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Engaging Undergraduates with Urban Planning and Sustainable Mobility: GenAI vs. Human Co-creation

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Abstract

Brief, low-cost in-class activities can introduce undergraduates to urban planning and sustainable mobility, although few studies measure what one achieves. As generative AI (GenAI) enters planning practice, we compare two ways of delivering one: a conversational GenAI agent that generates imagery as it speaks, and a human facilitator working with sketches. Fifty-five undergraduates, none studying planning or architecture and most in their first two years, completed both in counterbalanced order, about three minutes each, rating four attitudes on five-point scales before, between and after the sessions. The two modes moved different attitudes: among students who had met only their first method, support for cycling rose 0.63 of a point after the facilitator and 0.04 after the agent, and that advantage held once both sessions were counted. Willingness to participate in planning rose 0.39 after the agent and stayed flat after the facilitator, an exploratory result appearing at first contact only. A second, back-to-back session did not compound the first: willingness fell back whichever mode delivered it. Such an encounter triggers situational interest; it does not teach content. GenAI thus gives educators a low-cost way to stage that first encounter. The mode should therefore match the aim.

Keywords: Generative AI, Planning education, Student engagement, Sustainable mobility, Geography higher education

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1. Introduction

Introducing undergraduates to urban planning is difficult, and lecture-led instruction struggles to hold attention, where active and game-based formats do better (Georgakakos and Knighton, 2024; Hartt et al., 2020). Research on planning and geography education also lag the digital tools now shaping professional practice (Clayton et al., 2025; de Róiste et al., 2025). The sustainable mobility agenda those curricula serve is itself politically contested (Nall, 2018; Klein et al., 2022), which is part of why walking and cycling attitudes are unlikely to shift easily. Short, low-cost activities introducing planning to students who have not chosen it are attractive on reach, although the encounter's effect is rarely measured.

Generative artificial intelligence (GenAI) is now entering planning practice, drafting planning documents (Zhu et al., 2025), simulating how people move through a design (Noyman et al., 2026), and generating street-design imagery for participatory workshops (Awashra et al., 2025; Valença et al., 2025). Technological progress has outpaced evaluation recently, with technical systems and commercial platforms advancing rapidly (Wang et al., 2026; UrbanistAI, 2025; Huang et al., 2025; Phillips et al., 2024). The existing empirical work on GenAI in planning, which is largely online and public-facing, asks participants to rate AI-generated imagery without interacting with an agent (Cao et al., 2025; Ye et al., 2025). Another study reported that viewing such imagery raises support for sustainable transport policy among the general public (Dubey et al., 2024). However, whether such an agent engages students, not the general public, better than a human facilitator has not been tested.

The evidence on how people respond to GenAI in classrooms and workplaces is mixed. Although reported benefits include better engagement, motivation and lower anxiety among students (Yang, 2025; Fan et al., 2025), intrinsic motivation falls once AI-assisted work ends, and cognitive activity and task ownership are lower

(Wu et al., 2025; Kosmyna et al., 2025). In geography education, ChatGPT has been assessed as a support tool for instructors (Redican et al., 2025), and a university-wide survey reports that students and faculty use and view it at similar rates (Kim et al., 2025). Neither body of evidence currently points to what a student's first encounter with planning would produce.

To bridge this gap, in this study, we ask three questions: first, what does a single brief introductory exposure to planning do to undergraduate students' attitudes? Second, does the delivery mode matter for those students (a GenAI agent or a human facilitator)? Third, what would make a GenAI-delivered introduction more effective for them?

Our contributions are twofold. First, previous work used GenAI to produce images for people to look at, whereas our agent converses with each student and generates imagery throughout, so the whole encounter is with the agent. Second, we report the first controlled comparison, to our knowledge, of such an agent with a human facilitator. We measure four outcomes: willingness to participate in planning, attachment to place, support for walking, and support for cycling. The findings are relevant for geography and planning educators considering the use of GenAI for introductory and outreach settings.

2. Literature Review

In this study, we review two bodies of literature. The first one is on engaging students, which we measure, and the second one on engaging the general public, where the GenAI tools we test were built and evaluated. Subsection 2.1 covers the first; subsection 2.2 lies between the two and distinguishes classroom from workplace evidence; subsection 2.3 covers the second.

2.1. Engaging Students in Planning and Sustainable Mobility

Planning and geography education has faced a persistent difficulty in engaging students. Drawing students out in large classes is hard, but technology-mediated formative activities have been found to raise attendance and participation (Pering and Temple, 2023), and a game-based lecture engaged students more than its conventional counterpart (Hartt et al., 2020). Established, widely advocated pedagogies include service-learning (Botchwey and Umemoto, 2020), immersive community-based projects (Kennedy and Tilly, 2022), and challenge-based learning using the city as a laboratory (Sjöholm and Trygg, 2025). And reviews of smart mobility education call for similar frameworks (Khamis, 2025). Such courses are demanding (in that they run for weeks), need community partners, and depend on in-person delivery, which in geography outperforms online and remote delivery on sustainability learning (McCormick et al., 2024). They also reach only students already enrolled and already interested.

Both disciplines struggle in reaching those students who are not enrolled or interested in the course. In geography, secondary-school exposure is rare, the major is little known to arriving students, and many reach it only through a general-education course (Kolvoord and Peterson, 2024); planning has no comparable evidence. Few studies have measured what a first encounter does, and Knight and Robinson (2017) is a rare exception: after a single classroom exercise, 158 first-year undergraduates at one South African university more readily recognized the field's application to environmental and social problems. Short, low-barrier exposures are attractive on cost and reach, although the evidence for them so far comes from geography.

2.2. GenAI and Human Responses

Human responses to GenAI have been studied in classrooms and workplaces, with mixed findings. Among students, benefits include cognitive engagement, learning motivation (Yang, 2025), reduced anxiety and higher intrinsic motivation (Fan et al., 2025). Among workers, the clearest gain is productivity for the less experienced (Brynjolfsson et al., 2025). Negative findings run the other way; for example, intrinsic motivation falls and boredom rises once AI-assisted work ends (Wu et al., 2025), work alienation increases where AI substitutes for core tasks (Liu and Li, 2025), and cognitive activity and task ownership fall under large language model use (Kosmyna et al., 2025). In geography, ChatGPT has been assessed as a support tool for instructors preparing GIS assignments (Redican et al., 2025). In urban planning, Liang (2026) analysed 235 reflection journals from a semester-long Urban AI course taken by students already enrolled in planning. Both settings differ from a single brief encounter with students outside the field.

2.3. GenAI in Planning Practice and Public Engagement

In planning, GenAI's audience has mainly been the public and the professionals convening them. GenAI can now generate street networks, land use and building form (Cheng et al., 2023; Park et al., 2023), with some outperforming baselines on fidelity, compliance and diversity, and retaining human review at every stage (He et al., 2025). UrbanistAI has entered municipal workshops (UrbanistAI, 2025), and Preussner et al. (2025) report a field deployment that engaged citizens and stimulated creativity. A simulated case study in Seoul explored ChatGPT in planning (Quan and Lee, 2025), and Jiang et al. (2025) evaluated GenAI against gaps in Planning Support Systems. But Liu et al. (2025) found ChatGPT's landscape perceptions diverged sharply from human preferences, so human involvement still remains necessary.

