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Title: Behavioural Interventions for Micro-mobility Adoption: Low-hanging Fruits or Hard Nuts to Crack?

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**Behavioural Interventions for Micro-mobility Adoption:
Low-hanging Fruits or Hard Nuts to Crack?**

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Abstract:

This study explores the potential and challenges of applying behavioural interventions to promote micro-mobility adoption. Our online experiments with New York City residents showed that nudges and faming improved respondents' willingness to adopt e-scooters significantly. Moreover, our experiments spanned over the pre-, during- and post- COVID-19 lockdown period in New York City. Findings from this natural experiment revealed that the effect of these behavioural interventions varied significantly during the pandemic, likely due to a heightened level of health consciousness and a new perspective regarding social interactions. Behavioural tools cannot be taken off-the-shelf and applied as a blanket policy. Individual and group characteristics have to be assessed to devise the pre-eminent behavioural interventions for a particular target audience. More experiments across a wide range of economic, social, cultural, and political settings are needed to guide the application of behavioural interventions in transportation studies.

Keywords: innovation, shared economy, infrastructure, behavioural biases, social norm, loss aversion, prospect theory
JEL Classifications: R42, R48, D91

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1. Introduction

As congestion and pollution externalities from motor vehicles become increasingly problematic in cities, there is heightened resolve to depart from car-centrism towards embracing human-scaled urban design. Transport infrastructure necessarily form part of urban design, increasingly integrated with land-use planning. This paradigm shifts away from car-centric cities to more human-friendly ones is inextricably intertwined with supply-side infrastructural provision and demand-side commuter preferences. Micro-mobility, while still in nascent stages of development, plays an increasingly important role in this process.

Micro-mobility are small transport devices designed for human-scaled movement. They include bicycles, electric bicycles (e-bikes), electric scooters (e-scooters) and the like. In the last decade, micro-mobility saw unbridled growth. Bicycle-sharing schemes have burgeoned in popularity globally, from merely 5 schemes in Europe in 2000 to over 2000 schemes in 2020, with approximately 9 million bicycles worldwide (Meddin et al., 2020). Electric micro-mobility has also entered the picture, with the first dockless e-scooter sharing system rolled out in Santa Monica, USA in 2017. This new mode of transport is particularly popular in highly congested cities as an alternative 'first-and-last-mile solution' (House, 2019). The potential of micro-mobility to change the future of urban mobility and overcome existing automobile-related challenges, coupled with incipience of e-scooters as an incubator-type micro-mobility technology, sets the premise for this paper.

When e-scooters were first introduced to the public, the most glaring problem perhaps was public safety concern (see Table 4 in Gossling, 2020), magnified by media portrayal of injuries caused in e-scooter accidents. Ultimately, a growing number of studies proved that this is not a concern. For example, Yang et al. (2020) identified only 169 e-scooter-involved crashes from news reports across the US between 2017 and 2019; Nellamattathil and Amber (2020) noted that there are no serious injuries caused by e-scooter crashes by using data from Washington DC. Researchers moved on to investigate the environmental impacts of e-scooters in terms of electricity consumption (Brdulak et al., 2020; Hollingsworth et al., 2019), the potential to replace other more polluted transportation modes (James et al., 2019; Moreau et al., 2020; Zhu et al., 2020), and the optimal ways and places to use e-scooters (Bai and Jiao, 2020; Mathew et al., 2019; Zou et al., 2020). The combined effort in these academic endeavor shows that long-term environmental benefits of e-scooters outweigh their production and running cost significantly.

Consequently, the focus of micro-mobility research has switched from vehicles to users, with the aim of informing policies to promote and manage this new transport mode. The literature is expanding rapidly with mixed results. For example, whist surveys from New Zealand residents show that young people are more likely to adopt e-scooters (Curl and Fitt, 2020); evidence from Austin, USA suggests e-scooters are less popular in neighbourhoods with a higher proportion of youth (Jiao and Bai, 2020). The discrepancy in research findings is largely a result of the heterogeneity in the social and demographic background of the respondents. For instance, a study of university staff in the US reveals that e-scooters can make a positive contribution to gender and racial equity in transportation (Sanders et al., 2020); however, an online survey of the general public from four cities in New Zealand raises concern about the lack of access to supporting materials (i.e., smartphone and bank cards) for lower income people of colour to use shared e-scooters (Fitt and Curl, 2020). Rather than contradicting each other, these mixed findings actually point to the same direction: the behaviours of existing and potential e-scooter users must be studied through a combination of social, cultural, and economic lens, with a public policy orientation (Tuncer et al., 2020).

Recent studies along this direction generate some promising findings, as well as identify some critical areas for further investigations, such as user motives, expectations, perceptions and concerns (Eccarius and Lu, 2020; Polydoropoulou et al., 2020), and motivations of micro-mobility adoption relating to emotional well-being and human needs (Glenn et al., 2020). This study contributes to the literature by focusing on an emerging frontier in transportation research: the application of behavioural interventions in micro-mobility studies (Tomaino et al., 2020).

Behavioural interventions make use of psychology insights to support better decision making for both individuals and the society. They are most effective in areas where neither financial incentives nor government regulations work effectively. For example, default opt-in options are used in pension enrollment schemes to encourage participations (Thaler and Benartzi, 2004), presumed consent legislation has a positive effect on organ donation (Abadie and Gay, 2006), and the timing of commitment and payment significantly affect charitable donations (Breman, 2011). For the same reasons, behavioural interventions have also been widely used to promote energy conservation and environmental protection (see, for example, Gillingham and Palmer, 2014; Momsen and Stoerk, 2014; Pichert and Katsikopoulos, 2008; Schubert, 2017). Since Avineri pointed out the potential of applying behavioural insights in transportation almost a decade ago (Avineri, 2012), researchers have been testing these ideas in many areas such as carsharing (Namazu et al., 2018), transport mode choices (Ghader et al., 2019; Guidon et al., 2020; Rosenfield et al., 2020), and tradable mobility credits (Tian et al., 2019). The general consensus is that behavioural tools and models can help us to better understand commuter behaviours and to promote environmentally friendly travel decisions.

This study investigates the potential and challenges of applying behavioural interventions in the promotion of e-scooter adoption. Behavioural intervention tools have already been extensively tested in other areas. Will the application of behavioural intervention in e-scooter be straightforward and effective? What are the potential pitfalls that may prevent the effective use of behavioural interventions in e-scooter promotion? This paper set out to answer these questions by studying the applications of two most tested behavioural tools (i.e., nudges and framing) for e-scooter adoption. We also use the COVID-19 pandemic as a natural experiment to demonstrate the challenges of applying behavioural interventions in transportation studies.

The rest of the paper is organized into four parts. The first part gives the conceptual framework and testable hypotheses. Part two elucidates empirical strategies. Part three presents empirical findings. Finally, part four discusses policy implications and concludes the paper.

2. Conceptual framework and testable hypotheses

2.1 The determinants of e-scooter adoption

Existing studies on the adoption of e-scooters are limited. Our investigation starts from findings on similar micro-mobility vehicles. E-scooters are highly comparable to e-bikes, and also share similarities with other surveyed micro-mobility modes. Specifically, e-scooters share functional similarities with e-bikes, and to a lesser extent, bicycles. E-bikes are perceived as intermediaries between cars and bicycles (Popovich et al., 2014). Motorized scooters, too, are comparable to e-scooters in terms of basic operation. These similarities provide opportunities for drawing parallels between e-scooters and more established forms of micro-mobility. Knowledge from studies on these similar micro-mobility vehicles can help us to understand the relevant factors that can be transposed onto the germinating e-scooter market.

We use ISI Web of Science© to identify relevant literature. A preliminary search using keywords “scooter”, “bicycle” and “micro-mobility” was carried out before narrowing down with additional keywords including "barriers", "motivators" and "attitudes". The final dataset comprises 39 academic papers published in 20 leading journals across an array of disciplines (See the note of Table 1. A complete list of papers and journals can be found in Appendixes I and II). Majority of these journals are ranked within the first and second quartiles for their Journal Citation Report categories.

In Panel A of Table 1, we classify the barriers of micro-mobility vehicles (MMV) adoption into five categories: environmental, functional, infrastructural, legal, and social factors. The most prominent barriers are functional barriers such as safety concerns, followed by infrastructural and environmental barriers. Our observation is that studies on the physical barriers of micro-mobility adoption significantly outnumber those on social barriers.

In Panel B of Table 1, we break down the enablers of MMV adoption into intrinsic and extrinsic motivation by following the framework in (Deci and Ryan, 1985); Ryan and Deci (2000). Our inherent attitudes and perceptions affect the orientation of our motivations and subsequently, our actions. Actions driven by intrinsic motivations (IMs) are executed for innate gratification, while those driven by extrinsic motivations (EMs) are for a distinguishable result extricable from the act. Intrinsically-motivated behaviours are more sustainable than extrinsically-driven actions, because the reward for intrinsically-motivated behaviours is the act itself. However, both are crucial in policy-making because government policies cannot directly influence IMs, but must work through EMs to facilitate shifts in individual perceptions such as catalyzing integration and internalization.

