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# Digitalisation challenges adults' health, nutrition and lifestyle choices

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## ABSTRACT

**Background:** Fast digitalisation has transformed lifestyle patterns, food environments, and purchasing method behaviours among the urban populations. Increasing of the dependence on smart gadgets, digital platforms and online services has transformed dietary habits, a lack of physical activity, and food obtaining practices. These lifestyle changes contribution for the changes in intake of nutritional food and the risk of obesity in adults.

**Aim:** The present study aimed to identify the influence of digitalisation on food shopping behaviour, dietary intake, physical activity, and Body Mass Index (BMI) among metropolitan (urban) adults.

**Methods:** A cross-sectional survey study was conducted among 1,048 adults aged 25–45 years residing in a metropolitan (urban) region. Participants were categorised according to food shopping modes as digital, traditional, and hybrid (combination of both). Data collecting method was structured using a questionnaire method. Data were analysed using descriptive statistics, Chi-square tests, and one-way ANOVA with significance value set at $p < 0.05$.

**Results:** The most common shopping mode was hybrid (46.3%), digital (40.6%) and the last traditional (13.2%). Shopping mode and physical activity showed the data was significant (p=0.004**), whereas the traditional shoppers reported higher physical activity levels. Digital and hybrid shopping modes have a significantly higher frequency of consumption for fast food and have a high nutrients intake level as compared to the traditional shopping mode. Differences in energy intake and shopping modes for both genders show a statistically significant result ($p < 0.05$). However, no statistically significant relation was found between Shopping Mode and BMI, shows that the relationship between them was not statistically significant.

**Conclusion:** The digital services have significantly influenced the behaviour of adults in the urban region in shopping for food and their dietary patterns. An increase in the dependence on digital and hybrid shopping modes contributes to the higher consumption of fast foods and an increase in dietary intake. Public health strategies are being created to promote healthy and balanced dietary patterns, including active lifestyles, made an essential to reduce the risk of potential health issues associated with increasing dependence on the digitalised method for food environments.

**Keywords:** food shopping behaviour, Digitalisation, metropolitan, dietary pattern, physical activity, obesity.

# 1. Introduction

Digitalisation is restructuring adults' health, nutrition, and lifestyle choices by shifting their daily routines and increasing screen engagement, which leads towards behavioural shifts. It has transformed food shopping habits, dietary patterns, and nutritional quality, influencing the eating patterns of people. Simultaneously, reduced physical activity and energy imbalances are contributing to rising obesity risk, often reflected in increased Body Mass Index (BMI). Together, these changes highlight the health challenges modelled by an increasingly digital lifestyle.

## 1.1 LIFESTYLE PATTERN, DIGITAL INTEGRATION AND BEHAVIOURAL SHIFT ASSOCIATED WITH HIGH SCREEN ENGAGEMENT

Rapid digitalisation has shown a significant increase in daily living and lifestyle patterns in sedentary populations. In urban or metropolitan regions like Delhi NCR, digital technologies integrated into educational, professional, social and commercial domains have reshaped the lifestyle structure and behavioural routines. The modern world's increasing on the dependence on various digital platforms, and a hybrid working environment, with an increase in digital-mediated communication, such as video calls. Almost every individual is experiencing long hours of screen time, hybrid work, and professional structures, which contribute to long sitting and a lack of physical activity[1-4]. As the digital work pressure increases, an individual starts practising for Long sitting and working hours, sedentary time is increasing, meal consumption patterns become irregular, cooking and preparation at home keep declining, and lack of Physical exercise. The combination of high digital engagement and a heavy workload leave limited time for cooking and physical exercise. Additionally, digitalisation enhances convenience, accessibility, and efficiency, while simultaneously reducing opportunities for physical activity and active living[1,2,5,6].

All age groups have seen the rapid expansion of digital technology use in various devices such as smartphones, tablets, and laptops, and the application services have become an essential part of daily routines and lifestyle patterns. The influence of digital penetration extends beyond communication and work routine to food shopping/purchase, consumption behaviours, and lifestyle choices. The growth of the digital ecosystem[7-9]: has empowered instant service access, food ordering options are now 24/7, digital marketing exposures, and financial transactions have become easier. However, these conveniences may unintentionally promote a sedentary lifestyle routine and unhealthy dietary habits[1,2].

Digital workloads and excessive screen time have an impact on the reshaping of the lifestyle pattern by increasing the long sitting hours and reducing the energy expenditure daily[3], Stress-related eating behaviour pattern due to the high screen exposure at work[10], Outdoor activities and exercises[1,2], Irregular and skipping of meal patterns are commonly observed[11], and A sedentary lifestyle pattern may reduce metabolic efficiency over time.[1,2] The association of excessive digital or screen use causing[10,11] the Frequency of snacking consumption increases, Food preferences become calorie-dense and poor in nutrients, Consumption of processed food and sugary beverages increases, and High digital distraction and engagement cause the consumption of food mindlessly, reducing the awareness of portion sizes, satiety cues and increasing the likelihood of excess calorie intake[10,11].

## 1.2 TRANSFORMATION OF FOOD SHOPPING, DIETARY PATTERN AND NUTRITIONAL QUALITY

Digitalisation has completely evolved the food shopping behaviour among the population. Food procurement now occurs through three different modes: Traditional (Offline or Physical) Purchasing Mode[12], Digital (Online) Purchasing Mode and Hybrid or Both (Traditional/Physical/Offline and Digital/Online and Offline) Purchasing Mode.

Digital shopping systems offer convenience, save time, various discounts. And doorstep services[13-15]. However, greater access to these areas may increase exposure to ultra-processed and fast-food products, thereby influencing dietary patterns. Individuals with high screentime engagement are more likely to[7,8] Consume ready-to-eat and processed foods, Order calorie-dense meals via digital services, exhibit impulsive shopping behaviours, and engage in stress-induced ordering patterns. Thus, the digital shopping behaviour may directly or indirectly influence the nutritional quality of the food, which leads to an increasing risk of obesity

Digitalisation influences not only physical activity but also food choices, eating behaviour, dietary habits, and dietary quality. Individuals with high gadget use are more likely to[10,11], increasing the consumption of high-calorie and nutrient-poor food, preferences and high intake of processed food and sugary beverages, high dependency on convenience and fast food, Mindless eating while screen time, awareness is lacking about the portion size and nutritional requirements, and irregular meal timing.

Continuous digital addiction also increases susceptibility to advertising of food, promotions, discounts and impulsive shopping[7-9]. Over time, mindless eating during screen time reduces satiety awareness, and large portion sizes contribute to positive energy balance and increase the risk of obesity[1,2].

### 1.3 DECLINING IN PHYSICAL ACTIVITY, ENERGY IMBALANCE, AND OBESITY RISK RISING WITH BODY MASS INDEX ASSOCIATION

The lack of physical activity due to the increasing prevalence of digital-driven lifestyles. A remote work structure, online entertainment, digital communication and app-based services to minimise the required daily movements associated with[1-3], reduced daily energy expenditure, impaired glucose metabolism, increased fat accumulation, and higher risk of overweight and obesity. When the combination of the lack of physical activity and unhealthy dietary intake occurs the acceleration in the weight gain[1,2], and the long-term dysfunction of metabolism.