Planning support systems went underused in practice for a few decades, probably because practitioners never encountered or valued them (Vonk et al., 2005), but the field has used them as educational devices, measuring the learning produced (Pelzer and Geertman, 2014; Goodspeed, 2016), and Muller and Flohr (2016) did the same for geodesign. However, GenAI has not gone the same way, and three gaps exist. First, no study has compared a GenAI agent with a human facilitator on engagement outcomes; Preussner et al. (2025) gathered feedback on GenAI in planning but ran no such comparison. Second, existing work treats GenAI as a visualization tool; an agent that converses with participants throughout has not been examined. Third, the evidence comes from audiences already engaged with planning, leaving unexamined what such a tool does at first contact, and what would make that encounter more effective.

3. Data and Methods

Figure 1 shows the overall data collection and analysis process. Two site photographs anchored the engagement sessions: 6th Street and Zilker Park, an iconic street and an iconic park in Austin. Each student completed two sessions in sequence, one using the traditional engagement approach and one using the GenAI-powered approach, with the order randomized. Data were collected and analysed with a mixed-methods design combining quantitative attitude measures with qualitative feedback.

3.1. Experiment Designs and Data

We recruited undergraduate students at the University of Texas at Austin through its psychology participant pool, where students complete a set number of studies for course credit. Fifty-five students completed the study, all with complete records on the outcome measures. Each student completed the experiment individually, to avoid group dynamics.

Table 1 reports the sample. No student was enrolled in architecture or urban planning; the largest single group came from the College of Natural Sciences (21 of 55); and 45 of 55 (82%) were in their first or second year of study. Forty-three (78%) rated their own knowledge of urban planning as none or limited, and 12 rated it moderate or good; this is a self-rating and does not record prior exposure. All students reported at least some familiarity with AI tools, but 25 (45%) had never used an AI image generation tool. Age was not collected; year of study is reported in its place.

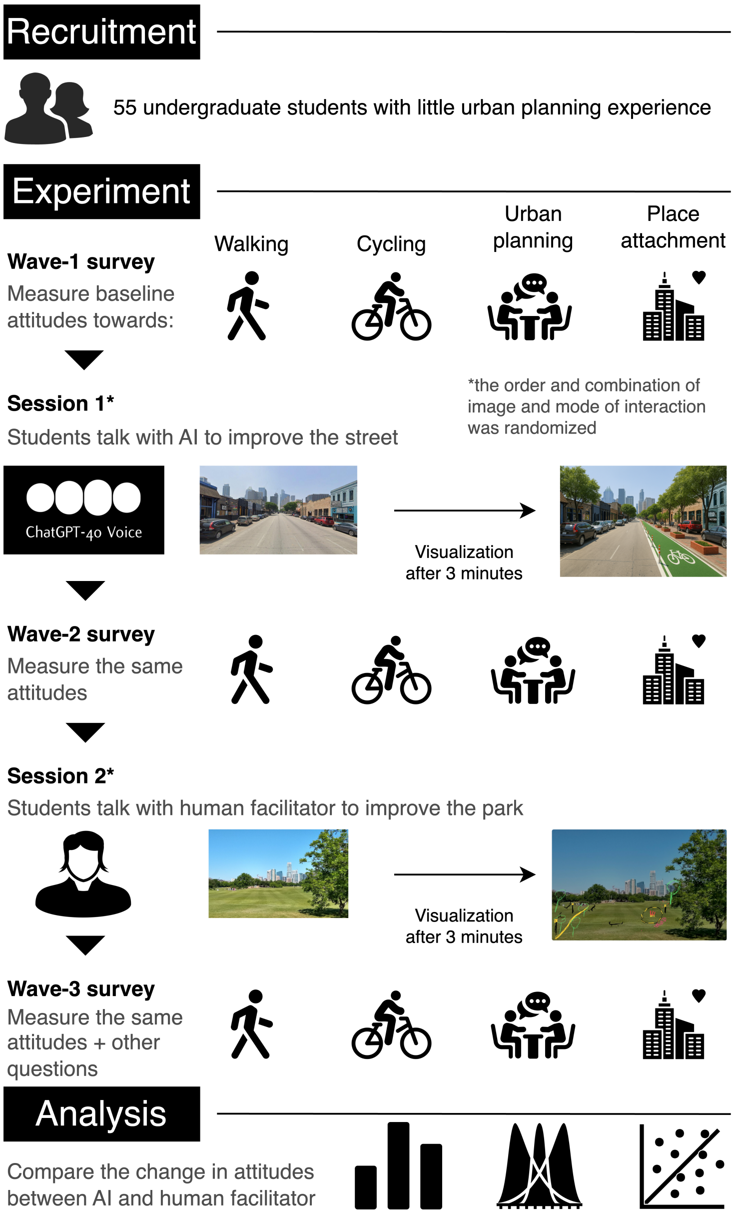


Figure 1: Overall research process and data collection framework. Each student completed both an AI-assisted and a conventional participatory planning session, with the order of the two methods and the two site images counterbalanced. In the final panel, the paired columns contrast the AI-assisted method (red) with the conventional method (purple) on the mean change in each of the four attitude outcomes; the column heights shown are schematic and do not represent study results, which are reported in Figure 2.

Table 1: Student characteristics ($N = 55$).

Characteristic	n	%
College or school at UT Austin		
College of Natural Sciences	21	38.2
College of Education	11	20.0
College of Liberal Arts	11	20.0
McCombs School of Business	5	9.1
Moody College of Communication	3	5.5
School of Nursing	2	3.6
College of Fine Arts	1	1.8
Steve Hicks School of Social Work	1	1.8
Year of study		
Freshman (1st year)	30	54.5
Sophomore (2nd year)	15	27.3
Junior (3rd year)	7	12.7
Senior (4th year)	3	5.5
Self-rated knowledge of urban planning		
No knowledge	9	16.4
Limited knowledge	34	61.8
Moderate knowledge	6	10.9
Good knowledge	6	10.9
Gender identity		
Woman	38	69.1
Man	17	30.9

Characteristic	n	%
Race/ethnicity		
Asian	19	34.5
White	18	32.7
Hispanic or Latino/a/x	11	20.0
Black or African American	5	9.1
Another race or ethnicity not listed	2	3.6
Primary mode of transportation in Austin		
Walking	31	56.4
Personal car	19	34.5
Cycling/scootering	3	5.5
Rideshare (Uber/Lyft)	2	3.6
Self-rated familiarity with AI tools		
Somewhat familiar (have used them occasionally)	38	69.1
Very familiar (use them regularly)	17	30.9
Ever used AI image generation tools		
No, never	25	45.5
Yes, once or twice	17	30.9
Yes, occasionally	10	18.2
Yes, frequently	3	5.5
Hometown type		
Suburban	33	60.0
Urban	20	36.4
Rural	2	3.6
Housing location		
Off-campus	34	61.8
On-campus	21	38.2

Notes: Percentages are of $N = 55$ and may not sum to 100 due to rounding. Planning knowledge is a self-rating, not a record of coursework or prior exposure. No student was enrolled in architecture or urban planning.

