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Mobility patterns and COVID growth: Moderating role of country culture

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\section*{Abstract}

The COVID-19 pandemic has resulted in countries reacting differently to an ongoing crisis situation. Latent to this reaction mechanism is the inherent cultural characteristics of each society resulting in differential responses to epidemic spread. Epidemiological studies have confirmed the positive effect of population mobility on the growth of infection. However, the effect of culture on indigenous mobility patterns during pandemics needs further investigation. This study aims to bridge this gap by exploring the moderating role of country culture on the relationship between population mobility and growth of COVID-19. Hofstede’s cultural factors; power distance, individualism/collectivism, masculinity/femininity, uncertainty avoidance, long-term and short-term orientation are hypothesised to moderate the effect of mobility on the reproduction number (R) of COVID-19. Panel regression model, using mobility data and number of confirmed cases across 95 countries for a period of 170 days has been preferred to test the hypotheses. The results are further substantiated using slope analysis and Johnson-Neyman technique. The findings suggest that as power distance, individualism and long-term orientation scores increase, the impact of mobility on epidemic growth decreases. However, masculinity scores in a society have an opposite moderating impact on epidemic growth rate. These Hofstede factors act as quasi moderators affecting mobility and epidemic growth. Similar conclusions could be not be confirmed for uncertainty avoidance. Cross-cultural impact, as elucidated by this study, forms a crucial element in policy formulation on epidemic control by indigenous Governing bodies.

Throughout human history, pandemic has been a recurring phenomenon. Etymologically the word \textit{pandemic} is derived from Greek \textit{pan} (all) and \textit{demos} (people), indicating a transmissible infection that spreads rapidly across geographical borders affecting large swaths of global population. Time and again pandemics have created havoc thus necessitating investigation into their potential causes and plausible controls.

In recent past, outbreaks of Zika, Ebola virus, SARS-Cov, MERS-Cov pandemics have been observed. Since the beginning of 2020, the world has virtually come to a standstill under the devastating impact of the COVID-19 pandemic. COVID-19 still remains a global threat to public health (Li \textit{et al.}, 2020) and as per John Hopkins Research Institute had affected more than 307 million people worldwide claiming 5.4 million lives by January 2022.

The current struggle against the COVID-19 pandemic relies highly on societal-level disease-control efforts such as mobility control and contact tracing (Hale \textit{et al.}, 2020; Zhu, Smetana, & Chang, 2021). In this vein, public health scientists especially are interested to...
understand factors like human mobility and its impact on the spread of the disease. Mobility refers to geo-spatial movement of the populace. In an epidemic situation, restricted mobility is expected thereby impacting the spread of the infection. The relationship of these two factors is important to understand the disease spread and control. This leads us to the first aim.

Aim 1: To examine the impact of population mobility on spread of COVID-19 infection

Understanding of population geospatial mobility and reproduction number is important to understand the disease spread and control. One of the factors that potentially creates a challenge for understanding the above relationship is the role of cross-cultural variation across countries. In the COVID-19 pandemic it was reported that some countries are better able to manage and control the disease than others using similar practices (Gokmen et al., 2021). Due to cultural variation, it is reasonable to expect differential response in cooperation by the citizens at individual /group level against various regulatory norms of the respective national governments. It has been proven by research that such structural make of cultural differentiation can be best understood through the national culture frameworks. This leads us to study aim 2:

Aim 2: To examine the role of country culture in predicting the relationship of population mobility and spread of COVID-19 infection

Impact of mobility on COVID-19 infection spread

The spread of infectious diseases during an epidemic and human behaviour are fundamentally intertwined (Funk et al., 2010, 2015; Gross & Blasius, 2008; Hébert-Dufresne et al., 2010). The unfolding of epidemics might induce people to modify their social contacts, habits, and mobility. Such epidemic induced behavioural changes might, in turn, affect the course of the outbreak. The current study intends to assess this effect of mobility behaviour in COVID-19 spread.

Human movement has been found to play an important role in spread of various diseases like malaria, cholera, measles, dengue and Ebola (Gog et al., 2014; Ferguson et al., 2005; Mari et al., 2012; Prothero, 1977; Wesołowski et al., 2012; Grenfell et al., 2001; Stoddard et al., 2009; Wesołowski et al., 2016). In our contemporary societies, where millions of people travel and commute every day within and across cities/regions, infectious diseases accelerate on a larger scale. Timely, accurate, and comparative data on human mobility are therefore critical for informing public health interventions. Population movement is expected to increase the disease prevalence by introducing pathogens and increasing the cases of primary infection1 into a susceptible population. Geospatial mobility also augments the cases of secondary infection2 by increasing social contacts between the susceptible and primary infected individuals. This leads us to hypothesise:

Hypothesis 1. During an epidemic, increase in human mobility would lead to a higher epidemic growth rate.

Culture and epidemic: theoretical background

The chief source of mobility diffusion in predicting the spread of an epidemic is linked to the Psycho/Social/Spatial structure of a population (Dushoff & Levin, 1995). The propensity of individual behaviour to mimic crowd psyche, is deep rooted in the phenomena of collective group behaviour (Le Bon, 1895). The shared values/cultures, are essential for group survival and act as a pre-requisite for social trust, solidarity and connectedness (Hofstede et al., 2010).

Researches have continually asserted the influence of culture as a key determinant of human behaviour, both at the individual and social/group level (Hofstede, 2001; Chiang, 2010). The perception of health and health related behaviour both at experiential and expressed level has cultural connotations (Bhui & Dinos, 2008). Cultural variations can be observed in individual level perceptions about disease etiologic, appropriate and preventive treatment, proper self-care, belief about human physiology, and even appropriate doctor-patient conduct. (Shaw et al., 2009). At the group level, factors and processes like social participation, and different forms of inclusion facilitating security, autonomy, and control – results in a strong common identity and sense of belonging. It can therefore be argued that population health involves consideration for collective imaginaries. This aspect is of relevance, given the scope of behavioural interventions both at top down i.e., through institutional level stated through government restrictions and at the bottom-up level i.e., through self-initiated behavioural adjustments during COVID-19 pandemic.

According to Health Belief Model behavioural change encompasses a wide range of (re)actions, in response to and affecting an external event. Event induced behavioural changes are classified into two categories. The first category, described as top-down, governmental interventions includes statutory and legal restrictions interrupting chains of infection by banning (or limiting) large gatherings, mobility within and across countries, as well as strict lockdown and cordon sanitary (Verelst et al., 2016).

The second category of behavioural change includes bottom-up, self-initiated changes that are implemented by individuals in accordance with their perceived risk and susceptibility to the event as well as the perceived barriers and benefits linked to each potential action changes which might accrue (Rosenstock, 1977; West et al., 2020; Gozzi et al., 2020, 2021). Perceived susceptibility refers to individual beliefs about the likelihood of contracting a disease while perceived risk refers to feelings about the seriousness of contracting an illness or of leaving it untreated. This also include evaluations of both medical (for example, death, disability, and pain) and

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1 Primary infection/case, in epidemiological terminology, refers to the individual who first brings the disease to a population or a subset of the population (termed as the susceptible population) (Giesecke, 2014).

2 Secondary infection/cases, in epidemiological terminology, refer to subsequent infection within the susceptible population from the primary case (often after contact with the infected or post an incubation period of the pathogen) (Giesecke, 2014)
possible social consequences (such as effects of the conditions on work, family life, and social relations) associated with the condition. Perceived benefits are defined as the individual’s beliefs regarding various gains obtained from different available options for reducing the disease threat. Perceived barriers include beliefs about the tangible and psychological costs associated with various advised actions (such as expense involved, negative side effects, inconvenience, or time-consuming).

Bottom-up, self-initiated decisions in an epidemic involve restricted social contacts with infected individuals, increased focus on hygiene, adoption of a health-conscious lifestyle, social distancing, increased use of personal protective equipment such as face masks. This also includes noticeable change in individual and community mobility patterns modifying conscious decisions to avoid/ not avoid crowded and public spaces.