Rapid digitalisation has transformed occupational structures, social interaction patterns, and food procurement systems among the metropolitan population. The increasing addiction to smartphones, computers/laptops, and digital services has contributed to prolonged sedentary behaviour, irregular meal consumption, irregular eating habits, and a lack of physical activity. These behavioural shifts are strongly associated with the rising of the obesity prevalence.

Globally, Obesity has nearly tripled over the past decades, Emerging As one of the most Significant public health concerns[5,6,16].

Sedentary behaviour states that the activities that require low energy expenditures while sitting have been positively associated with increased adipose and metabolic risk[1-3]. Individuals with higher screen exposure will have a higher Body Mass Index (BMI) than those with lower screen exposure[1,2.]

Digitalisation contributes to obesity through various interconnected factors includes increased sedentary behaviour[1-3], altered dietary behaviour characteristics by high intake of processed and calorie-dense foods, increased consumption of sugary and carbonated beverages, high digital engagement is associated with increased snacking frequency, high intake of processed, frozen, junk and fast foods, increasing of sugary and carbonated beverages, and mindless eating during screen exposure[10,11]. In metropolitan regions like Delhi NCR, digitalisation interacts with professional stress, limited time, and convenience food-driven choices, leading to the rise of obesity[17].

BMI classification based on the Asian BMI classification standard is referred to an important tool to evaluate the metabolic risk associated with obesity. Digital addiction, poor dietary habits, lack of physical activity, and professional work pressure accelerate weight gain, leading to weak metabolism and fat accumulation[1,2]. The combined effect of the high digital engagement, sedentary lifestyle pattern and unhealthy dietary behaviour increases the risk of obesity and cardiometabolic complications.

Public health strategies focusing on reducing sedentary screen time, increasing physical activity, encouraging healthy food choices, and controlling excessive food exposure are essential to reduce obesity risk in a digitally driven population.

## 2. Methods

### 2.1 STUDY OBJECTIVES

To identify the digitalisation impact on adults' health, nutritional intake, and lifestyle pattern behaviours.

(1) To identify the shopping mode patterns: digital, traditional, and hybrid.
(2) To identify the Body Mass Index of participants,
(3) To identify the physical activity of the participants and
(4) To analyse the dietary patterns and nutritional intake of the participants.

### 2.2 STUDY DESIGN

The current study was based on a cross-sectional survey study. A total of 1048 metropolitan (urban) adults were recruited using purposive sampling.

Participants were aged 25–45 years and actively engaged in food shopping through digital, traditional, or hybrid modes. The sample size was calculated using a 95% confidence level and 5% margin of error, based on an estimated 41% population prevalence in Delhi NCR. Written informed consent was obtained from all participants before data collection.

2.3 INCLUSION/ELIGIBILITY AND EXCLUSION CRITERIA:

Inclusion criteria: both genders (males and females); aged 25 to 45 years; residing in metropolitan areas; belonging to any BMI category; and apparently healthy.

Exclusion criteria: excluded individuals under 25 years of age or over 46 years of age, those diagnosed with chronic conditions (such as cardiovascular, renal, endocrine, respiratory, gastrointestinal, or liver diseases), pregnant or lactating women, bedridden individuals, and those who have recently experienced fractures or major injuries.

2.4 DATA COLLECTION TOOL:

Data were collected using a structured questionnaire that included:

- Demographic profile (education, occupation, lifestyle, living status)
- Food purchasing behaviour (online, offline, hybrid)
- Dietary habits

**Anthropometric Assessment**

Participants self-reported height and weight. BMI $= \frac{Weight\ (in\ Kg)}{Height\ (in\ m^2)}$. BMI classification followed Asian cut-offs recommended by the WHO [Source: WHO; Revised National Institute of Nutrition, RDA 2020][4-6]:

- Underweight: <18.5 kg/m²
- Normal: 18.5–22.9 kg/m²
- Overweight: 23–24.9 kg/m²
- Obese: ≥25 kg/m²

**Physical Activity**

Physical activity levels were assessed using the Global Physical Activity Questionnaire (GPAQ) developed by the World Health Organisation.

**Dietary Assessment**

Dietary intake was evaluated using a Food Frequency Questionnaire (FFQ) and three non-consecutive 24-hour dietary recalls. FFQ responses were categorised as never, daily, weekly, monthly, or occasionally based on consumption frequency.

**Statistical Analysis**

Data were coded and analysed using IBM SPSS Statistics (Version 29.0.0.0).

Descriptive statistics (mean, median, standard deviation, frequency, and percentage) were used to summarise the data. Inferential statistical analyses included: (1) Chi-square test, (2) One-way ANOVA, and (3) Tukey post hoc test. The statistical significance was set at $p < 0.05$.

2.5 ETHICS STATEMENT:

Ethical approval was obtained from the Institute before the study began. All participants gave their written consent before taking part. Confidentiality and anonymity were maintained throughout the research. The study followed established ethical principles for research involving people and did not include any invasive procedures.

# 3. Results

3.1 DEMOGRAPHIC PROFILE OF THE 1048 PARTICIPANTS

A total 1048 participants were included in the study.

Table 1, presents the percentage distribution of participants' demographic profiles. Most participants were aged 25-30 years (40.7%), followed by 30-35 years (24.8%), 40-45 years (15.7%) and 35-40 years (15.1%).

Male participants (61.3%), were twice as numerous as female participants (38.7%). Most of the participants were Hindu (91.1%), with smaller proportions identifying as Muslim (4.6%), Sikh (2.0%), Christian (1.6%), and other religions (0.7%).

More than half of the participants were Single (52.8%), while married (46.3%). In terms of dietary habits, non-vegetarian (48.9%), vegetarian (38.5%) and an eggetarian (12.7%).

The majority of participants hold professional degrees (60.9%), followed by graduates (35.0%). Most participants were employed as professionals (71.2%), followed by unemployed (15.0%), and smaller proportions in semi-professionals (9.9%) and skilled workers (2.4%).

Participant's socioeconomic status, 65.2% were classified as high-income group (HIG), 27.4% as middle-income group (MIG), and 7.4% as low-income group (LIG).