The supplementary materials present example conversations and outputs from both methods at both sites: AI-generated images and hand-drawn sketches.

Two engagement approaches were compared:

1. **Traditional approach:** An experimenter presented the site photograph and engaged the student in a discussion for approximately 3 minutes, covering the site's pedestrian, cyclist and user friendliness, inclusiveness and accessibility, and how it could be improved. The experimenter used follow-up questions to elicit detail, and could sketch ideas from the student's suggestions.

2. **GenAI approach:** The student interacted with a GenAI agent through ChatGPT's voice conversation feature, also for approximately 3 minutes, with the agent guiding the discussion and generating images from the student's suggestions in real time. Both approaches used the same set of topics (e.g., pedestrian safety, greenery).

Students were randomly assigned to one of four experimental orders, fully counterbalancing the approach (GenAI vs. Traditional) against the site (Street vs. Park), so that each student met one approach at one site and the other approach at the other.

3.1.1. How the GenAI agent was configured

The agent was not trained or fine-tuned for this study. It was a commercially available system, OpenAI's ChatGPT, configured entirely by a natural-language moderator prompt, reproduced in full in the supplementary materials. Each session ran in a new conversation, opened inside a single ChatGPT project, into which the experimenter pasted the moderator prompt together with the photograph of the site under discussion, so that the agent and the student were working from the same image. Students spoke to the agent using ChatGPT's voice mode, into which the experimenter typed two procedural instructions: one to begin the discussion, and one to generate an edited image. Sessions ran between 31 March and 11 April 2025, and GPT-4o served both the conversation and the image generation throughout.

Before and after each of the two sessions, we measured students' attitudes towards (1) walking, (2) cycling, (3) participating in urban planning, and (4) their attachment to the city of Austin. Place attachment is a long-established outcome in research on planning engagement (Manzo and Perkins, 2006), and willingness to participate is the disposition that participatory planning depends on. Walking and cycling support were included because sustainable mobility is a key planning topic where attitude change through engagement is both desired and challenging to achieve (Lindenau and Böhler-Baedeker, 2014; Dubey et al., 2024). After completing both sessions, students provided demographic and other background information (e.g., experience with GenAI and urban planning) and gave overall feedback on the experiment.

Table 2 lists the variables used in our analysis and their corresponding survey questions. The main outcome variables were measured using 5-point Likert scales ranging from "Strongly disagree" (-2) to "Strongly agree" (2), with "Neutral" as the midpoint (0). These measures were taken before the first session (wave 1), between sessions (wave 2), and after the final session (wave 3), allowing us to calculate change scores for each experimental condition.

3.2. Analysis Methods

We read change on the outcome measures as triggered situational interest, the first and most transient of the four phases in which interest develops (Hidi and Renninger, 2006); a three-minute exposure cannot evidence durable attitude change. The primary comparison is accordingly the change from the pre-session survey to the one taken between sessions (wave 1 to wave 2), which isolates a single first exposure; the change from the pre-session survey to the final one (wave 1 to wave 3), which combines both sessions, is reported alongside it and treated as exploratory.

The main text uses one inferential frame throughout: bootstrap ordinary least squares regression and paired or Welch t-tests, with 2,000 resamples. Table 7 uses that same frame to answer a different question. Thus, it is a moderator analysis fitted on session-level change, a separate quantity from the primary comparison, because a first-session-only model contains no within-student method comparison for student characteristics to be interacted with. A wave-level linear mixed model, reported in the supplementary materials, reaches the same conclusions. The regression equations, the covariate set, and resampling details are given there.

Every student completed both sessions, so anything the first session set in motion could carry into the second; only the comparison between students on their first session is free of that carryover. Alongside the raw change we report standardised mean differences: Hedges' g where the comparison is between the two groups of students, and Cohen's d where it is within a student. With 28 and 27 students in those two groups, the between-student comparison has 80% power to detect only effects of about 0.78 or larger, in either direction.

After the sessions, students selected each method's strengths and limitations from fixed multiple-choice lists that differed by method, for which we report selection frequencies. An optional open-ended comment, answered by 34 of 55 students, supplies the quotations below and is the sole input to the sentiment analysis. We used the emotion lexicon of Mohammad and Turney (2013) to classify emotional content in these comments (Silge and Robinson, 2016). This approach automatically

Table 2: Variables and corresponding survey questions

Variable	Survey Question/Description	Scale
Main Outcome Variables		
Walking attitudes	"I support policies that encourage walking in Austin"	5-point Likert
Cycling attitudes	"I support policies that encourage cycling in Austin"	5-point Likert
Planning participation	"I am willing to participate in urban planning processes"	5-point Likert
Place attachment	"I feel a strong connection to Austin"	5-point Likert
Demographic and Control Variables		
Gender	Student gender identity	Categorical
Race/Ethnicity	Student racial/ethnic background	Categorical
Primary Transportation	Most frequently used transportation mode	Categorical
Planning Knowledge	"Rate your knowledge of urban planning concepts."	Ordinal, 0–3
AI Familiarity	"How familiar are you with artificial intelligence (AI) tools?"	Ordinal, 1–2
AI Image-Tool Use	"Have you ever used AI image generation tools?"	Ordinal, 0–3
Hometown	Type of hometown (rural, suburban, urban)	Categorical
Experimental Design Variables		
GenAI First	Whether student experienced GenAI method first	Binary
Street First	Whether student experienced street scenario first	Binary

categorizes text into emotions (joy, trust, anticipation, etc.) and sentiment polarities (positive, negative).

4. Results

4.1. Change over a single first exposure

Every student went through both methods, so only the first session is free of carryover. Table 3 reports the change we treat as primary on it: the wave-1-to-wave-2 change, adjusted for site and for each student's own wave-1 score. The two groups move apart, and in opposite directions. Willingness to participate in planning rose 0.35 of a response category more after the GenAI agent than after the facilitator (95% CI [0.04, 0.68]), while support for cycling rose 0.41 less ([-0.74, -0.04]). Walking support and place attachment moved with neither.

Table 4 sets each group's effect against the other group's zero. Willingness rose 0.39 (SD 0.63) among the 28 students who met the agent first and 0.00 (SD 0.62) among the 27 who met the facilitator first. Cycling support rose 0.63 (SD 0.88) after the facilitator and 0.04 (SD 0.84) after the agent. Unadjusted, these are Hedges' $g = 0.62$ [0.12, 1.14] and $g = -0.68$ [-1.18, -0.17]. The coefficients above are baseline-adjusted, so the two sets of figures are not interchangeable. Wave-1 scores were balanced across the two groups on all four outcomes (all $p > .20$), but the GenAI group began 0.27 higher on cycling support, which is why adjustment shrinks that contrast from -0.59 to -0.41 while narrowing its interval.

