method suggested by. After that, We referred to relevant research (Imbens, 2000), utilized treatment effect and average dose-response function methods to evaluate the effect of child screen exposure on obesity, with GPSM model specified as a second-order polynomial. Regression results for the Fractional Logit model are presented in Table A4; GPSM equilibrium test results are provided in Table A5.

3.4.3. Expanded analysis

For hypothesis 1, considering the gender heterogeneity in the risk of screen exposure. Due to multiple reasons such as the concept of raising son to prevent aging and the power of rural clans(Murphy et al., 2011; Zhang & Ma, 2017), "son preference" remains deeply rooted in traditional socio-economic development, potentially persisting in rural areas. We perform gender group regression on Model 3, results see in Table 5.

For hypothesis 2, Amidst screen exposure's addictive potential, our analysis of intergenerational care prompts two critical queries: First, does the impact of such care on children vary with screen exposure levels? Second, does intergenerational care lessen the restrictive influence of parental supervision on screen time, irrespective of the level of screen exposure? To this end, we utilize quantile regression and interaction term models, results see in Tables 6 and 7.

Table 6
Screen exposure hazards for children in intergenerational care: based on quantile regression.

Variables	(1) 25%	(2) 50%	(3) 75%
Intergenerational care	1.072*** (3.534)	1.364*** (3.235)	2.346*** (3.500)
Control variables	Control	Control	Control
Time effect	Control	Control	Control
Regional effect	Control	Control	Control
Constant term	6.783* (1.769)	13.825*** (3.007)	22.447*** (6.002)
N	3224	3224	3224

Note: (a) *p < 0.1; **p < 0.05; ***p < 0.01; (b) Standard error t-values are in parentheses; (c) Control variables are as in Table 6; (d) Estimates are derived from bootstrap iterations 200 times.

Table 7
Screen exposure risks for children in intergenerational care: Variations by quartiles and parental home status.

Variables	(1) 25%	(2) 75%	(3) 25%	(4) 75%
Mother residence situation	−0.131*** (−4.103)	−0.410*** (−6.739)		
Father residence situation			−0.007 (−0.220)	−0.005 (−0.079)
Intergenerational care × Mother residence situation	0.048 (0.806)	0.249** (2.103)		
Intergenerational care × Father residence situation			0.018 (0.286)	0.268** (2.018)
Intergenerational care	0.781* (1.750)	0.024 (0.025)	0.937** (2.192)	0.089 (0.102)
Remaining control variables	Control	Control	Control	Control
Constant term	6.982*** (6.443)	17.844*** (6.787)	6.717*** (5.988)	17.863*** (6.682)
N	3224	3224	3224	3224

Note: (a) *p < 0.1; **p < 0.05; ***p < 0.01; (b) t-values under standard errors are in parentheses.

4. Results

4.1. Descriptive results

Table 1 shows that 40% of rural Chinese children from 2014 to 2018 received intergenerational care, suggesting widespread adoption of this care model in rural areas. However, the average weekly screen time for children in the sample exceeded 11 h, nearly reaching the 2-h daily limit recommended by the Chinese Physical Activity Guidelines (2021). The actual screen time may be higher due to CFPS lack of detailed internet-related screen activity data and the unsupervised nature of rural children's screen exposure. CHNS data in Table 2 further supports this, revealing that the average daily screen time for rural children was over 2 h from 2006 to 2011. The gender distribution in Tables 1 and 2 is balanced.

4.2. Intergenerational care and screen exposure, rural childhood obesity

(1) Intergenerational care and obesity in rural children. First, we preliminarily assessed the impact of children's screen exposure on exacerbating childhood obesity via intergenerational care.

Table 3 presents the marginal Probit regression results for models 1 and 2. Findings suggest that intergenerational care substantially raises the probability of obesity among rural children, with an increased likelihood of 5% compared to children without intergenerational care ($p < 0.01$), as shown in column 1. Child screen exposure serves as an intermediary through which intergenerational care affects rural childhood obesity. When controlling for screen exposure, the coefficient for intergenerational care reduces but remains significant.