**Table 1:** Demographic Profile percentage distribution (N=1048)

| Demographic Profile | | n (%) |
|---|---|---|
| Age | 25 – 30 yrs | 427 (40.7%) |
| | 30 – 35 yrs | 298 (28.4%) |
| | 35 – 40 yrs | 158 (15.1%) |
| | 40 – 45 yrs | 165 (15.7%) |
| Gender | Male | 642 (61.3%) |
| | Female | 406 (38.7%) |
| Religion | Hindu | 955 (91.1%) |
| | Christian | 17 (1.6%) |
| | Muslim | 48 (4.6%) |
| | Sikh | 21 (2.0%) |
| | Other religion | 7 (0.7%) |
| Marital sSatus | Single | 553 (52.8%) |
| | Married | 491 (46.9%) |
| | Divorced | 4 (0.4%) |
| Food habit | Vegetarian | 403 (38.5%) |
| | Eggetarian | 133 (12.7%) |
| | Non-Vegetarian | 512 (48.9%) |
| Education | Professional Degree | 638 (60.9%) |
| | Graduate | 367 (35.0%) |
| | Intermediate / Diploma | 43 (4.1%) |
| Occupation | Professionals | 746 (71.2%) |
| | Semi-Professional | 104 (9.9%) |
| | Clerical / Shop / Farm | 16 (1.5%) |
| | Skilled Worker | 25 (2.4%) |
| | Unemployed | 157 (15.0%) |
| Socioeconomic Status | HIG | 683 (65.2%) |
| | MIG | 287 (27.4%) |
| | LIG | 78 7.4%) |

Source: Primary Data Collected through a survey conducted in Delhi-NCR[18].

## 3.2 PARTICIPANTS' PREFERENCE FOR DIFFERENT SHOPPING MODES

Table 2, presents the Participants' distribution by Shopping Mode (N = 1048). The majority of participants preferred hybrid or both (traditional /physical/offline and digital/online) shopping mode (46.3%), followed by digital (online) shopping mode (40.6%), and the remaining 13.2% preferred traditional (offline/physical) shopping mode. The findings indicate that the majority of participants were shifting toward digital and hybrid shopping behaviours, whereas a smaller number of participants still preferred traditional shopping methods.

**Table 2:** Shopping Mode percentage distribution

| Shopping Mode | N (%) |
|---|---|
| **Digital** | 425 (40.6%) |
| **Traditional** | 138 (13.2%) |
| **Hybrid** | 485 (46.3%) |
| **Total (N)** | 10480.0%) |

Source: Primary Data Collected through a survey conducted in Delhi-NCR[18].

## 3.3 PARTICIPANTS BASED ON GENDER PREFERENCE FOR DIFFERENT SHOPPING MODES

Table 3, presents the distribution of shopping modes by gender.

Among male participants (N=642), the hybrid shopping mode (44.7%), followed by the digital shopping mode (42.2%), and the traditional shopping mode (13.1%).

Among female participants (N=406), the digital shopping mode (37.9%), followed by the traditional shopping mode (13.3%), and the hybrid shopping mode (8.8%).

Both genders preferred the hybrid and digital shopping modes over traditional shopping modes, with only minor differences between males and females.

**Table 3:** Gender based Shopping Mode percentage distribution

| Shopping Mode | | | Digital | Traditional | Hybrid |
|---|---|---|---|---|---|
| Gender | Male | N = 642 | 271 (42.2%) | 84 (13.1%) | 287 (44.7%) |
| | Female | N = 406 | 154 (37.9%) | 54 (13.3%) | 198 8.8%) |

Source: Primary Data Collected through a survey conducted in Delhi-NCR[18].

3.4 ANTHROPOMETRIC MEASUREMENTS OF THE PARTICIPANTS

Table 4 presents the anthropometric measurements (Table 4a) of participants, and the Asian BMI Classification based on the percentage distribution (Table 4b).

Table 4a shows the anthropometric measurements of participants across different shopping modes (N = 1048). One-way ANOVA was conducted to examine differences in the mean and standard deviation of height (m), weight (kg), and BMI (kg/m$^2$) across shopping modes.

Male participants, the highest mean height was observed in the hybrid shopping group (172.56 ± 8.73 cm), followed by the digital shopping group (172.21 ± 8.77 cm) and the traditional shopping group (171.82 ± 9.19 cm). The relationship between the shopping mode and height was not statistically significant ($F = 0.267$, $p = 0.766$).

For weight, the highest mean value was observed in the hybrid shopping group (81.04 ± 15.96 kg), followed by the traditional shopping group (79.10 ± 15.80 kg) and the digital shopping group (78.97 ± 15.69 kg). The relationship between the shopping mode and weight was not statistically significant ($F = 1.312$, $p = 0.27$).

The highest mean BMI was observed in the hybrid shopping group (27.11 ± 4.47 kg/m$^2$), followed by traditional (26.63 ± 3.99 kg/m$^2$) and digital (26.53 ± 4.44 kg/m$^2$) shopping groups. The relationship between the shopping mode and BMI was not statistically significant ($F = 1.285$, $p = 0.277$).

Female participants, the highest mean height was observed in the hybrid shopping group (161.43 ± 8.54 cm), followed by the traditional shopping group (161.32 ± 7.55 cm) and the digital shopping group (159.43 ± 8.09 cm). The relationship between the shopping mode and height was not statistically significant ($F = 2.739$, $p = 0.066$).

For eight, the highest mean value was observed in the traditional shopping group (68.97 ± 15.39 kg), followed by the hybrid shopping group (66.49 ± 13.95 kg) and the digital shopping group (66.23 ± 14.06 kg). The relationship between the shopping mode and weight was not statistically significant ($F = 0.796$, $p = 0.452$).

The highest mean BMI was observed in the traditional shopping group (26.37 ± 4.92 kg/m$^2$), followed by digital (25.98 ± 4.80 kg/m$^2$) and hybrid (25.41 ± 4.34 kg/m$^2$) shopping groups. The relationship between the shopping mode and BMI was not statistically significant ($F = 1.223$, $p = 0.295$).

Table 4b, shows the BMI classification of participants by shopping mode categories based on the Asian BMI classification (N = 1048).

Among male participants, obesity prevalence was highest in the hybrid shopping mode (73.5%), followed by digital (72.3%) and traditional (66.7%) shopping modes. The relationship between the shopping mode and BMI category was not statistically significant ($\chi^2 = 7.156$, $p = 0.307$).

Similarly, among female participants, obesity prevalence was highest in the hybrid shopping mode (72.2%), followed by digital (66.2%) and traditional (59.3%) shopping modes. The relationship between the shopping mode and BMI category was not statistically significant ($\chi^2 = 7.949$, $p = 0.242$).

The obesity prevalence was higher among the hybrid shopping mode in both genders; The relationship between the shopping mode and BMI category was not statistically significant.