Since no student was left without an activity, each group's comparison is the other method, so both estimates set one active method against another. Both are large by the standards of this literature, where single-session interventions measured against active alternatives pool at $g = 0.14$ (Schleider and Weisz, 2017), and Kraft (2020) treats 0.20 as large for education interventions, larger still when the intervention costs almost nothing. They come from the least well powered comparison in the study, so the magnitudes are uncertain and may well be overstated.

Table 3: Primary comparison: change over a single first exposure (wave 1 $\to$ wave 2) by mode

Term	Willingness to participate	Place attachment	Walking support	Cycling support
Panel A: primary (baseline-adjusted)				
GenAI (vs. Conventional)	0.35 [0.04, 0.68]*	0.12 [-0.17, 0.42]	-0.01 [-0.34, 0.33]	-0.41 [-0.74, -0.04]*
Site: Street (vs. Park)	0.03 [-0.28, 0.36]	-0.19 [-0.51, 0.16]	0.05 [-0.29, 0.42]	0.12 [-0.23, 0.47]
Baseline (wave 1)	-0.29 [-0.50, -0.12]*	-0.34 [-0.57, -0.13]*	-0.64 [-1.08, -0.27]*	-0.68 [-0.91, -0.41]*
Panel B: unadjusted				
GenAI (vs. Conventional)	0.39 [0.07, 0.71]*	0.14 [-0.18, 0.47]	-0.04 [-0.43, 0.33]	-0.59 [-1.04, -0.15]*
Panel C: full covariate set				
GenAI (vs. Conventional)	0.23 [-0.23, 0.63]	0.02 [-0.54, 0.53]	0.02 [-0.86, 0.64]	-0.44 [-1.41, 0.26]

Notes: OLS on each student's first-session change score, one observation per student ($N = 55$); the GenAI group is $n = 28$ and the conventional group $n = 27$, so the mode contrast is between students and free of carryover. Entries are coefficients with 95% bootstrap confidence intervals in brackets (2,000 resamples, seeded). Outcomes are 5-point Likert items coded -2 to $+2$, so 1.00 = one response category, and a positive coefficient favours the GenAI agent. An asterisk marks an interval that excludes zero where the term was estimable in over 99% of resamples; it is not a p-value. Panel A adjusts for each student's own wave-1 score, the one source of variation the counterbalancing does not control. Panels B and C repeat the contrast unadjusted and under the 15-covariate set of Table 7, whose full coefficients are in the supplementary material.

Table 4: Unconfounded between-students comparison using each student's first session only

Outcome	GenAI M (SD)	Conventional M (SD)	Difference [95% CI]	Hedges' g [95% CI]
Willingness to participate	0.39 (0.63)	0.00 (0.62)	0.39 [0.06, 0.73]	0.62 [0.12, 1.14]
Place attachment	0.11 (0.63)	-0.04 (0.65)	0.14 [-0.20, 0.49]	0.22 [-0.30, 0.75]
Walking support	0.11 (0.74)	0.15 (0.72)	-0.04 [-0.43, 0.35]	-0.06 [-0.57, 0.48]
Cycling support	0.04 (0.84)	0.63 (0.88)	-0.59 [-1.06, -0.13]	-0.68 [-1.18, -0.17]

Notes: Change from wave 1 to wave 2 only, before any exposure to the second method. GenAI $n = 28$, Conventional $n = 27$; difference is GenAI minus Conventional. Hedges' g is small-sample corrected, with a percentile bootstrap CI (2,000 resamples). These are effect sizes; the design has 80% power to detect only effects of 0.78 or larger, in either direction.

4.2. The second exposure, and the pooled comparison

Table 5 follows the four outcomes across the three measurements. Walking and cycling support accumulated, rising in the first session and again in the second. Walking support rose $+0.38$ [0.18, 0.58] in total, $d = 0.50$ [0.23, 0.90], and cycling support rose $+0.58$ [0.38, 0.80] in total, $d = 0.72$ [0.41, 1.12]. Willingness to participate did the reverse: it rose 0.20 [0.04, 0.36] over the first session, fell 0.27 [-0.44, -0.11] over the second, and finished 0.07 below where it began.

Table 6 sets each student's first-session change against their own second. Willingness is the only outcome on which the two sessions differ ($\Delta_1 - \Delta_2 = 0.47$ [0.17, 0.77], $t(54) = 3.18$, $p = .002$); on the other three the two sessions are indistinguishable. Willingness falls back whichever method comes second. Ceiling occupancy moves with it: the share answering "strongly agree" rises from 7% at wave 1 to

20% at wave 2 and returns to 11%. Tested directly, the method × order interaction spans zero on all four outcomes, as does total change by sequence (supplementary material). Because the design detects only effects of about 0.78 or larger, this is a failure to detect a difference in carryover, which is weaker evidence than showing there is none.

Pooling both positions returns the within-student comparison of the two methods, the design's central contrast, carrying the second session's carryover with it. Only cycling separates the methods (Figure 2): a difference of -0.47 [-0.87, -0.09], $d = -0.57$, with walking, planning and attachment indistinguishable. The same comparison between the two sites returns no difference on any outcome. Table 7 is a different model: it fits eight separate regressions, one per outcome for each method, each regressing that method's change score on student characteristics. None of the eight contains a term that contrasts the two methods, so the table cannot test whether the method contrast depends on who the student is, and we interpret no coefficient in it. Two of its three categorical controls also have a very small reference category, so a number of terms cannot be estimated in enough resamples to carry an interval at all.

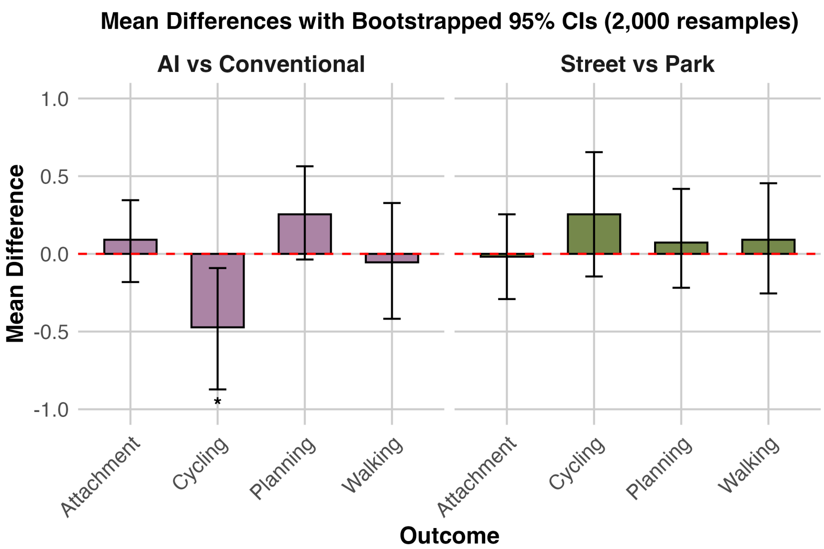


Figure 2: Within-student mean difference in attitude change, by method and by site. The mark denotes a bootstrap interval excluding zero.

