Science on the Move: How Experiential Pedagogy Shapes Human Capital*

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March 1, 2026

Abstract

Despite near-universal school enrollment across many developing economies, the provision of quality education that cultivates lifelong learning and the capacity to apply knowledge in novel circumstances remains elusive. We conduct a cluster-randomized controlled trial in public schools in Uttar Pradesh, India, partnering with the Agastya Foundation to evaluate a guided, discovery-based science pedagogy at two intensity levels: a high-intensity Mobile Science Lab (MSL) and a lower-intensity Lab-on-Bike (LOB). MSL improves motivational beliefs and self-perceptions—curiosity, self-confidence, aspirations, and perceived barriers—by 0.15–0.23 standard deviations, raises science-specific and general engagement by 0.17–0.22 standard deviations, and increases standardized test scores by 0.22–0.34 standard deviations across all subjects. LOB produces limited average effects, with gains concentrated among students completing all six sessions. These findings demonstrate that pedagogical design and delivery intensity are critical determinants of multidimensional human capital formation in low-capacity public school systems.

JEL: C93, D83, I21, I24, O15

Keywords: Experiential Pedagogy, Curiosity, Student Engagement, Randomized Controlled Trial, Human Capital, India.

*We thank Shubhro Bhattacharya, Palaash Bhargava, Alex Eble, Joshua Goodman, Shantanu Khanna, Cynthia Kinnan, Priya Mukherjee and participants at seminars in Ashoka University, Bennett University, Clark University, Patliputra University, Delhi School of Economics, Higher School of Economics, Plaksha University, Teachers College at Columbia University, Thammasat University, Tufts University, Warwick University, Indian Institute of Technology–Mumbai, University of Namur, World Bank (South Asia Gender Innovation Lab), and Shiv Nadar University and conference participants at North East Universities Development Consortium Conference (2024), 18th Annual Conference on Economic Growth and Development (Indian Statistical Institute, Delhi), 7th International Applied Development Economics Conference, and World Congress (2025) for helpful feedback. We thank Dibyajyoti Basak, Manvendra Singh, and Bharat Singhal for excellent research assistance. We are deeply grateful to Rama Prasad "Ramji" Raghavan, founder and chairperson of Agastya International Foundation, and to Venkateswar Rao Ketineni, Hariharan Ganesan, Sai Chandrasekhar, and Mukesh Kumar for their invaluable support, guidance, and commitment throughout the implementation of this intervention. We are grateful to the team at Quest Research and Development for their tireless work in carrying out the data collection. This study was approved by the IRB at New York University (IRB No.: HRPP-2022-95) and pre-registered with the AEA Trial Registry (RCT ID: AEARCTR-0010902). We gratefully acknowledge research funding from the New York University Abu Dhabi Development Group and Agastya International Foundation for conducting fieldwork.

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"For the mind does not require filling like a bottle, but rather, like wood, it only requires kindling to create in it an impulse to think independently and an ardent desire for the truth."

— Plutarch, *Moralia*, "On Listening to Lectures," §18 (48C–D),
trans. F.C. Babbitt (Loeb Classical Library, Vol. I, 1927)

1 Introduction

The concept of human capital has evolved beyond simple measures of educational attainment to encompass a broader set of capabilities. While years of schooling remain important, research increasingly highlights the role of higher-order cognitive skills (such as critical thinking and problem-solving) and non-cognitive skills (including perseverance, self-regulation, and social competence) in shaping both economic outcomes and broader life trajectories (Heckman and Kautz, 2012; Heckman and Mosso, 2014; Lindqvist and Vestman, 2011; Succi and Canovi, 2020). A growing literature shows that several of these dimensions are malleable in childhood (Alan and Mumcu, 2024), raising a central policy question: how to cultivate them where most children actually learn, in resource-constrained public schools. Yet instruction in such systems is typically teacher-centric and tightly syllabus-driven (Glewwe et al., 2020), and while effective at transmitting factual content, is not designed to cultivate higher-order cognitive capabilities or the non-cognitive dimensions that increasingly determine long-run outcomes. In this paper, we ask whether a guided, discovery-based pedagogy that elicits curiosity and questioning can shift what we term *multi-dimensional human capital* (MDHC)—defined as curiosity, self-confidence, self-efficacy, aspirations and perceived barriers, engagement, and scholastic achievement—in low-capacity public schools in India. These dimensions are grounded in established frameworks linking motivational beliefs, behavioral engagement, and academic performance (Fredricks et al., 2004; Lam et al., 2012), and evidence that curiosity, aspirations, and perceived barriers are malleable through targeted educational interventions (Alan and Mumcu, 2024; Carlana et al., 2022).

Demand for both higher-order cognitive and non-cognitive skills is rising in modern labor markets (Bowles et al., 2001; Deming, 2017; Edin et al., 2022; Waddell, 2006). While much of the evidence comes from high-income settings, the changing nature of work makes these skills increasingly salient globally (World Bank, 2018). Evidence from low-income contexts is growing: Adhvaryu et al. (2023) document substantial returns to soft-skills training in Indian manufacturing, suggesting that non-cognitive skills carry meaningful labor market returns even in contexts characterized by routine production work. Recent experimental work identifies promising classroom mechanisms, namely teacher-mediated curiosity pedagogy and inquiry-based science, demonstrating that curiosity and scientific thinking are malleable and can enhance learning (Alan and Mumcu, 2024; Nourani

et al., 2025). Yet two questions remain open. First, can such approaches shift the broader set of skills that constitute MDHC in low-capacity public systems? Second, can they be effective for students in upper-primary grades, where content is more technical and discovery-based teaching is more demanding?

We address these questions through a randomized controlled trial in the Indian state of Uttar Pradesh, partnering with Agastya International Foundation to layer a guided, discovery-based science module on top of business-as-usual instruction in grades 6, 7 and 8.[1] We test two delivery models: a high-intensity *Mobile Science Lab* (MSL), consisting of a van equipped with a portable lab and three instructors visiting monthly for four-hour sessions, and a lower-intensity *Lab-on-Bike* (LOB), consisting of one instructor with portable kits visiting monthly for two-hour sessions. Both models instantiate the same design principle of guided discovery anchored in hands-on tasks, while varying intensity and staffing—a design feature that permits us to identify how delivery intensity, rather than curriculum content, shapes human capital formation. We randomly assigned 27 schools to MSL (28 controls) and 41 schools to LOB (36 controls), covering nearly 14,000 students across 132 schools.[2] Sessions are highly interactive and student-centered: instructors pose simple science problems, guide hands-on experimentation, connect concepts to real-life examples, and encourage questioning throughout. In a typical government classroom in India, the teacher controls the majority of talk time; by contrast, students lead discussion for roughly 75 percent of session time in our intervention, a sharp departure from traditional pedagogy. The science focus provides a structured canvas for inquiry and directly responds to declining interest and performance in science across India (Loyalka et al., 2021).

We pre-specified three outcome families following the contextual model of student engagement in Lam et al. (2012), one of the most widely used frameworks for organizing motivational, behavioral, and achievement outcomes in educational research: *personal factors* (curiosity, self-confidence, self-efficacy, aspirations, perceived barriers), *engagement* (interest in science, self-assessed performance, perceptions of science teachers, attendance, enjoyment of schoolwork), and *achievement* (test scores). We estimate intention-to-treat effects separately for MSL and LOB. We also examine whether improvements in personal factors translate into greater engagement and, in turn, higher achievement, providing insight into the mechanisms through which discovery-based pedagogy operates.

The high-intensity MSL produced substantial gains across multiple dimensions of MDHC. Personal factors improved: curiosity by 0.18 sd, self-confidence by 0.16 sd, aspirations by 0.15 sd, and perceived barriers for further education by −0.23 sd, with a suggestive increase in self-

[1] Agastya International Foundation, established in 1999, is a leading Indian NGO recognized for its innovative approach to science education. As former President of India Dr. A.P.J. Abdul Kalam noted: "The lesson we derive from [the Agastya] experience is that innovative and student-friendly solutions are needed to enable scientific learning in the youth, especially those in rural and remote regions of the nations of the world." Its vision is "to build a new India of tinkerers, creators, innovators and solution-seekers."

