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Impacts of COVID-19 lockdown on time allocation for sedentary and physical activities – The context of Indian university students

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ABSTRACT

Introduction: Covid-19 pandemic has impacted individuals’ time allocation decisions. As it is known that university students display behaviors different from the general population, very few studies have examined their activity participation and time allocation behavior during the pandemic. The present study investigates the changes in time allocations to sedentary, physically active, and eat-sleep activities before and during the pandemic.

Methods: The study hypothesizes that active mode (walk, bicycle) and transit users would compensate for the physical efforts by increasing physical activities at home during the lockdown. Students’ perception of personal well-being, anxiety, and individual leisure during the pandemic and their impacts on time allocation decisions after controlling for demographic variables and temporal effects are also explored. A pan India behavioral data of 203 samples collected using an online survey conducted between May to July 2020, during India’s lockdown phase, is used for analysis. A series of segmented analyses (using ANOVA’s and Kruskal-Wallis Test) and empirical modeling (linear mixed-effect regression) were conducted based on the time use distribution.

Results: Findings showed that university students from low-income households and students who own a bicycle show a higher tendency to spend time in physical activities during lockdown periods. Students accessing college using active modes (before lockdown) allocate less time to sedentary and eat-sleep activities than physical activities during the lockdown period. Students’ perception of Leisure items among those who use active modes is significantly different from those of private and public mode users.

Conclusions: From a policy viewpoint, such investigation would help implicitly understand and publicize the health benefits of active modes and transit and encourage their use. For instance, policymakers and transport planners can temporarily allocate less-used motorized streets (due to the pandemic) to students who prefer walking and cycling as universities still function online in India.

1. Introduction

University students’ travel behavior is important for assessing the influence of long-term life decisions on impending mobility

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scenarios as well as future transportation planning and regulations (Zhou, 2012). According to the existing research (Nash and Mitra, 2019; Verma et al., 2016), students’ future mobility patterns are shaped by their habits, lifestyles, and conventions. For example, the experience students gain, and the lifestyle they adopt at university may considerably impact their travel behavior, which may cause significant changes in society in the future. Specifically, the possible effect of sedentary and physically active behaviors instilled during their adolescence and adulthood (time spent at a university) may greatly explain their attitude toward travel and future travel behavior (Schwanen et al., 2012). This notion motivates the authors to investigate the relationship between university students’ sedentary and physically-active lifestyle. The present work makes a two-fold addition to the literature in this area.

First, the paper investigates and compares the changes in time allocations to sedentary, physically active, and eat-sleep activities before and during the pandemic for university students. COVID-19 pandemic, since its outbreak, has posed a serious threat to human life across the globe. It has infected more than 105 million human beings and claimed nearly 2.3 million lives (Worldometer, 2020). This has led to the World Health Organization (WHO) declaring it a global pandemic. To contain the spread of the virus and ensure safety, governments and local authorities have turned to restrictive policy measures, such as lockdown, social distancing at public places, etc., to control and limit individuals’ outdoor exposures. The lockdown measures have led to the suspension of offices, shopping malls, recreational centers, and educational institutions. Specifically, the closing of educational institutions is expected to influence students’ mental and physical well-being (Odriozola-Gonzalez et al., 2020). For instance, unstructured leisure time available due to the closing down of colleges/universities may foster a more active lifestyle or increase time spent in sedentary behaviors, which can lead to adverse health effects (Boberska et al., 2018). The disruptions to academic activity, recreation opportunities and habits, and lack of peer interactions could also lead to emotional disorders and young adults’ ill-being (Gallo et al., 2020; Odriozola-Gonzalez et al., 2020). For example, riding a car with family members or friends for an out-of-home recreational activity could be mentally and socially rewarding for young adult members (Mokhtarian and Salomon, 2001). Additionally, as noted by the WHO, nearly 31% of the world’s population aged 15 years or above are physically inactive, and around 3.2 million deaths per year are due to this unhealthy lifestyle. Therefore, there is a need to assess the impacts of the lockdown on university students’ indoor and outdoor time allocation decisions and their physical and mental well-being. From a broad societal viewpoint, such a study would help understand behaviors and hint at policies and schemes to enhance university students’ overall well-being during an unprecedented situation like the COVID-19 pandemic.

Second, the study explores the students’ perception of personal well-being and anxiety, attitudes towards individual leisure during the pandemic, and their impacts on time allocation decisions after controlling for demographic variables and temporal effects, especially in a developing country like India. The general literature on activity participation, time allocation, and mental well-being of university/college-going students are relatively scarce, and very few Indian studies are based on this cohort (Sarangi and Manoj, 2020). The pandemic’s impacts on time use and travel decisions have also rarely been reported from Indian settings. The Indian government announced gradual nationwide lockdown measures on March 22, 2020, in response to the enormous surge in the daily reported infections and community transmissions. The lockdown measures are presently being lifted. However, public facilities have not seen much demand. There is a reduction in the use of retail and recreation places, parks, public transport, and workplaces by 28%, 30%, 17%, and 35%, respectively, when compared to the baseline period (median values for the corresponding day of the week from January 3 – February 6, 2020) (“COVID-19 Community Mobility Report,” n.d.). Besides, there is also a reported increase of 10% indoor time over the baseline period (“COVID-19 Community Mobility Report,” n.d.). These observations depict the changes in the lifestyle of Indians due to the pandemic and lockdown. However, the impacts of changes in lifestyle on time-use and activity participation are seldom discussed. The present study explores university students’ physically active and sedentary activity participation behavior during India’s lockdown phase. University students comprise nearly 39% of the Indian population (Ministry of Human Resource Development, 2016). As the nation is growing young, knowledge of students’ behavior changes would help urban and health policymakers devise strategies to ensure citizens’ physical and mental well-being.

Based on the above discussions, the objectives of the paper are as follows. First, it investigates the changes in time allocations to sedentary, physically active, and eat-sleep activities before and during the pandemic. The time allocation behaviors are also explored based on the commute mode and time spent traveling to the university before the lockdown. It hypothesized that active mode (walk, bicycle) and transit users would compensate for the physical efforts by increasing physical activities at home during the lockdown. Similarly, those who had spent a long-time in traveling are also expected to change their time allocation decisions during the pandemic lockdown. Such comparison also helps understand how experience with active modes and transit helps lead an active lifestyle during difficult times. Second, the study explores the students’ perception of personal well-being and anxiety, attitudes towards individual leisure during the pandemic, and their impacts on time allocation decisions after controlling for demographic variables and temporal effects. This part of the analysis helps identify the personal backgrounds that lead to different time-use choices and could be investigated with the nation’s socio-economic evolution from a broad policy viewpoint.

The study utilizes pan India behavioral data collected using an online survey conducted between May to July 2020, during India’s lockdown phase. The research hypothesizes that the lockdown brought changes to physically active, sedentary, and eat-sleep activity participation levels, and variations in the levels are analyzed through descriptive and statistical analysis. The remainder of the article is organized as follows. Section 2 reviews past studies that align with the present work, while Section 3 presents the survey design. The overview of the empirical framework used in the study is presented in Section 4. Section 5 describes the exploratory analysis done on the sample used for the present study. Section 6 elaborates on the results obtained from empirical models and highlights the potential policy implications of model findings. The final section (Section 7) summarizes the findings of the study and discusses the areas of future research.
2. Literature review

This section summarizes the works undertaken in the broad areas of in-home physical and sedentary activity participation of the general population before and during the pandemic.