4.3. *What students preferred and reported*

Students' self-reported responses at the end of both sessions showed a preference for the GenAI session (Figure 3a) and reported that it had expanded their thinking (Figure 3b). A retrospective item then asked how their interest had changed, on the same -2 to $+2$ range as the outcome measures: mean gains were $+1.04$ for civic

Table 5: Wave-by-wave decomposition of change ($N = 55$)

Outcome	Wave 1	Wave 2	Wave 3	Δ_1 (1→2) [95% CI]	Δ_2 (2→3) [95% CI]	Δ_{total} (1→3) [95% CI]
Willingness to participate	0.64 (0.73)	0.84 (0.79)	0.56 (0.81)	0.20 [0.04, 0.36]	-0.27 [-0.44, -0.11]	-0.07 [-0.25, 0.11]
Place attachment	0.82 (0.88)	0.85 (0.83)	0.95 (0.80)	0.04 [-0.13, 0.20]	0.09 [-0.05, 0.24]	0.13 [-0.02, 0.27]
Walking support	0.91 (0.55)	1.04 (0.67)	1.29 (0.60)	0.13 [-0.05, 0.31]	0.25 [0.05, 0.47]	0.38 [0.18, 0.58]
Cycling support	0.51 (0.79)	0.84 (0.74)	1.09 (0.62)	0.33 [0.09, 0.56]	0.25 [0.02, 0.49]	0.58 [0.38, 0.80]

Notes: Mean (SD) on the -2 to $+2$ Likert scale at each wave (1 before, 2 between, 3 after both sessions). Δ columns give mean within-student change with 95% percentile bootstrap CIs (2,000 resamples). Δ_1 and Δ_2 pool both methods by position, so differences reflect position, not method.

Table 6: Is the second session's change smaller? Position effects and ceiling occupancy

Outcome	Δ_1 (d_z [95% CI])	Δ_2 (d_z [95% CI])	$\Delta_1 - \Delta_2$ [95% CI]	t (df)	p	% at ceiling, W1/W2/W3
Willingness to participate	0.31 [0.06, 0.59]	-0.42 [-0.69, -0.17]	0.47 [0.17, 0.77]	3.18 (54)	0.002	7 / 20 / 11
Place attachment	0.06 [-0.21, 0.32]	0.16 [-0.13, 0.41]	-0.05 [-0.34, 0.23]	-0.39 (54)	0.700	22 / 20 / 24
Walking support	0.18 [-0.08, 0.49]	0.30 [0.05, 0.54]	-0.13 [-0.50, 0.24]	-0.69 (54)	0.495	9 / 20 / 36
Cycling support	0.36 [0.10, 0.68]	0.31 [0.06, 0.59]	0.07 [-0.34, 0.49]	0.35 (54)	0.725	7 / 13 / 24

Notes: d_z = within-student standardised change (mean change divided by the SD of the change), with percentile bootstrap CIs (2,000 resamples). $\Delta_1 - \Delta_2$ is a paired t-test of each student's first-session change against their own second; positive means the second session added less. "% at ceiling" is the share already answering "Strongly agree" (+2).

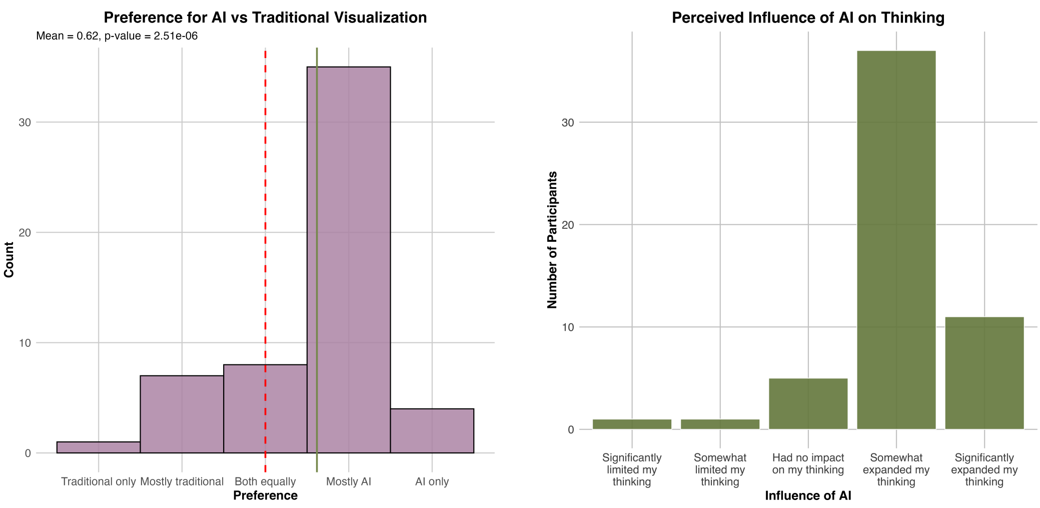
Table 7: Bootstrap Regression Results: AI vs Conventional Methods

Variable	Walk AI	Walk Conv	Cycle AI	Cycle Conv	Plan AI	Plan Conv	Attach AI	Attach Conv
Intercept	0.319	1.543	-1.285	1.558	1.284	-1.310	-0.213	-0.386
AI Familiarity	-0.029	-0.271	0.454	-0.203	-0.036	-0.188	-0.317	0.612
AI Image-Tool Use	-0.072	0.090	-0.113	0.044	-0.107	0.179	-0.097	-0.007
Gender: Woman	-0.108	-0.065	-0.151	0.180	0.005	0.228	0.104	0.068
Hometown: Suburban	-0.571†	0.186†	0.320†	-0.279†	-1.510†	1.260†	0.420†	-0.228†
Hometown: Urban	-0.440	0.112	0.863	-0.596	-1.435	1.177	0.169	-0.168
Planning Knowledge	0.156	-0.169	0.200	-0.095	0.034	0.009	0.142	-0.112
Primary Transportation: Personal car	0.190†	-0.611†	0.047†	0.028†	0.202†	-0.023†	0.029†	0.153†
Primary Transportation: Rideshare	0.314†	-0.991†	-0.478†	-0.289†	-0.701†	-0.204†	0.429†	0.049†
Primary Transportation: Walking	0.086	-0.897	0.070	-0.210	-0.025	-0.125	0.212	-0.239
Race/Ethnicity: Another race	0.565†	0.418†	0.173†	-0.062†	-0.001†	1.295†	-0.431†	0.448†
Race/Ethnicity: Asian	0.704*	-0.418	0.175	-0.161	0.277	0.161	0.307	-0.235
Race/Ethnicity: Black or African American	1.304	-0.858	-0.352	0.674	0.459	-0.288	0.310	-0.271
Race/Ethnicity: Hispanic or Latino/a/x	0.585	-0.299	0.621	-0.031	-0.125	0.323	0.190	-0.042
GenAI First	-0.124	0.014	0.264	-0.465	0.382	-0.262	-0.201	0.286
Street First	-0.439	0.111	-0.249	-0.144	-0.017	-0.061	0.136	-0.153

Notes: Bootstrap regression coefficients (2,000 resamples, seed 20250411). A coefficient is starred (*) iff its bootstrap 95% confidence interval excludes zero *and* its dropout—the share of resamples in which the term was inestimable—is below 1%; † marks a term whose dropout reaches 1%, for which no interval is quoted. No p-value ladder is reported. Full intervals and per-term dropout are in the supplementary material. The reference category for hometown is rural ($n = 2$); hometown coefficients are reported for completeness and are not interpreted. Race/ethnicity cell sizes: White 18, Asian 19, Hispanic or Latino/a/x 11, Black or African American 5, another race or ethnicity not listed 2. Subgroup coefficients are reported for completeness and are not interpreted.

engagement, +0.73 for walking, +0.42 for cycling and +0.64 for place attachment (Figure 4). Over those same two sessions the measured change in willingness to participate was −0.07. It is important to note that the two numbers measure different things: one is the difference between ratings taken before and after, the other a single judgement made at the end. Also, as before, we do not interpret the coefficients on student characteristics in that model (Table 8).