(2) Intergenerational care and rural child screen exposure. Table 4 shows OLS regression results based on model 3. Intergenerational care increases rural children's screen time by 1.509 h/week($p < 0.01$), a figure that may understate due to the low statistical value of CFPS data on children's screen exposure. Additionally, it increases older adults' screen time by 3.73 h/week($p < 0.01$), numerically a stronger effect. Potential reasons include: Older individuals typically have more free time than school-aged children, theoretically leading to more screen time. Grandchildren's screen exposure may encourage older adults to follow suit, further increasing their screen exposure. Additionally, filial piety practices in rural China may lessen supervision and constraints on older adults(Guo, Gao, Sun, & Feng, 2020), potentially exacerbating screen dependency and addiction, thus resulting in relatively longer screen times for elderly caregivers.

(3) Gender differences in the impact of intergenerational care. Table 5 reveals that among rural boys, the relationship between intergenerational care and screen exposure is stronger, the boys' group coefficient is 1.032 ($p < 0.05$), indicating a significant gender impact on ATE, while the girls' group coefficient of 0.763 is statistically insignificant ($p > 0.1$). Despite girls having higher body fat rates at birth, rural boys experience higher and faster rising obesity rates (Zhang et al., 2016). Gender disparities in screen exposure risk could contribute to this discrepancy. Associations between screen exposure and obesity may negatively affect learning, social skills, and emotional regulation, impeding children's human capital and personality development. Ultimately, gender disparities in intergenerational care's impact on rural children's screen exposure could exacerbate the gender gap in income, social capital, and competencies over time.

4.3. Intergenerational care and child screen exposure, parental supervision: based on addiction

Table 6 illustrates that intergenerational care is more harmful to rural children at greater exposure levels, the 75th percentile coefficient is 2.346, the highest. Due to the immediate utility, media products like TV, cell phones, and digital material are addictive (Sussman & Moran, 2013). Increased screen exposure fosters children's addiction. The previous theoretical analysis section pointed out that, grandparents struggle to curb, are inattentive, and are motivated to augment children's screen exposure. heightened addiction intensifies all three effects. Table 7 shows that intergenerational care modulates children's screen exposure in the presence of parents, with mothers exerting greater constraint than fathers, consistent with Chinese gender roles. The constraint is reduced by intergenerational care, especially for fathers.

4.4. The impacts and mechanisms of screen exposure on obesity in rural children

To probe the mechanism linking screen exposure and childhood obesity, we analyze CHNS data to deepen our understanding of Hypothesis 2. Table 8 presents results from models 4 to 7, with outdoor activity time as a continuous variable analyzed via OLS regression and the remaining explanatory variables as binary, necessitating Probit regression with marginal effects. Children's screen exposure directly exacerbates obesity, as the increase in screen exposure is directly accompanied by an increase in sitting time. The positive effect of children's screen exposure remained significant after adding "Unhealthy advertised food purchases" and "Outdoor activities time", but with lower values. A 7-h increase in weekly screen exposure will raise obesity by 4.9%. Screen exposure increased the frequency of unhealthy advertised food purchases in children by 3.2%, significant at the 1% level, while unhealthy advertised food purchases promoted obesity by 2.0%, significant at the 5% level. Outdoor activities time did not have a significant influence, possibly because the sample's weekly Outdoor activities time was too short (see Table 2).

Table 8
Effect of screen exposure on obesity in rural children and mechanisms.

Variables	(1) Childhood obesity	(2) Child obesity	(3) Unhealthy advertised food purchases	(4) Outdoor activities time
Child screen exposure	0.007** (2.380)	0.006** (2.296)	0.032*** (3.947)	0.042 (1.054)
Unhealthy advertised food purchases		0.020** (2.213)		
Outdoor activities time		−0.005 (−1.521)		
Control variables	Control	Control	Control	Control
Time effect	Control	Control	Control	Control
Regional effect	Control	Control	Control	Control
Constant term				1.061 (1.032)
F-statistic				4.567
R2				0.058
N	1900	1900	1900	1900

Note: (a) *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; (b) The first three columns in parentheses are z-values under robust standard errors, and the fourth column in parentheses is t-values under robust standard errors.