[2] AEA RCT Registry: https://www.socialscienceregistry.org/trials/10902.

efficacy. Science-specific engagement also increased, including interest in science, perceived understanding of the science teacher, and time spent on science outside school. General engagement rose as well, with higher enjoyment of school and classroom participation across subjects, without changes in attendance. Achievement improved across all state-administered test subjects (Science, Mathematics, English, and Hindi), though our more conceptually demanding assessment and a creativity task showed no average effects. Mediation patterns are consistent with improvements in personal factors feeding into engagement; by contrast, science gains persist after controlling for these mediators, consistent with a direct learning channel during lab sessions. Spillovers to non-science subjects are consistent with both a curiosity-based learning-state amplifier operating across domains and test-taking dynamics; the design does not permit a formal discrimination between these interpretations.

We find *no systematic changes* in teacher pedagogy, indicating that effects operate directly through the module rather than through shifts in regular classroom instruction. Broader personality traits (Big Five) and sociability remain largely unchanged, apart from a small decline in conscientiousness, suggesting that effects concentrate on education-relevant skills and behaviors rather than stable personality dimensions. By contrast, the lower-intensity LOB generated limited average effects: personal factors and engagement did not move, state-administered test score gains were generally absent (apart from a small, non-robust increase in English), and there were no detectable impacts on our conceptual assessment, creativity, or broader non-cognitive outcomes. The contrast between MSL and LOB underscores the importance of sufficient intensity and a salient, hands-on experience for discovery-based pedagogy to shift outcomes at scale in low-capacity public schools.

To examine plausible mechanisms, we use heterogeneity analyses that exploit variation in program exposure and design features. The patterns admit a parsimonious interpretation in which two functionally distinct channels operate: a motivational–epistemic channel, through which repeated exposure shifts curiosity, confidence, and engagement; and a direct cognitive channel, through which heightened attention during sessions improves encoding and short-run content retention. Impacts scale systematically with participation: within MSL, gains in personal factors and engagement emerge only after five to six sessions, with improvements of 0.15–0.25 sd in curiosity, self-confidence, aspirations, and classroom engagement, and little movement at lower exposure levels. By contrast, survey-based test performance does not display a comparable gradient, suggesting that content acquisition responds more immediately to exposure rather than requiring cumulative activation. In LOB, effects concentrate among students completing five or six sessions, who experience gains of approximately 0.24–0.26 sd across curiosity, self-confidence, and test performance, consistent with per-session intensity shaping the cumulative exposure required for motivational responses to materialize. Program features also shape effectiveness: students valuing hands-on experiments exhibit gains of 0.20–0.30 sd in personal factors and 0.15–0.18 sd in test

performance, consistent with experiments raising both informational surprise and attentional focus, while valuing instructional style predicts improvements in personal factors but not test performance, consistent with a predominantly motivational channel. Real-life examples display null or negative associations across both arms. Because session attendance and program preferences are endogenous, these within-arm patterns are descriptive; the primary causal evidence that intensity shapes effectiveness comes from the randomized contrast between MSL and LOB.

We also examine heterogeneity by student background. MSL effects are broadly similar across gender, baseline ability, and household wealth, consistent with high-intensity delivery substituting for household learning complements and cognitive scaffolding. In LOB, lower-asset students experience larger test gains (0.19 sd on the survey-based test), while lower-ability students exhibit weaker or negative interactions, suggesting that cognitive gains concentrate among students lacking home inputs while motivational shifts require sufficient baseline knowledge to generate meaningful informational gaps. Gender heterogeneity does not map cleanly onto either channel: MSL performance gains are somewhat larger for boys while LOB engagement gains are somewhat larger for girls, but neither pattern admits a clear mechanism interpretation. Taken together, the consistency of patterns across exposure gradients, program preferences, and student background provides internally coherent evidence that discovery-based pedagogy operates through at least two functionally distinct mechanisms, though a formal causal decomposition of these pathways lies beyond what our design can establish.

We further benchmark MSL's effect sizes against other rigorously tested education interventions. MSL's test score gains of 0.22–0.34 sd and non-cognitive improvements of 0.15–0.18 sd place it in the mid-to-upper range of interventions tested in comparable contexts. These effects match the upper end of remedial tutoring (Banerjee et al., 2007) but fall below technology-aided instruction (Muralidharan et al., 2019) and well below intensive teacher-transformation models (Nourani et al., 2025). MSL's science gain of 0.28 sd sits within the historical meta-analytic range of 0.26–0.35 sd from inquiry-based curricula (Bredderman, 1983; Shymansky et al., 1990; Weinstein et al., 1982) but below more recent estimates of 0.50–0.65 sd (Furtak et al., 2012; Schroeder et al., 2007), a gap that likely reflects implementation challenges in low-resource public systems where sustaining inquiry pedagogy at scale proves more difficult than in tightly controlled experiments. MSL's notable feature is its breadth: while most interventions target test scores alone, MSL simultaneously shifts curiosity (+0.18 sd), aspirations (+0.15 sd), and engagement (0.17–0.18 sd), outcomes that may generate long-run returns beyond what test scores predict (Kautz and Zanoni, 2014). At $5.56 per student annually, MSL achieves approximately 5.1–6.2 sd per $100, making it 1.7 to 2.0 times more cost-effective than remedial tutoring on academic outcomes alone. Evidence from Latin America further suggests that short-run estimates understate long-run returns: Bando et al. (2019) find that inquiry-based pedagogy effects grow from 0.14–0.18 sd initially to 0.23–0.39 sd after four years,

with the cost per 0.10 sd gain falling from $18 to $8.40 as benefits accumulate. Whether MSL follows a similar trajectory remains an open question without comparable follow-up data.

This study contributes to several strands of literature. *First*, we contribute to the literature on experiential and child-centric learning, particularly in low-capacity public education systems. While Alan and Mumcu (2024) show that teacher-mediated experiential pedagogy can stimulate curiosity among primary students in Turkey, our intervention relies on specialized instructors from an external organization rather than classroom teachers. This design responds directly to challenges in the Indian context, where teacher absenteeism and limited training effectiveness constrain pedagogical reforms (Kingdon and Teal, 2010; Muralidharan, 2012; Muralidharan and Sundararaman, 2011). Our intervention also extends beyond curiosity to additional non-cognitive outcomes, including engagement and self-efficacy, and focuses on middle school students (grades 6–8), a group often neglected in this literature. Our approach complements recent evidence on child-centric education solutions (Muralidharan et al., 2019) by demonstrating that discovery-based methods can challenge conventional pedagogy and sustain student engagement in science education.

Second, we expand the scope of large-scale evaluations of school-based interventions beyond cognitive outcomes. Much of the existing literature on school inputs and quality improvements, including investments in teaching materials, infrastructure, or tutoring (Banerjee et al., 2005; Carlana et al., 2022; Case and Deaton, 1999; Chin, 2005; Drèze and Kingdon, 2001; Duflo et al., 2015, 2012; Glewwe and Jacoby, 1994; Urquiola and Verhoogen, 2009), has primarily focused on test scores and years of schooling. Studies of inquiry-oriented pedagogy closer to our intervention (Bando et al., 2019; Nourani et al., 2025) also emphasize academic outcomes. We depart from this focus by examining how externally delivered science labs not only improve learning but also foster personal factors and engagement. We measure a broader set of skills, including curiosity, self-confidence, self-efficacy, and perceptions of barriers, addressing concerns in Heckman and Rubinstein (2001) and Jackson (2018) about the limitations of focusing solely on cognitive metrics. While non-cognitive skill interventions have shown long-term benefits in developed countries, they are typically delivered through after-school or mentoring programs (Kemple and Snipes, 2000; Kemple and Willner, 2008; Roder and Elliott, 2011). Evidence on delivering such interventions within low-resource public school systems remains limited. We provide an externally delivered, science-focused model that extends measurement beyond cognition while operating at system scale.