The argument stated above (refer Fig. 1), arcs the scope of culture related variation in understanding the impact of mobility on the spread of infection. Culture will act as a catalysing factor for the way health related interventions are applied by people and institutions which will determine the overall impact of the virus spread. Given the focus, the present study uses Hofstede’s framework of cultural diversity as a measure of the cultural constructs of the population and Google mobility data related to workplace and passenger transit to assess the mobility patterns.

Moderating role of Hofstede’s national culture

(Hofstede, 1991b, p. 1) has stated that culture refers to “the collective programming of the mind which distinguishes one category of people from another”. Hofstede’s dimensional approach to cultural variation includes; Power Distance, Individualism/Collectivism, Masculinity/Femininity, Uncertainty Avoidance and Long-term/Short-term orientation (Hofstede, 2001b; Hofstede & Michael, 1988).

Scientific researchers have used Hofstede’s model abundantly incorporating them as moderating variable to explain diverse social phenomenon such as employee engagement and burnout (Rattrie et al., 2019), organisational learning (Skerlavaj et al., 2013), online trust (Hwang & Kun Chang, 2012), tourist behaviour (Litvin et al., 2004; Pantouvakis, 2013) etc. Hofstede cultural factors have also been used to understand the effect of national culture on epidemic growth (Gokmen et al., 2021).

Power Distance

Power Distance (PD) refers to “the degree to which the less powerful members of a society accept and expect that power is distributed unequally. The fundamental issue here is how a society handles inequalities among people” (Hofstede, 2019, para. 6). Numerous social studies have reported the moderating impact of power distance on a number of outcomes, including conflict between personal preferences & social norms, mental health, perceived support systems (Farh et al., 2007; Lee & John, 2014; Lin et al., 2013). There is strong evidence that, in high power distance societies, people generally rely on central authorities and social systems thereby abiding more to the structured social norms (Zhu et al., 2021). In high power distance societies, social hierarchy is established and executed

![Diagram](image-url)  
Fig. 1. Framework Representing Moderating Role of Culture, Health Belief Model, Impact of Health Interventions and Disease Spread.
clearly and without reason (Gokmen et al., 2021). In COVID-19 epidemic, it is expected that mobility restrictions will be followed more strictly by high power distance countries, as there will be more compliance to central authorities and government systems. In such societies, Government restrictions will act as a perceived barrier in order to reduce perceived health risk (Rosenstock, 1977) by containing human mobility. For countries with similar mobility patterns, the growth of epidemic will be lower as the power distance increases. Therefore, we hypothesise:

Hypothesis 2a. : During an epidemic, power distance will moderate the relationship between ‘work place mobility’ and epidemic growth; such that the impact of ‘workplace mobility’ on epidemic growth decreases as power distance increases.

Hypothesis 2b. : During an epidemic, power distance, will moderate the relationship between ‘transit passenger mobility’ and epidemic growth; such that the impact of ‘transit passenger mobility’ on epidemic growth decreases as power distance increases.

Individualism/Collectivism

Individualistic culture refers to societies “where the ties between individuals are loose: everyone is expected to look after her/his immediate family only” (Hofstede, 2001a, p. 225). In Collectivist societies, individuals “are integrated into strong, cohesive in-groups, which throughout people’s lifetime continue to protect them in exchange for unquestioning loyalty” (Hofstede, 2001a, p. 225). Individuals from high collectivist culture mostly pose greater emphasis on pursuing group goals, and improving group level engagement (Ronen & Mikulincer, 2009). It has been also found that collectivists do not always act in the collective interest, especially when cooperative norms are bleak (Chen et al., 2007). For highly contagious diseases, the monitoring comes from individual level actions guided by perceived health benefits (Rosenstock, 1977) forcing the individual to act responsibly and maintain minimal contact norms. Societies which are higher on individualism would be more willing to enact individual level disease control measures (Zhu et al., 2021). Hence, we hypothesise that for individualistic countries there will be higher appreciation of self-initiated control measures such as mobility, thereby inversely impacting the epidemic growth.

Hypothesis 3a. : During an epidemic, individualism will moderate the relationship between ‘work place mobility’ and epidemic growth; such that the impact of ‘work place mobility’ on epidemic growth decreases in individualistic societies.

Hypothesis 3b. : During an epidemic, individualism will moderate the relationship between ‘transit passenger mobility’ and epidemic growth; such that the impact of ‘transit passenger mobility’ on epidemic growth decreases in individualistic societies.

Masculinity/Femininity

Masculinity refers to “a preference in society for achievement, heroism, assertiveness, and material rewards for success. [Masculine] Society at large is more competitive” (Hofstede, 2019, para. 10). Femininity, its opposite, stands for a “preference for cooperation, modesty, caring for weak and quality of life. [Feminine] Society at large is more consensus-oriented” (Hofstede, 2019, para. 10). Norms like opportunity to fulfill multiple social roles without social judgement are generally associated with feminine cultures. Feminine societies have lower associations with individual health related factors e.g., stress and burnout (Barnett, 2004) whereas in masculine cultures there is intense competition, ambition and need for power (Kåkol, Kisilowski, Kunikowski, & Uklanska, 2018) which is coupled with higher stress, burnout, and job dissatisfaction (Hofstede, 1980). Since feminine societies are more consensus oriented, hence for greater good, the cooperative behaviour such as restricted mobility will be higher to prevent epidemic growth and perceived health related benefits (Rosenstock, 1977) will maintain the quality of life. Whereas in masculine societies, for maintaining material rewards and competition, the mobility will be higher, thereby positively impacting the epidemic growth. Hence, we hypothesise that for masculine societies the impact of mobility will increase the impact on epidemic growth.

Hypothesis 4a. : During an epidemic, masculine societies will moderate the relationship between ‘work place mobility’ and epidemic growth; such that the impact of ‘work place mobility’ on epidemic growth increases in masculine societies.

Hypothesis 4b. : During an epidemic, masculine societies will moderate the relationship between ‘transit passenger mobility’ and epidemic growth; such that the impact of ‘transit passenger mobility’ on epidemic growth increases in masculine societies.

Uncertainty Avoidance

Uncertainty Avoidance refers to “the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity. The fundamental issue here is how a society deals with the fact that the future can never be known: should we try to control the future or just let it happen?” (Hofstede, 2019, para. 12). Cultures high in uncertainty avoidance are more rule bound, possess structured activities and strive for greater stability and security in their social systems. (Mahlich et al., 2018; Staufenbiel & Cornelius, 2010). In order to avoid their perceived health related susceptibility, individuals from such societies will curtail their movement during pandemic. Thus, we hypothesise that in situations of epidemic like COVID-19, high uncertainty avoidance countries will have greater control on mobility to ensure stable and secure society. Therefore,

Hypothesis 5a. : During an epidemic, uncertainty avoidance will moderate the relationship between ‘work place mobility’ and epidemic growth; such that the impact of ‘workplace mobility’ on epidemic growth decreases as uncertainty avoidance increases.

Hypothesis 5b. : During an epidemic, uncertainty avoidance will moderate the relationship between ‘transit passenger mobility’ and
epidemic growth; such that the impact of 'transit passenger mobility' on epidemic growth decreases as uncertainty avoidance increases.

Long-term/Short-term Orientation

Long-term/Short-term Orientation refers to the degree a culture will “maintain some links with its own past while dealing with the challenges of the present and the future” (Hofstede, 2019, para. 14). Long-term oriented societies are high on pragmatism and adapt to circumstantial situations. They thereby invest efforts to prepare for the future and incorporate virtues like perseverance and patience (Nevins et al., 2007). Individuals in a long-term oriented culture would be prepared to follow the rules in favour of their health due to perceived health related benefits for their citizens (Gökmen et al., 2021) Short-term oriented societies follow time honoured norms and view societal change with suspicion. Such societies would also assign less value to health states (Mahlich et al., 2018). Thus, during an epidemic like COVID-19 long-term oriented countries will have inverse relationship between workplace mobility and epidemic growth. Therefore, we hypothesise

Hypothesis 6a. : During an epidemic, long-term orientation will moderate the relationship between ‘work place mobility’ and epidemic growth; such that the impact of ‘workplace mobility’ on epidemic growth decreases for long-term orientated societies.