We find that functional EMs were the most prominent enablers, followed by infrastructural and social EMs, largely mirroring the barriers identified in Panel A. Although the total number of papers that studied EMs of MMV adoption nearly doubled those on IMs, the number of studies on the two most commonly mentioned IMs, i.e., environmental and health consciousness, is larger than all of the EMs. Environmental and health consciousness are important personal norms, which can predict mobility patterns (Bamberg et al., 2007). For example, pro-environment values enhance perceptions of electric cars (Schuitema et al., 2013), and attitudes towards physical activity also affect bicycle adoption (Wolf and Seebauer, 2014). This should apply to the adoption of e-scooters as well.

Based on the literature review, we choose the two most commonly studied IMs (i.e., environmental consciousness and health consciousness) and EMs (i.e., efficiency and social pressure) from Table 1 as the areas of focus. We design experiments to investigate whether two behavioural interventions (i.e., nudges and framing) affect e-scooter adoption attitudes through these four channels.

2.2 Nudges

Nudges are forms of choice architecture that "alter people's behaviour in a predictable way without significantly changing economic incentives", maintaining one's freedom to choose any alternative (Thaler and Sunstein, 2008, page 6). These psychological tools catalyze internalization processes of external incentives precisely because they allow individuals to choose freely, implying that the choice selected is readily integrated into the individual's psyche despite being externally-induced. Because they are less invasive than neoclassical policies, nudging allows individuals to maintain a higher degree of self-determination and personal engagement (Frey and Jegen, 2001; Frey and OberholzerGee, 1997).

Nudges are part of a behavioural approach to policy-making that has been on the rise. Where traditional paternalistic policies confine individuals' choice-sets, nudges are more libertarian because they allow people to opt-out, "preserving freedom of choice" (Thaler and Sunstein, 2003, page 179). This feature is particularly relevant to decisions that involve public goods such as roads and clean air. Such decisions are often difficult to be influenced with market incentives (i.e., fines or rewards) and government regulations. Instead, non-price-based, behavioural interventions are both economical and effective (Allcott and Mullainathan, 2010). For example, sending home energy report letters to residential utility customers comparing their electricity use to that of their neighbors reduced energy consumption by 2% in the US (Allcott, 2011). Effective, large-scale implementation of behavioural interventions can potentially reduce global carbon dioxide emissions by as much as 20% in ten years (Stern, 2011, Table 1, page 305).

In the areas of socio-environmental and transport policies, there has been a recent movement towards complementing neoclassical policies like rewards and sanctions with nudges to influence actions. However, most of the nudges explored in these studies are financial incentives or informational prompts, i.e., EMs (Anagnostopoulou et al., 2020; Byerly et al., 2018; Namazu et al., 2018; Rosenfield et al., 2020). These EM nudges are often not effective, and the exploration of the effect of IMs such as social norm and environmental consciousness is generally lacking. Therefore, we propose the following analytical model to capture the effect of both EMs and IMs in the decision of e-scooter adoption.

$$WTA = f(ENs, INs, X) + \varepsilon \,, \tag{1}$$

where WTA is a measurement of the willingness to adopt for e-scooters, ENs and INs are nudges targeting extrinsic and intrinsic motivations respectively, and X is a matrix of control variables.

Our survey of the literature suggest that nudges can encourage e-scooter adoption. To test this hypothesis, we expect $\frac{\partial WTA}{\partial ENs} > 0$ and $\frac{\partial WTA}{\partial INs} > 0$, or both extrinsic and intrinsic nudges affect e-scooter adoption decisions. Moreover, existing studies suggest that extrinsic nudges such as financial incentives may crowd out feelings of civic responsibility when promoting sustainable travel behaviours (Avineri, 2012). Consequently, we expect intrinsic nudges are more effective than extrinsic nudges in e-scooter adoption decisions, or $\frac{\partial WTA}{\partial INs} > \frac{\partial WTA}{\partial ENs}$. To summarize, three hypotheses are derived from equation (1) to test the effect of nudges as follows.

Hypothesis 1a: Extrinsic nudges encourage e-scooter adoption.
Hypothesis 1b: Intrinsic nudges encourage e-scooter adoption.
Hypothesis 1c: Intrinsic nudges are more effective than extrinsic nudges to encourage e-scooter adoption.

2.3 Framing

Whist the first hypothesis investigates whether nudges can affect e-scooter adoption decision, the second hypothesis aims to explore how nudges should be applied effectively. We focus on one of the most established behavioural biases in the literature: loss aversion. Specifically, we test whether framing the nudges in loss and gain domain, i.e., gain-loss framing, has a significant impact on the effectiveness of the behavioural interventions.

Gain-loss framing refers to phrasing choices in positive (gain) or negative (loss) terms. According to class economic theories, framing does not change the overarching message, and hence should not influence rational economic agents. However, empirical evidence often suggests the opposite. For example, messages seeking to alter behaviour have shown to be more effective when presented in the context of loss by inaction than gains by action (Tversky and Kahneman, 1981). Nevertheless, loss-framing is not always more persuasive than gain-framing (Steiger and Kuhberger, 2018). Gain-framing is more effective when promoting activities with positive outcomes (O'Keefe and Jensen, 2007), whilst loss-framing appeals when the objective is to prevent or detect negative outcomes (O'Keefe and Jensen, 2009). Moreover, gain-framing is more effective in encouraging preventive interventions such as physical activity (Gallagher and Updegraff, 2012; Halpin, 2018). In the context of e-scooter adoption, the nudges will highlight the benefits of commuting with e-scooters, which involves more physical activities than driving or riding a bus. Therefore, we expect that gain-framing nudges are more effective than loss-framing nudges, or $\left.\frac{\partial WTA}{\partial ENs}\right|_{gain-framing} > \left.\frac{\partial WTA}{\partial ENs}\right|_{loss-framing}$ and $\left.\frac{\partial WTA}{\partial INs}\right|_{gain-framing} > \left.\frac{\partial WTA}{\partial INs}\right|_{loss-framing}$. We form the second hypothesis according.

Hypothesis 2: Gain-framing nudges are more effective than loss-framing nudges to encourage e-scooter adoption.

2.4 The moderating effect of COVID-19 pandemic

Although the effectiveness of behavioural interventions has been confirmed in many empirical studies, the identified effects tend to vary according to context. Behavioural interventions leverage psychological and emotional reactions of stakeholders to manipulate their decisions and actions, and there is no reason to believe that people's preferences are constant across different social, political, and cultural background. Therefore, behavioural interventions need to be targeted to be effective (Costa and Kahn, 2013).

The policy implication of this characteristic of behavioural interventions is significant, because it suggests that there are no 'one-size-fits-all' solutions. Instead, even the most established behavioural tools, such as nudges, need to be empirically tested before rolling out in full scale. This is particularly relevant to our study, where complex constructs such as health consciousness and social influences are used in the design of nudges. There is no doubt that the level of health consciousness and social influence is different among countries from various development stages. Moreover, even among a reasonably homogeneous group of people, health consciousness and social awareness may change over time, making them fluid and sneaky constructs to capture in behavioural studies. In other words, there are many moderators of the effect of behavioural interventions, and they should be taken into account in policy or experimental designs.

To illustrate the effect of moderators, we use the COVID-19 pandemic as a natural experiment. At the time of the writing, the world is still in the middle of this pandemic. However, it has already changed people's perception about health and social interactions, particularly during the months-long lockdowns. We expect that the effect of nudges will be different before and after the lockdowns, i.e., $\left.\frac{\partial WTA}{\partial ENs}\right|_{pre-lockdown} \neq \left.\frac{\partial WTA}{\partial ENs}\right|_{after-lockdown}$ and $\left.\frac{\partial WTA}{\partial INs}\right|_{pre-lockdown} \neq \left.\frac{\partial WTA}{\partial INs}\right|_{after-lockdown}$. We derive the last testable hypothesis as follow.

Hypothesis 3: The effects of nudges are different before and after the COVID-19 lockdown.

Our analytical framework and testable hypotheses are summarized in Figure 1. The empirical strategy to implement the research design is outlined in the next section.