Third, our study contributes to the growing literature on child-centric pedagogy and adaptive learning. While child-centric approaches feature in Alan and Mumcu (2024) and Nourani et al. (2025), and related work documents the effectiveness of Teaching at the Right Level (Banerjee et al., 2016) and technology-enabled personalization (Muralidharan et al., 2019), evidence on how such approaches affect broader skill sets remains scarce. By documenting impacts on curiosity, engagement, and achievement among middle school students, we extend this literature to an

underexplored age group and demonstrate the viability of portable, externally delivered models in public systems. The evidence indicates that such interventions can usefully complement traditional instruction and foster multidimensional human capital in low-resource public schools.

Finally, this study contributes to the literature on alleviating supply-side constraints in science education by examining how alternative delivery models can address complementarities between pedagogy, laboratory infrastructure, and teacher capacity. While many developing-country schools, including those in India, possess basic science laboratories and trained teachers, the effective utilization of these resources for experiential learning remains limited (Pareek, 2019). The binding constraint is not the absence of infrastructure but rather teachers' limited capacity to employ inquiry-based pedagogical approaches that transform laboratories into spaces of active investigation. Regular schoolteachers in India often lack training in hands-on experimental methods and interactive instruction, instead relying on traditional teacher-centered approaches that result in laboratories being underused or confined to rote demonstrations rather than student-driven exploration (Brinkmann, 2015; Dyer et al., 2004). The *Mobile Science Lab* model directly targets this complementarity problem by bundling three essential inputs: portable experimental equipment, instructors trained in experiential pedagogy, and a curriculum designed for inquiry-based learning (Jones and Stapleton, 2017). Rather than merely supplying physical resources, this approach integrates pedagogical expertise with existing school infrastructure, illustrating how instruction quality and resource utilization are mutually reinforcing. This perspective underscores that overcoming barriers to effective STEM education requires not only capital investment in facilities but also coordinated improvements in pedagogical training and curriculum design that enable teachers and infrastructure to function as complements rather than substitutes (Fryer et al., 2018; Hanushek, 2020). By temporarily embedding specialized instructors who model effective laboratory teaching, the mobile-lab intervention raises the productivity of existing school resources while potentially generating knowledge spillovers to regular teaching staff.

2 Context, Intervention, and Experimental Design

2.1 Context

Despite near-universal enrollment, foundational learning in the Indian state of Uttar Pradesh – one the most populous state in India–remains weak. In ASER 2024, over 95 percent of children aged 6–14 were enrolled, yet only 56 percent of grade 5 students could read a grade 2 text and 39 percent could perform basic division (ASER Centre, 2024). By grade 8, numeracy deficits persist: roughly one–third can do division even though most can read a grade 2 text (ASER Centre, 2024). The challenge is less about access than classroom practice: instruction is syllabus–driven,

emphasizes rote methods, and rarely involves inquiry or experimentation. ASER observers reported that about four–in–five government classrooms had *teaching–learning materials* (TLM)[3] available; yet, conditional on TLM being present, displays of students' work were almost universal (over 95 percent) (ASER Centre, 2024). This pattern points to constraints in using materials for hands-on activities rather than a simple absence of materials. Structural factors compound these limits: historically high pupil–teacher ratios (about 66:1), low female representation (28 percent), and the absence of any female teacher in roughly 43 percent of elementary schools are documented in state administrative data (Motkuri, 2005).

These patterns point to system-level governance constraints rather than simple resource gaps. Kingdon and Muzammil (2009) document the central role of teacher unions, weak local accountability, and limited performance incentives in Uttar Pradesh's public school system. District-level human-development assessments show persistent disparities across regions, with education indicators lagging national averages (Maurya et al., 2015). Recent evidence suggests that apparent private–school advantages largely reflect differences in attendance and time on homework rather than superior pedagogy (Kumar and Choudhury, 2021), while community–school participation can raise foundational learning (Kumar et al., 2024). Within this context, science education faces acute constraints—scarce laboratory infrastructure, low teacher confidence in running experiments, and theory-heavy instruction—making Uttar Pradesh a natural setting to test whether structured, discovery-based science pedagogy can improve engagement and strengthen learning in under-resourced public schools.

2.2 The Intervention: Experiential Learning Pedagogy

Science instruction in India's rural upper-primary schools (grades 6–8) follows a teacher-centered, lecture-based model organized around textbook completion and rote memorization. Although official curricula include *activity boxes* designed to promote inquiry, resource constraints and institutional incentives leave these almost entirely unimplemented. Students thus encounter science as a body of facts rather than as a method of investigation, a form of what Freire (1970) calls the "banking" model of education, in which knowledge is deposited into passive recipients (Nourani et al., 2025).

The curriculum developed by Agastya International Foundation works within this system rather than against it. Sessions supplement rather than replace prescribed textbook content by transforming it into hands-on experience through three interdependent levers (Reeve, 2012; Skinner and Pitzer, 2012): *real-life relevance*, which connects abstract concepts to students' everyday environments; *curiosity stimulation*, which activates intrinsic motivation through hypothesis formation and guided experimentation; and *autonomy support*, which positions students as active constructors of knowledge

[3]TLM are instructional aids beyond the textbook—charts, posters, manipulatives, worksheets, models, science kits, and simple lab apparatus—intended to support active, student–centered learning.

rather than passive recipients. Each session follows a structured arc, comprising a curiosity-provoking opener (*super start*), collaborative small-group experimentation in which students predict outcomes before observing them, and a consolidating synthesis (*super finish*), designed to move students through a cognitive progression from surprise and questioning to observation, reasoning, and consolidation. Topics are synchronized with the school syllabus so sessions act as conceptual anchors for material already taught or soon to be introduced. Simple, portable kits make the approach feasible in resource-constrained classrooms, and random supervisory visits ensure fidelity to the model. Evidence from comparable discovery-based frameworks documents gains in conceptual understanding, persistence, and intrinsic motivation (Alan et al., 2019; Alan and Kubilay, 2025; Alan and Mumcu, 2024; Bando et al., 2019).

The two delivery arms, the *Mobile Science Lab* and the *Lab on Bike*, implement an identical curriculum through the same pedagogical sequence but differ in instructor team size, instruction time, and visit frequency, generating variation in cumulative exposure without altering content (Table 1). Detailed session design is described in Appendix C.

2.3 Experimental Design

We implement a cluster-randomized controlled trial in rural Uttar Pradesh to evaluate the impact of an experiential science curriculum on multiple dimensions of human capital. The intervention was implemented in partnership with Agastya International Foundation, a non-profit organization that designs and delivers hands-on science learning experiences for students and teachers across India.

The partnership leveraged Agastya's long-standing experience in developing mobile, low-cost science education models to reach under-resourced schools across India. By integrating structured experimentation and guided discovery within the regular school timetable, the intervention sought to promote scientific curiosity, enhance conceptual understanding, and improve engagement in science learning among upper-primary students.

Agastya provided the sampling frame of upper-primary (grades 6, 7 and 8) public schools in four districts—Ghazipur, Gonda, Lucknow, and Varanasi—selected to represent diverse socioeconomic and administrative contexts within Uttar Pradesh. The frame was designed to ensure geographic balance and feasible class sizes for experiential instruction, targeting approximately 30–40 students per instructor per session.[4] These four districts together capture meaningful variation in school infrastructure, teacher quality, and student demographics—ranging from the peri-urban context of Lucknow to the more rural blocks of Ghazipur and Gonda—allowing the intervention to be tested

[4]Operational thresholds guided eligibility and scale: for the higher-intensity Mobile Science Lab (MSL), the minimum total upper-primary enrollment per school (grades 6, 7 and 8 combined) was 120–160 students, with a district-level cap of 2,000–2,200 students; for the lower-intensity Lab on Bike (LoB), the corresponding thresholds were 60–80 students per school and 1,000–1,200 per district. These thresholds were based on prior-year enrollments to ensure logistical feasibility.

under heterogeneous administrative and resource conditions.