Hypothesis 6b. : During an epidemic, long-term orientation will moderate the relationship between ‘transit passenger mobility’ and epidemic growth; such that the impact of ‘transit passenger mobility’ on epidemic growth decreases for long-term orientated societies.

Method

The study aims to analyse the moderation effect of cultural factors on restricted mobility pattern of heterogenous population across different cultures affected by a pandemic and to assess the impact of this moderation on population specific pandemic growth. To achieve the same, proxies for cultural factor, mobility pattern and epidemic growth have been chosen. Panel regression (fixed effect model) with and without interaction terms (signifying interaction between mobility and cultural factors) are used to verify the hypothesis postulated above (refer Fig. 2).

Cultural factors

Country level Hofstede scores are used as a proxy for culture in this study. The Hofstede model of cultural factors at a national level consists of 5 factors, viz., Power Distance (PD), Individualism (IM), Masculinity (M), Uncertainty Avoidance (UA), and Long-term Orientation (LTO). In this study, these cultural factors for 95 countries are used as a moderating factor for mobility patterns in an epidemic affected society. The expectation is that these factors moderate mobility patterns which in turn affect the spread of epidemics.

Epidemic growth

Different variables have been used as proxy for COVID-19 epidemic growth. These include COVID-19 case recovery rate (Hassan et al., 2020; Kimhi et al., 2020), number of daily infected cases of COVID-19 per unit of population (Murray, 2021; Ang & Murray, 2021; Konarasinghe, 2020), COVID-19 test case positivity (Chiu & Ndeffo-Mbah, 2021; Furuse et al., 2021), COVID-19 morbidity and mortality rates (Imtiaz et al., 2020) among others. In the present study, COVID-19 Reproduction Number for each country is used as a proxy for epidemic growth. There is a long and successful history of using Reproduction Number to study epidemic dynamics (Macdonald, 1956; Kermack & McKendrick, 1937; Hethcote, 1976; Chowell et al., 2016). For COVID-19, the values of Reproduction Number over the course of the epidemic are expected to give wide insights into the epidemiology of the virus and provide details around determining the level of herd immunity, transmission potential and overall growth and spread of the infection (SET-C Steering Committee, 2020).

Reproduction Number is a metric to identify the spread, contagiousness and transmissibility of a disease (Delamater et al., 2019). At any time t from the start of the epidemic, Reproduction number (Rt) is defined as the number of secondary cases³ that arise from a typical primary case⁴ in a population completely susceptible to epidemic (Dietz, 1993). Reproduction number indicates if an infection within a population will turn into an epidemic. Values of Reproduction Number greater than 1 indicates an epidemic is likely (Diekmann et al., 1990).

The estimation of Reproduction Number, relies on two inputs – the growth rate (denoted as r) and the serial interval (SI) of the epidemic. The growth rate of an epidemic is defined as the change in the number of infected cases per unit of time (Ma, 2020a, 2020b). The serial interval (SI) of an epidemic is defined as the time interval between the onset of symptoms in the primary infector and secondary infectee (Rai et al., 2020). Serial Interval (SI) is calculated from infection data obtained via contract tracing. While the growth rate focuses only on the spread (growth or decline) of the infection, the serial interval provides details around the contagiousness and transmissibility of the disease. Both spread and contagiousness/transmissibility are the two facets of epidemic which are

³ Secondary cases refer to subsequent infection within the susceptible population from the primary case (often after contact with the infected or post an incubation period of the pathogen)(Giesecke, 2014).

⁴ Primary case, in epidemiological terminology refers to the individual who first brings the disease to a population or a subset of the population (termed as the susceptible population)(Giesecke, 2014).
Using growth rate and serial interval of the epidemic as inputs, a number of standard methods for estimation of Reproduction Number exists. These include, Exponential Growth approach (R\(_{\text{EG}}\)) (Wallinga & Lipsitch, 2007), Maximum Likelihood approach (R\(_{\text{ML}}\)) (White et al., 2009), and Time Dependent approach (R\(_{\text{TD}}\)) (Wallinga & Teunis, 2004). In R\(_{\text{EG}}\) approach, estimation of the reproduction number uses the exponential growth rate during the early phase of an outbreak of an epidemic. A maximum likelihood estimation process, assuming that the growth rate is Poisson distributed, is used in R\(_{\text{ML}}\) approach. In R\(_{\text{TD}}\) approach, reproduction number is computed as an average of all transmission networks\(^5\) within the population (i.e., utilising a time derived growth rate estimation process). For the purpose of this study, only the Time Dependent approach (R\(_{\text{TD}}\)) for estimating Reproduction Number of COVID-19 was considered. The Time Dependent approach is a preferred estimation technique compared to the Exponential Based (R\(_{\text{EG}}\)) and Maximum Likelihood (R\(_{\text{ML}}\)) approaches, because, it does not make any assumptions on the distribution of the epidemic growth rate (Wallinga & Teunis, 2004; Delamater et al., 2019).

Estimating Reproduction Number of COVID-19

**Growth rate**

The COVID-19 data for daily affected cases across 95 countries (collected for the period from February 15\(^{th}\) to July 31\(^{st}\) 2020 from John Hopkins Coronavirus Resource Centre), was used as an input for computing the growth rate.

**Serial interval**

Researches have suggested three estimates for the serial interval (SI) of COVID-19, viz, SI following Lognormal distribution - \(\mu=4.945, \sigma=3.635\) (Nishiura et al., 2020; Ma, 2020a, 2020b; Prete et al., 2021; Li et al., 2021), Weibull distribution - \(\beta=5.116, \eta=2.326\) (Nishiura et al., 2020; Li et al., 2021) and Gamma distribution - \(\kappa=4.8, \theta=2.3\) (Talmoudi et al., 2020; Zhao et al., 2020; Li et al., 2021). In this study, R\(_{\text{TD}}\) were computed against all three estimates of serial interval.

Using, the 3 estimates of SI and growth rate (computed from daily affected cases), 3 set of COVID-19 Reproduction Number estimates for each country has been generated. The computation has been done using R software package \(\text{“R0”}\)^6. The mean absolute percentage error (MAPE) between total number of infected cases predicted and the actual number of confirmed cases was also measured (Sahin & Tezcan, 2020). Annexure 1 lists the country-wise MAPE across 3 estimates of SI\(^7\). Based on the results, using lognormal distributed SI yielded the best fit (average 4.66% MAPE) compared to Weibull or Gamma distributed SI (4.96% and 5.90% MAPE respectively). The lognormal distributed SI R\(_{\text{TD}}\) estimates were therefore, chosen as a proxy for COVID-19 epidemic growth.

The accuracy of Reproduction Number estimates was tested by comparing the country – wise daily forecasts of COVID-19 infection cases and actual daily infected cases. Fig. 3 represents a graph of the cumulative global daily average of actual and predicted COVID-19 cases.

**Mobility pattern**

Access to mobility data has always been a challenge and the ongoing COVID-19 pandemic has highlighted this long-standing issue. Recent work has revealed the potential benefits of harnessing geo-located smartphone data to inform policy makers in making effective epidemic control decisions (Wang & Yamamoto, 2020; Yilmazkuday, 2021). For the purpose of this study, restricted mobility during the COVID-19 pandemic has been proxied by taking mobility data from Google Community mobility website (Google, 2020).