Table 1. Barriers and enablers of MMV adoption identified in the literature

Panel A: Barriers		Panel B: Enablers	
Factor	**Count (%)**	**Factor**	**Count (%)**
Function	*41 (51%)*	**Intrinsic motivation**	**58 (36%)**
Safety concerns	15 (19%)	Environmental consciousness	22 (14%)
Less efficient	8 (10%)	Health consciousness	18 (11%)
Limited range	6 (8%)	Enjoyment	15 (9%)
Lower comfort	5 (6%)	Collectivism	2 (1%)
Expensive	4 (5%)	Ego	1 (1%)
Heavy	3 (4%)	**Extrinsic motivation**	**103 (64%)**
Infrastructure	*14 (18%)*	*Function*	*61 (38%)*
Poor network	6 (8%)	Efficiency	15 (9%)
Lack parking	5 (6%)	Flexibility	8 (5%)
No lanes	3 (4%)	Economical	8 (5%)
Environment	*12 (15%)*	Safety	8 (5%)
Poor weather	9 (11%)	Comfort	7 (4%)
Poor terrain	3 (4%)	User-friendly	4 (2%)
Legal factors	*4 (5%)*	Greater reach	4 (2%)
Poor regulation	2 (3%)	Necessity	3 (2%)
Helmet law	1 (1%)	Overcoming terrain boundaries	3 (2%)
Poor information	1 (1%)	Increased load	1 (1%)
Social factors	*4 (5%)*	*Infrastructure*	*23 (14%)*
Car culture	2 (3%)	Parking	8 (5%)
Stigma	2 (3%)	Lanes	8 (5%)
Others	*5 (6%)*	Performance	7 (4%)
Stressful	2 (3%)	*Social factors*	*19 (12%)*
Lack skills	1 (1%)	Social pressure	15 (9%)
No bicycle	1 (1%)	Inclusivity	4 (2%)
Unfit to use	1 (1%)	*Others*	*2 (1%)*
Total	**80 (100%)**		**161 (100%)**

Note: The distribution of papers among different type of MMVs is bicycle: 20, bicycle (shared): 7; e-bike:11; e-bike (shared):1; e-scooter: 1; motorized scooter (shared): 1; and walking:2. The total number of factors is greater than the total number of papers surveyed (i.e., 39) because some papers studied multiple factors. The number of papers (in brackets) published in each of the journals surveyed is Cities (1), Computational Intelligence and Neuroscience (1), Ethnicity and Disease (1), International Journal of Environmental Research and Public Health (1), International Journal of Sustainable Transportation (2), Journal of Business Ethics (1), Journal of Epidemiology and Community Health (2), Journal of Public Policy and Marketing (1), Journal of Transport and Health (2), Journal of Transport Geography (2), Sustainability (3), Technological Forecasting and Social Change (1), Transport Policy (1), Transport Reviews (1), Transportation (2), Transportation in Developing Economies (1), Transportation Research Part A - Policy and Practice (7), Transportation Research Part F - Transportation Psychology and Behaviour (4), Transportation Research Record: Journal of the Transportation Research Board (5), and Travel Behaviour and Society (1).

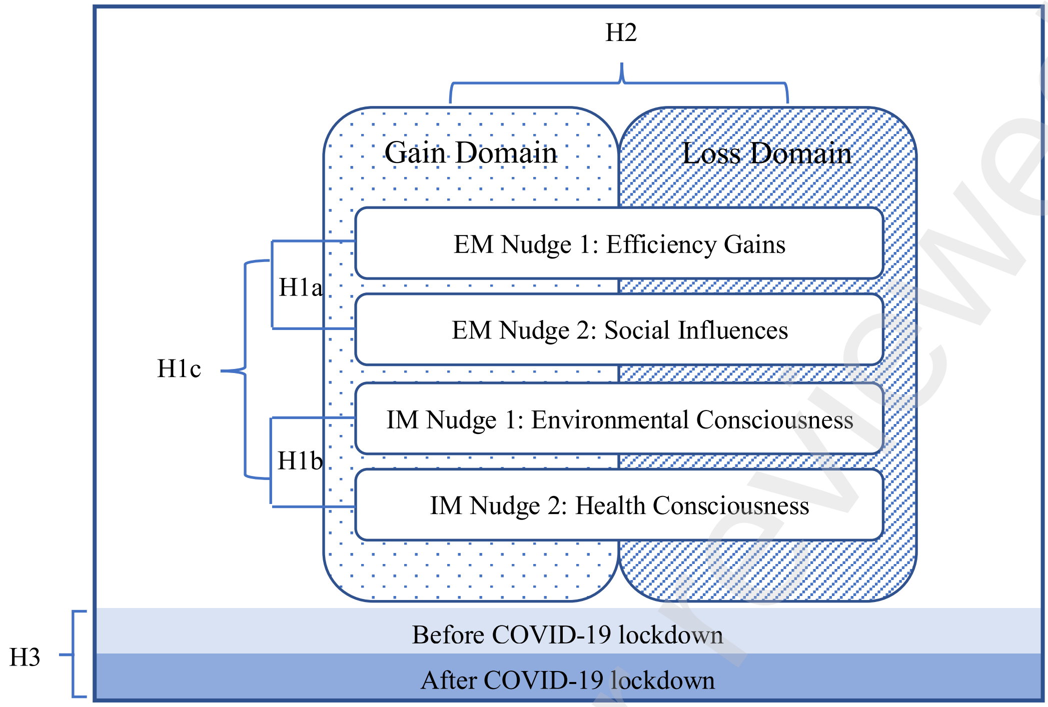

Figure 1: Analytical Framework

3. Empirical strategy

3.1 Study area

We choose New York City (NYC) as the study area given its current laws surrounding e-scooters and present attitudes towards micro-mobility. The market for micro-mobility emerged partially because of lack of public transport accessibility in certain areas. While bicycle-sharing (mainly Citi Bikes) is commonplace, e-scooter sharing has yet to be legalized. Under the current Vehicle and Traffic law, there are no laws governing the usage or provision of e-scooters. In June 2020, the Legislature passed the *New York State Senate Bill S5294A*, legalizing e-scooter services by adding Article 34-D to the Vehicle and Traffic law. However, the Bill has been vetoed by Governor Andrew Cuomo, who highlighted safety concerns.

While legal barriers impede supply of e-scooters and might affect demand-side preferences, NYC concurrently boasts a rich ground-up human-scaled development movement. The non-profit organization "Human-scale NYC"'s policy paper specifically calls for human-scaled transport that "rewire the city for less car-commuting (Allcott and Mullainathan, 2010, page 17). NYC is an ideal natural testbed for examining e-scooter adoption attitudes because e-scooters are not yet formally introduced, but there are potential markets for future implementation. The nascence of e-scooters makes potential user perceptions even more salient, as these attitudes will fundamentally influence legalization and future uptake of e-scooters in NYC.

At the tail-end of 2019, the novel coronavirus (Covid-19) was identified in Wuhan, China, and eventually inflated to a global pandemic. During our study period, NYC had been increasingly deemed the new Covid-19 epicenter, with the number of confirmed cases surpassing that of Hubei Province in China where the virus first emerged. Rising concerns have necessitated state-wide stay-home policies advocating social distancing. These policies, coupled with personal attitudes towards Covid-19, can have moderating effects on personal values and transportation preferences, which will be examined.

3.2 Experiment design

Our questionnaire consists of three parts. The first part asks questions about the current transportation mode and the reason of adoption. It also contains a question about the reason to (or not to) use e-scooter as the main transportation means, and three questions to check the respondent's knowledge about the current legislation regulating e-scooters in NYC. Respondents who are using e-scooters (which is a very small proportion) are directed to the last part. Respondents who are not current e-scooter users are asked the likelihood (from 0 to 100, with 100 being the most likely) for them to adopt e-scooter first, and then continue to part two.

Part two consists of eight blocks of nudge questions, to which respondents are randomly assigned. In each nudge blocks, there are two questions that are designed to implement one of the four type of nudges (i.e., environmental consciousness, healthy consciousness, efficiency gains, and social influences) in either the gain or loss domain. Each respondent will be assigned to one and only one of the eight blocks. The 16 questions in these nudge blocks can be find in Appendix III. For example, to check if environmental consciousness nudges can encourage e-scooter adoption, we ask two questions in the gain domain.

1) *The use of e-scooters emits no carbon or greenhouse gases and are less pollutive than motor vehicles. If you adopt e-scooters, you can help to preserve air quality and mitigate global warming. Considering this positive environmental impact, how likely are you going to use e-scooters?*
2) *Research shows that E-scooters are also 80 times more energy-efficient than motor cars and are more environmentally friendly, preserving our finite non-renewable energy resources. Taking this research into consideration, how likely are you going to use e-scooters?*

The scores from these nudge questions (from 0 to 100, with 100 being the most likely) will be compared with the scores from the last question in part one (i.e., How likely are you going to use e-scooters?) to verify the nudge effects as specified in Hypotheses 1 and 2 in Section 2.

All respondents, current e-scooter users or not, will answer questions in part three. These questions cover a wide range of demographic characteristics, such as annual household income, education, ethnic background, and religious background. These variables are used as controls to further explore the determinants of the willingness of adopting e-scooters. There are two group of variables gauging the current level of environmental and health consciousness of respondents. Because these two constructs are both latent and complex, we use multiple questions to obtain a reliable measurement. Specifically, we adopted four questions from the *Understanding Society* household panel data survey to measure environmental consciousness, and three questions to quantify health consciousness (see Appendix III). We then calculate environmental and health consciousness scores, i.e., *envscore* and *healthscore,* based on responses to questions regarding diets, exercising and environmentally-friendly practices. For example, the dummy variable *envscore* equals one when the sum of the four environmental consciousness variables is greater than the average, and zero otherwise. The dummy variable *healthscore* is calculated the same way. These two variables were used to categorize respondents into those with high and low environmental and health consciousness. Descriptive statistics of these control variables can be found in Table 2.

3.3 Empirical implementation

We use Qualtrics®, an internet-based survey platform, to design the questionnaire by using its branching logic and randomizer tools. The branching logic enables adaptation of the survey based on respondents' answers. Blocks and randomizer functions were used to divide non-adopters of e-scooter adoption into eight groups, each presented with a different set of nudge questions to investigate the effectiveness of nudges on IMs, EMS, and the impact of gain-loss framing. A pilot survey was rolled out to gauge responses and account for omitted factors, providing opportunity to refine questions. We then carried out the experiment using Amazon Mechanical Turk, a crowd-sourcing internet marketplace with participants from the USA and India predominately. For this survey, the geographical filter allowed NYC respondents to be selected. Each respondent was paid 1USD for the task, and the platform collected 0.4USD per completed questionnaire. Respondents used an average of 8 minutes to complete the questionnaire. A total of 3,054 valid questionnaires are collected between 18 February 2020 and 3 October 2020.