4.5. The impact of screen exposure on food preferences, exercise preferences, and mutual substitution relationships in rural children

After excluding the self-selection bias of children's screen exposure time, GPSM analysis presented in Fig. 2 establishes a clear association between child screen exposure and obesity. Fig. 2(a) and (b) show the mean dose-response function and the treatment effect, respectively, at varying treatment intensities (Bia & Mattei, 2008). Fig. 2(a) reveals an inverted "U" relationship between child screen exposure and obesity, with the impact peaking at 3.9–5.9 h(occurs at treatment intensity levels of approximately 0.4–0.6) of daily exposure. Fig. 2(b) reveals a pattern where the treatment effect initially decreases, turns negative, and then gradually becomes positive again. Regardless of the treatment intensity, it is evident that screen exposure in children has a promoting effect on childhood obesity. Theoretical analysis indicates that children's screen exposure can affect their dietary and exercise preferences. Time and budget constraints may foster a substitution relationship between diet and exercise, where repeated engagement in a behavior reduces its marginal value relative to others, prompting a shift in preferences. Screen exposure-induced unhealthy dietary preferences may initially rise then fall, whereas exercise preferences may initially decline before rising.

If confirmed, it will support the theory that screen exposure causes obesity by increasing children's unhealthy food preference, leading to more frequent purchases and excessive energy intake, and by weakening children's exercise preference, reducing the probability of exercise and energy expenditure. It will prove the substitution relationship between unhealthy food and exercise preerence and verify GPSM estimation results. CHNS only investigated the food and activity choices of children aged 12 and above, thus reducing the sample size. We used unhealthy

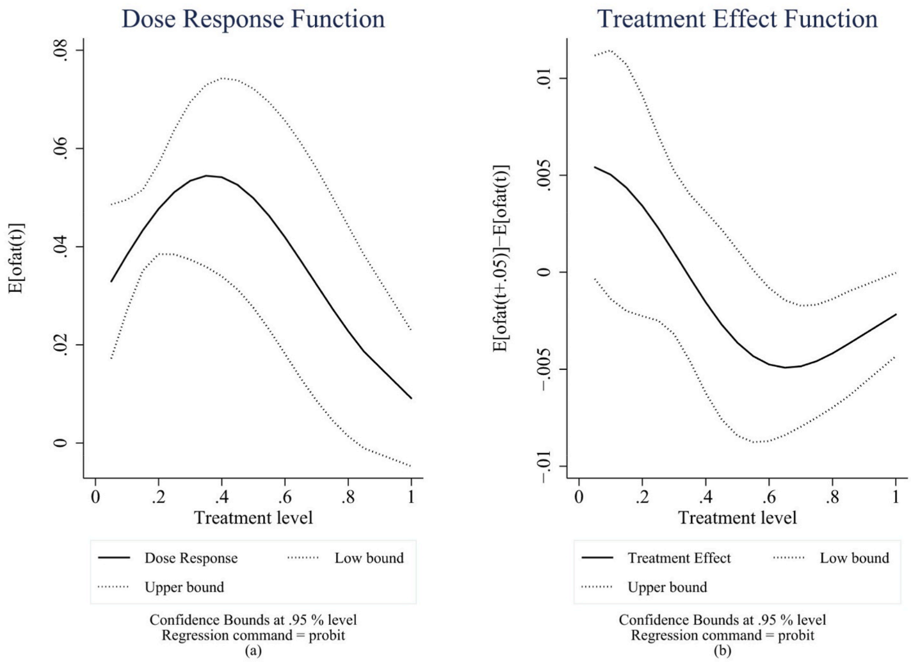

Fig. 2. GPSM analysis results.

Table 9
Child screen exposure and food campaign preferences.