Qualitative feedback matched the preference. Figure 5 reports what students selected as each method's strengths and limitations. Quality of the final visualization was among GenAI's selected strengths (43 against 7 for the traditional method), and difficulty controlling specific details was its most selected limitation (45). Creative freedom and control over details were among the facilitator's strengths (42 and 39), and its most selected limitation was students' own artistic ability (42). Students described the agent as making ideas concrete: "AI has a really cool way of making ideas come to life" and "as I was speaking I was able to think about more ideas". Sentiment in the open feedback was predominantly positive (Figure 6); for example, two students described a first encounter: "I've never done anything urban planning related so I had fun with this"; "this sparked my interest in urban planning a lot more."



(a) Preference for GenAI over traditional method.

(b) Perceived influence of GenAI on thinking.

Figure 3: Student preferences and perceptions of the GenAI method.

4.4. Improving a GenAI-delivered introduction

Regarding what would make the GenAI tool better, students named better control over image details (36), integration with maps and real locations (36), more accurate representation of ideas (27), faster generation (26) and more diverse design options (23); the first repeats the limitation they most often selected for GenAI

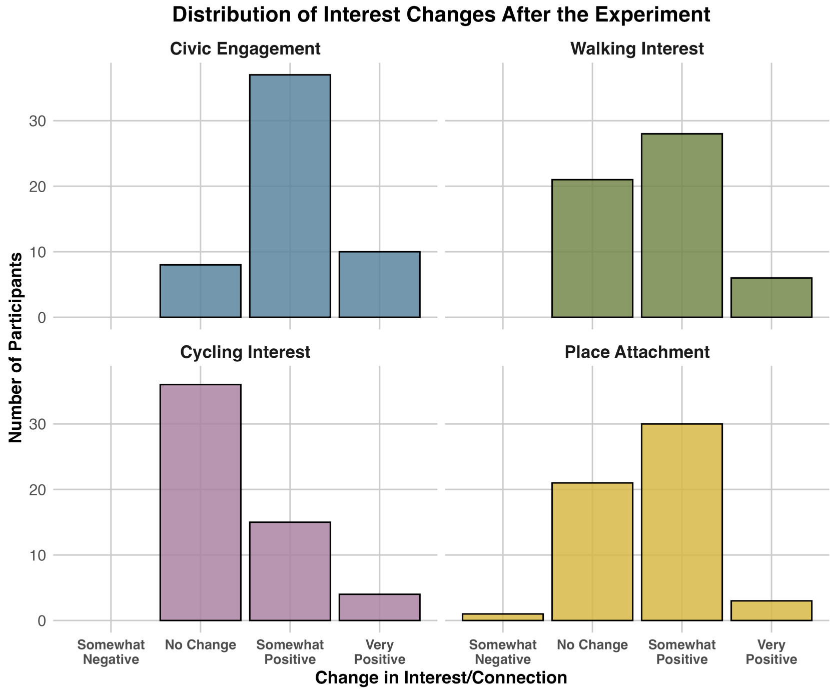


Figure 4: Distribution of retrospectively reported change in interest.

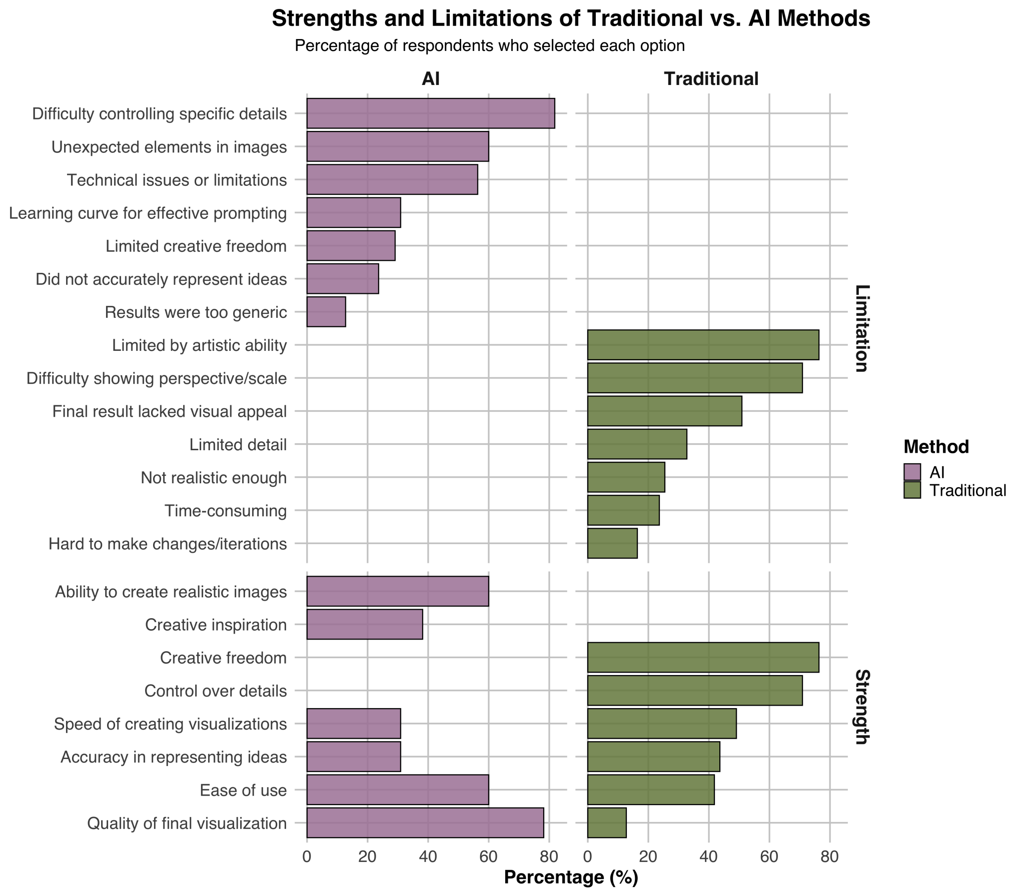


Figure 5: Comparison of strengths and limitations of GenAI and traditional methods.