On 1st March 2020, the first confirmed Covid-19 case was identified in NY State (West, 2020). Six days later on 07/03/2020, Governor Cuomo declared a state of emergency in NY (Mckinley and Sandoval, 2020). Since then, cases and fatalities have been increasing exponentially. As of 5 April 2020, New York State saw over 592 Covid-19-related fatalities in a day, and death tolls surged to around 3000 (Zoellner, 2020). Taking effect on 22 March 2020, Cuomo imposed a state-wide stay-home order, emphasizing work-from-home, closing of non-essential businesses, and stopping non-essential gatherings (Evelyn, 2020). There has been increasing worries about the healthcare system's capacity to manage burgeoning demands, as well as economic repercussions, amidst health concerns. The stay-home order has indubitably affected personal lifestyles, requiring people to acclimatize to sedentary and isolated routines. For subsequent analyses, the stay-home order will be referred to simply as "lockdown".

The first round of experiment was released before the first COVID-19 case was confirmed in NYC (i.e., 18 February 2020), and was terminated on 31 March 2020 when the targeted sample size was achieved. As a result, the original survey accidentally straddled two crucial time periods: pre- and during-lockdown. The sudden and major change in lifestyles, as well as psychological and emotional stress, would perhaps have influenced people's attitudes towards transport modes, and contaminated the dataset. However, this contamination can be harnessed as an opportunity, because it provides a platform for a natural experiment investigating the potential moderating effects of Covid-19 attitudes on nudge effects.

Nevertheless, upon close inspection of the data, we found that the lockdown period subsample (i.e., from 19 March 2020 when the lockdown was announced to 31 March 2020 when the experiment ended), the number of respondents per day is substantially larger than that in the pre-lockdown period. This is not surprising given the effect of lockdown. However, it does raise the concern of the quality of the data, because the sudden shock of the lockdown and the novelty of the pandemic may affect the validity and reliability of the answers from a group of people who suddenly found plenty of time staying online. Consequently, we rolled out the same experiment between 3 and 12 April 2020 (i.e., around the peak of the first wave), and again between 23 September 2020 and 3 October 2020 (i.e., when NYC well passed the first wave of the pandemic). Data collected from these three periods will be used to check the moderating effect of the pandemic robustly.

Table 2: Variable definition and descriptive statistics

Variables	Whole sample (18 Feb - 3 Oct)	Before Lockdown (18 Feb - 18 Mar)	During Lockdown (19 Mar - 31 Mar)	During Lockdown (3 Apr - 12 Apr)	Post Lockdown (23 Sept - 3 Oct)
Continues and dummy variables: mean and standard deviation (in brackets)					
Age (in years)	33.53 (10.91)	31.30 (10.60)	32.83 (10.65)	33.60 (10.45)	36.17 (11.52)
Gender (Male = 1)	0.46 (0.50)	0.43 (0.50)	0.43 (0.49)	0.50 (0.50)	0.50 (0.50)
Environmental consciousness score (0 – 5)	3.36 (0.65)	3.35 (0.63)	3.31 (0.66)	3.39 (0.63)	3.43 (0.65)
Health consciousness score (0 – 5)	2.19 (0.76)	2.20 (0.81)	2.20 (0.78)	2.28 (0.76)	2.09 (0.69)
Likelihood to use e-scooters (0 – 100)	31.47 (29.08)	35.26 (29.67)	30.25 (28.33)	30.91 (29.62)	32.17 (29.52)
Travel within the same district (Yes = 1)	0.71 (0.46)	0.71 (0.46)	0.70 (0.46)	0.71 (0.45)	0.72 (0.45)
Categorical variables: frequency count and proportion (in brackets)					
Annual household income					
Below $30,000	545 (18%)	106 (25%)	236 (18%)	97 (15%)	106 (16%)
$30,000 - $44,999	503 (16%)	74 (17%)	208 (16%)	114 (17%)	107 (16%)
$45,000 - $55,999	404 (13%)	51 (12%)	159 (12%)	87 (13%)	107 (16%)
$56,000 - $59,999	278 (9%)	27 (6%)	130 (10%)	56 (8%)	65 (10%)
$60,000 - $89,999	618 (20%)	77 (18%)	251 (20%)	132 (20%)	158 (23%)
$90,000 - $124,999	328 (11%)	36 (8%)	145 (11%)	83 (13%)	64 (9%)
$125,000 and above	378 (12%)	56 (13%)	156 (12%)	94 (14%)	72 (11%)
Job sector					
Educational and health services	610 (20%)	94 (22%)	289 (22%)	125 (19%)	102 (15%)
Professional and business services	401 (13%)	53 (12%)	174 (14%)	78 (12%)	96 (14%)
Financial activities	310 (10%)	30 (7%)	114 (9%)	65 (10%)	101 (15%)
Leisure and hospitality	163 (5%)	27 (6%)	66 (5%)	37 (6%)	33 (5%)
Other services	244 (8%)	43 (10%)	105 (8%)	58 (9%)	38 (6%)
Trade, transportation and utilities	114 (4%)	16 (4%)	46 (4%)	28 (4%)	24 (4%)
Construction	90 (3%)	4 (1%)	41 (3%)	25 (4%)	20 (3%)
Government	181 (6%)	24 (6%)	76 (6%)	43 (6%)	38 (6%)
Information	214 (7%)	23 (5%)	68 (5%)	52 (8%)	71 (10%)
Natural resources and mining	11 (0%)	1 (0.4%)	4 (0.003%)	1 (0%)	5 (1%)
Manufacturing	122 (4%)	14 (3%)	35 (3%)	23 (3%)	50 (7%)
Other	353 (12%)	59 (14%)	161 (13%)	71 (11%)	62 (9%)
Prefer not to say	241 (8%)	39 (9%)	106 (8%)	57 (9%)	39 (6%)
District					
Bronx	427 (14%)	54 (13%)	189 (15%)	92 (14%)	92 (14%)
Brooklyn	892 (29%)	120 (28%)	357 (28%)	191 (29%)	224 (33%)
Queens	828 (27%)	110 (26%)	354 (28%)	191 (29%)	173 (25%)
Manhattan	700 (23%)	115 (27%)	298 (23%)	149 (22%)	138 (20%)
Staten Island	207 (7%)	28 (7%)	87 (7%)	40 (6%)	52 (8%)
Education					
Primary school	5 (0.2%)	1 (0.2%)	0 (0%)	4 (0.6%)	0 (0%)
High school	548 (18%)	83 (19%)	249 (19%)	121 (18%)	95 (14%)
Associate degree	398 (13%)	74 (17%)	178 (14%)	84 (13%)	62 (9%)
Bachelor's degree	1415 (46%)	194 (45%)	572 (45%)	302 (46%)	347 (51%)
Master's degree	529 (17%)	60 (14%)	204 (16%)	118 (18%)	147 (22%)
Professional school degree	94 (3%)	9 (2%)	44 (3%)	23 (3%)	18 (3%)
Doctorate degree	65 (2%)	6 (1%)	38 (3%)	11 (2%)	10 (1%)
Ethnic background					
White	1861 (61%)	236 (55%)	768 (60%)	422 (64%)	435 (64%)
Hispanic, Latino or Spanish origin	304 (10%)	59 (14%)	131 (10%)	63 (10%)	51 (8%)
Black or African American	414 (14%)	56 (13%)	176 (14%)	71 (11%)	111 (16%)
Asian	381 (12%)	56 (13%)	172 (13%)	92 (14%)	61 (9%)
American Indian or Alaskan Native	19 (1%)	4 (1%)	5 (0.4%)	2 (0.3%)	8 (1%)
Middle Eastern or North African	27 (1%)	9 (2%)	12 (1%)	5 (1%)	1 (0.1%)
Others	48 (2%)	7 (2%)	21 (2%)	8 (1%)	12 (2%)
Religion					
Protestant	278 (9%)	26 (6%)	120 (9%)	64 (10%)	68 (10%)
Catholic	933 (31%)	112 (26%)	353 (27%)	186 (28%)	282 (42%)
Orthodox Christian	130 (4%)	18 (4%)	56 (4%)	27 (4%)	29 (4%)
Mormon	16 (1%)	3 (1%)	7 (1%)	5 (1%)	1 (0.1%)
Jew	133 (4%)	26 (6%)	49 (4%)	26 (4%)	32 (5%)
Muslim	104 (3%)	15 (4%)	48 (4%)	26 (4%)	15 (2%)
Buddhist	56 (2%)	8 (2%)	26 (2%)	12 (2%)	10 (1%)
Hindu	49 (2%)	6 (1%)	19 (1%)	7 (1%)	17 (3%)
Non-religious	1110 (36%)	171 (40%)	495 (39%)	260 (39%)	184 (27%)
Other	245 (8%)	42 (10%)	112 (9%)	50 (8%)	41 (6%)
Most frequently used transport mode					
Car	1743 (57%)	227 (53%)	734 (57%)	359 (54%)	423 (62%)
Public Transportation	903 (30%)	152 (36%)	394 (31%)	234 (35%)	123 (18%)
Walk	301 (10%)	36 (8%)	118 (9%)	60 (9%)	87 (13%)
Bicycle	87 (3%)	6 (1%)	32 (2%)	7 (1%)	42 (6%)
Others	20 (1%)	6 (1%)	7 (1%)	3 (0.5%)	4 (1%)
Sample size	3054	427	1285	663	679