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\(5\) Transmission network refers to a directed graph highlighting paths of infection transmission between infected and susceptible individuals within an observed population

\(6\) https://cran.r-project.org/web/packages/R0/index.html

\(7\) Data snapshot for country-wise daily estimates of Reproduction Number of COVID-19 (including daily infected case predictions for R\(_{\text{TD}}\) using all 3 SI estimations) are available at OSF Link
mobility data captures restricted mobility patterns of smartphone users across countries that had been affected by COVID-19. Since the beginning of the pandemic, Google has been collecting location wise mobility data (by tracking anonymous usage patterns of Google handheld devices, post voluntary declaration from global populace) for change in movement patterns across sub-regions, viz., grocery, pharmacy, park, residential, retail, recreation, transit stations and workplace. This mobility data has already found increasing acceptance in recent COVID-19 pandemic literature (Wang & Yamamoto, 2020; Yilmazkuday, 2021, 2020a, 2020b; Zhu et al., 2020; Nouvellet et al., 2021). In this study, decrease from baseline mobility for workplace and transit stations have been used.

The Google mobility data indicates a percentage change from baseline values of mobility in a region. A baseline day represents a normal value for that day of the week. The baseline day is the median value of the 5-week period between Jan 3 – Feb 6, 2020. Thus, for a country, a value of -16% in workplace mobility for Friday 1st March, 2020 indicates a 16% decrease from median baseline workplace mobility on a Friday for that country.

Google mobility data does not reflect all mobilities. It only captures mobility of users with Google handheld devices. Neither does the data show the purpose for which people move. To compensate for these two factors, in this study, mobility for workplace and transit stations have only been used. The purpose of commuting to workplace and transit can be assumed to be well defined and therefore better suited to elucidate the restrictions that the pandemic had imposed.

The plots in Fig. 4 show the global average workplace and transit mobility obtained from Google data.

Control variables

Adequate controls help cross-cultural studies to establish comparability or equivalence at each stage of the research process (Usuneir & Lee, 2009). A failure to establish this might potentially bias results and thereby misguiding the results and interpretations (Buil, de Chernatony, & Martínez, 2012). The present study includes certain macro and COVID-19 specific indicators as control measures.

GDP

It has been stated in cross-cultural studies that cultural dimensions are known to covary with affluence (Dastmalchian et al., 2020; Grigoryan et al., 2008; Hofstede, 2001c). The study therefore controls for GDP per capita (natural log – transformed) and then compares with controlled correlation.

Population density

Ecological level factors in physical environment are important issues to be considered in cross-cultural research (Raaij, 1978). Since the present study is exploring the relation between human mobility and spread, hence population density (Georgas et al., 2004; Georgas & John, 1995) might likely impact the variables under scope. Hence the study also controls for population density (natural log – transformed).

Cultural diversity index

Though the study follows standard indicators of Hofstede cultural dimensions, it is likely that within-country heterogeneity might impact the model. Understanding of the cross-cultural variations (Au, 1999; Sivakumar & Nakata, 2001) is crucial for capturing differences in COVID-19 responses across populace within a country. Hence, a cultural diversity index was introduced as a control to capture the within-country heterogeneity effects. The Cultural Diversity Index (Gören, 2013) measures the intra-national cultural
Fig. 4. Average global workplace and transit mobility during CoVid 19 observation period.
diversity across 180 different countries, using ethnicity, linguistic differences, economic – social and religious factors among indigenous population. Each country is assigned an index score between 0 to 1, with 0 being least culturally diverse and 1 being most diverse.

**COVID-19 Stringency Index (CSI)**

Government regulations during COVID-19 varied across countries, resulting in differentiated control and transmission of the pandemic (Born et al., 2021). This represents very specific context to understand the relations under consideration in the present study. To control for country specific idiosyncratic differences in COVID-19 policies and regulations, the COVID-19 Stringency Index (CSI) has been included as a control variable in the model. CSI, prepared by the Oxford COVID-19 Government Response Tracker (OxCGRT)

The structure of the data is in the form of cross-sectional and time series. Due to the data structure, endogeneity caused by

**Age vulnerability indicator**

Population age structure has been found to be critical factors in determining COVID-19 transmission and mortality (Dowd et al., 2020; Medford & Trias-Llimos, 2020). It has been observed that COVID-19 susceptibility increases with age, having highest susceptibility in the age bracket 40 – 65 years (Hu et al., 2021). To incorporate for demographic and population age structure differences across the 95 countries used in this study (and their effect in COVID-19 spread), an age vulnerability indicator is incorporated into the model. The Age Vulnerability Indicator for a country is set to 1 if the median age of the country’s population is greater than or equal to the highest vulnerability COVID-19 age bracket (or 0 otherwise).

Following equation represent the proposed research model that has been tested:

$$R_{tc} = \alpha + \sum_{H}^{} \beta_H H_c + \sum_{V}^{\text{PD,...,LTO}} (\gamma_{mob} H_c) + \sum_{H}^{\text{PD,...,LTO}} \eta_{H_c} + \sum_{c}^{} \delta_{c} D_{c} + \sum_{t}^{(1,2,...,T)} \xi_{t} D_{T} + \epsilon_{tc},$$

In the above equation: $R_{tc}$ = Reproduction number of a country c at an observation day t (within COVID-19 study period). $H_c$ = Hofstede factor for a country c. This includes Power Distance (PD), Individualism (IM), Masculinity (M), Uncertainty Avoidance (UA), and Long-term Orientation (LTO) scores for the country. $mob_{tc} = Rate\ of\ change\ (ROC)\ in\ mobility\ from\ baseline\ (B),$ for a country c at an observation day t (within COVID-19 study period). For the purpose of this study, rate of change in mobility from baseline has been studied for transit (TR) and workplace (WP) mobility only.$H_c * mob_{tc} =$ Interaction term, highlighting the moderating effect of the Hofstede factor $H_c$ on the baseline change in mobility (at day t) $mob_{tc}$ for a country c. $D_{c} =$ Dummy variables for each of the 95 countries {c}, $\alpha =$ Intercept term for the regression. $\beta_H, \gamma_{mob}$, $\eta_{H_c}$, $\delta_c$, $\eta_c =$ Panel regression coefficients. $\epsilon_{tc} =$ Regular error term.

To assess the effect of interaction on overall model fit, the model was run four times, first with the control variables only as predictors, second augmented with mobility factors as predictors, third with mobility and Hofstede factors and fourth as a full model with interaction terms. In all the four models, the two-way fixed effect of panel regression, w.r.t country and time varying were kept constant. The mobility factors viz. rate of change of transit mobility from baseline (Transit Mobility) and rate of change of workplace mobility from baseline (Workplace Mobility) were entered into the model separately.

**Data**

Excerpts of data used in the analysis is available at OSF Link. Data details include list of 95 countries, snapshot of country wise transit and workplace mobility (daily change from baseline), country wise daily confirmed COVID-19 cases, snapshot of computed country wise COVID-19 reproduction number (RML, REG, RTD, using different estimations of serial interval and the best fit, with lowest MAPE), country wise Hofstede cultural factors and control variables (GDP per capita, population density, Cultural Diversity Index, COVID-19 Stringency Index and age vulnerability indicator).

**Linear panel regression**

The structure of the data is in the form of cross-sectional and time series. Due to the data structure, endogeneity caused by
unobserved heterogeneity was expected. Breusch pegan (BP) test (p < 0.05) to check heteroskedasticity and Durbin-Watson (DW) test (p < 0.05) to check auto-correlation confirmed the same. To alleviate these issues, linear panel regression with Fixed effect or Random effect model are best suited. To confirm Fixed Effect or Random Effect in panel data regression, three tests were performed. First, the Chow-test was undertaken to compare Fixed Effect Model (FEM) with Common Effect Model (CEM). The Chow test results (P < 0.05) confirmed that FEM is preferred over CEM. Further, Hausman-test was carried out to compare FEM with Random Effect Model (REM). The Hausman-test results (p < 0.05), confirmed that FEM is preferred over REM. Lagrange Multiplier (LM) test to compare REM and CEM was not required as Chow-test and Hausman test suggested FEM to be the most appropriate. The results of the test are given in Table 1.

Fixed Effect panel data regression model decreases the multicollinearity and biases in the estimation process (Baltagi, 2008). To check multicollinearity, variation inflation factors (VIFs) were checked. The details of the VIF values are given in Table 2. The VIFs of the proposed model ranges between 1.169 to 3.387, which is significantly less than the recommended critical value of 10 for the consideration of multicollinearity (Hair et al., 2018), indicating no risk of multi collinearity.