To facilitate program delivery, treatment modalities were assigned at the district level: Ghazipur and Gonda implemented the higher-intensity Mobile Science Lab (MSL), while Lucknow and Varanasi implemented the lower-intensity Lab on Bike (LoB). Within each district, schools were stratified by geographic block and randomly assigned to treatment or control within strata, ensuring balanced representation of geographic and administrative units across arms. This cluster-randomized design allows for estimating causal impacts on student learning and engagement while maintaining operational feasibility and minimizing the risk of contamination across schools.

2.4 Sample Selection, Randomization, and Timeline

Sample Selection and Randomization. The study was conducted across four districts of Uttar Pradesh—Ghazipur, Gonda, Lucknow, and Varanasi—selected to capture socioeconomic and administrative diversity within the state. Agastya International Foundation provided the sampling frame of upper-primary (grades 6, 7 and 8) public schools. The sampling frame was constructed to ensure that each geographic block within a district contained treatment schools and that class sizes were suitable for hands-on instruction, targeting approximately 30–40 students per instructor per session.

From an initial list of 150 candidate schools, we excluded 14 prior to randomization—eight outliers (five very large schools, one very small school, and two English-medium schools) and six randomly dropped to stay within operational capacity—yielding a pre-randomization sample of 136 schools. Randomization was conducted at the school level, stratified by geographic blocks within each district. We used information from the Unified District Information System for Education Plus (UDISE and UDISE+) datasets.[5] Using the unique 11-digit UDISE school code, we merged our school list with the 2020 UDISE+ datasets to obtain baseline characteristics, including grade-wise enrollment, student caste composition, school infrastructure (classrooms, textbooks, uniforms, playgrounds), and teacher attributes (number, gender, and qualifications). We use administrative data from India's Unified District Information System for Education Plus (UDISE+), the successor to the District Information System for Education (DISE), which has been widely used in economic research on education and infrastructure (e.g., Adukia et al., 2020; Jagnani and Khanna, 2020; Khanna, 2023).

To facilitate program delivery, treatment modalities were assigned at the district level: Ghazipur and Gonda implemented the higher-intensity MSL model, while Lucknow and Varanasi implemented

[5]UDISE is one of the largest management information systems initiated by the Department of School Education and Literacy, Ministry of Education, Government of India, covering over 1.48 million schools, 9.5 million teachers, and 265 million students. UDISE+ is its updated digital platform, operational since 2018–19, which collects school-level data in real time for planning, resource allocation, and program monitoring.

the lower-intensity LoB model. Within each district, schools were stratified by geographic block and randomly assigned to treatment or control within strata.[6] The distribution of schools by district was as follows: Ghazipur (30 schools: 15 treatment, 15 control), Gonda (28: 15 treatment, 13 control), Varanasi (52: 27 treatment, 25 control), and Lucknow (26: 15 treatment, 11 control). Following randomization, 4 schools declined participation (three from the MSL treatment and 1 from the LoB treatment), yielding a final analysis sample of 132 schools: 55 in the MSL arm (27 treatment, 28 control) and 77 in the LoB strata (41 treatment, 36 control). The geographic distribution of study schools is shown in Figure 2.

Timeline. The intervention was implemented from August 2022 through February 2023, following permissions from the Uttar Pradesh Basic Education Board and formal consent from school administrations. Each treatment school received one monthly visit during the academic year, with every session structured according to the standardized experiential learning model described in Section 2.2 and in Table 1. Endline data collection took place from February to March 2023, approximately two weeks after the final Agastya session, allowing sufficient time for instructors to complete all scheduled visits.

2.5 Treatment Arms

The remaining 132 schools were assigned to three arms: two treatments and their respective control groups. Each treatment was evaluated against its own control arm within the same district–block strata. Both treatment arms implemented the same discovery-based science pedagogy but differed in instructional intensity, staffing, and logistical complexity.

Control schools were defined separately for each treatment arm to ensure within-strata comparability. The control group comprised 64 schools-28 schools in the MSL control group and 36 schools in the LoB control group-that continued business-as-usual instruction with no exposure to Agastya sessions, materials, or instructors. Students in control schools attended regular science classes following the standard teacher-centric, lecture-based pedagogy described in Section 2.2. Survey instruments, testing protocols, and data collection procedures were identical across all arms to ensure comparability.

2.5.1 Treatment Arm 1: Mobile Science Lab (MSL)

In Treatment Arm 1 (MSL), 27 schools in the treatment group and 28 schools in the corresponding control group were included. Treatment schools received the higher-intensity experiential learning intervention, delivered through monthly visits by a van equipped with portable science kits and

[6]Blocks (strata) by district: Ghazipur (Sadar, Manihari, Zakhania); Gonda (Jhanjhari, Mujhena); Lucknow (Chinhat, Mohanlal Ganj); Varanasi (Chiraigaon, Harhua 1, Harhua 2, Sewapuri, Kashi Vidyapeeth).

staffed by a three-member instructor team plus driver. Each instructor was primarily assigned to one grade level (6, 7, or 8) and conducted two separate two-hour sessions per monthly visit—one in the morning and one in the afternoon. Instructors rotated flexibly across grades to ensure standardized delivery while maintaining pedagogical consistency, and each student received approximately four hours of additional science instruction per month. Table 1 provides a summary. Sessions followed the structured pedagogical sequence described in Section 2.2: a *super start* activity to generate curiosity, student-led questioning, guided experimentation addressing those questions, and a *super finish* consolidation. Topics were synchronized with the state curriculum and textbook activity boxes, positioning MSL sessions as a supplement to regular classroom instruction. Because sessions replaced the regularly scheduled science period (and occasionally one additional period) on visit days, the net instructional addition was slightly lower than the nominal four hours. However, the experiential component introduced a fundamentally new learning mode that diverged sharply from standard lecture-based instruction.

The MSL program targeted schools with 120-160 total upper-primary students, with a district-level cap of 2,000-2,200 to ensure operational feasibility and manageable instructor workload. Implementation fidelity was maintained through standardized instructor training, detailed session plans with pre-specified experiments and key message charts, and unannounced monitoring visits by Agastya supervisors.[7] This intensive delivery model increased total science instructional time by approximately 4% relative to the standard 90 hours per year, though the qualitative shift in pedagogy—from passive listening to active experimentation-represents the primary mechanism of change.

2.5.2 Treatment Arm 2: Lab on Bike (LoB)

In Treatment Arm 2 (LoB), 41 schools in the treatment group and 36 schools in the corresponding control group were included. Treatment schools received a lower-intensity version of the same intervention, delivered by a single trained instructor traveling by motorbike with portable science kits. The instructor conducted one two-hour session per grade (6, 7, 8) during each monthly visit. Because a single instructor could not cover all grade sections in one day, visits typically spanned two consecutive days to ensure all students received instruction. Each student therefore received approximately two hours of additional science instruction per month, increasing total science instructional time by roughly 2 percent. Table 1 provides a summary.

The LoB curriculum, pedagogical sequence, instructor training, and monitoring protocols mirrored those of MSL. The key differences lay in staffing intensity (one instructor versus three), total monthly exposure time (2 hours versus 4 hours), and operational scale. The LoB model

[7]Instructors were randomly inspected by supervisors to ensure adherence to the pedagogical approach and session structure.

targeted schools with 60-80 total upper-primary students and a district-level enrollment cap of 1,000-1,200. As in MSL, sessions replaced the regularly scheduled science period and occasionally one additional period, meaning the net instructional addition was slightly below the nominal two hours. Nevertheless, the student-centered, experiential nature of the sessions represented a qualitative departure from standard instruction. This arm tests whether a lower-intensity, lower-cost delivery model can achieve meaningful impacts on student engagement, curiosity, and achievement—an important question for scaling discovery-based pedagogy in resource-constrained public systems.