Table 8: Regression Models of Change in Interest and Place Attachment

	Civic Engagement	Walking Interest	Cycling Interest	Place Attachment
Gender: Woman	0.393	0.582*	-0.091	0.159
Race/Ethnicity: Another race	$0.231^{\dagger}$	$0.146^{\dagger}$	$1.249^{\dagger}$	$0.502^{\dagger}$
Race/Ethnicity: Asian	0.553*	0.006	0.628*	0.260
Race/Ethnicity: Black or African American	0.461	-0.404	0.531	-0.443
Race/Ethnicity: Hispanic or Latino/a/x	0.199	0.420	0.425	0.105
Planning Knowledge	0.008	-0.031	-0.276	0.046
AI Familiarity	-0.088	0.263	-0.107	-0.230
AI Image-Tool Use	0.079	0.271*	0.056	0.138
GenAI First	-0.125	0.390	0.232	0.153
Street First	0.142	-0.034	-0.170	-0.109
Primary Transportation: Personal car	$0.634^{\dagger}$	$0.294^{\dagger}$	$0.279^{\dagger}$	$0.223^{\dagger}$
Primary Transportation: Rideshare	$0.263^{\dagger}$	$0.290^{\dagger}$	$-0.614^{\dagger}$	$0.244^{\dagger}$
Primary Transportation: Walking	0.261	0.277	-0.169	0.206
Hometown: Suburban	$-0.295^{\dagger}$	$0.269^{\dagger}$	$-0.201^{\dagger}$	$-0.903^{\dagger}$
Hometown: Urban	-0.248	0.553	-0.000	-0.996
Constant	0.406	-1.075	0.609	1.250
Observations	55	55	55	55
R^2	0.267	0.367	0.365	0.248
Adjusted R^2	-0.015	0.123	0.121	-0.042

Notes: Bootstrap regression coefficients (2,000 resamples, seed 20250411). A coefficient is starred (*) iff its bootstrap 95% confidence interval excludes zero *and* its dropout—the share of resamples in which the term was inestimable—is below 1%; † marks a term whose dropout reaches 1%, for which no interval is quoted. No p-value ladder is reported. Full intervals and per-term dropout are in the supplementary material. The reference category for hometown is rural ($n = 2$); hometown coefficients are reported for completeness and are not interpreted. Race/ethnicity cell sizes: White 18, Asian 19, Hispanic or Latino/a/x 11, Black or African American 5, another race or ethnicity not listed 2. Subgroup coefficients are reported for completeness and are not interpreted.

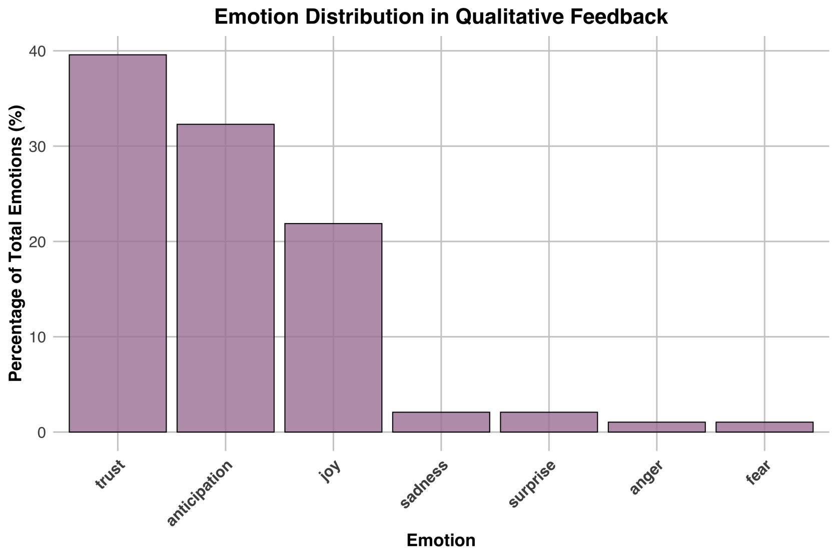


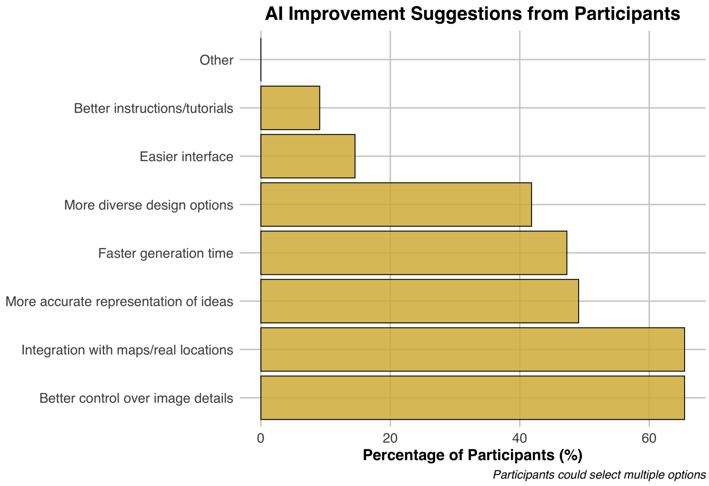
Figure 6: Emotion distribution in qualitative feedback.

(Figure 7a). As for what keeps them from taking part in planning, they named lack of time, lack of knowledge, complicated processes, doubt that their input would count, and inconvenient times and places (Figure 7b). Voting on proposed designs was much the most selected engagement format (39 of 55), followed by online surveys (24), design workshops using AI tools (22), social media (10), public meetings (6) and traditional design workshops (4) (Figure 7c). The 22 against 4 between the two workshop formats compares two tools inside one format.

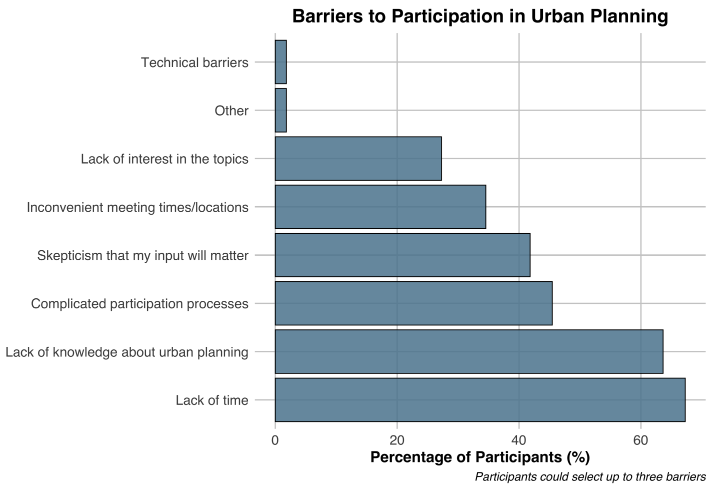
5. Discussion

A brief introductory session shifts attitudes, and the mode of delivery determines which. A single first exposure moved two of the four attitudes we measured, in opposite directions: willingness to participate in planning rose only after the GenAI agent, support for cycling only after the facilitator. The positive change for cycling support holds in the pooled within-student comparison as well as at first contact, and in both session positions, while the increase in willingness appears only at first contact. Despite these measured changes, it is also worth noting that, in terms of the four phases of interest development set out by Hidi and Renninger (2006), the shift sits at phase one, which is a response triggered and measured at the moment of exposure.