Although of a different scale and sort, the world has been dealing with another ‘pandemic’ – sedentary lifestyles that claim nearly 3.2 million lives every year (Pearson et al., 2014) and cost healthcare systems around the world billions of Dollars (Ding et al., 2016). The Covid-19 pandemic is expected to further add to the pressure on healthcare systems. Among the various studies on the impacts of the Covid-19 pandemic, researchers from different parts of the world have worked together to implement a worldwide online survey in multiple languages in April 2020 to explain better the impacts of lockdown measures and other restrictions on individual lifestyles and behaviors (Ammar et al., 2020). The study indicated that home containment due to the Covid-19 pandemic curtailed all physical activity (PA) intensity levels. An analysis of similar nature was conducted by Faulkner et al. (2020) using an online survey circulated in the United Kingdom (UK), Australia, New Zealand, and Ireland focusing on adults in the age bracket of 18–55 years. The study noted that females reported improvements in physical exercise levels, and younger adults (18–29 years) witnessed a reduction in participation levels in physical exercises. In the USA, Dunton et al. (Dunton et al., 2020a; 2020b; 2020c) investigated the effects of imposed home confinement on PA and sedentary activity (SA) during the Covid-19 pandemic. Some of their works (Dunton et al., 2020b; 2020c) focused on US adults (sample size 262), while others (Dunton et al., 2020a) paid attention to US children (sample size 211). Dunton et al. (2020b, 2020c) concluded that the vulnerable population sub-groups (especially individuals who are Hispanic or belong to lower-income households) are worst affected by the Covid –19 pandemic. Dunton et al. (2020a) concluded that pandemic-induced short-term shifts in PA and SA behaviors might become chronic in children leading to a high risk of cardiovascular disease and obesity issues. Along similar lines, Bhutani and Cooper (2020) conducted an online survey among US adults. A chi-squared test was used to check the changes in PA and SA levels since the Covid-19 outbreak. Statistical analysis revealed that the differences were significant between genders, while Body Mass Index (BMI) categories did not show distinct patterns. These findings were supported by Barkley et al. (2020) who collected data from university students and employees across the US. The study noted that the closing of physical activity facilities had a disproportionate effect on the university population’s physical activity levels. In Brazil, Schuch et al. (2020) evaluated the time allocation to PAs and SAs (pre-pandemic versus during the pandemic) among self-isolated Brazilians. A total of 877 participants were included, and econometric models were used for the analysis. The study indicated that younger adults, unmarried individuals, and those involved in paid work showed more significant reductions in time allocation to PAs or an increase in the duration of SAs. The correlation between watching TV and computer usage with unhealthy diet/ultra-processed food intake was explored using logistic regression models by Werneck et al. (2020). Gender, age group, highest academic achievement, and skin color were found to influence eating habits. Silva et al. (2020) performed a study similar to Werneck et al. (2020) but explicitly focused on Brazilian adults with a chronic disease.

In Italy, Gallé et al. (2020) administered an electronic questionnaire among students of three universities. The time spent using electronic devices showed a significant increase compared to the pre-lockdown period, whereas the time allocated to walking witnessed substantial reductions. During the confinement period, the engagements in PAs by boys and girls were primarily linked to their active lifestyle before the pandemic. Cellini et al. (2020) administered an online survey among Italians to collect data on sleep patterns, digital media usage, and subjective experience during the pandemic. They observed decreased sleep quality, especially in respondents with more depression levels, stress, and anxiety syndrome. Ingram et al. (2020) reported degrading emotional well-being and increasing health issues during the pandemic by identifying lifestyle constraints and changes in activity participation behaviors among the UK and Scottish citizens. An independent cross-sectional study was done to analyze the psychological impacts of Covid-19 among students and staff belonging to a Spanish university (O드리오조-la-González et al., 2020). The study reported that (levels of) stress, anxiety, and depression rose by 28.14%, 21.34%, and 34.19%, respectively, relative to the pre-pandemic times. Besides, students from non-technical disciplines (e.g., Social Science, Arts & Humanities, Law, etc.) reported better ratings on mental health attributes (stress, anxiety, and depression) relative to engineering and architecture students. On average, university staff reported lower mental health scores than students. A similar study conducted in France (Husky et al., 2020) among university students revealed behavior changes identical to the findings of O드리오조-la-González et al. (2020). Sañudo et al. (2020) performed multiple regression analysis on the data collected seven days before and during the pandemic period from 20 young Spanish adults. The study concluded that the time allocation to smartphone use and sleeping increased during the pandemic time, whereas the time spent on physical activities decreased. Studies conducted in other parts of Europe - Croatia (Sekulic et al., 2020), Belgium (Constandt et al., 2020), Austria (Pieh et al., 2020; Schnitzer et al., 2020), Portugal (Pombo et al., 2020), and Switzerland (Cheval et al., 2020) - have concluded that lockdown measures impacted physical and sedentary activity behaviors of adults. In China, Wang et al. (2020) examined the two-way effects of the Covid-19 pandemic on health outcomes and quality of life (QOL) amongst adults. The results revealed that more than 50% of the respondents reported a reduction in the time allocated to PAs, while for SAs, the time allocation increased compared to pre-lockdown situations. Prolonged sitting time and stress levels were found to negatively affect QOL, similar to the findings of Qi et al. (2020). Kang et al. (2020) specifically focused on the interdependency between PA and mental health among Chinese adolescents. The study reported that boys revealed better mood states than girls, and senior high school students (Grade 3) revealed higher mood disturbance. Studies of similar nature were conducted in other Asian countries, e.g., Rahman et al. (2020) in Bangladesh, Ong et al. (2020) in Singapore, and Pragholapati (2020) in Indonesia, to study physical inactivity and sedentary behaviors during the Covid-19 lockdown. Gallo et al. (2020) conducted an observational study to examine the impact of isolation measures on diet and PA patterns among biomedical students of a university in Brisbane, Australia. While the study reported reductions in both sexes’ physical activity levels during the pandemic, females reported increased energy intake.

In summary, the earlier studies have shown that the Covid pandemic has impacted individuals’ time allocation decisions. It has...
been noted that university students also witness significant changes in activity participation indoors and outdoors. As it is known that university students display behaviors different from the general population, very few studies (Barkley et al., 2020; Galle et al., 2020; Odriozola-Gonzalez et al., 2020) have examined their time allocation behavior during the pandemic. The possible substitution or complementary effects of out-of-home activity participation restrictions on in-home activity choices has also not been studied in the literature. While it is known that travel using active modes and transit is restricted during the pandemic, it would be interesting to know how the active and transit mode users allocate time to different activities during the pandemic. From a policy viewpoint, such investigation would help implicitly understand and publicize the health benefits of active modes and transit and encourage their use. The literature review reveals that few studies have discussed university students’ time allocation decisions in India during the pandemic. The present article aims to contribute along these lines.

3. Data

The primary data required for the present study was collected using an online questionnaire survey conducted between May and June of 2020. The questionnaire was prepared in English and disseminated via emails to various intermediate and graduate colleges across India (since the focus group of the present research is students). The college/university list was compiled from the All India Council for Technical Education (AICTE) (“Government of India, All India Council for Technical Education,” n.d.) and Ministry of Human Resource Development (MHRD) (“Institutions | Government of India, Ministry of Education,” n.d.) database and the list was segregated state-wise across India. A weighted random sampling was done (to avoid selection bias), where the weights were determined by taking the ratio between the total list of available higher education colleges/universities for a state and population count for that state in the age group of 15–59 years as per the 2011 census (Census of India 2011; 2020). The emails were dispatched to these randomly chosen institutes across all states of India. Prior to implementation, to validate the initial draft, a pilot test was carried out by randomly selecting and mailing the questionnaire link to 30 post-graduate students from the authors’ institute. The questionnaire was tested for content, applicability, wording sequence, and level of difficulty. Based on the pilot data, minor modifications in the length of the questionnaire were incorporated by reducing the number of sub-activities and items measuring perception of individuals.

The questionnaire consisted of six sections. ‘Part-A’ of the questionnaire collected information on students’ physical appearance...
(height and weight), university/college location details, time spent in university/college on weekdays in academic-related activities before lockdown, and residence address (before and during the lockdown). Part-B and Part-C, respectively, asked the students to self-report the number of episodes undertaken and time allocated (expressed in hours and minutes) to sedentary, physical, and eat and sleep activities during and before the lockdown period. A set of eight sub-activities were asked under sedentary activity (SA) that was taken from the widely accepted and validated Adolescent Sedentary Activity Questionnaire (ASAQ) (Chu et al., 2018; Guimarães et al., 2013). At the same time, all the sub-activities asked under physical activity (PA) were taken from the International Physical Activity Questionnaire (IPAQ), developed and authenticated globally across 12 countries (Craig et al., 2003). The SA included questions centered on study activities, television viewing, performing activities on computers, tablets, etc., playing board games such as chess, ludo, etc., and other leisure time activities (Chu et al., 2018). PA included a mix of vigorous and moderate physical activities. ‘Part-D’ gathered information on the respondents’ travel details before the lockdown, while ‘Part-E’ recorded their socio-demographic information. The final part (Part F) was designed to collect students’ perceptions of leisure, personal well-being, and anxiety during the lockdown period. A total of 631 responses were collected at the end of the survey, out of which 249 were fully complete (response rate of 39.46%). However, after screening out 46 survey forms due to incorrect survey responses, data from 203 survey forms are used for further analysis. Incorrect (or biased) responses were those survey forms where the total time spent across all activity episodes in a day exceeded 24 h or if there was a significant difference in the reported and actual time taken to reach the university campus from the place of residence. The travel time between these origin and destination pairs was calculated using the Google API key and gmaps-distance (Zarruk and AuthorAnonymous, 2018) package in R software. Fig. 1 depicts the spatial distribution of the respondents’ university locations.

