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AI-generated visuals of car-free US cities help improve support for sustainable policies

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Rachit Dubey[1], Mathew D. Hardy[2], Thomas L. Griffiths[2,3,5] & Rahul Bhui[1,4,5]

Americans are often reluctant to support policies that aim to meaningfully change transportation. Here we show how new techniques from artificial intelligence can be harnessed to increase public support for green policies. We use text-to-image generative AI models to create re-imagined, car-free versions of various streets in America and find that across two large-scale survey studies (N = 3,129), viewing these re-imaginations significantly increases support for a hypothetical sustainable transport bill.

America is highly reliant on personal cars for transportation[1,2]. This dependence is problematic because cars contribute to climate change and release far more greenhouse emissions than public transportation, walking and biking[3]. Car ownership is also expensive and constitutes a substantial financial burden for low-income individuals and households[4]. Further, cars waste an enormous amount of space in cities, leading to traffic and urban sprawl[5]. Thus, given their enormous negative environmental and societal impact, it is important to urgently reduce vehicle ownership and usage in America[6,7].

One way to approach this problem is to target individual consumers and encourage them to change their behaviour[8]. However, nudges to reduce private vehicle usage are often unsuccessful in shifting commuter behaviour[9]. This is primarily because America's infrastructure is extremely car-centric and thus using more sustainable modes of transportation is currently very inconvenient to consumers. To combat this issue, urban planners and policymakers are encouraged to increase investment in public transit infrastructure, thereby making car-free transportation more convenient and approachable[10]. Unfortunately, public transportation has increasingly become a polarizing topic within the United States, and both American public and elected officials are generally reluctant to support policies that try to increase these investments[11,12].

Here we show how this issue can be potentially addressed by combining insights from behavioural science with recent advances in artificial intelligence (AI). A rich literature in psychology has shown that humans have a remarkable ability to imagine the future and subsequently regulate their behaviour and emotions to realize that future[13,14]. Consumer behaviour research has also demonstrated that evoking the imagination can be an effective strategy, wherein vivid imageries are used to help consumers imagine an experience and thus influence their buying behaviours[15,16].

Guided by this work, we use text-to-image generative AI models to illustrate the possible consequences of increased investment in public transport with the goal of influencing policy support. We first present people with views of what popular American streets look like today (Fig. 1, left). Then, using generative AI, we show people what those 'same' streets would look like if they were redesigned for pedestrians and public transportation (Fig. 1, right). That is, we evoked people's imagination of what it would be like to live in a less car-reliant neighbourhood. We hypothesized that helping people imagine future American cities that are car-free might make them more amenable to policies that try to bring about this change.

At the outset, we emphasize that our work does not suggest that using AI-generated visuals is universally better than similar human-generated visuals for improving public opinion for green policies. Rather, our aim is to highlight the importance of helping people imagine possible outcomes of sustainable transport policies. In our view, AI serves as a useful 'tool' to easily generate highly realistic and personalized images of hypothetical future cities at scale. By highlighting the promise of AI-generated visualizations, our work also constructively contributes to the literature on the use of visualizations for promoting pro-environmental behaviours[17,18].

In Study 1, participants (N = 1,529) first read a summary of a hypothetical transport bill, which proposed to make dramatic changes to the American infrastructure (refer to Supplementary Information for details). The bill was intentionally worded to be ambitious and antagonistic to test whether our approach would be effective for similar proposals that often become polarizing in the real world[19]. Participants were then randomly assigned to one of the three conditions: the 'baseline' condition, the 'visual control' condition, or the 'AI imagination' condition (see Methods and Supplementary Fig. 1). The 'baseline' condition aimed to measure people's baseline support for the

[1]Sloan School of Management, MIT, Cambridge, MA, USA. [2]Department of Psychology, Princeton University, Princeton, NJ, USA. [3]Department of Computer Science, Princeton University, Princeton, NJ, USA. [4]Institute for Data, Systems, and Society, MIT, Cambridge, MA, USA. [5]These authors jointly supervised this work: Thomas L. Griffiths and Rahul Bhui. e-mail: rachitd@mit.edu