Findings

Descriptive statistics

The descriptive statistics of the dependent variable (Reproduction Number of COVID-19), predictors (Transit Mobility and Workplace Mobility), moderating variables (5 Hofstede cultural factors) and control variables (natural log of population density, Cultural Diversity Index and COVID-19 Stringency Index) can be found in Table 3.

Reproduction number represents the spread of COVID-19 disease. A value greater than 1 represents that epidemic is likely, with increasing Reproduction number indicating intensification of the disease spread. The mean of Reproduction Number of COVID-19, was 1.40 ± 0.81, with very small variability around the mean. Independent variables Transit and Workplace Mobility represents the percentage change in mobility from the median baseline (5-week period between Jan 3 - Feb 6, 2020). The mean for Transit mobility was -36.36 ± 25.27 and Workplace mobility was -26.26 ± 21.72. The negative values of mobility factors indicate an average decrease in mobility from baseline values.

Values of Power Distance Range from 11 to 104, a higher value represents a country with a high-Power Distance. Similarly, Individualism/Collectivism scores ranges from 6 to 91, where high score represents country with higher individualism characteristic and low score represents countries from collectivist societies. Masculinity/Femininity scores ranges from 5 to 110, where higher score represents masculine society and lower score represents feminine societies. The range of Uncertainty Avoidance Score is 8 to 104. A high Uncertainty Avoidance score indicates societies that are uncomfortable with uncertain situations while, low scores indicate comfortability with uncertain situations. Long Term/Short term Orientation scores range from 3.5 to 100, with high scores representing long term-futuristic orientation.

Mean Power Distance was 64.32 ± 21.59, Individualism was 39.51 ± 22.58, Masculinity was 47.92 ± 18.78, Uncertainty Avoidance was 67.47 ± 23.50, Long-Term Orientation was 44.65 ± 23.50.

Linear panel data regression analysis results

The analysis to test the hypotheses was based on linear panel data regression (fixed effect model). To check the interaction effect, we developed 4 models; (1) Model 1 includes only the control variables (natural log of GDP per capita, natural log of population density, Cultural Diversity Index and COVID-19 Stringency Index). (2) Model 2 checks the main effect and includes the independent variables. (3) Model 3 includes the moderators. (4) Model 4 includes the interaction terms.

Table 1
Test Results for Chow Test & Hausman Test.

| Mobility Type | Model | Test   | Test-Statistics | p-value | Result |
|---------------|-------|--------|----------------|---------|--------|
| Transit Mobility | Model 1 | Chow Test | 15.556 | 0.000 | FE |
|                |       | Hausman Test | 910.94 | 0.000 | FE |
|                | Model 2 | Chow Test | 16.571 | 0.000 | FE |
|                |       | Hausman Test | 1321.2 | 0.000 | FE |
|                | Model 3 | Chow Test | 12.68  | 0.000 | FE |
|                |       | Hausman Test | 1210.4 | 0.000 | FE |
|                | Model 4 | Chow Test | 9.29  | 0.000 | FE |
|                |       | Hausman Test | 158.31 | 0.000 | FE |
| Workplace Mobility | Model 1 | Chow Test | 15.556 | 0.000 | FE |
|                |       | Hausman Test | 910.94 | 0.000 | FE |
|                | Model 2 | Chow Test | 13.811 | 0.000 | FE |
|                |       | Hausman Test | 979.84 | 0.000 | FE |
|                | Model 3 | Chow Test | 9.91  | 0.000 | FE |
|                |       | Hausman Test | 777.6 | 0.000 | FE |
|                | Model 4 | Chow Test | 8.1 | 0.000 | FE |
|                                |       | Hausman Test | 779.79 | 0.000 | FE |

Notes: Model 1: Control Variables, Model 2: Main model, Model 3: With Moderators, Model 4: With Interaction Terms.
variables (Transit Mobility and Workplace Mobility) separately, together with the control variables. (3) Model 3, adds 5 moderating variables Power Distance (PD), Individualism (IM), Masculinity (M), Uncertainty Avoidance (UA), and Long-Term Orientation (LTO) (4) Model 4 included the interaction effect between the moderators and independent variable. We examined the contribution from Model 1 to Model 4 by comparing the significance of the F-statistic associated with the change in $R^2$ (Pedhazur & Liora Pedhazur, 2013). The results are summarised in Table 4.

### Main effect

While Model 1 captures the effect of the control variables (natural log of GDP per capita, natural log of population density, Cultural Diversity Index and COVID-19 Stringency Index), the main effect is captured in Model 2, where the association of the independent test variables viz. rate of change of Transit and Workplace Mobility from baseline are checked separately. Transit Mobility ($\beta=0.09$, $p<0.00$) and Workplace Mobility ($\beta=0.09$, $p<0.00$) have a significant positive relationship with Reproduction Number of COVID-19.

### Moderators

The effect of 5 moderating variables is captured in Model 3. Like Models 1 and 2, in Model 3 Transit and Workplace Mobility have been included separately.

With Transit Mobility as main factor, moderating variables Power Distance (PD) ($\beta=-0.88$, $p<0.00$), Individualism (IM) ($\beta=-2.74$, $p<0.00$) and Uncertainty Avoidance (UA) ($\beta=-0.57$, $p<0.00$), have significant negative relationship while Long-Term Orientation (LTO) ($\beta=3.93$, $p<0.00$) has significant positive relationship with Transit Mobility. The relationship of Masculinity (M) with the dependent variable is not significant.

With Workplace Mobility as main factor, a near similar observation is noted. Moderating variables Power Distance (PD) ($\beta=-0.94$, $p<0.00$), Individualism (IM) ($\beta=-3.37$, $p<0.00$) and Uncertainty Avoidance (UA) ($\beta=-0.78$, $p<0.00$), have significant negative relationship while Long-Term Orientation (LTO) ($\beta=4.79$, $p<0.00$) has significant positive relationship with Workplace Mobility. Unlike Transit Mobility where the relationship of Masculinity (M) with the dependant variable is not significant, in case of Workplace Mobility, Masculinity (M) ($\beta=-0.17$, $p<0.05$) has a significant negative relationship.
Moderating effects

In Model 4, the interaction effects of the moderating variables, viz., Power Distance (PD), Individualism (IM), Masculinity (M), Uncertainty Avoidance (UA), and Long-Term Orientation (LTO) are observed together. Like Models 1, 2 and 3, in Model 4 Transit and Workplace Mobilities have also been included separately.

In case of relationship between Transit Mobility and Reproduction Number of COVID-19, except Masculinity (M), other 4 moderating variables, viz., Power Distance (PD), Individualism (IM), Uncertainty Avoidance (UA), and Long-Term Orientation (LTO) act as quasi moderators (Sharma et al., 1981). As in Model 3, a similar sign and significance was observed for all the moderating variables. Thus, for Power Distance (PD) and Individualism (IM), both the moderating variable and interaction effect of the moderating variable are negative and significant (PD: $\beta=-0.89$, $p<0.00$ & PD*Transit: $\beta=-0.32$, $p<0.00$; IM: $\beta=-2.32$, $p<0.00$ & IM*Transit: $\beta=-2.32$, $p<0.00$).