4. Statistical methodology

The study aims to model the changes in behaviors over time, i.e., the time allocation behavior before and during the lockdown periods, after controlling for socio-demographic attributes. As the data includes repeated observations (before and during the lockdown) from the same individual, the linear mixed-effects (LME) model is considered in the present study. In LME, the means are predicted as fixed effects and are identical for all persons, while the residuals are modeled by random effects and vary from person to person (Verbeke and Molenberghs, 2006). The advantage of the LME framework is that the residuals are allowed to be correlated. Hence, the inferences are unbiased, unlike a linear regression model where if the independence assumptions of the error terms are violated, the inferences are biased (Liu et al., 2012).

The LME framework, first proposed by Laird and Ware (1982), is expressed as:

| Table 1 |
|---|---|---|
| **Variables** | **Share in %** | **Variables** | **Share in %** |
| **Individual Attributes** | | **Vehicle Ownership** | |
| Gender | | Car | |
| Male | 54.19 | Yes | 39.41 |
| Female | 45.81 | No | 60.59 |
| **Age (in years)** | | Two-Wheeler | |
| 18–25 | 48.77 | Yes | 75.86 |
| 25–30 | 26.60 | No | 24.14 |
| 30–35 | 24.63 | Bicycle | |
| **Highest Completed Degree** | | Yes | 59.61 |
| Intermediate | 38.92 | No | 40.39 |
| Graduation | 24.63 | College Information | |
| Above Graduation | 36.45 | Spatial Location | |
| **Marital Status** | | North Zone | 23.64 |
| Single | 75.37 | East Zone | 33.01 |
| Married | 24.63 | West Zone | 24.63 |
| **BMI Proportion** | | South Zone | 18.72 |
| Obese/Overweight | 40.89 | Place of Stay | |
| Underweight/Healthy | 59.11 | With parents | 34.98 |
| **Household Characteristics** | | **College Information** | |
| Family Size | 4.47 (1.75) | Inside Campus | 36.45 |
| Presence of Kids | | College Duration | 28.57 |
| Yes | 16.26 | (in minutes) | 504.44 (84.22) |
| No | 83.74 | Mode to access campus | |
| Household Income | | Private | 23.15 |
| Low | 41.87 | Public | 33.50 |
| Middle | 34.98 | Active | 43.35 |
| High | 23.15 | Travel Time to Campus | |
| Change Time to Campus | | <20 min | 52.71 |
| Change Time to Campus | | 20–45 min | 24.14 |
| Change Time to Campus | | >45 min | 23.15 |

* Mean (Std. dev.).
\[ y_i = X_i \beta + Z_i Y_i + \epsilon_i \]

The subscript \( i \) is the basic unit of analysis, i.e., representing each individual on which observations are repeated. \( y_i \) is a \( n_i \times 1 \) dimensional vector of observed time spent in various activity type for the \( i \) th individual, \( X_i \) is an \( n_i \times b \) design matrix of known covariates, \( \beta \) is a vector of \( b \times 1 \) dimension representing the fixed effect coefficients, \( Z_i \) is a matrix of dimension \( n_i \times g \) denoting the random effects, \( Y_i \) is a \( g \times 1 \) vector of random scores, and \( \epsilon_i \) is a vector of within-subject residuals. \( \epsilon_i \) are assumed to have a normal distribution with mean 0 and a covariance matrix \( \sigma^2 \text{I}_n \), where \( \text{I}_n \) is the \( n_i \)-dimensional identity matrix. The fixed effect coefficients \( \beta = (\beta_1, \beta_2, \ldots, \beta_k)^T \) does not vary over period \( T \) (for the present study, \( T = 2 \)). The random-effects denoted by \( Y_i = (Y_{i1}, Y_{i2}, \ldots, Y_{ig})^T \) vary among individuals and are assumed to have a normal distribution with means 0 and covariance matrix \( G \).

Thus, it can be said that Equation (i) consists of two parts – a fixed-effects conditional means model (variation between individuals) denoted by \( X_i \beta \) and \( Z_i Y_i + \epsilon_i \) denotes the random-effects model (variation within an individual). The covariance matrix for the random-effects model is given by (Liu et al., 2012):

\[ V = ZGZ^T + \sigma^2 \text{I}_n \]

The first term \( ZGZ^T \) represents the group variance, and the second term, \( \sigma^2 \text{I}_n \) represents the residual variance. Once \( V \) is specified, the fixed effect coefficient \( \beta \)'s can be estimated using (Verbeke and Molenberghs, 2006):

\[ \hat{\beta} = (X^TV^{-1}X)^{-1}(X^TV^{-1}Y) \]

From Equation (iii), it is clear that the regression coefficients in an LME framework are dependant on the covariance matrix of the residuals in contrast to a general linear regression model. The covariance matrix of residuals can be estimated through various methods, as indicated by Liu et al. (2012). The present study uses the restricted maximum likelihood (REML) criterion to evaluate the covariance matrix. For more details on other methods of estimating covariance matrix and further insights on the LME approach, please refer to Hox and Roberts (2011); Liu et al. (2012).

5. Descriptive analysis

5.1. Socio-demographics

The summary of the socio-demographic variables is presented in Table 1. Categorical variables are reported in percentages, while the continuous variables are summarized through sample moments. Table 1 indicates that nearly 49% of the students are in the age bracket 18–25 years, an expected finding. More than 75% of students reported being single. The study also collected information on the current weight (in Kg) and height (in ft and in) of the respondents to be able to calculate the Body Mass Index (BMI) statistics. In the

| ITEM NO | PERSONAL WELL-BEING ITEMS | ITEM SCORE |
|---------|---------------------------|------------|
| PW1     | Your standard of living   | 3.41 (1.21) |
| PW2     | Your health condition     | 3.65 (1.20) |
| PW3     | Your ability to tackle daily problems and much-needed break | 3.53 (1.10) |
| PW4     | Your relationships with family members | 3.83 (1.23) |
| PW5     | Your safety consciousness and of your family members | 3.79 (1.08) |
| PW6     | Your community connectedness during COVID Pandemic | 3.05 (1.18) |
| PW7     | The security measures by Govt. to limit the spread of COVID | 3.41 (1.18) |
| PW8     | Your strength/energy to see through such times | 3.42 (1.13) |

| ITEM NO | ANXIETY ITEMS | ITEM SCORE |
|---------|---------------|------------|
| IA1     | I feel nervous and anxious | 2.82 (1.27) |
| IA2     | I am afraid for no reason | 2.56 (1.19) |
| IA3     | I am upset and feel panicked about the current situation | 2.76 (1.28) |
| IA4     | My life is falling apart during this emergency time. | 2.56 (1.18) |
| IA5     | I stay calm and think clearly. | 3.48 (1.17) |
| IA6     | I am fresh and generally have a good night’s rest. | 3.75 (1.22) |
sample, 59.11% of individuals were found to be ‘underweight/healthy’ (BMI ratio <25), slightly above the reported 57.99% among the age group of 20–29 years in India (“India: body mass index by age group, 2020 | Statista,” n.d.), thus validating the survey outcomes.