**Table 4:** Anthropometric Measurements distribution

Table 4a: *Anthropometric Measurements*

| Shopping Mode | Gender | | | | | |
|---|---|---|---|---|---|---|
| | Male | | | Female | | |
| | Height (in cm) | Weight (in kg) | BMI (kg/m2) | Height (in cm) | Weight (in kg) | BMI (kg/m2) |
| Digital (N = 425) | 172.21 ± 8.77 | 78.97 ± 15.69 | 26.53 ± 4.44 | 159.43 ± 8.09 | 66.23 ± 14.06 | 25.98 ± 4.80 |
| Traditional (N = 138) | 171.82 ± 9.19 | 79.10 ± 15.80 | 26.63 ± 3.99 | 161.32 ± 7.55 | 68.97 ± 15.39 | 26.37 ± 4.92 |
| Hybrid (N = 485) | 172.56 ± 8.73 | 81.04 ± 15.96 | 27.11 ± 4.47 | 161.43 ± 8.54 | 66.49 ± 13.95 | 25.41 ± 4.34 |
| F-test | 0.267 | 1.312 | 1.285 | 2.739 | 0.796 | 1.223 |
| *p*-Value | 0.766 | 0.27 | 0.277 | 0.066 | 0.452 | 0.295 |

One way ANOVA
* = p<0.05
** = p<0.01

Table 4b: *Body Mass Index (BMI) Classification*

| Shopping Mode | Gender | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Male | | | | Female | | | |
| | Underweight | Normal weight | Overweight | Obese | Underweight | Normal weight | Overweight | Obese |
| Digital (N = 425) | 5.90% | 14.40% | 7.40% | 72.30% | 4.50% | 18.20% | 11.00% | 66.20% |
| Traditional (N = 138) | 4.80% | 14.30% | 14.30% | 66.70% | 5.60% | 14.80% | 20.40% | 59.30% |
| Hybrid (N = 485) | 3.10% | 12.20% | 11.10% | 73.50% | 2.00% | 15.70% | 10.10% | 72.20% |
| Chi-Sq | 7.156 | | | | 7.949 | | | |
| *p*-Value | 0.307 | | | | 0.242 | | | |

Chi-square test
* = p<0.05
** = p<0.01
Source: BMI, Asian Classification

Source: Primary Data Collected through a survey conducted in Delhi-NCR[18].

## 3.5 PHYSICAL ACTIVITY PERCENTAGE DISTRIBUTION OF THE PARTICIPANTS

Table 5, presents the physical activity percentage distribution of the participants

Table 5a, shows the overall physical activity of the participants (N = 1048). Participants who prefer traditional shopping reported the highest engagement in physical activity (68.1%), compared to hybrid (53.8%) and digital shoppers (52.2%). Conversely, physical inactivity was more prevalent among digital (47.8%) and hybrid (46.2%) shoppers than among traditional shoppers (31.9%). The relationship between the shopping mode and physical activity engagement was statistically significant ($\chi^2$ = 11.181, p = .004*). These findings suggest that individuals dependent on traditional shopping modes may demonstrate relatively higher physical activity levels than those who prefer digital or hybrid shopping modes.

Table 5b, shows the types of physical activity among physically active participants. Among participants who engaged in physical activity, walking was the most reported activity across all shopping modes. Walking was highest among traditional shopping mode (70.2%), followed by hybrid (63.2%) and digital shopping modes (56.3%). The relationship between the shopping mode and type of physical activity was not statistically significant ($\chi^2$ = 6.989, p = 0.322).

Table 5c, shows the physical activity level (or intensity) of the shopping mode among physically active participants. Light-intensity activity was most common in traditional shopping mode (70.2%), followed by hybrid (63.2%) and digital shopping modes (56.3%). Moderate and heavy activity levels showed minor variations across groups. The relationship between the shopping mode and physical activity intensity level was not statistically significant ($\chi^2$ = 6.659, p = 0.155).

**Table 5:** Physical Activity percentage distribution of the participants

Table 5*a*: Physical Activity percentage *distribution*

| Shopping Mode | Physical Activity | | Chi-square | *p*-Value |
|---|---|---|---|---|
| | Yes | No | | |
| Digital (N = 425) | 222 (52.2%) | 203 (47.8%) | 11.181 | .004* |
| Traditional (N = 138) | 94 (68.1%) | 44 (31.9%) | | |
| Hybrid (N = 485) | 261 (53.8%) | 224 (46.2%) | | |

Table 5*b*: *Active participants' specific* Physical Activity

| Shopping Mode | Activities | | | | Total | Chi-square | *p*-Value |
|---|---|---|---|---|---|---|---|
| | Walk | Gym | Yoga | Exercise | | | |
| Digital (N = 222) | 56.30% | 7.20% | 10.40% | 26.10% | 100.00% | 6.989 | 0.322 |
| Traditional (N = 94) | 70.20% | 5.30% | 5.30% | 19.10% | 100.00% | | |
| Hybrid (N = 261) | 63.20% | 4.60% | 8.80% | 23.40% | 100.00% | | |

Table 5*c*: Physical Activity *Level of Active Participants*

| Shopping Mode | Activity Level | | | Chi- square | *p*-Value |
|---|---|---|---|---|---|
| | Light | Moderate | Heavy | | |
| Digital (N = 222) | 56.30% | 36.50% | 7.20% | 6.659 | 0.155 |
| Traditional (N = 94) | 70.20% | 24.50% | 5.30% | | |
| Hybrid (N = 261) | 63.20% | 32.20% | 4.60% | | |

Chi-Square test
* = p<0.05
** = p<0.01

Source: Primary Data Collected through a survey conducted in Delhi-NCR[18].

## 3.6 JUNK/FAST FOOD AND DESSERT CONSUMPTION ACROSS SHOPPING MODES

Table 6, Percentage distribution of junk/fast food consumption across shopping modes (n=1048).

Table 6a, presents the frequency distribution of junk and fast-food consumption across different shopping modes

Hybrid shoppers showed a higher tendency to consume fast-food items weekly including patties/ samosa (52.4%), pav bhaji (57.9%), chips/nachos (57.9%), and noodles/pasta (58.4%).

Digital shopping mode had higher daily consumption of food items, such as cutlets/kachori (24.7%), noodles/pasta (17.6%), and South Indian dishes (22.1%) whereas traditional shopping mode has lower consumption frequency, with many participants representing monthly consumption or lower intake of food items such as cholle kulche/bhature (58.0%) and burgers (52.2%).

The relationship between the shopping mode and junk/fast food was statistically significant for various fast-food items, including cholle kulche/bhatura ($\chi^2$=39.871, p<.001**), cutlets/kachori ($\chi^2$=26.63, p<.001**), patties/samosa ($\chi^2$=26.354, p<.001**), pav bhaji ($\chi^2$=18.188, p=.020*), South Indian dishes ($\chi^2$=27.531, p<.001**), burgers ($\chi^2$=24.004, p=.002*), chips/nachos ($\chi^2$=46.657, p<.001**), noodles/pasta ($\chi^2$=56.166, p<.001**), and other snack items ($\chi^2$=36.018, p<.001**).

The relationship between the shopping mode and pizza consumption was not statistically significant ($\chi^2$=15, p=.059).

These findings show that individuals using digital and hybrid shopping modes tend to consume fast-food products more frequently than traditional shopping mode, suggesting a potential relationship between digital shopping behaviours and the increase in availability and accessibility of convenience foods.

Table 6b, presents the frequency distribution of dessert consumption across different shopping modes. For dessert consumption, a significant association was found ($\chi^2$ = 18.279, p = 0.006*), with the highest proportion of participants reporting no consumption among traditional shoppers (52.9%), compared with digital (43.8%) and hybrid shoppers (48.9%).

The findings suggest that digital and hybrid shopping modes are associated with more frequent consumption of several junk and fast-food items compared with traditional shopping methods.