4. Empirical findings

4.1. Determinants of E-scooter Adoption (pre-nudge)

In the first part of the questionnaire, we ask respondents to provide reason for being a current e-scooter user or non-user. The answers to these two questions are summarised in Table 3. The results illustrate that there are indeed many parallels between e-scooter adoption barriers and motivators and those from the literature review. Interestingly, one of the biggest obstacles in adoption attitudes is the lack of e-scooters, be it ownership or provision of shared rental systems. This is unique to e-scooters as a budding technology which has yet to be officially rolled out state-wide. The embryonic nature of e-scooters is further buttressed by the indication of poor information as a significant adoption impediment. Many respondents have never heard of e-scooters or do not know much about its quality. The lack of reliable knowledge remains a hindrance to adoption. On the other hand, some motivators include user-friendliness of e-scooters and enhancing the mobility of disabled people unable to use conventional bicycles. However, this supposedly advantageous convenience is fascinatingly indicated as a barrier for one health-conscious respondent who expressed preference for more active modes like walking.

At the end of the first part of the questionnaire, all non-users were asked about the likelihood for them to adopt e-scooters (from 0 to 100, with 100 being the most likely). This is the measurement of willingness to adopt (*WTA* hereafter) before behavioural interventions. Descriptive statistics in Table 2 shows that the overall WTP is around 30, and slightly lower in the during- and post-lockdown periods. We built a regression model to investigate the determinants of e-scooter adoption as follows.

$$WTA = \beta_0 + \beta_1 healthscore + \beta_2 envscore + \beta_3 age + \beta_4 gender + \beta_5 income + \sum_{i=1}^{10} \alpha_i\, job_i + \sum_{i=1}^{4} \gamma_i\, edu_i + \sum_{i=1}^{5} \delta_i\, ethi + \sum_{i=1}^{9} \theta_i\, reli_i + \varepsilon \tag{1}$$

where job_i, edu_i, $ethi$, and $reli_i$ are dummy variables for job sector, education attainment, ethnic background, and religion group respectively. We omitted categories with very small respondents, the lowest education attainment, white, and non-religious groups as the base category for these variables. Included categories can be found in the first column of Table 4. Coefficient estimates of these included categories is the relative difference between the omitted category and the included ones. In general, we found that younger males are more likely to adopt e-scooters. WTA is negatively related to household income level and education attainment. Respondents who are working in business, finance and IT sectors are more likely to use e-scooters. Finally, ethnic and religious background also affect the WTA of e-scooters, although the effects various across different phases of the pandemic.

Table 4 shows that both health and environmental consciousness are statistically significant for current adoption behaviour. The negative *healthscore* coefficient indicates that a more health-conscious respondent is less likely to be a current e-scooter adopter. On the other hand, the positive coefficient for *envscore* indicates that the more environmentally conscious an individual is, the more likely he or she is to be a e-scooter adopter. This is consistent with the features of e-scooters and e-bikes: green but not quite active (Bucher et al., 2019; Sun et al., 2020).

It is worth noting that the effect of health consciousness is not significant before the lockdown, but turned to be large and significant as the effect of pandemic rippled through. The awareness of environmental sustainability, on the other hand, demonstrated an opposite trend. Its positive effect on e-scooter adoption ceased to be significant in later phases of the sampling period. Our conclusion is that the pandemic made New York residents keener to get active due to health concerns. Health-conscious individuals are less likely to adopt e-scooters because they prefer more active transport modes such as cycling or walking. This is consistent with the findings on transport mode adoption reported in Table 2, where the proportion of respondents cycling increased by five folds and the share of public transportation dropped by 50%.

We further explore the determinants of WTA of e-scooters by examining the current transport modes of non-adopters. The results are are also broken down by lockdown periods (see Table 5). For example, for respondents who used cars as their primary mode of transportation, their likelihood to adopt e-scooters is 30.27, 36.01, 31.04, 31,75, and 24.59 for the whole sampling period and each of the four pandemic sub-sample periods, respectively. Two conclusions can be drawn from Table 5. Firstly, people who travel by public transportation or foot are more likely to adopt e-scooters than motorists and cyclists. Second, there is a marked decrease in likelihood to adopt after the lockdown across all four transport modes. These findings, once again, suggest that the pandemic might have a significant moderating effect on the determinants of e-scooter WTA. We further explore this issue in the final part of this section.

4.2. The Effects of Nudges

To understand how nudges influenced e-scooter WTA, we conducted paired two sample t test to compare each respondent's pre-nudge and post-nudge WTA. Pre-nudge WTA was measured by asking respondents how likely they were to adopt e-scooters after being presented a brief on basic safety features and functions of e-scooters; post-nudge WTA by asking respondents their likelihood of adopting e-scooters after being randomly presented one of eight nudges. In Table 6, we first report the average difference of WTA before and after a specific nudge. For example, the average difference in WTA for environmental nudges during the entire sampling period is 8.99, or an 8.99-point increase in the likelihood of e-scooter adoption as a result of being nudged with environmental incentives. The null hypothesis of this paired samples t-test is the mean WTA difference is zero, or environmental nudges do not work. The p-value of this test is reported in the brackets. The null hypothesis is rejected at the 1% level, which means environmental nudges increase the likelihood of e-scooter adoption.

The difference between pre-nudge and post-nudge WTAs are significantly positive for all nudges, which means nudges increased the likelihood of e-scooter adoption across the board. This finding support Hypotheses 1a and 1b: both IM and EM nudges encouraged e-scooter adoption effectively.

Moreover, the overall effect size is different between IM nudges and EM nudges, and particularly between the environmental nudges (8.99), and the social nudges (2.23). We conduct a two-independent sample t test on the post-nudge WTA scores between the IM and EM nudge groups. The results are reported in the second part of Table 6. We find that IM nudges, on average, will increase e-scooter WTA by 10.46 points over EM nudges. This is more than 30% of further improvement given the average pre-nudge WTA is 31.47 (see Table 2). The difference is also significant at the 1% level. We find support to Hypothesis 1c as well.

Table 3: Reasons to or not to use e-scooters

	Whole sample (18 Feb - 3 Oct)	Before Lockdown (18 Feb - 18 Mar)	During Lockdown (19 Mar - 31 Mar)	During Lockdown (3 Apr - 12 Apr)	Post Lockdown (23 Sept - 3 Oct)
Reasons to use e-scooter					
1. They are fun to ride around	8.61%	4.68%	5.84%	4.83%	20.03%
2. They seem easy and safe to ride	6.22%	3.04%	4.12%	2.71%	15.61%
3. They can get me to my exact desired destination	6.09%	4.45%	4.28%	3.47%	13.11%
4. The distance I'm travelling is just right for e-scooters	5.73%	4.92%	3.50%	3.02%	13.11%
5. They seem more environmentally friendly than cars or other modes of transport	4.35%	2.58%	2.41%	3.17%	10.31%
6. They seem fast and can get me to my destination quickly	3.90%	2.11%	2.65%	2.87%	8.39%
7. E-scooters can enhance my job (e.g. delivery etc.)	2.42%	1.17%	1.32%	0.90%	6.77%
Reasons not to use e-scooter					
1. I do not own an e-scooter	56.68%	66.28%	59.22%	60.18%	42.42%
2. I am not interested in riding an e-scooter	33.76%	32.08%	36.34%	36.20%	27.54%
3. The roads are dangerous or not suitable for riding on with e-scooters	33.53%	35.60%	36.65%	35.90%	24.01%
4. The distance I'm travelling is too far	32.22%	37.70%	35.49%	31.83%	22.97%
5. I do not know how to ride an e-scooter	31.70%	36.07%	34.32%	32.73%	22.97%
6. E-scooters seem dangerous to use	23.61%	25.06%	23.50%	26.85%	19.73%
7. None of my family / peers use e-scooters	18.63%	21.78%	19.22%	20.36%	13.84%
8. I have never heard of e-scooters before	12.51%	12.65%	15.02%	12.07%	8.10%
9. E-scooters are inconvenient to use	9.07%	9.13%	9.96%	7.69%	8.69%