The table also summarizes household characteristics and vehicle ownership details. An average respondent has four members at home, and nearly 85% do not have kids in their family. Responses on household income were recorded through three sub-categories, namely – high (more than 60,000 INR), middle (25,000–60,000 INR), and low (Below 25,000 INR). The income segmentation was adopted from the Ministry of Statistics and Program Implementation (MOSPI) (MOSPI, 2011). The sample consisted of close to 42% of low-income households, followed by 35% of high-income households. In terms of vehicle ownership, close to 40% of households (in which the respondent is a college-going student) owned a car, which is relatively high than the national average (Ghate and Sundar, 2014). The college information category captured details on the college’s location, present residential information, time spent at college, the mode used to access the college/university (before lockdown), and travel time to the university. Based on respondents’

Table 3
Kruskal-Wallis Test of Perception-based Items with Gender, Age, and Mode used (n = 203).

| ITEM NO | GENDER | MW Test H Score | AGE (in years) | KW Test H Score | MODE USED | KW Test H Score |
|---------|--------|----------------|---------------|----------------|-----------|----------------|
|         | Male   | Female         | 18-25         | 25-30          | >30       | Active         | Private        | Public        |
| IL1     | 3.38   | 3.14           | 2.35          | 3.36           | 3.28      | 3.08           | 1.31           | 1.41          | 3.06          | 3.24          | 3.24          | 2.46          |
| IL2     | 2.32   | 2.70           | 3.89**        | 2.54           | 2.34      | 2.89           | 4.95*          | 2.43          | 2.83          | 2.51          | 2.18          |
| IL3     | 3.94   | 3.47           | 4.78**        | 3.93           | 3.76      | 3.48           | 2.79           | 3.93          | 3.57          | 3.71          | 1.92          |
| IL4     | 3.62   | 3.23           | 3.93**        | 3.69           | 3.29      | 3.38           | 5.01*          | 3.82          | 3.21          | 3.25          | 11.33***      |
| IL5     | 3.79   | 3.67           | 0.51          | 3.93           | 3.60      | 3.30           | 5.51*          | 3.99          | 3.47          | 3.60          | 6.01**        |
| IL6     | 2.95   | 2.91           | 0.06          | 2.93           | 2.96      | 2.90           | 0.05           | 2.97          | 3.35          | 2.64          | 5.56*         |
| IL7     | 3.24   | 3.16           | 0.25          | 3.22           | 2.79      | 3.60           | 6.73**         | 3.17          | 3.01          | 3.38          | 2.03          |
| IL8     | 2.79   | 2.85           | 0.04          | 2.74           | 2.52      | 2.84           | 10.91***       | 2.61          | 3.15          | 2.85          | 5.76*         |
| IL9     | 3.03   | 2.88           | 0.72          | 2.83           | 3.05      | 3.12           | 2.13           | 2.91          | 2.91          | 3.06          | 0.65          |
| IL10    | 2.56   | 2.12           | 4.01**        | 2.31           | 2.37      | 2.64           | 1.53           | 2.25          | 2.83          | 2.32          | 5.36*         |

Note: H-score value significant at 90%, 95%, and 99% CI is denoted by *, ** and ***, respectively.
college/university location, the sample had the highest representation from the East zone, followed by the West. For the place of stay during the lockdown period, 36.45% of students reported staying inside the campus, while 28.57% reported staying outside campus, and the remaining share of students indicated staying with their parents/family members. The term college duration refers to the average time (expressed in minutes) a student used to spend on the college/university campus for academic-related activities before lockdown. Concerning mode choice to access college/university campus, active mode (by foot and bicycle) share was highest (43.35%) followed by public modes (by paratransit, public transport, and college/university provided vehicles) share, i.e., 38.50% and private modes (by cars or motorized two-wheelers). For travel time to campus, nearly 53% of the respondents reported having fewer than 20 min, indicating more than half of the respondents spend comparatively less time traveling.

5.2. Perceptions

Table 2 presents the measurement items used to evaluate the three primary latent attributes: individual leisure, personal well-being index, and anxiety level. A list of 10 items was asked to evaluate the perception of respondents on individual leisure (IL). Similarly, to measure various dimensions of personal well-being (PW) and anxiety level (AL) during the pandemic period, a set of eight and six items were, respectively, presented to the respondents. The IL items were taken directly from Ragheb’s work (1980) with minor modifications to suit the study’s purpose. The PW items were picked selectively from a set of 22 items under the Quality of Life (QOL) index originally developed by Cummins (1997) and verified by Lau et al. (2005); Linley et al. (2009) under different contexts. The statements to evaluate AL were taken from the scholarly work of Gerolimatos et al. (2012). The questions’ responses were noted on a 5-point Likert scale with ‘1’ as Strongly Disagree (Highly Dissatisfied for PWI attribute) to ‘3’ as Cannot say and ‘5’ as Strongly Agree (Highly Satisfied) to the statements. The perception-based items and the item score (Mean (SD)) for IL, PW, and IA attributes are shown in Table 2.

Table 2
Description of the Activity types and time spent in those activities before and during lockdown (n = 203).

| ACTIVITY TYPE       | ID | ACTIVITY DESCRIPTION                                                      | PARTICIPATION SHARE IN % | TIME SPENT (in minutes) |
|---------------------|----|---------------------------------------------------------------------------|---------------------------|-------------------------|
| Sedentary Activities| SA1| Watching Television                                                      | 76.36                     | 62.44 (52.28)           |
|                     | SA2| Using computer for leisure; Playing games in mobile/TV/Computer          | 67.49                     | 59.04 (52.09)           |
|                     | SA3| Using a computer for education, Self-studying after college hours; Taking online courses | 71.43                     | 93.03 (74.47)           |
|                     | SA4| Chatting with friends on WhatsApp, Facebook, Zoom, or other social networking sites | 88.67                     | 84.80 (58.23)           |
|                     | SA5| Sitting around; Hanging out with friends; listening to music; Religious activities | 86.21                     | 79.95 (53.84)           |
|                     | SA6| Reading Newspaper, Novels or other articles/hooks in your leisure         | 41.38                     | 19.83 (13.42)           |
|                     | SA7| Playing Board games such as Chess, Carrom, Ludo, etc.                    | 29.06                     | 35.93 (18.37)           |
|                     | SA8| Doing Handicraft, Origami or Playing/Learning a musical instrument       | 35.47                     | 30.07 (19.63)           |
|                     |    | All Sedentary Activities Combined*                                        |                           | 390.69 (128.23)         |
| Physical Activities | PA1| Walking leisurely                                                        | 84.24                     | 53.33 (41.22)           |
|                     | PA2| Taking short bicycle rides, Jogging; Light Frisbee; Bowling games, Casual swimming etc. | 66.50                     | 33.59 (31.97)           |
|                     | PA3| Gardening; Household tasks such as bike washing, room cleaning           | 59.11                     | 33.88 (29.73)           |
|                     | PA4| Yoga, aerobics, Pranayama, or other light exercises like Stretching, taking dance classes | 59.61                     | 33.54 (30.34)           |
|                     | PA5| Doing exercise with weights and equipment either at the Gym or at home  | 40.39                     | 28.25 (20.18)           |
|                     | PA6| Playing outdoor games such as tennis, football, cricket etc.             | 53.20                     | 39.09 (34.61)           |
|                     | PA7| Playing indoor games, i.e., badminton, squash or Doing boxing, martial arts, etc. in free time | 48.28                     | 32.99 (26.92)           |
|                     | PA8| Running, swimming competitively, or other vigorous exercises to stay healthy | 43.35                     | 24.61 (18.52)           |
|                     |    | All Physical Activities Combined*                                         |                           | 207.24 (100.89)         |
| Eat Sleep Activities| ES | All Eat & Sleep Activities Combined* (Eating Food/Drinking Tea, juice; Sleeping, Personal care such as bathing, grooming, etc.) | 397.02                    | 207.24 (100.84)         |
Further, to compare the variation of item scores for IL, PW, and IA items across gender, age, and mode used variables, various non-parametric statistical tests were used. The respondents were asked to rate the items on a scale of 1–5. Thus, each item receives a single score per individual, and ratings are an example of an ordinal measurement scale. Hence, the ‘Kruskal-Wallis (KW)’ test was used for age and mode used variable, as they have three separate groups of participants, while ‘Mann-Whitney (MW)’ test was used for gender as it has two categories. The obtained H-score for both these tests follows a chi-square distribution and, if found significant, indicates the differences between groups are large and highly unlikely to have occurred by chance (Miriciou and Atkinson, 2017).