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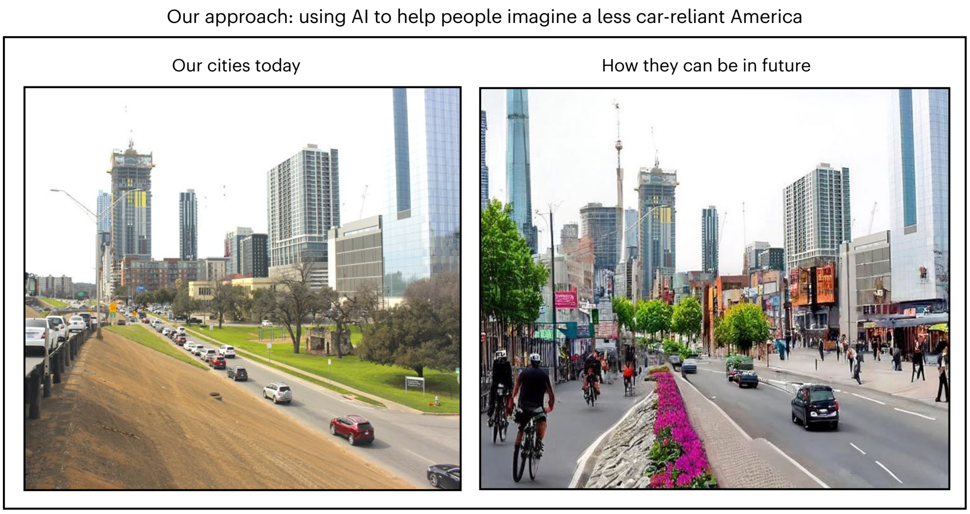

Fig. 1 | Life with and without sustainable transportation. American infrastructure is heavily reliant on cars (left; taken from Google street maps). Here we use generative AI to help people imagine the possible outcomes of increased investment in public transportation (right; generated using Dall-E 2).

hypothetical bill. The 'visual control' condition included simple, cartoonized visual illustrations to capture the spirit of the changes proposed by the bill. These illustrations did not aim to explicitly evoke imagination and were added to ensure that the effects of our intervention were not driven by simple visual cues and/or saliency effects. The 'AI imagination' condition used AI-generated visuals (that were photorealistic) to evoke people's imaginations.

Figure 2a plots the support ratings (on a 1–10 scale) for the hypothetical transport bill for participants in each condition. Participants in the AI imagination condition (mean (M) = 6.4, s.d. = 3.1) were significantly more likely to support the bill than participants in both the baseline condition (M = 5.4, s.d. = 3.1; $t(995) = -4.98$, $P < 0.01$) and visual control condition (M = 6.0, s.d. = 3.0; $t(980) = -2.099$, $P = 0.036$).

Since partisanship is a robust predictor of voter support for transportation policies, surpassing individual factors such as education, race or income[12,20], we investigated the impact of our intervention on the basis of participants' self-reported party affiliation. We found that our approach was particularly effective among Republican participants (N = 257, Fig. 2b). Republican support for the bill in the AI imagination condition (M = 4.8, s.d. = 3.2) was significantly higher compared with the baseline (M = 3.7, s.d. = 2.9; $t(185) = -2.45$, $P = 0.01$) and the visual control condition (M = 3.5, s.d. = 2.7; $t(155) = -2.78$, $P < 0.01$). Republican participants also self-reported as being more willing to sign a petition to support the bill compared with those in the control condition; 32.5% of Republican participants in the AI imagination condition reported willingness to sign the petition, significantly more than Republicans in the baseline condition (proportion: 17.6%; $z = 2.34$, $P = 0.018$) and visual control condition (proportion: 16.7%; $z = 2.28$, $P = 0.023$). We observed a similar pattern of results among participants who identified as Democrats or Independents; however, the magnitude of the difference between the conditions was not as large (see Supplementary Information).