2.6 Conceptual Framework

We organize our predictions around a model in which instructional context shapes learning through two distinct but interacting channels. The first is a *direct cognitive pathway*, through which hands-on experimentation improves comprehension and retention of scientific concepts by promoting active processing and conceptual integration. The second is an *indirect motivational pathway*, through which changes in students' epistemic states alter engagement, persistence, and effort. Following Lam et al. (2012), engagement, encompassing participation, persistence, emotional connection to learning, and cognitive investment, functions as the central mechanism translating pedagogy into learning outcomes (see Figure 1). When pedagogy activates intrinsic motivation, strengthens self-beliefs, and supports autonomy, it alters not only what students learn but how they engage with learning tasks and perceive their own competence. While both channels likely operate simultaneously, the pattern of non-cognitive shifts and component heterogeneity we document is consistent with a central role for the motivational pathway in translating experiential pedagogy into sustained learning gains.

The experiential learning intervention modifies the instructional context through three interdependent levers aligned with core principles of self-determination theory (Reeve, 2012; Skinner and Pitzer, 2012). The first, *real-life relevance*, connects abstract scientific concepts to students' everyday experiences and local environments, strengthening perceptions of competence by making science accessible and meaningful. The second, *curiosity stimulation*, encourages students to ask questions, form hypotheses, and explore relationships through hands-on experimentation, thereby activating intrinsic motivation and deepening cognitive engagement. Curiosity here is understood as a drive aroused by structured incongruity, namely situations in which competing beliefs or expectations cannot be simultaneously satisfied, that motivates knowledge acquisition through its resolution (Berlyne, 1954). This drive arises not from novelty alone but from the perception of a specific, potentially resolvable gap between what one knows and what one wishes to know (Loewenstein, 1994); effective pedagogy must therefore make knowledge gaps salient before inquiry can take hold. The third, *autonomy support*, allows students to design experiments, interpret results, and articulate reasoning collaboratively, positioning learners as active participants in knowledge construction

rather than passive recipients of information (Fredricks et al., 2004). While the intervention does not explicitly target relatedness, its cooperative structure, through peer collaboration in experiments and group discussions, may foster social connections that further support engagement. Together, these features primarily support students' needs for competence and autonomy, which underpin sustained engagement with learning tasks.

Instruction that supports autonomy, provides optimal challenge, and acknowledges students' perspectives promotes ownership over learning and facilitates the internalization of academic goals. In our setting, external instructors use guided inquiry and low-cost experimentation to connect curricular concepts to familiar contexts, reinforcing both perceived competence and task value. The learning process unfolds through a progression: curiosity is first triggered by surprise and questioning, then nurtured through observation and experimentation, and finally consolidated through student-led synthesis and reflection. Surprise, triggered by violations of prior expectations, precedes and activates curiosity and confusion, both of which independently promote knowledge exploration (Berlyne, 1954; Vogl et al., 2020, 2019). Importantly, these *epistemic emotions* are categorically distinct from *achievement emotions* such as pride and shame: they are triggered by cognitive incongruity rather than by success or failure, and their effects on exploration are consistently positive and mediated through curiosity (Vogl et al., 2020, 2019). This distinction matters for interpretation. Because the intervention targets epistemic states rather than performance feedback, shifts in curiosity, self-confidence, and engagement may precede and potentially mediate improvements in academic achievement. Moreover, because epistemic engagement and sustained cognitive effort are not subject-specific, improvements in students' motivational orientation may generate achievement gains that extend systematically beyond the focal subject, helping to explain the robust gains observed in mathematics and language outcomes alongside science.

Two structural features of this process inform our interpretation of the empirical patterns. The first is *temporality*: motivational and engagement shifts may emerge gradually through repeated exposure, while academic gains reflect both immediate content learning and subsequent consolidation. The second concerns the *role of instructional intensity*. Theory suggests that curiosity is unlikely to arise without a prior knowledge base; it intensifies as students accumulate partial understanding and become aware of specific gaps rather than scaling uniformly with exposure (Loewenstein, 1994). Furthermore, stimuli are most curiosity-arousing at an intermediate degree of familiarity, as too much novelty yields insufficient cognitive conflict to sustain engagement while full assimilation eliminates it (Berlyne, 1954). Together, these theoretical properties suggest that motivational responses may be non-linear in dosage, with meaningful activation of the indirect pathway potentially requiring sufficient cumulative exposure. By contrast, content learning may accumulate more steadily with attendance. We do not treat these as causal claims established by our design; session attendance is endogenous and dose-response patterns are descriptive. Rather, this theoretical backdrop motivates

our focus on the randomized contrast between MSL and LOB as the primary source of causal evidence that intensity shapes effectiveness, and informs our interpretation of the descriptive within-arm patterns as broadly consistent with these predictions.

The broader institutional and social context mediates how these mechanisms unfold. Because instruction is externally delivered, the intervention primarily alters students' learning experiences rather than teacher behavior or classroom pedagogy more broadly. Treatment effects may therefore vary with students' baseline ability, household resources, and participation intensity, reflecting either compensatory dynamics, where the intervention fills gaps for disadvantaged students, or reinforcing patterns, where benefits accrue to those more able to engage with experiential content. Under lower-intensity delivery, where epistemic activation depends more heavily on prior knowledge to render informational gaps salient, reinforcing patterns along baseline ability are more likely to emerge. The framework does not presuppose strong ability sorting in treatment effects: if epistemic activation operates through shifts in perceived competence and task value rather than through advanced prior knowledge, effects may emerge broadly across baseline achievement levels rather than concentrating among the highest-performing students. Family background and peer interactions may further influence receptivity and the persistence of gains. Heterogeneous treatment effects are thus expected primarily along dimensions of delivery intensity and engagement with specific program components rather than pre-existing socioeconomic or academic stratification.

In sum, this framework posits that by realigning classroom practice, even for a limited portion of instructional time, with principles of competence, autonomy, and curiosity, experiential pedagogy can generate meaningful improvements in motivation, engagement, and learning. Rather than transforming stable personality traits, the intervention operates by shifting context-specific epistemic states that govern how students interact with academic material. When sufficiently sustained, these shifts translate into durable cognitive effort and academic gains that extend systematically beyond the focal subject. In low-capacity systems where conventional instruction often constrains curiosity and participation, even modest but salient departures toward inquiry and self-driven exploration may yield potentially large returns in both engagement and achievement.

3 Data Collection, Outcomes Measures, and Validity of the Experimental Design

Our analysis combines administrative data with original survey data collected from students and teachers. Administrative datasets are used to implement school-level randomization, assess balance, and measure academic achievement outcomes. Survey data provide complementary information on student characteristics and post-intervention outcomes that are not captured in administrative

records.

3.1 Administrative Records

3.1.1 School-Level Administrative Data (UDISE)

We use school-level administrative data from the Unified District Information System for Education (UDISE) to construct the sampling frame and implement school-level randomization. UDISE data from the 2020 rounds provide comprehensive pre-intervention information on enrollment, teacher characteristics, and school infrastructure, allowing us to ensure stable measurement of school characteristics prior to program implementation. The variables used for stratification and balance checks span three broad domains: enrollment measures, including grade-wise enrollment, the female share of students, and caste composition; teacher characteristics, capturing the number of teachers, their gender composition, and qualifications; and indicators of physical infrastructure, such as the presence of a boundary wall, the number of classrooms and buildings, availability of toilets and electricity, playgrounds and medical facilities, and the distribution of textbooks and uniforms. Together, these variables allow us to verify that treatment and control schools are comparable along dimensions that plausibly shape learning environments.