The results are shown in Table 3. In general, it is observed that male students were found to have a higher mean score for most items indicating their higher level of acceptance than female students. However, the difference in mean score for both the gender categories was found to be insignificant for anxiety (IA) items. Similar trends were also observed for age (except IAS) and mode used (except for IAE) for anxiety items. Besides, mode used categories (except for PW4) had no significant effect on items related to personal well-being (PW). On the other hand, mean scores obtained for the three Age categories varied significantly across PW items (except PW6 and PW7). On examining, we found that students in the age group of 18–25 years had a higher mean score than other age groups for most PW items. Moreover, for the leisure items, it was found that the perception of active users towards Leisure activities are good opportunities for social contacts (IL4) is significantly different from those of private and public mode users. Intuitively, during the time of survey when severe lockdown was imposed, the general population socialized with neighbors or friends primarily through leisure activities like small strolls or a leisurely walk with adequate social distance. Another interesting observation from Table 3 was that students above 30 years do not frequently get involved in leisure activities (IL8) as they believe it is a waste of time (IL10), evident from their higher mean scores for both these items.

Clearly, the segmented non-parametric analysis of perception-based items showed some interesting patterns and results, which is helpful in these unforeseen times. An exploratory factor analysis followed by a confirmatory factor analysis was carried out on the perception-based items (belonging to the individual attributes) to filter these items further and explore the underlying latent structure.

5.3. Activity participation and time allocation

The survey captured the activity participation behaviors before and during the lockdown period. The respondents were asked to provide their episode frequency and time allocation details for the activities conducted indoors and outdoors. A detailed description of the type of activity, activity episodes (share in %), and time spent in those activities (mean (SD)) and results of the paired t-test is shown in Table 4. Among the individual sedentary activities, the difference between the mean time spent before and during the lockdown in watching television, movies (SA1), and reading newspapers, novels, or other articles/books in leisure (SA6) were insignificant. A possible explanation can be that university students (in the age bracket of 18–35 years) own single or multiple electronic gadgets, e.g., smartphones, laptops, tablets/iPad, etc., unlike students from high-school or intermediate. So, digital technology provided a welcome source of alternative forms of connection and entertainment during pandemic times. In contrast, the mean difference between time allocation to remaining sedentary activities is found to be significant. The total time spent watching TV (SA1) and playing games on mobile/TV/Computer (SA2) during the lockdown by university students of India is found to be 167 min (73 min for SA1 and 94 min for SA2) which is comparatively lower than Polish nationals (240 min) in early adulthood (aged 18–34 years) (Czenczek-Lewandowska et al., 2021), adults aged 20–29 years from US (4.8 h per day for SA1 activity) (Zachary et al., 2020), and Brazilian adults (2.83 h in the age group of 18–30 years) (Malta et al., 2020). However, the average time spent on the computer for educational purposes (SA3) by Indian university students (136 min or 2.27 h) is comparable to that of US adults (2.5 h for the age group of 20–29 years) (Zachary et al., 2020). The mean time spent chatting with friends on social networking sites (SA4) and reading newspapers, novels, or other articles/books in leisure (SA6) are almost comparable to the reported durations of these activities among UK adults (18–30 years) (Fancourt et al., 2020). Overall, it is observed that the time allocations to most sedentary activities are increased during the lockdown. Although there is no agreement on the exact limit of excessive sedentary time (Stamatakis et al., 2019), the sedentary activity durations of Indian university students are higher compared to the European (Cheval et al., 2020; Gallè et al., 2020), and the US (Bhutani et al., 2020; Dunton et al., 2020a) settings. The time use decisions of Indian university students are also observed to be different from that of the case in Bangladesh (Rahman et al., 2020).

Table 4 also reports a declining trend in physical activity participation. The percentage of participation and time allocation has decreased during the lockdown period compared to the pre-lockdown times except for activity PA3. The difference between the time spent on different PA activities before and during the lockdown is significant at the 5% level. The time spent on PA1 activity by Indian university students is significantly less than that of Italian students (480 min) (Gallè et al., 2020). It was also observed that the university populace of India increased their time spent in ES activities by 28 min on average during lockdown with reference to before lockdown period (i.e., before March 2020). In contrast, the study by Rezaei and Grandner (2021) on six major US cities reveals that 18–29-year-olds increased their sleep duration by 13 min on average during the pandemic period in 2020 (from January to April) as...
compared to the previous year.

A series of one-way ANOVA has been performed to understand the impacts of travel mode on the university on time-use decisions (Nieuwenhuijsen and Khreis, 2020; Waddell et al., 2019). The time spent in each sub-activities under each primary activity has been aggregated for the ANOVA analysis due to the limited sample size (n = 203). Table 5 presents the ANOVA tests’ outcomes to identify travel mode influences and time spent traveling on time allocation to sedentary, physical, and eat-sleep activities before and during the lockdown. A p-value of 10% was considered for the ANOVA test to assess the significance level. In cases where the difference was found to be significant, a posthoc analysis was performed.

As can be seen from Table 5, time spent in sedentary and eat-sleep activities (both before and during lockdown) is highest among university students who use private modes to travel to college. Further, the posthoc analysis reveals that the mean difference in time spent for sedentary activities between active and private mode users is significant for both cases. The trends in time spent on physical activities across the three groups indicate that active mode users spend the highest time, followed by public mode users (Waddell et al., 2019). Although the trends are similar before and during the lockdown times, the mean time difference was significant only for the before lockdown scenario.

The ANOVA analysis reveals that sedentary and physical activity participation decreases before lockdown as travel time increases, while it is precisely the opposite for eat-sleep activities. This difference may be due to less availability of free time or the exhaustion of traveling outdoor for such a prolonged duration and hence taking adequate rest. However, no such patterns or trends were observed for mean time spent in various activities segmented by travel time during the lockdown period.

Overall, the descriptive analysis revealed significant differences in time use between lockdown and pre-lockdown situations. However, the actual correlations between dependent variables (whether it is a complementary or substitution effect) and time use are still unknown. Modeling efforts are made in the next section to quantify this relationship.

Table 5
ANOVA Test of Activity time allocation.

| MODE USED | Before Lockdown (Time Spent in min) | During Lockdown (Time Spent in min) |
|-----------|-------------------------------------|-------------------------------------|
|           | Active [1]  | Private [2]  | Public [3]  | Total  | Active [1]  | Private [2]  | Public [3]  | Total  |
| Sedentary | 331.59      | 410.80      | 405.51      | 390.69 | 445.11      | 550.40      | 462.06      | 496.43 |
| F-Score   | 7.085       |             |             |        | 13.54       |             |             |        |
| Post-Hoc  |             |             |             |        |             |             |             |        |
| Test      | 1-2**, 1-3, 2-3** |    |             |        | 1-2**, 1-3, 2-3** |    |             |        |
| Physical  | 222.73      | 181.60      | 204.93      | 207.24 | 102.95      | 81.69 (44.42) | 94.57 (63.89) | 93.89 (58.84) |
| F-Score   | 5.655       |             |             |        |             |             |             |        |
| Post-Hoc  |             |             |             |        |             |             |             |        |
| Test      | 1-2**, 1-3, 2-3* | |             |        | 1-2, 1-3, 2-3 | |             |        |
| Eat-Sleep | 395.81      | 407.87      | 384.12      | 397.02 | 414.26      | 445.32      | 425.81      | 425.32 |
| F-Score   | 3.222       |             |             |        |             |             |             |        |
| Post-Hoc  |             |             |             |        |             |             |             |        |
| Test      | 1-2*, 1-3, 2-3** | |             |        | 1-2, 1-3, 2-3 | |             |        |