Table 4

Moderated Regression Estimates.

|                     | Model 1       | Model 2       | Model 3       | Model 4       |
|---------------------|---------------|---------------|---------------|---------------|
| **Main Effect**     |               |               |               |               |
| Workplace Mobility  | 0.09**        | 0.10**        | 0.24**        |               |
| **Moderators**      |               |               |               |               |
| Power Distance (PD) | -0.94**       | -1.09**       |               |               |
| Individualism (IM)  | -3.37**       | -3.64**       |               |               |
| Masculinity (M)     | -0.17*        | -0.15*        |               |               |
| Uncertainty Avoidance (UA) | -0.78** | -0.81** |               |               |
| Long-Term Orientation (LTO) | 4.79** | 5.04** |               |               |
| **Moderating Effects** |             |               |               |               |
| PD*Workplace        | -0.29**       |               |               |               |
| IM*Workplace        | -0.08**       |               |               |               |
| M*Workplace         | 0.06**        |               |               |               |
| UA*Workplace        | 0.25**        |               |               |               |
| LTO*Workplace       | -0.11**       |               |               |               |
| **Control Variables** |           |               |               |               |
| Cultural Diversity Index | 0.22** | 0.24** | 2.48** | 2.6** |
| COVID19 Stringency Index | -0.14** | -0.08** | -0.11** | -0.11** |
| Log (GDP Per Capita) | 0.36** | 0.4** | 4.31** | 4.56** |
| Log (Population Density) | 0.02 | -0.02 | -3.68** | -3.87** |
| Age Vulnerability   | 0.25** | 0.32** | -7.37** | -7.82** |
| Fixed Time Effect   | Yes           | Yes           | Yes           | Yes           |
| Country Time Effect | Yes           | Yes           | Yes           | Yes           |
| Adj R²              | 0.605**       | 0.608**       | 0.629**       | 0.637**       |
| F                   | 86.75**       | 87.48**       | 88.63**       | 89.87**       |
| ∆Adj R²             | 0.03          | 0.021         | 0.008         |               |
| ∆F                  | 0.73          | 1.15          | 1.24          |               |

Notes: Model 1: Control Variables, Model 2: Main model, Model 3: With Moderators, Model 4: With Interaction Terms. *,**Significant at 0.05 and 0.01 levels, respectively.

Moderating effects

In Model 4, the interaction effects of the moderating variables, viz., Power Distance (PD), Individualism (IM), Masculinity (M), Uncertainty Avoidance (UA), and Long-Term Orientation (LTO) are observed together. Like Models 1, 2 and 3, in Model 4 Transit and Workplace Mobilities have also been included separately.

In case of relationship between Transit Mobility and Reproduction Number of COVID-19, except Masculinity (M), other 4 moderating variables, viz., Power Distance (PD), Individualism (IM), Uncertainty Avoidance (UA), and Long-Term Orientation (LTO) act as quasi moderators (Sharma et al., 1981). As in Model 3, a similar sign and significance was observed for all the moderating variables. Thus, for Power Distance (PD) and Individualism (IM), both the moderating variable and interaction effect of the moderating variable are negative and significant (PD: $\beta=-0.89$, $p<0.00$ & PD*Transit: $\beta=-0.32$, $p<0.00$; IM: $\beta=-2.32$, $p<0.00$ & IM*Transit: $\beta=-2.32$, $p<0.00$).
β=-0.07, p<0.00). For Uncertainty Avoidance (UA), while the moderating variable itself is negative, the interaction effect of the moderating variable is positive and significant (UA: β=-0.35, p<0.00 & UA*Transit: β=0.28, p<0.00). The situation is opposite for Long Term Orientation (LTO), where the moderating variable is positive, while the interaction effect of the moderating variable is negative and significant (LTO: β=-3.22, p<0.00 & LTO*Transit: β=-0.08, p<0.00). Masculinity (M) acts as a pure moderating variable (Sharma et al., 1981) in the model. For this Hofstede factor, while the moderating variable itself is non-significant, the interaction effect of the moderating variable is positive and significant (M*Transit: β=0.04, p<0.05)

In case of relationship between Workplace Mobility and Reproduction Number of COVID-19, all 5 moderating variables, viz., Power Distance (PD), Individualism (IM), Masculinity (M), Uncertainty Avoidance (UA), and Long-Term Orientation (LTO) act as quasi moderators (Sharma et al., 1981). As in Model 3, a similar sign and significance was observed for all the moderating variables. Thus, for Power Distance (PD) and Individualism (IM), both the moderating variable and interaction effect of the moderating variable are negative and significant (PD: β=-1.09, p<0.00 & PD*Workplace: β=-0.29, p<0.00; IM: β=-3.64, p<0.00 & IM*Workplace: β=-0.08, p<0.00). For Masculinity (M) and Uncertainty Avoidance (UA), while the moderating variables itself are negative, the interaction effect of the moderating variables are positive and significant (M: β=-0.15, p<0.05 & M*Workplace: β=0.06, p<0.00; UA: β=-0.81, p<0.00 & UA*Workplace: β=0.25, p<0.00). The situation is opposite for Long Term Orientation (LTO), where the moderating variable is positive, while the interaction effect of the moderating variable is negative and significant (LTO: β=5.04, p<0.00 & LTO*Workplace: β=-0.11, p<0.00).

Effect size

The effect size of moderation was assessed with f-square, the ratio between the variation explained by the interaction term and the total variation of the dependent variable in question (Aiken & Stephen, 1991). A meta-analysis of previously published research utilising moderation models found that the average effect size of moderation is 0.009, much lower than that of small direct effects of around 0.02 (Aguinis et al., 2005). As per Kenny’s (2016), the interaction effect size of moderating factors is small when f-square =.005, medium when f-square =.01 and large when f-square =.025. The effect size of moderation terms in the main model for transit mobility is 0.083 and 0.080 for workplace mobility, indicating a large effect size.

The hypothesis test results are provided in Table 5.

Table 5

Hypothesis Test Results.

| Hypotheses | Moderator | Relationship | Support for Hypothesis |
|------------|-----------|--------------|------------------------|
| H1a        | Power Distance | During an epidemic, increase in human mobility would lead to a higher epidemic growth rate. | Supported |
| H2a        | Power Distance | During an epidemic, power distance will moderate the relationship between ‘work place mobility’ and epidemic growth; such that the impact of ‘work place mobility’ on epidemic growth decreases as power distance increases. | Supported |
| H2b        | Power Distance | During an epidemic, power distance, will moderate the relationship between ‘transit passenger mobility’ and epidemic growth; such that the impact of ‘transit passenger mobility’ on epidemic growth decreases as power distance increases. | Supported |
| H3a        | Individualism | During an epidemic, individualism will moderate the relationship between ‘work place mobility’ and epidemic growth; such that the impact of ‘global work place mobility’ on epidemic growth decreases in individualistic societies. | Supported |
| H3b        | Individualism | During an epidemic, individualism will moderate the relationship between ‘transit passenger mobility’ and epidemic growth; such that the impact of ‘transit passenger mobility’ on epidemic growth decreases in individualistic societies. | Supported |
| H4a        | Masculinity | During an epidemic, masculine societies will moderate the relationship between ‘work place mobility’ and epidemic growth; such that the impact of ‘work place mobility’ on epidemic growth increases in masculine societies. | Supported |
| H4b        | Masculinity | During an epidemic, masculine societies will moderate the relationship between ‘transit passenger mobility’ and epidemic growth; such that the impact of ‘transit passenger mobility’ on epidemic growth increases in masculine societies. | Supported |
| H5a        | Uncertainty Avoidance | During an epidemic, uncertainty avoidance will moderate the relationship between ‘work place mobility’ and epidemic growth; such that the impact of ‘work place mobility’ on epidemic growth decreases as uncertainty avoidance increases. | Not Supported |
| H5b        | Uncertainty Avoidance | During an epidemic, uncertainty avoidance will moderate the relationship between ‘transit passenger mobility’ and epidemic growth; such that the impact of ‘transit passenger mobility’ on epidemic growth decreases as uncertainty avoidance increases. | Not Supported |
| H6a        | Long-Term Orientation | During an epidemic, long-term orientation will moderate the relationship between ‘work place mobility’ and epidemic growth; such that the impact of ‘work place mobility’ on epidemic growth decreases for long-term orientated societies. | Supported |
| H6b        | Long-Term Orientation | During an epidemic, long-term orientation will moderate the relationship between ‘transit passenger mobility’ and epidemic growth; such that the impact of ‘transit passenger mobility’ on epidemic growth decreases for long-term orientated societies. | Supported |
Fig. 5. a: Interaction Plot - Effect of Power distance on Workplace mobility and Reproduction no of COVID-19. b: Johnson-Neyman plot of Region of Significance: Effect of Power Distance on Workplace Mobility and Reproduction Number.
Fig. 6. a: Interaction Plot- Effect of Power distance on Transit mobility and Reproduction no of COVID-19. b: Johnson-Neyman plot of Region of Significance: Effect of Power Distance on Transit Mobility and Reproduction Number.
Hypotheses testing results

Power distance

Power distance (PD) is a quasi-moderator for the relationship between work place/transit mobility and reproduction number of COVID-19. When power distance increases, the impact of work place and transit mobility on epidemic growth decreases. Thus, it supports H2_a and H2_b.