In the pre-registered Study 2, we replicated the results of Study 1 using a different set of visuals (N = 1,600; refer to Fig. 2a). We also saw a similar pattern for Republican participants, although not all effects were significant (see Fig. 2b and the Supplementary Information for detailed analysis). Study 2 also investigated potential mechanisms that drive support for the AI-generated visuals (refer to Fig. 2c). Participants in the AI imagination condition (M = 8.4, s.d. = 1.8) rated that they were able to better imagine the perceived outcomes of the bill than participants in both the baseline condition (M = 7.0, s.d. = 2.4; $t(998) = -10.5$, $P < 0.01$) and visual control condition (M = 6.6, s.d. = 2.6; $t(1056) = -13.1$, $P < 0.01$). Participants in the AI imagination condition (M = 6.0, s.d. = 3.0) also felt that the implementation of the bill would significantly improve their lives compared with participants in the baseline condition (M = 5.2, s.d. = 3.0; $t(998) = -3.87$, $P < 0.01$) and visual control condition (M = 5.4, s.d. = 3.0; $t(1056) = -3.0$, $P < 0.01$). This suggests that our intervention was effective because it helped people imagine how a sustainable transport bill can positively improve their lives.

Drawing on two large-scale survey studies, this article demonstrates that providing the public with visual representations of the positive impacts of sustainable transport policies increases support for the policies and shows how text-to-image generative AI can be a useful tool to achieve that goal. Our method showed promise in shifting the opinion of Republicans, who are usually the largest opponents of such policies[12]. While there is considerable discourse in the literature about the challenges of shifting citizens' climate beliefs (particularly those of Republicans)[21], our work suggests that support for green policies can be improved across party lines and without directly intervening on people's climate beliefs. That is, instead of trying to shift an individual's stance about climate change, an alternative avenue of research could be to improve support for sustainable policies by helping people envision the positive outcomes of those policies. This approach could help build broad-based support for ambitious policies, transcending ideological divides.

Our study has a number of limitations, which present opportunities for future research. For one, the different images used in the different conditions varied across many attributes (for example, colour, salience and so on) which may have impacted participants' judgements. This discrepancy might be a source of confound and should be noted in the interpretation of our results (although see Supplementary Information where we analyse the colour properties of the images and find that the images used in visual control condition and AI imagination condition are similar in the dimension of 'colourfulness'). Next, participants in our study were provided with a hypothetical transport bill and future work should investigate whether our approach will be effective for real-world transport proposals. Further, our study only collected participants' willingness to sign a petition and it is important to assess whether our intervention can be scaled up to prompt real-world civic action. More generally, this line of work is important, as it can help inform whether using AI to harness people's imaginations is a viable strategy to effectively communicate and improve support about sustainable policies.