TRAVEL TIME

| Activity Type | Before Lockdown (Time Spent in min) | During Lockdown (Time Spent in min) |
|---------------|-------------------------------------|-------------------------------------|
|               | <20 [1]  | 20-45 [2]  | >45 [3]  | Total  | <20 [1]  | 20-45 [2]  | >45 [3]  | Total  |
| Sedentary     | 402.87   | 389.25     | 382.14    | 390.69 | 527.80   | 455.11     | 467.55     | 496.43 |
| F-Score       | 0.289    |             |             |        | 6.232*** |             |             |        |
| Post-Hoc      | 1-2, 1-3, 2-3 | |             |        | 1-2, 1-3, 2-3, 2-3 | |             |        |
| Test          |         |             |             |        |           |             |             |        |
| Physical      | 219.63   | 203.62      | 183.67     | 207.24 | 98.36 (64.22) | 99.29 (60.20) | 78.08 (42.45) | 93.89 (58.84) |
| F-Score       | 4.904*** |             |             |        | 1.235    |             |             |        |
| Post-Hoc      | 1-2**, 1-3, 2-3 | |             |        | 1-2, 1-3, 2-3 | |             |        |
| Test          |         |             |             |        |           |             |             |        |
| Eat-Sleep     | 385.23   | 398.84      | 404.49     | 397.02 | 426.35   | 424.18      | 424.15      | 425.32 |
| F-Score       | 0.977    |             |             |        | 0.009    |             |             |        |
| Post-Hoc      | 1-2, 1-3, 2-3 | |             |        | 1-2, 1-3, 2-3 | |             |        |
| Test          |         |             |             |        |           |             |             |        |

*, ** and *** indicate significant at 90%, 95% and 99% confidence level, respectively. Values in the bracket denote the standard deviation.
6. Statistical analysis

The following sections discuss the results of the statistical analysis. Section 6.1 describes the factor analysis outcomes, and the estimates of the linear mixed model (LMM) are presented in Section 6.2.

6.1. Factor analysis

A principal component analysis (PCA) was conducted on the statements related to perceptions of individual leisure (IL), personal well-being (PW), and anxiety level (AL). The Kaiser-Meyer-Olkin (KMO) values obtained are 0.71, 0.79, and 0.72 for IL, PW, and AL attributes, respectively, indicating the usability of the data for PCA as the accepted cutoff for KMO is 0.6 or higher (Cerny and Kaiser, 1977). Subsequently, Promax (oblique) rotation technique was used for factor extraction. The following criteria were followed to obtain a refined pattern matrix of latent factors and item loadings. Eigenvalue should be greater than 1 for the acquired factors; item loadings on latent factors must not be below 0.40 (Tabachnick and Fidell, 2007) with no cross-loadings; and reliability values (Cronbach alpha) should be above 0.5 for all the factors (Lance et al., 2006). The pattern matrix revealed three latent factors for the IL attribute, two latent factors for PW, and one for AL attributes.

Confirmatory factor analysis (CFA) was then employed on the PCA results to confirm the linear relationship between the measurement items and latent factors. The CFA results are presented in Table 6. The measurement items significantly load on the latent factors at a 95% confidence level as per the table. For the IL attribute, seven out of ten items are found to have a loading of 0.4 or higher, with three items loading on Leisure Satisfaction (IL_SAT), two items on Leisure Participation (IL_PAT), and two items on Leisure Attitude (IL_ATT). It may be noted that during the PCA, items IL6, IL2, and IL1 loaded on IL_PAT and items IL9, IL7, and IL10 on IL_ATT. However, in CFA, items IL6 and IL9 were rejected from factors IL_PAT and IL_ATT, respectively. The CFA results for personal well-being and anxiety attributes were the same as the PCA pattern matrix. Squared Multiple Correlation (SMC) values for the perception items varied between 0.23 and 0.69, suggesting moderate to high reliability. Perception items accounted for 55%, 49%, and 41% of the average variance explained (AVE) for IL_SAT, IL_PAT, and IL_ATT factors. Similarly, the AVE values for personal well-being and anxiety attribute are close to 40% or higher. Composite reliability (CR) values for all the latent factors were above the cutoff limit of 0.6 (Loewenthal and Lewis, 2001). The latent factors’ correlation values were also close to 0.6 (magnitude wise) or higher and significant at a 95% confidence level.

The CFA model fit measures are reported in Table 7. The table shows that all fit measures are well within the recommended values prescribed by Schreiber et al. (2006), validating the CFA process carried out on the present data. Then, the latent factors’ factor scores are extracted and used as fixed effects in the LME model results presented in Section 6.2. Psych (Revelle, 2020) and Lavaan (Rosseel, 2012) libraries associated with R statistical software (R Core Team, 2022) were used for PCA and CFA analysis, respectively.

### Table 6

Outputs of CFA.

| Factor Name & Notation | Item No | Item Reliability | AVE  | CR   | Correlation |
|------------------------|---------|------------------|------|------|-------------|
| **CFA RESULTS FOR INDIVIDUAL LEISURE** | | | | | |
| Leisure Satisfaction (IL_SAT) | IL5 | 0.87 | 0.55 | 0.86 | [SAT↔PAT] −0.59 (−6.31) |
| | IL4 | 0.76 | 0.49 | 0.76 | [SAT↔PAT] −0.70 (−5.09) |
| | IL3 | 0.56 | 0.41 | 0.76 | [SAT↔ATT] 0.66 (5.66) |
| Leisure Participation (IL_PAT) | IL2 | 0.73 | 0.49 | 0.76 | [PAT↔ATT] −0.70 (−5.09) |
| | IL1 | −0.67 | −0.65 | 0.42 | |
| Leisure Attitude (IL_ATT) | IL7 | 0.67 | 0.41 | 0.69 | [SAT↔ATT] 0.66 (5.66) |
| | IL10 | −0.60 | −0.44 | 0.26 | |
| **CFA RESULTS FOR PERSONAL WELL-BEING** | | | | | |
| Quality of Life (PW_QOL) | PWI1 | 0.73 | 0.41 | 0.77 | [QOL↔PSW] 0.60 (4.87) |
| | PWI2 | 0.61 | 0.36 | 0.40 | |
| Psychological Well Being (PW_PSW) | PWI4 | 0.67 | 0.36 | 0.73 | |
| | PWI8 | 0.62 | 0.31 | |
| | PWI7 | 0.50 | 0.26 | |
| **CFA RESULTS FOR ANXIETY LEVEL** | | | | | |
| Personal Anxiety (AL_PER) | AL1 | 0.79 | 0.37 | 0.78 | |
| | AL2 | 0.62 | 0.47 | |
| | AL3 | 0.57 | 0.30 | |
| | AL6 | −0.56 | −0.58 | 0.31 | |
| | AL5 | −0.47 | −0.98 | 0.44 | |
6.2. Linear mixed-effects model results

6.2.1. Model-fit indices

A series of Linear Mixed-Effects (LME) models were developed for each activity type (SA, PA, ES) using the 'lme4' (Bates et al., 2015) package in R (R Core Team, 2022) that accounted for two major characteristics of the data. First, the time allocated to each activity type before and during the pandemic for a student could be correlated. Second, the time allocation decision could be potentially influenced by both fixed effects (including gender, age, BMI, etc.) and random effects (captured as a time variance dummy with before lockdown denoted as ‘1’ and during lockdown as ‘2’). Here, the time allocation behavior before the announcement of home confinement measures corresponds to the reference group in the LME model. REML optimization is used for model estimation since it is concluded that variance components would be biased when LME models are estimated with the maximum likelihood (ML) technique (Bates, 2005). The fixed effect coefficients, random effect parameters, and model fit indices of the LME models are shown in Table 8. The final model log-likelihood (LL) was found to be significantly different (p < 0.05) from the intercept-only model LL. The marginal R-squared values describe the amount of variance accounted for by fixed effects and can be thought of as analogous to adjusted R². In contrast, conditional values account for the variation in fixed and random effects (Nakagawa and Schielzeth, 2013). In Table 8, the difference between R² conditional and R² marginal values are highest for the LME model corresponding to PA activity, suggesting that the variance explained by random effects is highest for PA activities.