Variables	Unhealthy Foods			Healthy Foods		Activity
	(1) Fast food	(2) Snacks	(3) Drinks	(4) Fruits	(5) Vegetables	(6) Sports
Child screen exposure	0.103* (1.748)	0.136** (2.554)	0.278*** (3.293)	−0.132 (−1.143)	−0.059 (−0.527)	−0.221*** (−5.361)
Child screen exposure squared	−0.018* (−1.715)	−0.015*** (−3.027)	−0.041*** (−4.269)	0.018 (1.053)	0.010 (1.092)	0.029*** (3.834)
Control variables	Control	Control	Control	Control	Control	Control
Time effect	Control	Control	Control	Control	Control	Control
Regional effect	Control	Control	Control	Control	Control	Control
N	818	914	964	1006	1005	920

Note: (a) *p < 0.1; **p < 0.05; ***p < 0.01; (b) z-values under robust standard errors are in parentheses.

food preferences (including fast food, snacks, beverages), healthy food preferences (including fruits, vegetables), and exercise preference (sports) as explained variables, and child screen exposure and its squared term as explanatory variables, controlled for other related variables, regional fixed effects, and time fixed effects.

Table 9 reveals that screen exposure initially had a positive effect on all three unhealthy food preferences, but after the inflection point, the positive effect began to fade, demonstrating an inverted "U"-shaped relationship. Fast food, snack, and beverage inflection points are 2.86, 4.53, and 3.39 h/day. In contrast, exercise preference shows a "U" shaped relationship of decreasing and then increasing, the inflection point is 3.81 h/day. When the law of diminishing marginal utility applies, the reduction of unhealthy dietary preferences and the increase of exercise preferences require further excessive screen exposure to achieve this, this is undoubtedly unrealistic. In fact, unhealthy food and video entertainment cultural products are not ordinary commodities, both of which are addictive: food addictions and media addictions (Gearhardt & Hebebrand, 2021; Andreassen et al., 2017), which means that the law of diminishing marginal utility may be not applicable, and the inflection point in the graph may not arrive. Overall, screen exposure will increase the probability of obesity in children. Before the turning point of preference shift arrives, screen exposure increases unhealthy food preferences and lowers exercise preferences, resulting to more unhealthy food purchases and less time spent outdoors.

5. Discussion

We explored the effects of intergenerational care on rural children's obesity and the intermediate mechanisms of screen exposure. Intergenerational care increased rural children's screen exposure. In 2016, China embarked on the "Healthy China 2030″ plan, stipulating a minimum of 1 h daily physical activity for school-aged children.[10] Our finding suggest that the rise in intergenerational care is associated with increased screen exposure among children, potentially crowding out outdoor playtime and impeding the realization of the prescribed plan. In addition, the screen exposure hazard of intergenerational care has a spillover effect, increasing the screen exposure of the elderly. Our study highlights an additional contemporary concern: the digital era exacerbates the risks, including the potential for digital addiction, associated with intergenerational care for the elderly. Intergenerational care posed a greater risk of screen exposure for rural boy. "Son preference" has always been considered detrimental to the healthy development of girls (Le & Nguyen, 2022). We provide an interesting viewpoint that prioritizing boys over girls can also be detrimental to boys' physical health. Quantile regressions show that intergenerational care weakens parental monitoring, especially for fathers, for rural children with higher exposure levels. Xiao (2016) noted that young mothers hold significant influence over childcare decisions, while grandparents predominantly serve as caregivers, that parental monitoring effectively mitigates children's screen time (Gentile, Reimer, Nathanson, Walsh, & Eisenmann, 2014). However, this study contends that there is intergenerational conflict between grandparents and parents regarding screen exposure issues. We find that increased screen time among children is a determinant of obesity, mediated by prolonged sitting and heightened susceptibility to advertisements for unhealthy foods, which collectively diminish energy expenditure and concurrently elevate caloric intake, exacerbating obesity prevalences. Previous research suggests a substantial role for social disparities in screen media exposure as a driver of corresponding inequalities in childhood obesity (Oude Groeniger et al., 2020). Our investigation offers additional empirical support for this conceptual link. The United Nations Children's Fund (UNICEF) reports indicate that in China, childhood overweight and obesity are linked to a rise in the consumption of ultra-processed foods and beverages.[11] Despite prior research, the rationale for the escalating consumption of highly processed foods among Chinese children remains elusive. While accessibility has been posited as a contributing factor (Ravensbergen et al., 2016), this study offers novel evidence that screen exposure is altering dietary preferences, thereby mediating the influence of food accessibility. Using GPSM and second-order polynomial estimate, we found that screen exposure in children reinforced preferences of unhealthy snack, fast food, and beverage, and weakened preferences of physical activity. Furthermore, the relationship between screen exposure and unhealthy dietary preferences exhibited an inverted "U"-shape due to diminishing marginal utility and time constraints, while the relationship with physical activity preferences was "U"-shaped, resulting in a non-linear positive effect of screen exposure on childhood obesity. Moreover, despite the law of diminishing marginal utility, it is concerning that rural Chinese children struggle to counteract screen-induced obesity. This struggle is largely attributed to the addictive qualities of unhealthy foods and media entertainment (Domoff, Sutherland, Yokum, & Gearhardt, 2021; Sun & Zhang, 2021). The digital era's continuous online entertainment development and handheld device proliferation further complicate the issue, making addressing it without external help daunting, especially considering intergenerational care. Furthermore, China's ongoing urbanization, as rural youth and middle-aged workers migrate to cities for better wages, enhances family welfare (Combes et al., 2020). However, screen exposure from intergenerational care contributing to rural childhood obesity may partially undermine the benefits of urban non-agricultural employment and rural human capital development.