3.1.2 Student Achievement Data

We measure academic achievement using student-level administrative test score data obtained from Block Education Offices. Our primary academic outcome is based on the *Nipun Assessment Test* (NAT), a statewide, externally administered standardized assessment conducted by the Government of Uttar Pradesh. Because the NAT is designed and implemented independently of the intervention, it provides an objective measure of learning outcomes that is not subject to experimenter influence. The NAT was administered in December 2022 to students in Grades 6, 7, and 8 in Science, Mathematics, Hindi, and English. The assessment consisted of multiple-choice questions recorded on Optical Mark Recognition (OMR) sheets (see Figure A.1) and was administered under standardized protocols monitored by the state government.[8] Completed OMR sheets were digitized shortly after test completion using the official government application, ensuring timely processing and minimizing scope for manipulation. A subsequent round of the NAT was conducted in September 2023, focusing on Science and Mathematics. Together, these administrative test scores provide externally validated measures of academic performance that complement survey-based outcomes.

[8]The state planned to ensure a fair and transparent assessment through flying squads at the block level, strict monitoring, and cross-vigilance (Source: https://timesofindia.indiatimes.com/education/news/nat-2023-nipun-assessment-test-begins-in-council-schools-across-uttar-pradesh/articleshow/103565887.cms). The marks were scanned through the "Saral App" (mobile application) after the assessment. The total exam duration was 1:30 hours, and all subject questions were combined.

3.2 Student Surveys

3.2.1 Pre-Intervention Student Survey

A student-level survey was administered after school-level randomization and prior to the start of the intervention (July 2022, N = 12,318) in 132 school using OMR sheets. This survey collected information on students' demographic and socioeconomic characteristics, including gender, parental education, household assets, and household size. While comprehensive in capturing student characteristics, the survey deliberately excluded measures of primary learning or non-cognitive outcomes to minimize respondent burden and avoid priming effects. These data serve two distinct purposes: documenting the composition of the study sample and enabling robustness checks that condition on student-level characteristics.

Our primary specifications rely on randomization alone for identification, consistent with McKenzie (2012) and recent guidance from Kerwin et al. (2024). Including baseline controls is not required for consistency and may reduce statistical power when baseline data are incomplete. Moreover, conventional balance tests at the individual level are prone to over-rejection in large samples, potentially leading to unnecessary concerns about randomization quality. We therefore present our main results controlling only for the school-level characteristics used in the randomization procedure. Specifications that additionally include pre-intervention student-level controls are reported as robustness checks.

3.2.2 Endline Student Survey

The endline student survey, administered after the intervention concluded (February–March 2023) across 131 schools ($N \approx 11{,}000$), forms the primary dataset for all empirical analyses. One school from the Lab on Bike group declined to participate in the endline data collection. The survey was conducted in classrooms by trained enumerators using pencil-and-paper instruments recorded on OMR sheets (see Appendix D.2 for a description of the variables and the scales used). The timing of this survey was chosen to coincide with the end of the academic year while minimizing disruption to regular instruction, and it provides the primary source of information on post-intervention student outcomes that are not available in administrative records.

The choice of OMR sheets was motivated primarily by cost considerations relative to the most natural alternative–tablet–or smartphone-based data collection using platforms such as SurveyCTO. Implementing digital surveys at the scale of this study would have been substantially more costly. By contrast, OMR-based data collection allowed the per-student survey cost to be kept below $2, making it feasible to administer a detailed student survey across a large number of schools. In addition to lowering costs, the use of OMR sheets reduced data entry errors by eliminating manual transcription and enabled rapid processing of responses through automated scanning. OMR sheets

also incorporated anonymous barcode identifiers that facilitated reliable linkage of student responses across survey rounds while preserving confidentiality. Taken together, these considerations made OMR-based surveys a practical and reliable approach for collecting high-quality student-level data in this context, despite the constraint that survey questions needed to be structured in a multiple-choice format.

To ensure high coverage, enumerators coordinated with schools in advance, tracked student rosters, and conducted follow-up visits in cases of above-average absenteeism. As a result, coverage in the endline survey was high and balanced across treatment and control schools.

3.3 Teacher Survey

We also administered short surveys to science teachers in both the post-randomization and post-intervention periods. The teacher survey collected information on demographic characteristics, educational background, teaching experience, instructional practices, and pedagogical beliefs (see Appendix D.3 for a description of the variables and the scales used). These data are used primarily to document baseline instructional environments and to assess whether the intervention affected reported teaching practices, rather than to identify treatment effects.

3.4 Outcome Variables

Our outcome measures follow the contextual model of engagement (Lam et al., 2012), which conceptualizes student outcomes as arising from the interaction of motivational beliefs, engagement behaviors, and academic performance. This framework allows us to examine whether experiential science instruction affects not only what students learn, but also how they perceive learning and how they engage with school. We organize outcomes into two groups. Primary outcomes—reported in Tables 2–5—capture changes in motivational beliefs, engagement, and achievement directly targeted by experiential pedagogy. Secondary outcomes—reported in Table 6—capture broader spillovers, higher-order skills, and exploratory non-cognitive traits. Appendix D provides detailed survey instruments, response scales, and index construction.

3.4.1 Primary Outcomes

Primary outcomes capture changes in motivational beliefs, engagement, and science achievement directly targeted by experiential pedagogy. We organize them into three families: personal factors, engagement factors, and student performance.

Personal Factors. We measure five outcomes reported in Tables 2: curiosity, self-confidence, barriers to education, aspiration, and self-efficacy. Curiosity and self-confidence are drawn from

two sub-components of the Attitudes Toward Critical Thinking Scale (ATCT) developed for adolescents by Manassero-Mas et al. (2022), which adapts elements of the California Critical Thinking Dispositions Inventory originally designed for adults. Curiosity is measured using five items on a seven-point Likert scale capturing students' intrinsic inclination to explore new ideas and enjoy the learning process (e.g., "I am curious because I try to find out what I don't know"; "I enjoy learning new things"; one item is reverse-coded). Self-confidence is measured using six items on the same scale, reflecting trust in one's own reasoning and problem-solving abilities (e.g., "I am able to understand things by myself"; "I notice that I reason better and better"; one item reverse-coded). Aspiration captures the highest level of education students intend to complete (up to Class 8, Class 10, Class 12, or a college degree), following Carlana et al. (2022). Self-efficacy measures students' perceived likelihood of achieving a college degree, independent of their stated aspiration. Barriers to education aggregates students' assessments of four potential obstacles to achieving their educational aim: economic resources, family needs and expectations, gender or caste prejudice, and not feeling academically up to the standard. These measures are collected at endline only, as they capture dispositions shaped by exposure to inquiry-based pedagogy rather than pre-existing traits.

Engagement Factors. We measure six outcomes reported in Table 3, spanning affective, behavioral, and cognitive dimensions of engagement (Fredricks et al., 2004): science interest, self-perceived performance in science, understanding of the science teacher, school enjoyment, a composite engagement index, and attendance. Science interest is constructed from three items assessing students' enjoyment of science, their perception that science explains how the world works, and their interest in conducting experiments. Understanding of the science teacher is an index of five items capturing perceived clarity of instruction—whether the teacher is easy to understand, provides clear answers to questions, explains science well, uses varied teaching methods, and re-explains topics when needed. Self-perceived performance in science aggregates five items on students' academic self-concept in science, including beliefs about doing well, learning quickly, and not finding science confusing or harder than other subjects. School enjoyment is measured by a single item on students' enjoyment of going to school. The composite engagement index is adapted from Skinner et al. (2009) and aggregates items covering effort, participation, attention, listening carefully, homework completion, help-seeking, independent study, and engagement with science outside the classroom. Attendance is measured using students' self-reported number of days absent in the past week, so that lower values correspond to higher attendance.

Student Performance. We measure science learning using two complementary approaches. First, we administer curriculum-aligned science assessments distinguishing between rote-based questions that test factual recall and application-based questions that require students to apply scientific reasoning to novel scenarios.[9] Second, we use student-level administrative test scores

[9]For example, a rote-based question asks students to identify the medium in which sound travels fastest (solid, liquid, gas, or vacuum). In

from the *Nipun Assessment Test* (NAT), a statewide standardized assessment administered by the Government of Uttar Pradesh across Grades 6–8 in December 2022, covering Science, Mathematics, Hindi, and English. Because the NAT is designed and administered independently of the research team, it provides externally validated achievement measures not subject to experimenter influence. We use NAT science scores as the primary achievement outcome and also use the September 2023 NAT round (Science and Mathematics) to examine persistence of impacts. To assess spillovers beyond science, we additionally analyze NAT scores in mathematics, Hindi, and English.