**Table 6:** Food Consumption percentage distribution of the participants

| Table *6a*: Junk/Fast Food | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Junk/Fast Food | | Frequency | | | | | Chi-square | p-Value |
| | | Daily | Twice a week | Weekly | Twice a month | Monthly | | |
| Cholle Kulche/Bhature | Digital (N = 425) | 15.10% | 4.00% | 42.60% | 1.40% | 36.90% | | |
| | Traditional (N = 138) | 2.90% | 4.30% | 33.30% | 1.40% | 58.00% | 39.871 | <.001** |
| | Hybrid (N = 485) | 9.50% | 4.30% | 50.10% | 1.90% | 34.20% | | |
| Cutlets / Kachori | Digital (N = 425) | 24.70% | 2.40% | 44.90% | 0.70% | 27.30% | | |
| | Traditional (N = 138) | 36.20% | 1.40% | 45.70% | 2.20% | 14.50% | 26.63 | <.001** |
| | Hybrid (N = 485) | 19.80% | 1.40% | 52.40% | 0.60% | 25.80% | | |
| Patties / Samosa | Digital (N = 425) | 13.20% | 4.00% | 52.20% | 1.40% | 29.20% | | |
| | Traditional (N = 138) | 2.90% | 4.30% | 43.50% | 1.40% | 47.80% | 26.354 | <.001** |
| | Hybrid (N = 485) | 12.80% | 4.30% | 52.40% | 1.90% | 28.70% | | |
| Pav bhaji | Digital (N = 425) | 27.10% | 4.00% | 47.10% | 1.40% | 20.50% | | |
| | Traditional (N = 138) | 31.20% | 4.30% | 47.80% | 1.40% | 15.20% | 18.188 | .020* |
| | Hybrid (N = 485) | 19.00% | 4.30% | 57.90% | 1.90% | 16.90% | | |
| South Indian Dishes | Digital (N = 425) | 22.10% | 1.40% | 47.30% | 0.50% | 28.70% | | |
| | Traditional (N = 138) | 11.60% | 2.90% | 37.00% | 0.00% | 48.60% | 27.531 | <.001** |
| | Hybrid (N = 485) | 16.70% | 2.10% | 50.70% | 0.40% | 30.10% | | |
| Burger | Digital (N = 425) | 11.10% | 4.00% | 52.00% | 1.40% | 31.50% | | |
| | Traditional (N = 138) | 2.90% | 4.30% | 39.10% | 1.40% | 52.20% | 24.004 | .002** |
| | Hybrid (N = 485) | 10.10% | 4.30% | 46.20% | 1.90% | 37.50% | | |
| Chips / Nachos | Digital (N = 425) | 24.20% | | 53.90% | 3.30% | 18.60% | | |
| | Traditional (N = 138) | 42.00% | | 43.50% | 2.20% | 12.30% | 46.657 | <.001** |
| | Hybrid (N = 485) | 15.50% | | 57.90% | 3.10% | 23.50% | | |
| Noodles & Pastas | Digital (N = 425) | 17.60% | 4.20% | 41.90% | 0.50% | 35.80% | | |
| | Traditional (N = 138) | 0.00% | 3.60% | 50.70% | 1.40% | 44.20% | 56.166 | <.001** |
| | Hybrid (N = 485) | 9.50% | 4.10% | 58.40% | 0.80% | 27.20% | | |
| Pizza | Digital (N = 425) | 27.80% | 4.20% | 50.40% | 0.50% | 17.20% | | |
| | Traditional (N = 138) | 26.10% | 3.60% | 51.40% | 1.40% | 17.40% | 15 | .059 |
| | Hybrid (N = 485) | 17.90% | 4.10% | 56.30% | 0.80% | 20.80% | | |
| Other | Digital (N = 425) | 25.40% | 3.50% | 48.50% | 0.70% | 21.90% | | |
| | Traditional (N = 138) | 45.70% | 3.60% | 40.60% | 0.70% | 9.40% | 36.018 | <.001** |
| | Hybrid (N = 485) | 23.50% | 3.90% | 55.70% | 0.60% | 16.30% | | |

| Table *6b*: *Dessert* | | | | | | |
|---|---|---|---|---|---|---|
| Desserts | Frequency | | | | Chi-square | p-Value |
| | Daily | Weekly | Monthly | No | | |
| Digital (N = 425) | 9.40% | 11.10% | 35.80% | 43.80% | | |
| Traditional (N = 138) | 6.50% | 15.20% | 25.40% | 52.90% | 18.279 | .006* |
| Hybrid (N = 485) | 4.90% | 16.50% | 29.70% | 48.90% | | |

Chi-Square test
* = p<0.05
** = p<0.01

Source: Primary Data Collected through a survey conducted in Delhi-NCR[18].

3.7 DISTRIBUTION OF BEVERAGE CONSUMPTION ACROSS DIFFERENT SHOPPING MODES

Table 7, presents the percentage distribution of beverage consumption across different shopping modes (N=1048).

Daily milk consumption was common across all shopping modes, with the highest proportion observed among the traditional shopping mode (68.8%), followed by the digital (64.9%) and hybrid shopping modes (59.8%). The relationship between milk consumption and shopping mode was statistically significant ($\chi^2 = 35.093$, $p < .001$**).

Tea consumption was also predominantly reported daily across all groups; however, no statistically significant relationship was observed between tea consumption and shopping mode ($\chi^2 = 11.681$, $p = 0.069$).

Coffee consumption showed a significant relationship with shopping mode ($\chi^2 = 30.670$, $p < .001$**). Daily coffee consumption was highest among the traditional shopping mode (39.9%), followed by hybrid (34.6%) and digital (30.8%) shopping modes.

Juice consumption showed a significant relationship with shopping mode ($\chi^2 = 24.079$, $p < .001$**). Weekly consumption was most common among the hybrid shopping mode (42.9%), followed by the traditional (39.1%) and the digital (30.1%) shopping modes.

Carbonated drink consumption showed a significant relationship with shopping mode ($\chi^2 = 30.298$, $p < .001$**). Monthly consumption was the most frequently reported pattern, particularly among traditional shopping mode (53.6%), followed by hybrid (46.4%) and digital (37.4%) shopping modes.

Significant associations were observed for most beverages except tea.