This study's limitations involve: the incomplete harmonization of the CFPS and CHNS dataset temporal discrepancies, the lack of precision in characterizing grandparental attributes. Additionally, the study does not adequately differentiate between types of screen exposure. Future research with more detailed screen exposure context data is needed to address these gaps.

6. Conclusion

To our knowledge, this is the first article to use empirical analysis to investigate how intergenerational care heightens obesity prevalence in children by affecting screen exposure. We also thoroughly discuss how screen exposure changes dietary and exercise behavioral preferences. Nevertheless, the Chinese government has not accorded significant attention to the issue of childhood obesity associated with screen exposure, failing to incorporate relevant measures into the Healthy Children Action Improvement Plan (2021–2025).[12]

In rural China, intergenerational care will persist. This research conclusion offers a policy basis for government departments to mitigate childhood obesity resulting from intergenerational care, based on child screen exposure generation and pathways.

First, weaken the pathways of child screen exposure generation. 1) Leverage rural elders' information channels to enhance awareness of child screen exposure risks. 2) Establish high-quality child care institutions in rural areas, conduct regular physical exams for intergenerational care providers, reducing intergenerational care difficulty. 3) Educate parents about children's digital media addiction to foster prevention and reduce screen exposure.

Second, weaken the pathways of screen exposure effects in children. 1) Educate rural families on nutrition and exercise to highlight dietary risks and activity benefits. 2) Ban and penalize unhealthy food ads in children's programming. 3) Enhance safety and fun at rural outdoor activity facilities.

Conflict of interest disclosure

All the authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethics approval and informed consent

The CFPS and CHNS data do not contain any private information about the study subjects and are not individually identifiable. As a result, our data analysis does not involve human subjects, thereby raising no ethical concerns.

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Conflict of interest

We declare that no conflict of interest exits in the submission of this manuscript, and all authors have read and approved the submitted manuscript. The manuscript is original and has not been published or accepted for publication, either in whole or in part. All the authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

CRediT authorship contribution statement

Xueying Wang: Writing – review & editing, Writing – original draft, Software, Data curation. **Yun Zhang:** Writing – review & editing, Software, Methodology, Data curation, Conceptualization.

Declaration of competing interest

None.

Data availability

The link to the publicly available database used was shared in the article

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Appendix A. Supplementary data

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