Table 4: Determinants of willingness to use e-scooters – regression results

Variables	Whole sample (18 Feb - 3 Oct)		Before Lockdown (18 Feb - 18 Mar)		During Lockdown (19 Mar - 31 Mar)		During Lockdown (3 Apr - 12 Apr)		Post Lockdown (23 Sept - 3 Oct)	
Intercept	45.35	(0.00)	31.28	(0.01)	41.29	(0.00)	52.83	(0.00)	61.98	(0.00)
Environmental consciousness score (0 – 5)	2.71	(0.00)	5.50	(0.04)	2.68	(0.04)	2.03	(0.32)	0.78	(0.73)
Health consciousness score (0 – 5)	-4.62	(0.00)	-1.51	(0.45)	-4.10	(0.00)	-5.46	(0.00)	-8.63	(0.00)
Age (in years)	-0.41	(0.00)	-0.31	(0.04)	-0.35	(0.00)	-0.53	(0.00)	-0.53	(0.00)
Gender (Male = 1)	4.07	(0.00)	5.48	(0.10)	6.09	(0.00)	-0.65	(0.79)	2.21	(0.43)
Annual household income	-0.96	(0.00)	-0.74	(0.34)	-0.56	(0.21)	-1.77	(0.01)	-0.79	(0.26)
Job sector										
Educational and health services	1.37	(0.43)	2.43	(0.59)	1.40	(0.59)	-0.73	(0.85)	5.83	(0.19)
Professional and business services	4.10	(0.04)	4.39	(0.45)	4.63	(0.12)	-0.63	(0.89)	9.53	(0.04)
Financial activities	6.81	(0.00)	12.37	(0.12)	5.45	(0.11)	7.45	(0.13)	9.01	(0.09)
Leisure and hospitality	2.53	(0.34)	-9.90	(0.14)	8.25	(0.04)	-0.74	(0.89)	9.12	(0.16)
Other services	-0.73	(0.74)	3.33	(0.55)	-2.42	(0.49)	-5.16	(0.27)	2.75	(0.62)
Trade, transportation and utilities	1.59	(0.62)	1.65	(0.85)	-1.84	(0.70)	9.30	(0.15)	1.05	(0.91)
Construction	5.83	(0.12)	32.39	(0.27)	14.28	(0.01)	-3.32	(0.62)	3.64	(0.73)
Government	1.78	(0.48)	3.53	(0.62)	-3.11	(0.41)	4.23	(0.42)	4.84	(0.42)
Information	7.52	(0.00)	14.60	(0.08)	2.47	(0.55)	5.82	(0.28)	11.33	(0.04)
Manufacturing	6.55	(0.06)	3.07	(0.76)	4.30	(0.46)	12.80	(0.10)	8.67	(0.20)
Education										
Bachelor's degree	-0.37	(0.79)	1.78	(0.63)	-1.47	(0.47)	2.06	(0.48)	-4.72	(0.15)
Master's degree	-0.17	(0.93)	6.03	(0.26)	-3.67	(0.19)	7.86	(0.04)	-6.90	(0.11)
Professional school degree	-4.85	(0.16)	0.42	(0.97)	-8.50	(0.09)	1.92	(0.78)	-11.77	(0.16)
Doctorate degree	-7.96	(0.04)	-8.64	(0.50)	-4.69	(0.36)	-4.44	(0.63)	-29.75	(0.01)
Ethnic background										
Hispanic, Latino or Spanish origin	6.17	(0.00)	-3.37	(0.49)	7.18	(0.01)	11.09	(0.01)	6.15	(0.22)
Black or African American	2.87	(0.11)	4.31	(0.39)	4.20	(0.12)	0.72	(0.86)	-0.77	(0.85)
Asian	3.53	(0.06)	3.79	(0.45)	4.55	(0.10)	3.98	(0.30)	0.60	(0.89)
American Indian or Alaskan Native	10.84	(0.25)	-17.62	(0.33)	-9.19	(0.64)	36.73	(0.20)	37.86	(0.03)
Middle Eastern or North African	15.36	(0.01)	17.87	(0.13)	21.09	(0.02)	-12.02	(0.46)	52.26	(0.08)
Religion										
Protestant	-2.91	(0.27)	-13.33	(0.10)	-2.86	(0.46)	-2.54	(0.67)	4.92	(0.42)
Catholic	2.93	(0.19)	-4.46	(0.46)	-1.43	(0.67)	9.33	(0.06)	11.49	(0.03)
Orthodox Christian	6.84	(0.05)	2.28	(0.79)	1.92	(0.70)	13.47	(0.07)	22.63	(0.03)
Mormon	18.85	(0.03)	49.00	(0.02)	7.51	(0.59)	10.44	(0.45)	--	--
Jew	-5.95	(0.07)	-17.12	(0.04)	-5.61	(0.28)	-2.56	(0.74)	-0.22	(0.98)
Muslim	-2.46	(0.53)	-11.15	(0.31)	-4.97	(0.37)	5.43	(0.54)	1.89	(0.85)
Buddhist	6.73	(0.13)	10.84	(0.35)	4.21	(0.53)	3.57	(0.71)	17.82	(0.12)
Hindu	19.92	(0.00)	27.00	(0.08)	21.89	(0.01)	18.32	(0.15)	5.76	(0.66)
Others	-3.39	(0.11)	-9.60	(0.09)	-4.08	(0.20)	1.65	(0.73)	0.87	(0.87)
R square	0.1021		0.1737		0.1026		0.1514		0.1878	
Adjusted R square	0.0901		0.0893		0.0748		0.1011		0.1266	

Note: p-values in brackets. *Mormon* is not included in the Post Lockdown (23 Sept – 3 Oct 2020) period due to the lack of respondents from this religious group.

Table 5: Average likelihood to adopt e-scooters by transport mode (0 – 100)

Mode	Whole sample (18 Feb - 3 Oct)		Before Lockdown (18 Feb - 18 Mar)		During Lockdown (19 Mar - 31 Mar)		During Lockdown (3 Apr - 12 Apr)		Post Lockdown (23 Sept - 3 Oct)	
Car	30.27	(31.55)	36.01	(33.79)	31.04	(30.94)	31.75	(31.12)	24.59	(30.98)
	n=	1744	n=	228	n=	735	n=	360	n=	424
Public Transportation	33.59	(33.13)	37.11	(32.82)	33.70	(33.19)	33.92	(32.92)	28.23	(33.43)
	n=	904	n=	153	n=	395	n=	235	n=	124
Walking	31.59	(31.55)	40.36	(32.56)	33.81	(32.08)	29.67	(31.31)	26.29	(29.97)
	n=	302	n=	37	n=	119	n=	61	n=	88
Bicycle	17.41	(25.92)	17.17	(23.10)	20.53	(28.39)	16.86	(25.22)	15.17	(25.09)
	n=	88	n=	7	n=	33	n=	8	n=	43

Note: Standard deviations in brackets.

4.3. Framing effects

We conducted two independent samples t tests to investigate the effect of framing. Specifically, we test if nudges framed in the gain domain are more effective than those framed in the loss domain. The results are reported in the last part of Table 6. The average difference of WTA between the gain and loss domain nudges are given first, followed by the p-value corresponding to the null hypothesis of zero difference. The sample size of each sub-sample (i.e., gain domain vs. loss domain subsamples) are also provided. The difference in WTA between the gain and loss domain during the entire sampling period is 10.46. In other words, nudges framed in the gain domain can increase the likelihood of e-scooters adoption by 10.20 points on average. The null hypothesis of no framing effect (i.e., no difference between nudges in the loss and gain domain) is rejected at the 1% level. This finding support Hypothesis 2.

Wansink and Pope (2015) posit that the effectiveness of framing depends on individual-specific factors like their level of subject knowledge. Loss-framing is more effective for respondents familiar with the subject, as they harbour enough understanding to feel loss-averse. Conversely, faced with an audience lacking information about the matter, gain-framing has proven more effective, because respondents lack awareness for fear-based loss-framing to work. Instead, they respond better to gain-framed messages. Referring to Table 3, 31.70% of the respondents indicated that a reason why they did not adopt e-scooters was “I don’t know how to ride an e-scooter”, and 12.51% given the reason of “I have never heard of e-scooters before”. It would seem plausible to assume that a good proportion of NYC residents are not well-acquainted with e-scooters. Therefore, gain-framing nudges worked better than loss-framing nudges in our sample. The test results not only support Hypothesis 2, but also are consistent with other empirical evidence within the sample.

4.4. The moderating effect of the COVID-19 pandemic

By comparing the tests on nudge and framing effects across the four sampling periods in Table 6, we now verify the moderating effect of the COVID-19 pandemic. Firstly, the overall effect of IM and EM nudges are different among the pre-, during- and post-lockdown periods. The difference between IM nudges and EM nudges is only 1.08 before the lockdown, indicating that there is no statistical difference between the two types of nudges, although both types of nudges can effectively encourage the adoption of e-scooter. However, the gap between the effectiveness of the two types of nudges widened during the lockdown period and became statistically significant. When the city is recovering from the first wave (i.e., the post-lockdown period), the difference between the two types of nudges is over 20 points. This pattern suggests that the pandemic has changed people’s perceptions and subsequently their responses to intrinsic and extrinsic incentives.

We proceed to investigate which IM or EM nudges has changed their effects over the sampling period. The tests on specific IM and EM nudges reveal that the effect of health nudges dropped steadily and significantly from the pre-lockdown period to the post-lockdown period, i.e., from 6.28 to 2.17. Due to the pandemic, New Yorkers are more health conscious when choosing transport modes; they did not response to health nudges because e-scooters are less active than walking and cycling. Meanwhile, the effect of social nudges followed a similar trend, with a rather large drop during the lockdown period (0.35) and a insignificant, small difference in the post-lockdown period (1.16). It seems that the social distancing practice during the pandemic somehow made social nudges less effective.