3.4.2 Secondary Outcomes

Secondary outcomes capture broader higher-order skills and non-cognitive traits that, in the conceptual framework, arise indirectly as changes in motivation and engagement translate into sustained learning behaviors beyond the directly targeted domain. These outcomes are reported in Table 6.

Creativity. We measure creativity using a divergent thinking task based on the Alternative Uses Test. Students are asked to generate alternative uses for common objects (e.g., plastic bottles, old newspapers, and rags). We construct two measures: (i) fluency, defined as the total number of valid uses generated, and (ii) originality, based on independent evaluations by coders blind to treatment status. This non-self-reported measure captures whether experiential learning translates into enhanced creative thinking.

Sociability and Big Five Personality Traits: As exploratory outcomes, we examine whether exposure to experiential, inquiry-based instruction affects students' social behavior and personality traits related to learning and exploration. Sociability is proxied by the number of friends students report. Personality is measured using a short inventory adapted from the Ten-Item Personality Inventory (TIPI) developed by Gosling et al. (2003), providing brief measures of the Big Five traits: extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience. These outcomes are not direct targets of the intervention and are therefore interpreted cautiously, as suggestive evidence on broader non-cognitive spillovers rather than central program impacts.

3.5 Independent Variables

Participation Intensity. Participation intensity is measured by the number of sessions each student reported attending. To minimize recall bias, enumerators listed each session by topic on the blackboard at endline, helping students identify which sessions they had attended. Among treated

contrast, an application-based question asks students to rank the force of friction experienced by a toy car on different surfaces (wet marble floor, dry marble floor, newspaper, and towel), requiring conceptual application to a novel scenario.

students, reported attendance ranged from 0 to 6 sessions.[10] Students with no or inconsistent responses are conservatively assigned zero sessions. The average number of sessions attended is 3.6 for MSL and 3.1 for LoB; excluding these students, the averages are 3.9 and 3.6, respectively.

Pedagogical Features. To examine which components of the intervention drove student engagement, we exploit variation in what students reported enjoying about the sessions. Students were asked to identify which aspects they liked most from a pre-defined list: group activity, science experiments, real-life examples, freedom to express, and instructional style; students could select multiple options or indicate they enjoyed none. Among MSL students, science experiments were the most commonly liked feature (49%), followed by instructional style (19%). The pattern is similar for LoB students, with science experiments again ranked first (40%) and group activities and instructional style each cited by 17–18% of students. Approximately 5% of students in both arms reported not enjoying any aspect of the intervention. For the empirical analysis, we define a binary indicator for each feature equal to one if a student reported liking that attribute, and interact these indicators with the treatment dummy.

Household Wealth. We construct a household asset index to proxy for socioeconomic status. The index aggregates information on housing quality (number of rooms and roof material), ownership of durable assets (motor vehicles, television, and phone type), and livestock holdings. These items are reported by students in the endline survey and are standard proxies for household wealth in settings where income data are unreliable or unavailable. We standardize the index relative to the control-group mean and standard deviation, and define a low-asset dummy equal to one for students below the median, which is used in heterogeneity analyses.

3.5.1 Index Construction and Social Desirability

For outcomes measured using multiple survey items, we construct standardized indices by aggregating the relevant component items and normalizing them relative to the control-group mean and standard deviation. Prior to aggregation, items are recoded as necessary to ensure consistent directionality across questions, so that higher values uniformly correspond to more favorable outcomes. Unless otherwise noted, treatment effects are reported in standard deviation units, facilitating comparison across outcomes measured on different scales and constructed from different underlying items.

Because several outcomes rely on self-reported measures, we additionally administer a short social desirability scale originally developed by Crowne and Marlowe (1960) and subsequently adapted into a reliable and valid short form by Hays et al. (1989). This measure allows us to assess

[10]The full distribution for MSL is as follows: 0 sessions (58 or 2%), 1 session (384 or 13.4%), 2 sessions (315 or 11%), 3 sessions (278 or 9.8%), 4 sessions (316 or 11%), 5 sessions (470 or 16.4%), and 6 sessions (828 or 28.9%); an additional 214 students (7.5%) gave no or inconsistent responses. For LoB: 0 sessions (121 or 2.7%), 1 session (682 or 15%), 2 sessions (558 or 12.3%), 3 sessions (671 or 14.7%), 4 sessions (425 or 9.3%), 5 sessions (455 or 10%), and 6 sessions (1,045 or 22.9%); 598 students (13.1%) provided no or inconsistent responses. These students are assigned zero sessions and a separate indicator dummy is included in all specifications.

whether treatment effects are driven by differential response tendencies rather than substantive changes in students' behaviors or beliefs. Social desirability scores are included in robustness analyses, and the estimated treatment effects are not sensitive to their inclusion. Appendix D.4 provides detailed item-level descriptions, response scales, and index construction for the social desirability scale.

3.6 Validity of the Experimental Design

3.6.1 Baseline Balance

We assess randomization validity by examining pre-intervention balance in school-level characteristics drawn from the 2020 round of the Unified District Information System for Education (UDISE), which were used to stratify schools prior to assignment. These data capture three broad dimensions of the school environment: enrollment characteristics (total enrollment in Grades 6, 7 and 8, female share, and caste composition), teacher characteristics (number of teachers, gender composition, qualification levels, non-teaching staff, and student–teacher ratios), and physical infrastructure (boundary walls, buildings and classrooms, toilet facilities, playgrounds, electricity, medical facilities, and the distribution of free textbooks and uniforms per student).

Baseline balance statistics are reported in Appendix A for the final analysis sample, which excludes four schools—three in the MSL arm and one in the LoB arm—that declined to participate after randomization.[11] For the Mobile Science Lab (MSL) intervention, Appendix Table A.1 shows that treatment and control schools are well balanced across virtually all enrollment, teacher, and infrastructure characteristics. Differences in mean enrollment, gender composition, caste shares, teacher staffing, student–teacher ratios, classroom availability, and access to core facilities are small in magnitude and statistically insignificant. The only exception is the presence of concrete boundary walls, which is more common among treatment schools; this difference is isolated and does not extend to other infrastructure measures or translate into systematic differences in the composite infrastructure index.

For the Lab on Bike (LoB) intervention, Appendix Table A.2 presents a similarly detailed comparison. Treatment and control schools are closely balanced in terms of enrollment size, gender composition, caste composition, and most infrastructure indicators. At the same time, LoB treatment schools exhibit modestly higher baseline teacher staffing levels, lower student–teacher ratios, and a greater number of teachers with graduate degrees. These differences reflect variation in pre-existing teacher resources rather than student composition or physical infrastructure, and we account for them in the main empirical specification by controlling for the full set of school-level covariates.

[11] Appendix Tables B.7 and B.8 report balance for the full randomized samples of 30 treatment and 28 control schools (MSL) and 42 treatment and 36 control schools (LoB), prior to any attrition.

Taken together, the balance results for both interventions are consistent with successful randomization and suggest that estimated treatment effects are unlikely to be driven by systematic pre-treatment differences between treatment and control schools.

3.6.2 Descriptive Statistics

Appendix Table A.3 reports student-level descriptive statistics for the post-randomization sample of 14,203 students surveyed at baseline—5,750 in Mobile Science Lab (MSL) schools (2,863 treatment and 2,887 control) and 8,453 in Lab on Bike (LoB) schools (4,392 treatment and 4,061 control). The table summarizes student characteristics by intervention type and is intended to describe sample composition rather than to assess treatment–control balance.