**Table 7:** Beverage percentage distribution of the participants

| Beverages | | Frequency | | | | Chi-square | p-Value |
|---|---|---|---|---|---|---|---|
| | | Daily | Weekly | Monthly | No | | |
| Milk | Digital (N = 425) | 64.90% | 10.40% | 16.20% | 8.50% | 35.093 | <.001** |
| | Traditional (N = 138) | 68.80% | 7.20% | 18.80% | 5.10% | | |
| | Hybrid (N = 485) | 59.80% | 21.00% | 15.50% | 3.70% | | |
| Tea | Digital (N = 425) | 50.60% | 14.40% | 15.80% | 19.30% | 11.681 | 0.069 |
| | Traditional (N = 138) | 55.10% | 9.40% | 21.70% | 13.80% | | |
| | Hybrid (N = 485) | 54.60% | 14.00% | 18.60% | 12.80% | | |
| Coffee | Digital (N = 425) | 30.80% | 27.80% | 25.90% | 15.50% | 30.67 | <.001** |
| | Traditional (N = 138) | 39.90% | 13.80% | 38.40% | 8.00% | | |
| | Hybrid (N = 485) | 34.60% | 17.90% | 35.30% | 12.20% | | |
| Juice | Digital (N = 425) | 36.20% | 30.10% | 26.40% | 7.30% | 24.079 | <.001** |
| | Traditional (N = 138) | 34.80% | 39.10% | 23.20% | 2.90% | | |
| | Hybrid (N = 485) | 25.80% | 42.90% | 23.10% | 8.20% | | |
| Carbonated Drinks | Digital (N = 425) | 16.00% | 20.50% | 37.40% | 26.10% | 30.298 | <.001** |
| | Traditional (N = 138) | 9.40% | 19.60% | 53.60% | 17.40% | | |
| | Hybrid (N = 485) | 14.40% | 24.90% | 46.40% | 14.20% | | |

Chi-Square test
* = p<0.05
** = p<0.01

Source: Primary Data Collected through a survey conducted in Delhi-NCR[18].

3.8 RECOMMENDED DIETARY ALLOWANCES (RDA) AND ESTIMATED AVERAGE REQUIREMENT (EAR) OF THE PARTICIPANTS

Table 8, presents the RDA and EAR of the participants (N=1048).

Table 8a, shows the RDA (24-hour recall) of the participants based on the shopping mode. One-way ANOVA was conducted to examine differences in nutrient intake across shopping modes (N=1048), separately for males and females.

Among female participants, significant differences were observed only for energy intake ($F = 16.774$, $p < .001$**). Digital shopping mode reported the highest mean energy intake (2258.46 ± 516.23 kcal/day), followed by hybrid shopping mode (2219.32 ± 367.87 kcal/day), while traditional shopping mode had lower intake (1889.55 ± 186.15 kcal/day). No significant differences were observed across shopping mode for protein ($p = 0.323$), CHO ($p = 0.901$), or fat intake ($p = 0.422$). Energy intake among females across all shopping modes exceeded the Estimated Average Requirement (EAR).

Among male participants, significant differences were observed across shopping modes for energy, protein, carbohydrate, and fat intake. Energy intake was highest among the digital shopping mode (2306.28 ± 464.64 kcal/day), followed by the hybrid (2222.90 ± 370.54 kcal/day) and the traditional (2182.35 ± 355.89 kcal/day) shopping modes ($F = 4.283$, $p = 0.014$*). Protein intake was also significantly higher among the digital shopping mode (73.48 ± 17.28 g/day) compared to the traditional (68.08 ± 19.54 g/day) shopping mode ($F = 3.551$, $p = 0.029$*). Significant differences were observed for CHO intake (F = 10.884, p < .001**) and fat intake (F = 11.164, p < .001**), with digital and hybrid shoppers reporting higher intakes compared to the traditional shopping mode. While all shopping modes, mean energy and fat intake exceeded the recommended levels.

Table 8b, shows the proportion of participants meeting or exceeding the Estimated Average Requirement (EAR) based on shopping mode

A significantly higher proportion of digital and hybrid shopping modes exceeded the EAR for energy and protein intake compared to traditional shopping mode (p < .001** for all comparisons).

Among males, over 90% of digital and hybrid shopping modes consumed energy above the EAR, whereas most traditional shopping mode were below the EAR threshold.

Similarly, among females, digital and hybrid shopping modes demonstrated markedly higher proportions exceeding EAR for both energy and protein intake compared to the traditional shopping mode.

**Table 8:** Recommended Dietary Allowances (RDA) and Estimated Average Requirement (EAR) of the participants

Table *8a*: *Recommended Dietary Allowances (RDA)* of the participants

| Gender | Nutrients Intake | Energy (EAR kcal/d) | Protein (EAR g/d) | CHO (g/d) | Fat (g/d) |
|---|---|---|---|---|---|
| Female | RDA | 1500 | 36.3 | 249 | 20 |
| | Digital | 2258.46 ± 516.23 $^{b}$ | 73.03 ± 19.87 | 305.57 ± 63.52 | 59.62 ± 23.09 |
| | Traditional | 1889.55 ± 186.15 $^{a,c}$ | 72.00 ± 19.21 | 307.60 ± 59.83 | 60.83 ± 22.26 |
| | Hybrid | 2219.32 ± 367.87 $^{b}$ | 70.19 ± 15.39 | 303.90 ± 48.42 | 57.47 ± 15.97 |
| | F-test | 16.774 | 1.135 | 0.104 | 0.864 |
| | Sig. | **<.001**** | 0.323 | 0.901 | 0.422 |
| | | | | | |
| Male | Nutrients Intake | Energy (EAR kcal/d) | Protein (EAR g/d) | CHO (g/d) | Fat (g/d) |
| | RDA | 1700 | 42.9 | 316 | 25 |
| | Digital | 2306.28 ± 464.64 $^{b,c}$ | 73.48 ± 17.28 $^{b}$ | 312.58 ± 57.30 $^{b}$ | 60.83 ± 21.17 $^{b}$ |
| | Traditional | 2182.35 ± 355.89 $^{a}$ | 68.08 ± 19.54 $^{a}$ | 281.71 ± 63.44 $^{a,c}$ | 49.33 ± 22.57 $^{a,c}$ |
| | Hybrid | 2222.90 ± 370.54 $^{a}$ | 70.78 ± 17.17 | 303.23 ± 45.53 $^{b}$ | 58.17 ± 16.70 $^{b}$ |
| | F-test | 4.283 | 3.551 | 10.884 | 11.164 |
| | Sig. | **0.014*** | **0.029*** | **<.001**** | **<.001**** |

EAR = Estimated Average Requirement
RDA = Recommended Dietary Allowances
Post Hoc Test
a= correlation mean difference significantly less than 0.05 in the Digital Shopping Mode
b= correlation mean difference significantly less than 0.05 in Traditional Shopping Mode
c= correlation mean difference significantly less than 0.05 in Hybrid Shopping Modes
One-way ANOVA
* = p<0.05
** = p<0.01
Source: RDA, ICMR (2020)

Table *8b*: *Estimated Average Requirement (EAR)* of the participants

| Gender | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| EAR | Energy | | Protein | | Energy | | Protein | |
| Range | < 1700 | > 1700 | < 42.9 | > 42.9 | < 1500 | > 1500 | < 36.3 | > 36.3 |
| Digital (N = 425) | 8.90% | 91.10% | 4.40% | 95.60% | 6.50% | 93.50% | 1.30% | 98.70% |
| Traditional (N = 138) | 82.10% | 17.90% | 25.00% | 75.00% | 66.70% | 33.30% | 20.40% | 79.60% |
| Hybrid (N = 485) | 5.60% | 94.40% | 4.20% | 95.80% | 1.00% | 99.00% | 0.50% | 99.50% |
| F-test | 292.217 | | 48.004 | | 182.205 | | 53.734 | |
| *p*-Value | <.001** | | <.001** | | <.001** | | <.001** | |

EAR = Estimated Average Requirement
One way ANOVA
* = p<0.05
** = p<0.01
Source: RDA, ICMR, (2020)

Source: Primary Data Collected through a survey conducted in Delhi-NCR[18].