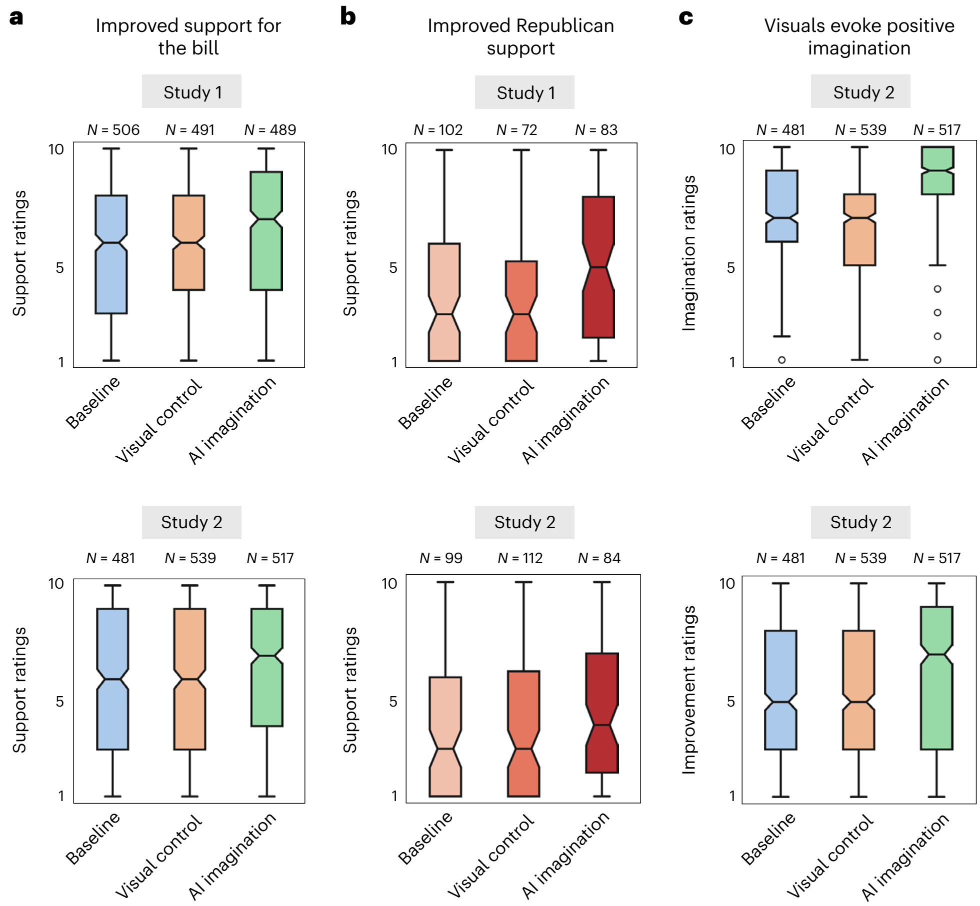

Fig. 2 | Results. a, Our intervention increases support for the hypothetical transport bill. For all graphs, the top and bottom partitions of the notched boxes show the first and third quartiles, respectively, and the median is shown as a black line inside the box. The upper whiskers show the maximum values within 1.5 times the interquartile range above the third quartile, and the lower whiskers show the minimum values within 1.5 times the interquartile range below the first quartile. The notches display the confidence interval around the median. The numbers of participants in each condition are shown at the top of the graphs. **b**, Our approach tends to increase Republican support. **c**, Imagination and improvement ratings from Study 2.

Methods

Study 1

We recruited 1,529 US-based participants from the online research platform Prolific and paid them US$0.50 for participation (our study took ~2 min to complete). All experiments were approved by Princeton's Institutional Review Board. For both experiments, informed consent was obtained from all participants before the experiments began.

At the beginning of the experiment, participants read a hypothetical transport bill and were randomly assigned to one of the three conditions (see Supplementary Information for details). Participants were informed that the bill had three main proposals: to increase investment in public transportation, to improve and expand sidewalks for better walkability and to build dedicated bus and bike lanes on major roads. After reading each proposal, they were taken to a screen that showed them a 'before' image (which was a visual of a popular American street for example, the I-35 in Austin, Texas) and an 'after' image (which showed how the proposal would change that street). In each condition, participants were presented with the same 'before' images but were presented with different 'after' images. The 'after' images in the baseline condition contained a brief textual description of the proposal's outcome. The 'after' images in the visual control condition provided a simple visual illustration to highlight the spirit of the changes. The 'after' images in the AI imagination condition were generated using DALL-E 2's[22] inpainting feature to illustrate how the street would be altered by the bill's proposal (participants were not informed that the images were generated using AI). All experimental stimuli, including the prompts used to generate images using Dall-E 2, are included in the Supplementary Information.

After seeing the different visuals of the bill's proposals, participants were asked to provide, on a scale of 1–10, their subjective ratings of how much they would support the hypothetical bill (where 1 indicated 'strongly oppose' and 10 indicated 'strongly support') and were also asked a 'yes/no' question of whether they would be willing to sign a petition to support the bill. Finally, at the end of the study, participants were asked to self-report their party affiliation ('Democrat', 'Independent', 'Republican' or 'N/A').