Finally, the pandemic changed the effect of framing as well. During the pre-lockdown period, when New Yorkers were still oblivious of the impending public health crisis, the gain-raming and loss-framing nudges are not statistically signficant (i.e., the p-value of the t test is

0.15). However, as the city went through the lockdown period, the difference between the two types of framing almost doubled and became statistically significant. The effect size during the post-lockdown period, gain-framing nudges outperformed loss-framing nudges by as much as 19.18 points. Due to the pandemic, New Yorkers were much more health conscious, and subsequently more responsive to gain-framing nudges, which are more effective for encouraging preventive activities such as using e-scooters instead of public transportations.

In summary, we find evidence to support Hypothsis 3. The effectiveness of nudges and framing, and the effect of specific IM or EM nudge in encouraging e-scooter adoption varied during the pandemic. The moderating effect of the COVID-19 pandemic is significant.

Table 6: T tests results

Effects	Whole sample (18 Feb - 3 Oct)	Before Lockdown (18 Feb - 18 Mar)	During Lockdown (19 Mar - 31 Mar)	During Lockdown (3 Apr - 12 Apr)	Post Lockdown (23 Sept - 3 Oct)
Nudge effect* (WTA after – WTA before)					
Environmental nudge	8.99 (0.00)	10.00 (0.00)	9.27 (0.00)	7.29 (0.00)	9.68 (0.00)
(IM1)	n= 629	n= 93	n= 277	n= 147	n= 112
Health nudge	5.46 (0.00)	6.28 (0.00)	6.62 (0.00)	5.38 (0.00)	2.17 (0.15)
(IM2)	n= 624	n= 85	n= 279	n= 144	n= 116
Efficiency nudge	5.81 (0.00)	6.40 (0.00)	5.55 (0.00)	6.39 (0.00)	5.17 (0.00)
(EM1)	n= 620	n= 93	n= 273	n= 145	n= 109
Social nudge	2.23 (0.00)	4.57 (0.03)	3.01 (0.00)	0.35 (0.79)	1.16 (0.42)
(EM2)	n= 638	n= 88	n= 274	n= 155	n= 121
IM vs. EM ** (IM – EM)	10.46 (0.00)	1.08 (0.74)	8.62 (0.00)	7.47 (0.00)	21.44 (0.00)
	n=1311 vs. 1743	n=192 vs. 235	n=585 vs. 700	n=301 vs. 362	n=233 vs. 446
Framing effect ** (gain – loss)	10.20 (0.00)	4.59 (0.15)	8.01 (0.00)	7.25 (0.00)	19.18 (0.00)
	n=1326 vs. 1728	n=194 vs. 233	n=588 vs. 697	n=306 vs. 357	n=238 vs. 441

Note: The null hypothesis is the average difference in the probability to adopt is zero. P-values are given in brackets. *: Paired t tests. **: Two independent samples t tests.

5. Conclusions and policy implications

Using online experimental data collected from New York City, this paper investigates the potential and challenges of applying behavioural interventions to promote e-scooter adoption. Our findings suggest that both nudges and loss/gain framing significantly affected respondents' willingness to adopt e-scooters; behavioural interventions can be effective tools to promote the use of e-scooters. Moreover, we run three rounds of the online experiments over a period of eight months, covering the pre-, during- and post- COVID-19 lockdown period in New York City. Findings from this natural experiment reveal that the effect of nudges and lose/gain framing varied significantly during the pandemic, likely due to a heightened level of health consciousness and a new perspective regarding social interactions.

The effect size of nudges, framing, and the pandemic is not negligible. For example, environmental nudges improved respondents' WTA by over 25% during the whole sampling period; the difference between framing the nudges in the gain and loss domains can be as large as 30% of the original effect size; and the effect of framing almost quadrupled from the pre-lockdown to the post-lockdown period. If implemented correctly, these behavioural interventions could effectively encourage the general public to adopt e-scooters.

Transportation is indeed a "fertile context for consumer psychology research". (Tomaino et al., 2020, page 419). These findings echo Avineri's observation about the potential of implementing behavioural interventions to a travel behaviour context (Avineri, 2012).

This research reveals the net positive environmental additionality of e-scooters and reinforcing the importance of behavioural interventions towards e-scooter adoption. Nudges are both important and effective in raising e-scooter WTA through various mechanisms, including appealing to personal attributes, shaping people's motivations and via different framing dimensions. E-scooters are a part of this micro-mobility movement towards more people-centric and sustainable mobility, and have enormous potential to become a ubiquitous part of forthcoming urban transport. Behavioural interventions can be at the catalytic forefront of this paradigm shift, and governments at various levels can seek to harness the potential of the useful nudge instruments and loss/gain frames explored in this research to pave the way for a promising future of sustainable urban transport.

Our research also highlights the challenges of implementing behavioural interventions. The COVID-19 pandemic provided us a unique opportunity to observe how much preferences can change over a short period of time, such that the effectiveness of behavioural interventions is distinctively different before and after the lockdown. Nudges and loss/gain framing affect decisions through manipulating people's psychological and cognitive responses. As a result, the effectiveness of these behavioural tools depends heavily on the economic, social, and cultural background of targeted population, as well as the institutional and political settings of the wider environment. These tools cannot be taken off-the-shelf and applied as a blanket policy. Individual and group characteristics have to be assessed to devise the pre-eminent behavioural interventions for a particular target audience. Behavioural interventions are both low-hanging fruits and hard nuts to crack. The tools are readily available; however, the implementation is both an art and a science. More experiments across a wide range of economic, social, cultural, and political settings are needed to guide the application of behavioural interventions in transportation studies.

This study adds value to the fast-growing behavioural science literature with evidence from the transportation sector. The next step is to move from stated preference to revealed preference, or from intention to action. Specifically, we studied respondents' willingness to adopt e-scooters (i.e., stated preference or intention), instead of their actual adoption of e-scooter (i.e., revealed preference of action). In reality there is usually a gap between intention and action. It is, therefore, very important to investigate how effective behavioural interventions are in real life settings. Such studies will be challenging because separating the net effect of behavioural factors in real life settings is difficult. However, the findings could be of greater external validity and more instructive for policy makers.

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Appendix A: List of academic journals surveyed

Name of Journal	Number of Papers	Impact Factor (2018)	5-year Impact Factor	Publisher Location	Journal Citation Report (JCR)® Category	Rank in JCR® Category	Quartile in JCR® Category
Cities	1	3.853	4.299	UK	Urban Studies	2 of 40	Q1
Computational Intelligence and Neuroscience	1	2.154	2.107	USA	Mathematical and Computational Biology Neurosciences	18 of 59 200 of 267	Q2 Q3
Ethnicity and Disease	1	1.154	1.237	USA	Public, Environmental and Occupational Health (in SCIE edition)	154 of 186	Q4
International Journal of Environmental Research and Public Health	1	2.468	2.948	Switzerland	Environmental Sciences Public, Environmental and Occupational Health (in SSCI edition) Public, Environmental and Occupational Health (in SCIE edition)	112 of 251 38 of 164 7 of 186	Q2 Q1 Q2
International Journal of Sustainable Transportation	2	2.586	2.899	USA	Environmental Studies Green and Sustainable Science and Technology Transportation	45 of 116 4 of 6 13 of 36	Q2 Q3 Q2
Journal of Business Ethics	1	3.796	4.98	Netherlands	Business Ethics	33 of 147 2 of 54	Q1 Q1
Journal of Epidemiology and Community Health	2	3.872	4.124	UK	Public, Environmental and Occupational Health (in SCIE edition) Public, Environmental and Occupational Health in (SSCI edition)	27 of 186 10 of 164	Q1 Q1
Journal of Public Policy and Marketing	1	2.457	2.46	USA	Business	66 of 147	Q2
Journal of Transport and Health	2	2.583	2.774	UK	Public, Environmental and Occupational Health (in SSCI edition) Transportation	32 of 164 14 of 36	Q1 Q2
Journal of Transport Geography	2	3.56	4.473	UK	Economics Geography Transportation	36 of 363 8 of 83 7 of 36	Q1 Q1 Q1
Sustainability	3	2.592	2.801	Switzerland	Environmental Sciences Environmental Studies Green and Sustainable Science and Technology	105 of 251 44 of 116 3 of 6	Q2 Q2 Q2
Technological Forecasting and Social Change	1	3.815	4.04	USA	Business Regional and Urban Planning	32 of 147 6 of 39	Q1 Q1
Transport Policy	1	3.19	3.43	UK	Economics Transportation	45 of 363 11 of 36	Q1 Q2
Transport Reviews	1	6.648	6.309	UK	Transportation	2 of 36	Q1
Transportation	2	3.457	3.851	USA	Engineering, Civil Transportation Transportation Science and Technology	17 of 132 8 of 36 12 of 37	Q1 Q1 Q2
Transportation in Developing Economies	1						
Transportation Research Part A - Policy and Practice	7	3.693	4.371	UK	Economics Transportation Transportation Science and Technology	34 of 363 6 of 36 10 of 37	Q1 Q1 Q2
Transportation Research Part F - Transportation Psychology and Behaviour	4	2.36	3.006	UK	Psychology, Applied Transportation	30 of 82 19 of 36	Q2 Q3
Transportation Research Record: Journal of the Transportation Research Board	5	0.748	0.956	USA	Engineering, Civil Transportation Science and Technology	110 of 132 33 of 37	Q4 Q4
Travel Behaviour and Society	1	3.218	3.353	Netherlands	Transportation	10 of 36	Q2