## 4. Discussion

### 4.1 PREVALENCE OF DIGITAL, TRADITIONAL, AND HYBRID FOOD SHOPPING MODES

This study found the prevalence of different shopping modes among the population and the relationship between health and lifestyle patterns. The study findings revealed that 46.3% of participants preferred a hybrid (both digital and traditional) shopping mode, whereas the digital shopping mode was opted by the participants were 40.6%, and the remaining 13.2% prefers the traditional shopping mode. These analyses indicate a clear preference towards the digital shopping mode behaviour. The growing population's interest in the digital shopping mode, by making their choices easier, convenient, accessible, affordable, reasonable, door-to-door services and time-saving. Guleria (2019)[19], Gupta and Sethi (2015)[20], and Isswani and Chaturvedi (2019)[21] observed similar results in an increasing of the prevalence of digital shopping behaviour among the urban (metropolitan) population. particularly in urban populations. There was a minor difference in the shopping mode pattern based on gender. Both have a high preference for digital and hybrid shopping modes over the traditional shopping mode. These results show that the digitalisation of shopping patterns has influenced behaviour among genders, reflecting a wider and busier lifestyle change in metropolitan behaviour in their daily routine environments.

Crane et al. (2021)[22] study also highlighted that the convenience, product-wide range and pricing influence the population to shift toward the online shopping platform, while the current study shows similar interest in a majority of the participants preferred hybrid and digital shopping modes, indicating a different shopping mode pattern behaviour.

Gillespie et al. (2021)[23] study analyses that the younger participants, educated and influenced through the lifestyle and situational factors, while the current study showed younger participants (40.7% of 25-30 yrs) and educated (60.9% of professionals), support the preference towards the digital shopping mode.

Cong et al. (2021)[24] and Kerkadi et al. (2019)[25] both observed similar outcomes that the lifestyle behaviour and digital food environment influence the dietary pattern and obesity risk, while the current study showed a similar suggestion that the increase in the usage of digital and hybrid shopping modes contributes to changes in lifestyle, food accessibility and consumption patterns.

The findings from both the studies Claypool et al. (2020)[26] and Mishra et al. (2018)[27] observed similar outcomes about the urbanisation and lifestyle transition significantly influenced dietary habits and obesity occurrence, while the current study states the similar outcome by conducted in Delhi NCR region, metropolitan (urban) lifestyle patterns contributively to increase dependency on digital food shopping mode leads to increasing of obesity and risk.

Behavioural change, especially during the lockdown periods, increased the unhealthy eating habits demonstrated by Cherikh et al. (2020)[28], which further strengthens the current study result, which denotes digital accessibility to food may influence the consumption and lifestyle behaviour pattern.

Sivanesan et al. (2017)[29], study displays similar findings, the preference for online shopping widely increasing, primarily due to ease and convenience, while offline shopping remains dominant for purchasing food. The current study stated the shifting towards the hybrid and digital shopping modes, suggesting that the population's behaviour keeps evolving, where individuals verify the food products in a combination of convenience and physicality.

### 4.2 BODY MASS INDEX OF PARTICIPANTS

The current study analysed the anthropometric measurements: BMI variations in different shopping modes. Male participants had the highest mean BMI, which was observed in the hybrid shopping mode (27.11 ± 4.47 kg/m²), followed by the traditional shopping mode (26.63 ± 3.99 kg/m²) and digital shopping mode (26.53 ± 4.44 kg/m²). whereas the female participants had the highest mean BMI in the traditional shopping mode (26.37 ± 4.92 kg/m²), followed by digital shopping mode (25.98 ± 4.80 kg/m²) and hybrid shopping mode (25.41 ± 4.34 kg/m²). These differences between the BMI and Shopping mode were not statistically significant.

BMI classification follows the Asian criteria, which shows that the majority of the participants (both genders) fell into the category of obese, followed by the overweight categories, throughout all shopping methods. In the hybrid shopping mode, both genders had the majority of participants in the obese category. The relationship between BMI categories and shopping modes was not statistically significant. According to Yousif, Kaddam and Humeda (2019)[30], who analysed the anthropometric measurements and BMI distribution in an adult group. Their study showed the average value of mean BMI was 22.8 kg/m², with the majority of the participants falling into the category of normal weight. The current study showed a majority of the participants falling into the obese category, signifying the rise of obesity in metropolitan populations. The relationship between the BMI and shopping modes was statistically not significant. The majority of the participants have higher BMI values in hybrid and digital shopping modes, which reflects their metropolitan lifestyle patterns, sedentary behaviour and consumption of high-calorie foods.

Keeble et al. (2021)[31] study provides strong support for the relationship between accessibility to food delivery outlets and obesity that indicates the easily access to dietary behaviour plays a crucial role, while the current study reflects that the dietary behaviour among the hybrid and digital shopping mode participants showed higher obesity prevalence.

Gu et al. (2021)[32] observed that lifestyle factors like sedentary habits and unhealthy diet lead towards the obesity risk and also Pellegrini et al. (2020)[33] studied the weight gain associated with unhealthy eating behaviour due to disturbing of lifestyle that supports the concept of behavioural change linked with convenience food access may influence BMI outcome which shows the similar result in the present study finds that the higher BMI was found among the population prefers mostly the digital and hybrid shopping modes.

Harahap et al. (2020)[34] and Stephens et al. (2020)[35] both studies detected the similar pattern of increasing frequency of online food ordering leads to higher obesity risk due to accessibility and convenience whereas the current study didn't find statistically significant relationship between the BMI and shopping mode, data shows the higher obesity prevalence among hybrid and digital shopping mode participants due to the behavioural association.

Nicolaidis (2019)[36] study identified the environmental and lifestyle factors such as sedentary behaviour, dietary intake and urban living, these factors also support the current findings about the participants showing the higher BMI levels across all the shopping modes, especially in metropolitan regions.

## 4.3 PHYSICAL ACTIVITY LEVELS OF PARTICIPANTS

Physical activity patterns were analysed in relation to shopping modes. The results revealed a statistically significant relationship between shopping modes and physical activity ($p = 0.004^{**}$). It was found that participants using traditional shopping modes show the highest physical activity level (68.1%), as compared to hybrid shopping mode (53.8%) and digital shopping mode (52.2%). This was possibly because in traditional shopping modes, individuals have to move physically, i.e., visit markets and stores physically, whereas in digital shopping modes, they don't required to move physically, and they get their goods delivered at home. Physically active participants, showing the physical activity type and their intensity (level), it was found that the relationship between the active physical activity type and different shopping modes was not statistically significant. It was found that the majority of the participants prefer walking, followed by exercise, yoga and gym. It was also found that the majority of the physically active participants preferred to do the light intensity activity regardless of their shopping modes. Yousif, Kaddam, and Humeda (2019)[30] found the partial similarity with the current study that males (18.5%) have high physical activity levels, whereas females (32.9%) have low physical activity levels, whereas the current study shows that there was no significant difference between the physically active intense (level) activity and the shopping mode pattern.