Slope analysis and region of significance

The plot of simple slope analysis is illustrated in Figs. 5a & 6a. 5a represents the plot of association between workplace mobility and reproduction number at 3 levels of Power Distance Score (Mean + 1 SD, Mean and Mean - 1 SD). The effect of Workplace mobility was stronger (observed by the steepness of the slope) for Reproduction number with low power distance score (Mean - 1 SD). Similarly Fig. 6a represents the plot of association between transit mobility and reproduction number at 3 levels of Power Distance Score (Mean + 1 SD, Mean and Mean - 1 SD). In both Figs. 5a and 6a, the slope of the graphs (between Reproduction number and workplace or transit mobility) become less steep (weaker), as the Power Distance score increases (from mean -1 SD to mean +1 SD). This indicates, that work place or transit mobility have a lower impact on reproduction number as the Power Distance of the societies increase.

A similar observation is noted in the Johnson-Neyman plots (illustrated in fig. no 5b & 6b). In 5b and 6b, the slope of workplace/transit mobility is plotted on y-axis and Power Distance score on x-axis. It is observed that as Power Distance scores increase, the slope (effect) of workplace/transit mobility on reproduction number of COVID-19 decreases.

Furthermore, using the Johnson-Neyman technique (Johnsoin & Fay,1950), we probed the interaction at different values of the moderator to determine at what score of Power Distance, the effect of workplace and transit mobility on reproduction number became significant (refer Table 6). Per Johnson-Neyman analysis, Power Distance has significant moderating effects on the Reproduction Number of COVID-19, below the scores of 96.67 and 99.29 for workplace and transit mobility respectively. This includes 92% and 95% of the sample in case of workplace and transit mobility respectively.

Individualism

Individualism (IM) is a quasi-moderator for the relationship between work place/transit mobility and reproduction number of COVID-19. When Individualism increases, the impact of work place and transit mobility on epidemic growth decreases. Thus, it supports H3_a and H3_b.

Slope analysis and region of significance

The plot of simple slope analysis is illustrated in Figs. 7a and 8a. Similar to the slope analysis given in the above section, in both Figs. 7a and 8a, the slope of the graphs (between Reproduction number and workplace or transit mobility) become less steep (weaker), as the Individualism score increases (from mean -1 SD to mean +1 SD). A similar observation is noted in the Johnson-Neyman plots (illustrated in fig. no 7b & 8b). As Individualism scores increase, the slope (effect) of workplace/transit mobility on reproduction number of COVID-19 decreases.

Furthermore, when the interaction was probed using Johnson-Neyman Technique (refer Table 6), Individualism had significant moderating effects on the Reproduction Number of COVID-19, for the entire range of the observed values [10.00, 91.00].

Masculinity

Masculinity (M) is a quasi-moderator for the relationship between work place mobility and reproduction number of COVID-19. It acts as a pure moderator for the relationship between transit mobility and reproduction number of COVID-19. When masculinity increases, the impact of work place and transit mobility on epidemic growth increases. Thus, it supports H4_a and H4_b.

Slope analysis and region of significance

The plot of simple slope analysis is illustrated in Fig. 9a & 10a. 9a represents the plot of association between workplace mobility and reproduction number at 3 levels of Masculinity Score (Mean + 1 SD, Mean and Mean - 1 SD). The effect of Workplace mobility was stronger (observed by the steepness of the slope) for Reproduction number with high Masculinity score score (Mean + 1 SD). Similarly Fig. 10a represents the plot of association between transit mobility and reproduction number at 3 levels of Masculinity Score (Mean + 1 SD, Mean and Mean - 1 SD). In both Figs. 9a and 10a, the slope of the graphs (between Reproduction number and workplace or transit mobility) become less steep (weaker), as the Masculinity score increases (from mean -1 SD to mean +1 SD). This indicates, that workplace or transit mobility have a lower impact on reproduction number as the Masculinity of the societies increase.

Table 6

| Range of observed values | Johnson-Neyman Interval* |
|--------------------------|--------------------------|
|                          | Workplace Mobility       | Transit Mobility       |
| PowerDistance            | [11.00, 104.00]           | [96.67, 115.81]        | [99.29, 118.28] |
| Individualism            | [10.00, 91.00]            | [119.00, 398.47]       | [128.65, 491.98] |
| Masculinity              | [5.00, 110.00]            | [-250.27, -21.38]      | [-4973.49, -30.70] |
| UncertaintyAvoidance     | [8.00, 104.00]            | [23.17, 39.43]         | [21.94, 41.87] |
| LongTermOrientation      | [3.53, 100.00]            | [101.19, 146.47]       | [119.68, 211.57] |

* Predictor is significant (p < 0.05) outside the specified moderator interval
Fig. 7. a: Interaction Plot- Effect of Individualism on Workplace mobility and Reproduction no of COVID-19. b: Johnson-Neyman plot of Region of Significance: Effect of Individualism on Workplace Mobility and Reproduction Number.
Fig. 8. a: Interaction Plot - Effect of Individualism on Transit mobility and Reproduction no of COVID-19. b: Johnson-Neyman plot of Region of Significance: Effect of Individualism on Transit Mobility and Reproduction Number.
Fig. 9. a: Interaction Plot- Effect of Masculinity on Workplace mobility and Reproduction no of COVID-19. b: Johnson-Neyman plot of Region of Significance: Effect of Masculinity on Workplace Mobility and Reproduction Number.
Fig. 10. a: Interaction Plot: Effect of Masculinity on Transit mobility and Reproduction no of COVID-19. b: Johnson-Neyman plot of Region of Significance: Effect of Masculinity on Transit Mobility and Reproduction Number.
Fig. 11. a: Interaction Plot- Effect of Uncertainty Avoidance on Workplace mobility and Reproduction no of COVID-19. b: Interaction Plot- Effect of Uncertainty Avoidance on Transit mobility and Reproduction no of COVID-19.
Fig. 12. a: Interaction Plot- Effect of Long-Term Orientation on Workplace mobility and Reproduction no of COVID-19. b: Johnson-Neyman plot of Region of Significance: Effect of Long-Term Orientation on Workplace Mobility and Reproduction Number.
Fig. 13. a: Interaction Plot - Effect of Long-Term Orientation on Transit mobility and Reproduction no of COVID-19. b: Johnson-Neyman plot of Region of Significance: Effect of Long-Term Orientation on Transit Mobility and Reproduction.
mobility) become less steep (weaker), as the Masculinity score decreases (from mean +1 SD to mean -1 SD). This indicates, that work place or transit mobility have a higher impact on reproduction number as the Masculinity of the societies increase.

A similar observation is noted in the Johnson-Neyman plots (illustrated in fig. no 9b & 10b). In 9b and 10b, the slope of workplace/transit mobility is plotted on y-axis and Masculinity score on x-axis. It is observed that as Masculinity scores increase, the slope (effect) of workplace/transit mobility on reproduction number of COVID-19 increases.

Furthermore, when the interaction was probed using Johnson-Neyman Technique (refer Table 6), Masculinity had significant moderating effects on the Reproduction Number of COVID-19, for the entire range of the observed values [5.00, 110.00].