Appendix B: List of academic papers surveyed

Paper	Micro-mobility	Study Area	Sampling Period	Sample Size	Methods
Biehl et al. (2019)	Bicycle	Chicago, USA	2016	24	Sentiment classification model
Sharma et al. (2019)	Bicycle	Seoul, South Korea	2018	190	Regression analysis
Nehme et al. (2016)	Bicycle	Austin, Texas, USA	2014	803	ANOVA
Hazen, Overstreet and Wang (2015)	Bicycle	Beijing, China		421	Co-variance based structural equation model
Claudy and Peterson (2014)	Bicycle	Dublin, Ireland	2011	936	SPSS AMOS 18, Tucker-Lewis Index, RMSEA
Zorilla, Hodgson and Jopson (2019)	Bicycle	Mexico City, Mexico	2015	401	Theory of Planned Behaviour - Survey
Fyhri et al. (2017)	Bicycle	Oslo, Norway	2013	5460	ANOVA
Prati et al. (2019)	Bicycle	Hungary, Italy, Spain, Sweden, Netherlands, UK		2397	MANOVA
Festa and Forciniti (2019)	Bicycle	Rende, Italy	2016	286	Crossed statistical analysis
Maldonado-Hinarejos, Sivakumar and Polak (2014)	Bicycle	London, UK	2010	1985	Multinomial logit model (MNL)
Underwood et al. (2014)	Bicycle	Davis, California, USA		54	Qualitative study
Heinen and Handy (2012)	Bicycle	Delft, the Netherlands; Davis, USA	2009 - 2010	31	Qualitative study
Panter et al. (2010)	Bicycle	Norfolk, UK	2012	2012	Multilevel statistical modelling
Gatersleben and Appleton (2007)	Bicycle	Surrey, UK	2000	389	Transactional model of behaviour change
Dill and Voros (2007)	Bicycle	Portland, Oregon, USA	2005	556	Qualitative study
Vandenbulcke et al. (2011)	Bicycle	Belgium		589 municipalities	OLS
Zhao et al. (2018)	Bicycle	Beijing, China		1427	Multinomial logistic regression analysis (MLRA)
Garcia et al. (2019)	Bicycle	Valencia, Spain	2017	1641	Exploratory factor analysis (EFA)
Wang et al. (2018)	Bicycle (shared)	Beijing, China		424	OLS
Yin, Qian and Singhapakdi (2018)	Bicycle (shared)	Suzhou, China	2014	755	Structural equation modelling approach using AMOS 21
Oates et al. (2017)	Bicycle (shared)	Birmingham, Alabama	2015 - 2016	633	Retrospective cross-sectional analysis
Faghih-Imani and Eluru (2015)	Bicycle (shared)	Chicago, USA	2013	12000	Multinomial logit model (MNL)
Fishman, Washington and Haworth (2012)	Bicycle (shared)	Queensland, Australia	2011	900	Qualitative study
Bachand-Marleau, Lee and El-Geneidy (2012)	Bicycle (shared)	Montreal, Canada	2010	1432	Binary logistic model
Shaheen et al. (2011)	Bicycle (shared)	Hangzhou, China	2010	806	Qualitative study
Lorenc et al. (2008)	Bicycle, Walking	UK	1995 - 2005	7 major databases	Qualitative study
Simsekoglu and Klockner (2019)	E-bike	Norway		910	Hierarchical multiple regression analysis
Lin, Wells and Sovacool (2018)	E-bike	Nanjing, China		399	Qualitative study
Wolf and Seebauer (2014)	E-bike	Austria	2009 - 2011	1398	Structural equation model
Popovich et al. (2014)	E-bike	Sacramento, California, USA	2011	27	Qualitative study
Fishman and Cherry (2016)	E-bike	North America and Australia	NA	553 (North America), 529 (Australia)	Secondary studies
MacArthur, Dill and Person (2014)	E-bike	North America	2013	553	Qualitative study - Likert scale
Rose (2012)	E-bike	North America			Secondary studies
Leger et al. (2019)	E-bike	Waterloo, Canada		37	Qualitative study
Langford et al. (2013)	E-bike (shared)	Knoxville, Tennessee, USA	2012	22	Qualitative study - Likert scale
Lin, Wells and Sovacool (2018)	E-bike, Bicycle	Nanjing, China		1003	Regression analysis
Fang, Xu and Chen (2014)	E-bike, Bicycle, Walking	Tangshan, China		419	Multinomial logit model (MNL)
Seebauer (2015)	E-scooter, E-bike	Austria	2009 - 2011	1688	Sturctural equation model
Aguilera-Garci, Gomez and Sobrino (2020)	Motorized scooter (shared)	Spanish cities	2018	335	Generalized ordered logit model

Appendix C: Experiment questions and nudge designs

Questions	Variable name
Environmental consciousness questions	
How often do you keep the tap running while brushing your teeth?	*Envcons1*
How often do you switch off the lights in rooms when they are not being used?	*Envcons2*
How often do you recycle paper products?	*Envcons3*
How often do you take your own shopping bag when out shopping?	*Envcons4*
Health consciousness questions	
In the past week, how many days did you engage in recreational physical activity for more than 30 minutes that was enough to raise your breathing/heart rate?	*Healthcons1*
Do you read the nutrition labels on your grocery items/when ordering food from a diner?	*Healthcons2*
How important is it for you to eat healthily?	*Healthcons3*
Nudges (gain-framing)	
- The use of e-scooters emits no carbon or greenhouse gases and are less pollutive than motor vehicles. If you adopt e-scooters, you can help to preserve air quality and mitigate global warming. Considering this positive environmental impact, how likely are you going to use e-scooters? - Research shows that E-scooters are also 80 times more energy-efficient than motor cars and are more environmentally friendly, preserving our finite non-renewable energy resources. Taking this research into consideration, how likely are you going to use e-scooters?	IM1
- Riding e-scooters is a form of low-intensity workout. This can clock some exercise into our busy schedules and help us keep healthy. Taking this physical health benefit into consideration, how likely are you going to use e-scooters? - Research shows that active and outdoor modes of transport like e-scooters can also make users happier, more relaxed and less anxious. Taking this mental health benefit into consideration, how likely are you going to use e-scooters?	IM2
- Compared to cycling and walking, e-scooters are faster and can save you time on your daily commute. Taking this benefit into consideration, how likely are you going to use e-scooters? - Compared to motor vehicles and public transportation, e-scooters provide more flexibility. You can use it whenever you want, and it brings you right to the doorstep of your exact destination, saving you the trouble of walking from the parking lot/bus stop/subway station to your destination. Taking this benefit into consideration, how likely are you going to use e-scooters?	EM1
- E-scooters are the latest mobility technology and very popular modes of transport in other cities like San Francisco. Market research shows that many people enjoy riding e-scooters for leisure and use them as transport to work. Taking this research finding into consideration, how likely are you going to use e-scooters? - Market research shows that e-scooters are considered a fun way to get around, and provide opportunities for socialisation and social interaction. People enjoy riding e-scooters with their friends and family and spend quality time together. Taking this research finding into consideration, how likely are you going to use e-scooters?	EM2
Nudges (loss-framing)	
- Traditional motor vehicles emit a lot of greenhouse gases which contribute to both pollution and global warming. Research shows that if environmentally-friendly modes of transport like e-scooters are not used, the deterioration of air quality is likely to accelerate in the coming decades. Taking this research into consideration, how likely are you going to use e-scooters? - Statistics show that motor vehicles also consume 80 times more energy than e-scooters. By not adopting more energy-efficient transport modes like e-scooters, we are wasting 80 times more energy and depleting our finite non-renewable energy resources more quickly. Taking these statistics into consideration, how likely are you going to use e-scooters?	IM1
- By not using more active modes of transport like e-scooters, you may increase your risk to health problems as a result of inactivity, such as obesity and diabetes. Taking these physical health risks into consideration, how likely are you going to use e-scooters? - Research shows that by not using active and outdoor modes of transport like e-scooters, you may also increase your vulnerability to anxiety and depression. Taking this mental health risk into consideration, how likely are you going to use e-scooters?	IM2
- Cycling and walking are much slower than e-scooters. You can waste many hours of your time each week by not using e-scooters, but instead cycling or walking to your destination. Taking this potential loss of productive time into consideration, how likely are you going to use e-scooters? - Motor vehicles and public transportation are less flexible than e-scooters. Parking lots are often a distance away from destinations and public transportation follow fixed schedules. You can waste hours of your time each week by not using e-scooters and instead driving or taking public transportation. Taking this potential loss of flexibility into consideration, how likely are you going to use e-scooters?	EM1
- Market research shows that e-scooters are considered a fun way to get around, and provide opportunities for socialisation and social interaction. If you do not use e-scooters or other social mobility forms, you may be missing out on great opportunities to bond with friends and family. Taking this potential loss of socialisation opportunities into consideration, how likely are you going to use e-scooters? - E-scooters are the latest mobility technology gaining popularity rapidly in many other cities like San Francisco. Market research shows that e-scooters are becoming more normalised and many people ride them for leisure and to work. Not using e-scooters could soon be seen as being backwards or make you stand out. Taking this recent development into consideration, how likely are you going to use e-scooters?	EM2