Random effects consist of group variance (or random intercept), residual variance (or random error variance), and intraclass correlation coefficient (ICC) expressed in percentage. The group variance accounts for the variations in time allocation decisions between before and during pandemic groups. The residual variance calculates time-demeaned variables between university students, i.e., the individual-specific deviations of time-averaged values (Hox and Roberts, 2011). For SA, PA, and ES activities, there is more variation within the group or between individuals (σ²_SA = 0.858, σ²_ES = 0.756, and σ²_PA = 0.861) than between the groups (τ²_SA = 0.365, τ²_PA = 0.620, and τ²_ES = 0.191). The ICC value for SA activity is 29.844%, i.e., about 30% of the total variation in the time spent on SA activities can be accounted for by the group to which each student belongs. In other words, nearly 30% of the variation for SA activities unexplained by fixed effects covariates in the LME model can be attributed to the grouping variable (time variance dummy with before lockdown denoted as ‘1’ and during lockdown as ‘2’). Similarly, 45.06% and 18.16% of the total variation in time spent in PA and ES activities, respectively, unexplained by fixed effects, are accounted for by clustering or grouping variable. Therefore, university students’ physical activity patterns before and during lockdown are strongly correlated among the three activities, as suggested by the higher value obtained for the intraclass correlation coefficient. It may be noted that the ICC values are significantly different from zero, thus, validating the applicability of multilevel modeling to the longitudinal data used in the present study. Finally, the fixed effect coefficients significant at the 90% confidence level or higher are reported.

6.2.2. Discussion of fixed effects

The fixed effects coefficients associated with the LME models for time spent in SA, PA, and ES activities are summarized in Table 8. The fixed intercept for each model was significant (except that of PA activity). It can be interpreted as the mean of the outcome (time spent in that activity) when all the predictors assume zero value. Table 8 indicates that the average time spent in eat-sleep activities during lockdown (DL) as opposed to before lockdown (BL) period by male students is 0.276 times more than female students. Simultaneously, ‘Gender’ did not have any significant association (at 90% CL) with time spent in SA and PA activities. However, earlier studies noted that female students in the US, South Korea (Sa et al., 2020), and China (Wang et al., 2020) are more inclined to spend higher among younger students (β = −0.189 for 18–25 years) relative to those aged 25 years or above. Similar observations were found by Rahman et al. (2020) in Bangladesh. With an increase in education levels (highest completed degree), students allocate more time to SA and ES activities and relatively less time to PA activities during the lockdown than before lockdown. The finding conflicts with previous research conducted among Brazilian (Silva et al., 2020) and Belgian (Constandt et al., 2020) adults. It was reported that adults with a higher degree were more physically active during the pandemic period. University students identified as ‘single’ are found to allocate more time for PA activities than married students. Married students have additional responsibilities and family obligations during such emergency times, and hence they find it challenging to allocate time to PA activities. BMI showed a significant relationship

| Table 7 | Fit indices for CFA models. |
|---------|-----------------------------|
| Indices Type | Fit Indices | Recommended Value | Leisure | Personal Well-Being | Anxiety |
| Absolute Fit Indices | χ²/(df) | <5.00 | 13.02/(11) = 1.18 | 8.17/(8) = 1.02 | 7.33/(5) = 1.47 |
| | RMSEA (Root Mean Square Error Approximation) | <0.08 | 0.030 | 0.010 | 0.048 |
| | SRMR (Standardized Root Mean Square Residual) | <0.08 | 0.033 | 0.028 | 0.037 |
| Comparative Fit Indices | IFI (Incremental Fit Index) | >-0.90 | 0.982 | 0.991 | 0.973 |
| | CFI (Comparative Fit Index) | >-0.90 | 0.981 | 0.988 | 0.969 |
| | TLI (Tucker-Lewis Index) | >-0.90 | 0.972 | 0.976 | 0.958 |
### Table 8
LME results for Sedentary, Physical, and Eat & Sleep Activities.

| FIXED EFFECTS | ACTIVITY TYPE | Sedentary (SA) | Physical (PA) | Eat & Sleep (ES) |
|---------------|---------------|----------------|---------------|-----------------|
| Intercept     | −0.367**      | 0.239          | −0.147*       |
| Individual Attributes |         | |               |
| Gender (ref Female) | | | | |
| Male          | −            | −              | 0.276*        |
| Age (ref 30–35 years) | | | | |
| 18–25 years   | −            | −0.189**       | −             |
| 25–30 years   | −0.132**     | 0.214***       | −0.232***     |
| Completed degree (ref above graduation) | | | | |
| Intermediate  | −            | −0.241***      | 0.389***      |
| Graduation    | 0.150**      | −              | 0.258*        |
| Marital Status (ref Married) | | | | |
| Single        | −            | 0.122**        | −0.131*       |
| BMI Proportion (ref Underweight/healthy) | | | | |
| Obese/overweight | 0.134**     | −0.060*        | 0.065**       |
| Household Variables | | | | |
| Family Size   | −0.032***    | 0.041***       | −             |
| Presence of Kids (ref No) | | | | |
| Yes           | 0.294***     | −0.254*        | −             |
| Household Income (ref High) | | | | |
| Low           | −0.101*      | −              | −0.102**      |
| Middle        | −            | 0.120***       | −             |
| Vehicle Ownership | | | | |
| Car (ref No)  | −            | −0.054*        | −             |
| Two-Wheeler (ref No) | | | | |
| Yes           | −            | −0.103**       | −             |
| Bicycle (ref No) | | | | |
| Yes           | 0.073*       | 0.053*         | −             |
| College Information | | | | |
| Spatial Location (ref South Zone) | | | | |
| North Zone    | −            | −              | −             |
| East Zone     | −            | −              | −             |
| West Zone     | −            | −              | 0.230**       |
| Place of Stay (ref Outside campus) | | | | |
| Inside Campus | −            | −              | −             |
| With parents  | 0.176*       | −0.066*        | −             |
| College Duration | 0.028**   | −0.034**       | −             |
| Mode to access campus (ref Public) | | | | |
| Private       | 0.192***     | −0.139**       | 0.258***      |
| Active        | −0.673*      | −              | −0.163*       |
| Travel Time to Campus (ref <20 min) | | | | |
| 20-45 min     | 0.355***     | −0.148**       | −0.145*       |
| >45 min       | 0.365***     | −0.202***      | −0.164**      |
| Latent Variables | | | | |
| Leisur Factors | | | | |
| Leisure Satisfaction | 0.073**   | −              | −0.073**      |
| Leisure Participation | −         | −0.063**       | −0.069**      |
| Leisure Attitude | −           | −0.069*        | −0.057***     |
| Well-Being Factors | | | | |
| Quality of Life | −0.042*     | −              | −             |
| Psychological Well-Being | −0.101** | 0.060**         | −             |
| Anxiety Factor | 0.112***     | −              | −0.057**      |
| RANDOM EFFECTS | | | | |
| Group Variance ($\sigma^2$) | 0.365      | 0.620          | 0.191         |
| Residual Variance ($\sigma^2$) | 0.858      | 0.756          | 0.861         |
| ICC (in %)    | 29.844       | 45.058         | 18.156        |
| MODEL PARAMETERS | | | | |
| Intercept Only LL [DF] | −559.986[3] | −481.672[3]    | −574.351[3] |
| Final Model LL [DF] | −512.811[20]| −437.232[22]  | −541.140[19] |
| $R^2_{\text{Marginal}}$/$R^2_{\text{Conditioned}}$ | 0.176/0.244 | 0.242/0.416  | 0.165/0.194 |
| No of Groups   | 2            | 2              | 2             |
| No of Observations | 203      | 203            | 203           |

Note: *, **, and *** significant at 90%, 95% and 99% Confidence level (CL) respectively. Values in the square bracket show degrees of freedom (or no of estimated parameters).
(irrespective of the sign) with the time allocated to each activity type. The negative coefficients obtained for PA activities (or positive association between BMI and SA & ES activities) are in corroboration with the general assumption that obese or overweight (BMI ratio ≥ 25) individuals are reluctant to spend time in PA activities (Wang et al., 2020).

Regarding the household variables, an addition of a family member corresponds to a 0.041 min increase and a 0.032 min decrease in the time spent in PA and SA activities, respectively. This correlation could indicate a more critical requirement for more household duties of light physical intensity when many family members live together (Silva et al., 2020), thus limiting their unstructured leisure time. The presence of children in households (possibly married students) negatively influences the time spent in PA activities, which is in line with the observations of Constanti et al. (2020), who carried out a study on Belgian adults. University students from low-income households tend to allocate more time to PA activities and spend less time in SA and ES activities. In contrast, studies from other settings reveal that (Dunton et al., 2020a, 2020c; Rahman et al., 2020) adults (age 18–35 years) from low-income households tend to allocate less time to PA activities. It may be possible that the ownership and use of private modes lead to a more comfort-oriented and sedentary lifestyle and could influence PA activity participation level. This correlation is relevant at a time when car ownership is increasing in Indian cities (Ghate and Sundar, 2014). Interestingly, bicycle ownership has a significant positive association with PA activity durations, revealing that bicycle owners are more likely to spend time in physical activities.