This shows that the shopping mode does have an impact on the physical activity, but there was no impact of the specific and intense level of physical activity.

Kolota and Glabska (2021)[37] study showed the decline in physical activity combined with increasing of unhealthy eating behaviour during the lifestyle transition, particularly during lockdown. This aligns with the current study, where the participants preferred digital (47.8%) and hybrid (46.2%) shopping, demonstrating a high lack of physical activity.

Bray et al. (2016)[38] highlighted that regular physical activity (up to 150 minutes per week) was crucial to perform and maintain a healthy body weight while preventing obesity, whereas the current study showed that those participants who preferred traditional shopping modes had a higher physical activity level (68.1%), indicating the supplementary physical movements associated with traditional shopping modes.

4.4 DIETARY PATTERNS AND NUTRIENT INTAKE

The study identifies the relationship between the dietary pattern and nutritional intake with shopping mode. Dietary intake has a relationship with the shopping modes, showing a statistically significant difference among male participants, whereas there was no statistically significant difference among female participants. In males, the digital shopping mode has a higher nutritional intake of nutrients than the traditional shopping mode. The relationship between nutritional intake and the shopping modes shows the data was statistically significant: Energy ($p = 0.014^*$), protein ($p = 0.029^*$), CHO ($p < .001^{**}$), and fat ($p < .001^{**}$). The result shows that the digital shopping mode was linked with a higher dietary intake pattern. In females, the digital shopping mode has a higher nutritional intake of nutrients than the traditional shopping mode. The relationship between nutritional intake and the shopping modes shows that the data were not statistically significant for protein, CHO, and fat, except for Energy (<.001**), with the digital shopping mode having the highest energy intake than the hybrid shopping mode. NIN–ICMR (National Institute of Nutrition, Indian Council of Medical Research) (2020)[4] recommended that the Estimated Average Requirement (EAR) for energy and protein intake in both genders across all shopping modes has a tendency towards high energy consumption among the selected population. The current study shows that the relationship between fast food consumption patterns and the shopping modes was statistically significant, except for pizza. Hybrid shopping mode participants had a high consumption of fast foods, i.e. patties/samosa, chips/nachos, noodles/pasta, and South Indian dishes, whereas digital shopping mode participants had higher daily consumption of fast food. While the traditional shopping mode participants have low consumption and higher monthly consumption of fast food. A previous study conducted by Ho et al. (2016)[39] observed that fast food consumption increases among the metropolitan (urban) population due to the convenience and accessibility, and another study conducted by Majid et al. (2021)[40] among medical interns has higher consumption of fast food, including behaviour towards unhealthy and irregular dietary meal patterns. The current study shows that the relationship between beverage consumption and shopping mode was statistically significant for milk, coffee, juice, and carbonated drinks, except for tea. Traditional shopping mode participants have high consumption of milk and coffee daily, followed by digital and hybrid shopping modes, which have different and flexible patterns for beverages like juices and carbonated drinks. Previous research conducted by Green et al. (2016)[41] showed that dietary patterns influence health status, whereas the current study showed the evolution of digitalisation and shopping behaviour may be a factor for shifting the dietary meal intake pattern, due to the convenience and availability of fast food instantly. The study indicates that digital and hybrid shopping modes may increase access towards the convenience and high-calorie food products that contribute to high nutritional intake levels.

Dhas (2022[42] highlighted the importance of the education of nutrition to improve dietary habits, suggesting that awareness interventions might help to reduce the unhealthy consumption trends observed among digital shopping participants.

Mizia et al. (2021)[43] and Sedibe et al. (2018)[44] both studies show a similar outcome about the irregular dietary habits and unhealthy food consumption patterns leading to obesity risk, which relates to the current study findings showing that the higher the intake of fast foods and beverages among participants in digital and hybrid shopping modes.

The effect of cultural and environmental factors on dietary intake was observed by Samaddar et al. (2020)[45], aligns with the current study, where participants demonstrated that the varied dietary behaviours were influenced by accessibility and convenience of food options.

Previous research conducted by Sun et al. (2020)[46] established a strong positive association between unhealthy food intake and weight gain, which resembles the present study's observation about the consumption of higher caloric and fat intake among digital and hybrid shopping mode participants.

LIMITATIONS

Limitations faced by the researcher in the future are

- The sample was drawn based on the Indian National Capital Region, Delhi-NCR, which limited the results based on the different regions and cultural backgrounds, varying in lifestyle patterns, shopping patterns, and dietary habits. Different regions lead to different insights.
- Longitudinal study or comparison of different regions or countries can be done to get their current or recent research results with different findings or percentages.

FUTURE IMPLICATIONS

Based on the present study, to diversify the research based on the:

- Students (schools and colleges)
- Employees (companies, medical staff, etc.)
- Patients and Hospitality (healthy, medically diagnostic)
- Locations (Countries, States, Cities, etc.)
- Other factors (genetic, environmental)

## 5. Conclusions

The study showed that digitalisation impacts adults' food shopping behaviours, relationships with BMI, physical activity, and their dietary meal intake patterns. The study showed highly preferences towards the digital and hybrid shopping mode patterns that participants prefer their convenience and benefit by saving their time in metropolitan (urban) regions.

BMI variation in different shopping modes shows no statistically significant. The majority of the participants belong to the obese category, followed by the overweight category. Digital and hybrid shopping mode participants had a high BMI range. The relationship between the shopping mode and BMI was not statistically significant. Other factors of lifestyle patterns lead to weight gain.

The current study found that the traditional shopping mode participants were more physically active than digital and hybrid shopping mode participants, because of the movements like visiting the stores and shops physically. The physical activity type and intensity were similar in all shopping modes, whereas walking was the most common activity.

Shopping mode participants had a different dietary intake pattern, especially for male participants. Participants of the digital shopping mode consume more energy, protein, CHO and fats, whereas for females, energy intake was the only significant difference among other nutrient intakes.

Mean energy intake is higher than the recommended values, leading to high calorie consumption. Digital and Hybrid shopping mode participants prefer to consume more convenience and fast foods. Digital shopping platforms made their life easier by providing access of high calories options.

Products or food shopping method via digital platforms is changing the behaviour, lifestyle and dietary habits of the population. Digital and hybrid shopping modes offer various discounts, marketing, convenience, and door-to-door services, which are leading towards the lack of physical activity and higher intake of calorie-dense food, i.e. junk food, etc. These lifestyle behaviour changes lead to long-term health risks, which necessitate educating the population regarding the awareness for nutritional education, active lifestyle patterns, and promoting and guiding the population towards healthy food choices in digitalisation world.

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None.

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