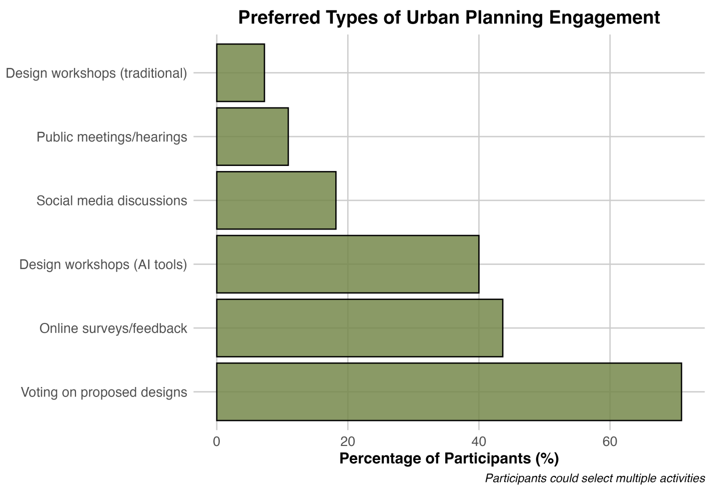
A second exposure did not compound the first. For instance, willingness to participate rose over the first session and fell over the second whichever method delivered it, while walking and cycling support accumulated across both. Interest triggered this way develops further only when later activities repeat and extend it,



(a) GenAI improvement suggestions from students.



(b) Barriers to participation in urban planning.



(c) Preferred types of urban planning engagement.

Figure 7: Future improvements and participation preferences.

with the support and challenge that sustained interest requires (van der Hoeven Kraft, 2017).

What students asked of the tool converges on one thing: how closely the image matches what they meant, or the place they stood in. Control over details, which they wanted from the agent, was among the facilitator's most selected strengths.

5.1. Implications for teaching and outreach

The activity our students completed is a first-contact format, and it transfers with little modification. An instructor needs a phone or tablet running a conversational GenAI agent with image generation, or paper and markers for the facilitator-led version; a street, park or plaza the audience already walks through; and about three minutes per student. It assumes no prior knowledge, no equipment of the student's own and no enrolment. Students rarely meet either field before choosing a major (Kolvoord and Peterson, 2024; Palazzo et al., 2021), so our findings can inform educators and potentially reproduce our approach in outreach settings (e.g., an outreach table, the opening session of an introductory geography, environment or design course, or a departmental open day).

Two of our results depended on the order. One mode moved willingness and the other moved cycling support, so an instructor whose aim is recruitment and one whose aim is mobility attitudes should not assume the same opener serves both. And a second short session immediately afterwards added nothing to willingness, even though it changed both the method and the site; another session of that kind is therefore unlikely to build on a first contact, and we did not test what should come instead.

The format's other pedagogical property is reach. None of our students studied planning or architecture; 78% reported no or limited planning knowledge; 69% were women; 67% were not White. In geography, the gender make-up of bachelor's degrees has been broadly stable since 1986, and bachelor's conferrals to Black students have barely grown since 2010 (American Association of Geographers, 2023a,b). We recruited through a university participant pool, never at an outreach table, so a format with no prior-knowledge or enrolment requirement plausibly reaches students the standard pipeline misses.

6. Limitations and Future Work

Several limitations bound what this study can claim, and each points to future work. The first is duration: three minutes is a real constraint, although a single ten-minute canvassing conversation has durably shifted a far more entrenched attitude (Broockman and Kalla, 2016). Across seventy studies of imagined intergroup contact the time spent was not a significant moderator, whereas the degree of elaboration on the imagined situation was, and more of it produced stronger effects (Miles and Crisp, 2014). Because both findings come from social psychology, they bound brevity without settling it for education, and the gap they leave is durability: we measured at the end of the session and never again.

The second is precision: the between-student comparison has 80% power to detect only effects of about 0.78 or larger, in either direction. Because we report four outcomes without adjusting for one another, neither first-session contrast clears the stricter threshold that four comparisons require ($p = .014$ and .024 against .0125). Both are estimates that call for replication.

The third is that we cannot say for whom the format works best, because two of the three categorical student characteristics have a reference category of two or three students, so many of their terms cannot be estimated in enough resamples to carry an interval. We interpret no coefficient in those models, and nothing here shows the format serves everyone equally.

The fourth is measurement and setting: our outcomes are single-item attitude ratings, which we read through situational interest as an interpretive frame; we administered no validated situational-interest instrument. The study is also 55 students at one university, two mainstream planning scenarios in one city, and one conversational model.

The research this motivates is narrow: whether the shift persists, whether the mode dissociation replicates, and what the format does when it opens an actual course.

7. Conclusion

We delivered a brief, structured first encounter with planning to 55 undergraduates, measurably shifting their attitudes, with delivery format shaping which attitude responded: the GenAI agent raised willingness to participate in planning, the human facilitator raised support for cycling, and neither raised the other. A second back-to-back session did not compound the first. Students preferred the agent and reported large gains from it, although the measured change did not follow those preferences.

For the tool, students' requests centred on how well the image matched their intent. For deployment, the format is cheap enough for an outreach table or a course opener, and the mode should match the aim, since recruitment and mobility attitudes need different ones. We measured a triggered response at the moment of exposure and did not test whether it lasts. Establishing that, and testing the mode difference where a real course begins, is where this work points.

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Disclosure statement

The authors report there are no competing interests to declare.

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Ethical approval and informed consent

This study was approved by the Institutional Review Board of The University of Texas at Austin (STUDY00007102). All students gave informed consent before taking part. Consent was obtained verbally rather than in writing, given the brief, minimal-risk nature of the on-site sessions.

Declaration of generative AI use

Generative AI was the intervention under study; the AI-generated images are study stimuli, not research findings. Students conversed with OpenAI's ChatGPT, which generated images in real time. The image model was GPT-4o, confirmed by C2PA Content Credentials embedded in the generated files; the model serving the voice conversation was not logged, although GPT-4o was ChatGPT's default model throughout data collection (31 March–11 April 2025). Full prompt records are retained and available on request, and the prompts are reproduced in the supplementary material. Separately, during manuscript preparation the authors used Claude Sonnet 4 (Anthropic) to format tables and copy-edit. The authors have checked both tools' terms of use and confirm their suitability for publication, confirm the originality and accuracy of the content, and take full responsibility for the integrity of the whole article, including the accuracy of all references.

Data availability statement

A reduced, de-identified analysis dataset and the R analysis code supporting this study will be deposited in Figshare upon acceptance. Identifiers, session metadata and the demographic variables not used in the analysis are removed, which reduces but does not eliminate the risk of re-identification in a small sample. The audio recordings, conversation transcripts and open-ended survey responses are not available, as they contain student speech that cannot be reliably de-identified.

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