The results suggest that students from the West zone (with reference to the students from the South zone) of India are more likely to spend time in ES activities during the lockdown period. This finding may be attributed to the fact that states from the West zone were severely impacted by the Coronavirus (Covid19India, 2020), and hence, strict lockdown measures were enforced to check its spread. As for the place of stay, students staying with their parents during the lockdown are found to spend more time in SA activities. A study conducted among Italian undergraduate students (Galle et al., 2020) found that off-site students staying with their families during the lockdown spent more time on sedentary activities like online grocery shopping. Concerning the impact of college duration, the natural log of college duration is given as input to control for scaling of estimates. The model also shows that the higher the college duration, the lower the likelihood of spending time in PA activities among university students, which is quite apparent. With an increase in college duration, academic pressure increases, and students’ interest in allocating time to PA activities decreases, all else being equal. The impact of the college/university mode use before lockdown on students’ activity time allocation behavior was also examined in the model. It was found that students accessing college using active modes (before the lockdown) allocate less time on SA and ES activities compared to the time spent on PA activities during the lockdown period. This correlation may be attributed to taking short walks or in-home exercises such that their habit of walking/cycling to stay healthy is maintained. The model shows that university students tend to spend more time on sedentary activities irrespective of the travel time category (less than 20 min taken as reference) and relatively less time in PA and ES activities during the lockdown. This correlation may stem from the observation that universities/colleges were closed during the lockdown period, hence no travel time constraints.

All the three factors associated with leisure seemed to negatively load the duration of time spent in PA (except leisure satisfaction) and ES activities during lockdown compared to before the lockdown period. Since leisure time is closely associated with sedentary behaviors (Cheval et al., 2020), it can be said that students who received a higher perception score for leisure factors are more inclined to spend time in SA activities. On the other hand, well-being factors (Quality of Life and Psychological Well-Being) are negatively associated with the time spent in SA activities. Simultaneously, a positive association was observed between the ‘Psychological Well-Being’ factor and time spent on PA activities. This association suggests that university students who perceive the quality of life and psychological well-being to be an essential part of their daily lives are likely to spend an increased time in PA (Maugeri et al., 2020) comparatively less time in SA activities. Students with a high score on the ‘Anxiety’ factor experienced a negative change in the time spent on ES activities, which may be due to boredom, uncertainty, and feeling of getting stuck in one place, as highlighted by studies performed in Italy (Cellini et al., 2020; Maugeri et al., 2020). Conversely, the positive association between the AL factor and SA activities may indicate that students are more likely to have higher screen time as a coping strategy to recover from negative moods and undesirable emotions experienced due to lockdown.

6.3. Policy and planning implication

The globe is slowly returning to normalcy from the COVID-19 pandemic; nevertheless, there are still a lot of challenges to be mitigated. One of them is the physical and emotional well-being of adults (University students) in these times of social distancing where they are confined to home isolation. Most of India’s universities are still closed, and academics are being shifted to online mode, resulting in a decreased out-of-home activity participation and reduced demand for travel among students. This is supported by the observation in Table 4 that the difference in average screen time related to watching TV (SA1) or using a computer for leisure and playing games in mobile/TV/Computer (SA2) before and during lockdown was observed to be 45 min (167 min during lockdown as compared to 122 min before lockdown). Besides, time spent in sedentary and eat-sleep activities (both before and during lockdown) is highest among university students who use private modes to travel to college, as shown in Table 5. Thus, indulgence in sedentary activities has impinged their physical activity and well-being levels. However, the results from Table 3 (a Kruskal-Wallis Test between Leisure perceptions and Mode Use) indicated that the perception of university students who used active modes to access campus for Leisure items is significantly higher than those of private and public mode users. Intuitively, it can be explained as in times of social distancing, students will seldom venture out of their residence, and when they do, they will prefer leisure walks or short-distance cycling to maintain their well-being and physical activity levels. In addition, the results from Table 7 indicate that bicycle ownership has a significant positive association with PA activity durations, revealing that bicycle owners are more likely to spend time in
physical activities. So, policymakers and transport planners can temporarily allocate less-used motorized streets (due to the pandemic) to students who prefer walking and cycling.

Furthermore, it has been well-documented that the higher the participation in physical activities, the lower is the risk of cardiovascular diseases and mortality rate. Moreover, in these times of pandemic, preparedness is the key to mitigate such unwarranted situations. Though the Indian government has tried to encourage its citizens to be more involved in physical activities through the ‘Arogya Setu’ App, we believe it has not been that effective. Instead, the slogans for motivation should be segmented based on socio-demographic characteristics. As Table 7 suggests, with an increase in education levels (highest completed degree), students allocate more time to Sedentary and Eat-sleep activities and relatively less time to Physical activities during the lockdown than before lockdown. University students from low-income households show a higher tendency to spend more time on physical activities and spend less time in Sedentary and Eat-Sleep activities. Simultaneously, a positive association was observed between the ‘Psychological Well-Being’ factor and time spent on Physical activities. This association suggests that university students who perceive the quality of life and psychological well-being as an essential part of their daily lives are likely to spend more time in physical activities (Maugeri et al., 2020) and comparatively less time in sedentary activities. Such observations support the fact that policies aimed at keeping active and healthy must focus on segments of the population to be more effective and pronounced.

7. Conclusion

The present study investigates the time allocation decisions regarding sedentary, physical, and eat-sleep activities during the COVID-19 induced lockdown. Towards this objective, the paper utilized online survey data captured during the lockdown phase in India. Time allocation to different sedentary and physically active activities of a sample of university students before and during the lockdown phase are reported in the survey. The study employed descriptive and statistical analysis to explore the time use decisions of students. Students’ perception of personal well-being and anxiety, attitudes towards individual leisure during the pandemic, and their impacts on time allocation decisions are also explored. Some of the key highlights of the present research include:

➢ During the lockdown period, sedentary activity (SA) durations of Indian university students are higher compared to the European and US adults, although the average time spent in eat-sleep (ES) activities is relatively low.
➢ With an increase in education levels (highest completed degree), students allocate more time to SA and ES activities and relatively less time to physically active (PA) activities during the lockdown than before lockdown in contrast with the research done on Brazilian and Belgian adults.
➢ Indian university students from low-income households show a higher tendency of allocating time to PA activities and spend less time in SA and ES activities, which conflicts with the studies done in developed countries during the lockdown period.
➢ Bicycle ownership has a significant positive association with PA activity durations, revealing that bicycle owners are more likely to spend time in physical activities.
➢ Students accessing college using active modes (before the lockdown) allocate less time to SA and ES activities than PA activities during the lockdown period.
➢ Students’ perception of Leisure items among those who use active modes to access college is significantly different from those of private and public mode users.
➢ Students with a high score on the ‘Anxiety’ factor experience a negative change on the time spent on ES activities, which may be due to uncertainty, and the feeling of getting stuck in one place.

The present study, however, has its limitations and scope that may be explored in the future. The absence of electronic media in rural India and the lengthy nature of the questionnaire limited the final sample collected. The immediate extension is, therefore, to carry out the study using a broad sample. The model findings are based on small sample and future research with large samples would enhance the representativeness of university students, and the generalizability of the study. Another limitation of our study was the self-reporting of BMI measures (height and weight) and duration of time spent in various activities before and during the lockdown, which may sometimes get overestimated or underestimated. Further, a cross-sectional analysis of the association between sedentary, physical, and eat-sleep behaviors before, during, and after lockdown can be explored.

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Author’s contribution

The authors confirm their contributions to the article as follows. First Author – Conceptualization, online questionnaire design, data curation, model building and interpretation, and article writing. Second author – Conceptualization, supervision, model building, interpretation, and article writing. Third author - online questionnaire design, data curation, formal analysis, and article writing.

Declaration of competing interest

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for
publication elsewhere.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

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