Uncertainty Avoidance

Uncertainty Avoidance was found to act as a moderator in defining the relationship between change in workplace/transit mobility and reproduction number of COVID-19. But it is found that as uncertainty avoidance scores increase, change in workplace/transit mobility from baseline increases the reproduction number of COVID-19. The positive and increasing slopes is also seen in Fig. 11a and b. The results appear contrary to the hypothesis that when uncertainty avoidance increases, the effect of mobility on epidemic growth decreases. Therefore, H5b and H5c cannot be accepted.

Long-term Orientation

Long Term Orientation (LTO) is a quasi-moderator for the relationship between work place/transit mobility and reproduction number of COVID-19. When long term orientation increases, the impact of work place and transit mobility on epidemic growth decreases. Thus, it supports H6a and H6b.

Slope analysis and region of significance

The plot of simple slope analysis is illustrated in Figs. 12a and 13a. Similar to the slope analysis given in the above section, in both Figs. 12a and 13a, the slope of the graphs (between Reproduction number and workplace or transit mobility) become less steep (weaker), as the long-term orientation score increases (from mean -1 SD to mean +1 SD). A similar observation is noted in the Johnson-Neyman plots (illustrated in fig. no 12b & 13b). As long-term orientation scores increase, the slope (effect) of workplace/transit mobility on reproduction number of COVID-19 decreases.

Furthermore, when the interaction was probed using Johnson-Neyman Technique (refer Table 6), long term orientation had significant moderating effects on the Reproduction Number of COVID-19, for the entire range of the observed values [3.53, 100.00].

Discussion

Spread of epidemic and its effect on human population is determined conjointly by the transmittable nature of the pathogen and characteristics of the host population like national culture (Merler & Ajelli, 2010). Different countries have reacted and responded to the ongoing COVID-19 situation differently (Babu et al., 2021; Ihekweazu & Agogo, 2020; Oh et al., 2020). This has attracted researchers to explore the impact of culture on COVID-19 growth (Gokmen et al., 2021; Kumar, 2021; Ibanez & Gyanendra Singh, 2020). The researches have established significant direct impact of cultural factors on COVID-19 growth. There are another set of studies which explored the impact of human mobility on COVID-19 spread (Kartal et al., 2021; Wang & Yamamoto, 2020; Yilmazkuday, 2020a, 2021; Zhu et al., 2020; Nouvellet et al., 2021; Carteni et al., 2020) and indicated the direct influence of mobility restrictions on COVID-19 growth. The paper is an attempt to examine the moderating effect of culture on population mobility and the COVID-19 spread.

In this study, the direct impact of mobility on COVID-19 spread and moderating effect of culture have been found significant. Comparisons between societies in different parts of the world clearly shows how culture can affect human behaviour (Chiang, 2005; Soares et al., 2007). Cultural differences between societies result in profoundly different behaviours, beliefs, values, and norms among individuals. The cultural content of a society’s collective belief about illness and sanctioned treatments also impact an individual’s health related behaviour (Bhui & Dinos, 2008). Evidences of impact on spread and control of epidemiological diseases viz. Tuberculosis (Mason et al., 2016), Ebola (Fairhead, 2016) due to cultural factors have been validated by previous studies.

There are a modest number of theories like Theory of Reasoned Action (TRA), Theory of planned behaviour (TPB), Social Cognitive Theory, Health Belief Model, Theory of subjective culture, The Transtheoretical model that are used to investigate health behaviour. In these theories, cultural variables are considered to be distal variables which indirectly affect behavioural intention. Therefore, it can be expected that, certain population groups are more likely to increase their movement (behaviour) due to different cultural background.

Health Belief Model (HBM) has been one of the most widely used conceptual frameworks in health behaviour research. It is widely used to explain change and maintenance of health-related behaviours and act as a guiding framework for health behaviour interventions. As per HBM, an individual will take action to prevent, screen for, or control illness conditions due to perceived susceptibility, seriousness/severity/risk, benefits and barriers.

It was found, when Power Distance scores increase, the impact of mobility on COVID-19 infection decrease. In high power distance cultures, people are characterised as obedient to higher positions and authority (Hofstede & Michael, 1984). In such societies, government enforced restrictions like constrained mobility, lockdown, social-distancing and mandatory masking/sanitisation, vaccinations drive testing etc can be interpreted as perceived barriers. It is expected that the populace would follow the restrictions imposed by the authorities and therefore help in reducing the rate of COVID-19 Infection.

Societies with high individualistic scores, had been correlated with “variety”, “enjoyment in life” and “pleasure” (Hofstede & Michael, 1984). However, the results show that in high individualistic societies, the impact of mobility on the infection rate of COVID-19...
reduces. It can be inferred that propensity of low social embeddedness and more focus on self-reliance in individualistic societies (Heu et al., 2019) would lead to self-initiated control behaviour. The perceived risk of being unattended during an epidemic and cost of negative side effects such as affected health, restricted hedonic activities during infection etc guide individuals from such societies to curb their movement, thereby reducing COVID-19 spread.

It was found that high masculinity scores would strengthen the effect of mobility on COVID-19 spread. Self-control behaviour is low in Masculine societies compared to Feminine societies (Hofstede & Michael, 1984). Therefore, it can be anticipated that, in high masculine societies, the spread of infection would increase, as people would not be able to control their outgoing or assertive behaviour. The perceived benefits of restrictive mobility for individuals from Masculine societies are not lucrative as they thrive for higher achievement and heroism (Hofstede & Michael, 1984). On the other hand, individuals from Feminine societies will be affected by social consequences such as effect of COVID-19 on family life, and social relations and therefore would restrict their mobility.

Uncertainty Avoidance is associated with “risk-avoiding” and “don’t-rock-the-boat” behaviour (Hofstede & Michael, 1984). Amongst people from high uncertainty avoidance cultures, the perceived susceptibility and perceived risk associated with individual behaviour is higher. In an epidemic situation, such as during COVID-19, these would restrict mobility and therefore, decrease the spread of infection. However, this study failed to confirm the same. The answer of this anomaly could be hidden in the fact that people from high uncertainty avoidance societies have desires of predictability and familiarity to social situations (Webster & Arie, 1994). Therefore, even in unprecedented emergency situations, such as an epidemic, desires of predictability might supersede. This could induce individuals to venture out and inspect the COVID-19 situation for themselves. It might also be noted that Hofstede score for Uncertainty Avoidance has yielded conflicting results in various cross-cultural studies (Venaik & Brewer, 2010; Brewer & Venaik, 2011). In an epidemic, they are expected to plan their movement and prevent the spread of infection. This study also confirms the same for COVID-19.

Limitations

While the study encompasses 95 countries and tries to tie up epidemic spread with cultural and mobility factors at a global scale, individual country-wise and culture specific nuances cannot be ignored. The study would benefit greatly, by further elucidating similar patterns across homogenous country clusters (specified by GLOBE, Ronen-Shenkar). Furthermore, for a pandemic with multiple waves and long time period (as is the case of COVID-19), additional research needs to be carried out for later time periods. The current study limits itself to the peak of the first wave (from Feb - July 2020).

The study also includes, only two proxies for mobility (transit and workplace). Intent of human mobility is varied and cannot be captured only through wireless tagging. Sample based mobility patterns at a local level would greatly enhance the discerning distinctions in epidemic spread vis-à-vis directed mobility. The authors suspect that the results concerning uncertainty avoidance can be explained by such approaches.

Conclusion

Despite mobility restrictions imposed at a national or international level, the restricted mobility patterns follow a distinct trend, often latent to the affected population’s behavioural trends in question – thus affecting the spread of pandemic (Espinoza et al., 2020). The direct impact of culture on COVID-19 growth has been confirmed by few studies (Gokmen et al., 2021). However, this study emphasizes on the indirect moderation effect of culture on COVID-19 growth affected by changes in mobility. Culture has always played an important role in predicting human behaviour. Cross-cultural impact, as explicated by this study, could form a crucial element in policy formulation for epidemic control by indigenous Governing bodies. Policy makers at a global scale working in tandem with local Governments further need to be cognizant of this idiosyncratic nature of the cultural dimensions and its effect on the pathogen spread. This study can be a helpful precursor in this regard.

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