We excluded participants who failed a simple attention check as well as participants who spent less than 4 seconds reading the bill. This led to the exclusion of 46 participants, leaving 1,486 participants for our analysis—506 for the baseline condition, 491 for the visual control condition and 489 for the AI imagination condition (768 Democrats, 437 Independents and 257 Republicans in total across conditions, with 24 participants choosing not to provide any party affiliation data). All data analysis was performed using Python 3.12.1.

Study 2

We recruited 1,600 US-based participants from Prolific and paid them US$0.50 for participation. Before collecting the data, we pre-registered the study, including the data collection and analysis plan (https://osf.io/mhfu6). Following the pre-registered exclusion criteria, we removed 55 participants from the final analysis, leaving 489 for the baseline condition, 539 for the visual control condition and 517 for the AI imagination condition (767 Democrats, 433 Independents and 295 Republicans in total across conditions, with 50 participants choosing not to provide any party affiliation data).

This study had two aims. First, we aimed to conduct a replication of our results using a different set of images. Towards this end, we generated a new set of visuals using Stable Diffusion's[23] inpainting feature. Second, we aimed to identify potential mechanisms that drive support for the AI-generated visuals. Participants were additionally asked to rate on a scale of 1–10, how much the visuals shown to them helped them imagine the potential outcomes of the bill. They were also asked to rate on a scale of 1–10, how much they thought the implementation of the hypothetical bill would improve their lives. All experimental stimuli are included in the Supplementary Information.

Reporting summary
Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability
Anonymized participant data for all our experiments are available at https://github.com/rachit-dubey/car-free-america.

Code availability
The code to run the analyses and reproduce the figures is available on GitHub at https://github.com/rachit-dubey/car-free-america.

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Author contributions
R.D. and M.D.H. developed the study concept. R.D. wrote the software, conducted experiments and analysed the data. T.L.G. and R.B. supervised the study design and data analysis. All authors discussed the results. R.D. drafted the paper, and M.D.H., T.L.G. and R.B. provided critical revisions. All authors approved the final version of the paper for submission.

Competing interests
The authors declare no competing interests.

Additional information
Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41893-024-01299-6.

Correspondence and requests for materials should be addressed to Rachit Dubey.

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Corresponding author(s): Rachit Dubey

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	For both experiments, we used the online platform Prolific to recruit subjects and collect their data. Images used in Study 1 were produced using Dall-E 2. Images used in Study 2 were produced using Stable Diffusion.
Data analysis	We analyzed the data using Python 3.12.1.

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

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All stimuli and materials used for our Experiments are reported in the Supplemental Information. There is not a pre-registration for Experiment 1. Experiment 2 was pre-registered and the pre-registration, which includes data collection and analysis plan, can be found here: https://osf.io/mhfu6. All data for Study 1 and Study 2 is available on this publicly accessible repository: https://github.com/rachit-dubey/car-free-america

Human research participants

Policy information about studies involving human research participants and Sex and Gender in Research.

Reporting on sex and gender	This information has not been collected
Population characteristics	At the end of our experiment, we collected participants' political affiliation. A detailed analysis of our results based on subjects' political affiliation is reported in the manuscript. We didn't collect any other information from the participants (e.g., age, gender, etc).
Recruitment	In Experiment 1, we recruited 1529 US-based participants from the online research platform Prolific and paid them \$0.50 for participation (our study took approximately 2 minutes to complete). In Experiment 2, we recruited 1600 US-based participants from Prolific and paid them \$0.50 for participation (our study took approximately 2 minutes to complete).
Ethics oversight	All experiments were approved by Princeton's IRB board. Informed consent was obtained from participants prior to their participation, the text of which was approved by the Princeton IRB board.

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

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Behavioural & social sciences study design

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Study description	All studies reported in the paper are Quantitative. In Study 1, at the beginning of the experiment, participants read a hypothetical transport bill and were randomly assigned to one of the three conditions. Participants were informed that the bill had three main proposals ---to increase investment in public transportation, to improve and expand sidewalks for better walkability, and to build dedicated bus and bike lanes on major roads. After reading each proposal, they were taken to a screen that showed them a ``before'' image (which was a visual of a popular American street e.g., the I-35 in Austin) and an ``after'' image (which showed how the proposal would change that street). In each condition, participants were presented with the same ``before'' images but were presented with different ``after'' images. The ``after'' images in the baseline condition contained a brief textual description of the proposal's outcome. The ``after'' images in the visual control condition provided a simple visual illustration to highlight the spirit of the changes. The ``after'' images in the AI imagination condition were generated using DALL·E 2's inpainting feature to illustrate how the street would be altered by the bill's proposal (participants weren't informed that the images were generated using AI). After seeing the different visuals of the bill's proposals, participants were asked to provide, on a scale of 1-10, their subjective ratings of how much they would support the hypothetical bill (where 1 indicated ``strongly oppose'' and 10 indicated ``strongly support'') and were also asked a yes/no question of whether they would be willing to sign a petition to support the bill. Finally, at the end of the study, participants were asked to self-report their party affiliation (`Democrat', `Independent', `Republican', or `N/A'). In Study 2, we replicated Study 1 using a different set of images. Additionally, we aimed to identify potential mechanisms that drive support for the AI-generated visuals. Participants were additionally asked to rate on a scale of 1 – 10, how much the visuals shown to them helped them imagine the potential outcomes of the bill. They were also asked to rate on a scale of 1 – 10, how much they thought the implementation of the hypothetical bill would improve their lives.
Research sample	In Experiment 1, we recruited 1529 US-based participants from the online research platform Prolific and paid them \$0.50 for participation (our study took approximately 2 minutes to complete). In Experiment 2, we recruited 1600 US-based participants from Prolific and paid them \$0.50 for participation (our study took approximately 2 minutes to complete). Except political affiliation, we didn't collect any other demographic information from the subjects (note that our sample wasn't a representative sample). We choose to use this sample for our experiments because our aim was to test the general effects of harnessing the imagination using AI-generated visuals on support for sustainable transport policy (independent of characteristics such as gender, age, etc).

Sampling strategy	In both Experiment 1 and Experiment 2, participants were randomly assigned to one of three conditions -- the baseline condition, the visual control condition, and the AI imagination condition. The sample size for both studies was chosen based on a power analysis based on the results of prior pilot studies. Importantly, we choose the sample size prior to collecting the data (which is noted in the pre-registration as well).
Data collection	For both studies, we collected data using the online research platform Prolific. All participants took part in our study using Computer (through an online interface). No researcher wasn't present with the participants as they took part in our study -- participants took part in the study online through their personal computer without any researcher being present with them.
Timing	Experiment 1 data was collected in December 2022 (over a period of 1 week using Prolific). Experiment 2 data was collected in August 2023 over a period of 1 week (using the online platform Prolific)
Data exclusions	In Experiment 1, we excluded participants who failed a simple attention check as well as participants who spent less than 4 seconds reading the bill. This led to the exclusion of 46 participants, leaving 1483 participants for our analysis—506 for the baseline condition, 491 for the visual control condition, and 489 for the AI imagination condition. In Experiment 2, we followed the above guideline when excluding data. Following this, we removed 55 participants from the final analysis—leaving 489 for the baseline condition, 539 for the visual control condition, and 517 for the AI imagination condition.
Non-participation	This data was not collected as the recruitment was done via the online platform, Prolific (participants could freely decide to drop the study anonymously)
Randomization	In both Experiment 1 and Experiment 2, participants were randomly assigned to one of three conditions -- the baseline condition, the visual control condition, and the AI imagination condition.

Reporting for specific materials, systems and methods

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Methods

n/a	Involved in the study
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