Both samples exhibit broadly similar demographic and socioeconomic profiles. Students are concentrated in lower grades: in MSL schools, 38% of students are in Grade 6, 35% in Grade 7, and 27% in Grade 8; in LoB schools, the corresponding shares are 39%, 32%, and 28%. Average student age is 12.7 years in MSL schools and 12.8 years in LoB schools, with near gender parity—approximately 53% of students are female in both samples. Parental education levels reflect the predominantly rural context: fathers have, on average, 8.4–8.6 years of schooling and mothers about 7.0–7.1 years across the two intervention areas.

The main difference between the samples arises in occupational composition. In MSL schools, 37% of fathers are employed in agriculture, compared with 27% in LoB schools, with a corresponding shift toward other occupations (including non-working) in the LoB area. Shares of self-employed and salaried fathers are similar across interventions, at roughly 20–21% and 10–12%, respectively. Household characteristics are also comparable: average household size is 7.2 members in MSL schools and 6.8 members in LoB schools, and the household wealth index is nearly identical across samples (2.85–2.86).

Overall, these descriptive statistics indicate that students across the two intervention areas are drawn from similar populations, with modest differences reflecting local economic conditions rather than systematic selection. The largely rural and resource-constrained setting of the sample provides important context for interpreting the intervention effects estimated in subsequent sections.

3.6.3 Implementation Fidelity and Program Exposure

Exposure to the intervention was tracked through three complementary sources: (i) instructor attendance logs recording session completion and duration, (ii) student self-reports of participation captured in the endline survey, and (iii) classroom observations during unannounced monitoring visits conducted by Agastya supervisors. Overall compliance was high: 96% of scheduled MSL sessions and 94% of scheduled LoB sessions were completed as planned. Among students in

treatment schools, 78% in MSL and 72% in LoB attended at least four of the six monthly sessions, meeting the pre-specified threshold for substantive exposure to the intervention. No control school received any Agastya sessions, materials, or instructor visits, effectively eliminating concerns about cross-arm contamination. Instructor logs and monitoring records corroborate these attendance figures, indicating minimal reporting bias.

3.7 Pre-Analysis Plan

We adhere to our Pre-Analysis Plan (PAP), which is available and timestamped at RCT ID: AEARCTR-0010902.

The PAP pre-specified our two treatment arms (Mobile Science Lab and Lab-on-Bike), the intent-to-treat estimation strategy with block fixed effects and school-level controls, cluster-robust standard errors at the school level, and our approach to multiple hypothesis testing using FDR-corrected q-values following Benjamini and Hochberg (1995). Our primary outcomes—curiosity, self-confidence, creativity, and commitment and engagement—and secondary outcomes, including content-based learning, aspirations, time use, and attendance, were specified in advance. The PAP also pre-specified heterogeneity analyses along socioeconomic characteristics, parental education, wealth, gender, grade, teacher motivation, and program exposure, as well as the attrition analysis using Lee bounds. Our empirical analysis follows these pre-specified elements closely.

We depart from the PAP in two respects. First, the PAP specified a single index for commitment and engagement; in the paper we disaggregate this into science-specific and general engagement components to provide a richer picture of the intervention's effects, consistent with the conceptual framework. Second, the PAP did not anticipate the availability of externally administered statewide test scores from the Nipun Assessment Test (NAT), which we incorporate as our primary achievement measure given its independence from the research team. We also report additional exploratory analyses—including dose-response patterns by sessions attended, heterogeneity by program components valued by students, and evidence on mediation-consistent mechanisms—that go beyond the PAP but provide insight into the channels underlying our main findings.[12]

4 Estimation Strategy

We estimate the intent-to-treat (ITT) effects of two experiential science pedagogy interventions—the Mobile Science Lab (MSL) and Lab-on-Bike (LOB) on student outcomes. Because each intervention was randomized against its own control group within distinct districts, we estimate their impacts

[12]See Banerjee et al. (2020) for a discussion of the costs and benefits of strict PAP adherence, recommending that the final paper be judged as a distinct object from the "results of the PAP."

separately and do not pool the two experiments. Let $TREAT_s^j$ denote treatment assignment, where $j \in \{\text{MSL}, \text{LOB}\}$, taking the value one if school s received intervention j and zero otherwise. Our baseline empirical specification is:

$$y_{isb} = \alpha_b^j + \beta^j TREAT_s^j + \gamma^j X_s + \epsilon_{isb}^j, \tag{1}$$

where i indexes students in school s located in geographic block b. The outcome y_{isb} denotes student-level measures of motivational beliefs, engagement with school, or academic performance. We include block fixed effects α_b^j because randomization was stratified by block within districts; each block is an administrative sub-division of a district typically consisting of a cluster of villages and sometimes small towns.[13]

Because treatment is assigned at the school level, we cluster standard errors by school. To improve estimation precision, we additionally control for the vector of school-level covariates X_s used in the randomization procedure. These include standardized measures of school resources—non-teaching staff, toilets, graduate teachers, free textbooks, and free uniforms—each scaled by total enrollment in grades 6–8, as well as a school infrastructure index constructed as the sum of five binary indicators capturing the presence of a boundary wall, playground, electricity, medical checkup facilities, and a library. The coefficient of interest, β^j, identifies the causal effect of assignment to intervention j. Throughout the paper, we interpret these estimates as intent-to-treat effects and, for ease of exposition, refer to $TREAT_s^j$ simply as MSL or LOB when presenting results.

We examine heterogeneity in treatment effects along two dimensions using pre-intervention student and school characteristics. First, we explore heterogeneity with respect to treatment-specific characteristics Z_{isb}, such as participation intensity or students' reported liking of specific intervention attributes:

$$y_{isb} = \alpha_b^j + \beta^j TREAT_s^j + \delta^j \left(TREAT_s^j \times Z_{isb}\right) + \gamma^j X_s + \epsilon_{isb}^j. \tag{2}$$

The variables Z_{isb} are observed only for students exposed to the intervention and are set to zero for control students by construction. As such, the interaction coefficient δ^j captures differences in treatment effects associated with variation in participation or reported engagement with specific program features, but does not identify causal moderation effects due to potential selection into participation intensity. We therefore interpret these estimates as descriptive.

Second, we examine heterogeneity by predetermined student- and school-level characteristics I_{isb}, including gender, household wealth, baseline academic ability, and teacher quality measured prior to the intervention:

[13] A block is an administrative sub-division of a district, typically consisting of a cluster of villages and sometimes small towns.

$$y_{isb} = \alpha_b^j + \beta^j TREAT_s^j + \delta^j \left(TREAT_s^j \times I_{isb}\right) + \phi^j I_{isb} + \gamma^j X_s + \epsilon_{isb}^j. \tag{3}$$

Including the main effect ϕ^j ensures that δ^j captures differential treatment effects rather than level differences across subgroups. Teacher quality varies at the grade–school level, but because treatment assignment occurs at the school level, we continue to cluster standard errors by school throughout.

Finally, given the large number of outcomes examined, we address concerns about multiple hypothesis testing using two complementary approaches. We report family-wise error rate (FWER) adjusted p-values using Holm–Bonferroni corrections within outcome families, and false discovery rate (FDR) q-values following Benjamini and Hochberg (1995). These adjustments help distinguish robust treatment effects from chance findings arising from multiple comparisons.

5 Main Results

5.1 Student Engagement with Experiential Pedagogy

The intervention was enthusiastically received by students who participated. Among those who attended at least one session, 81% of students in the Mobile Science Lab (MSL) arm rated the sessions as *good* or *very good*, with only 9% reporting dissatisfaction. In the Lab-on-a-Bike (LoB) arm, 76% of participating students gave positive ratings, while 14% expressed dissatisfaction. When asked what they enjoyed most, students overwhelmingly highlighted the hands-on nature of the instruction: 53% of MSL students and 46% of LoB students cited science experiments as their favorite component, followed by the instructors' explanation style (21% in MSL, with similar patterns in LoB). Notably, 36–39% of students reported that learning through hands-on experimentation was entirely new to their educational experience, and 19–26% found the instructors' teaching approach refreshingly different from regular classroom instruction. Together, these responses suggest that the intervention successfully introduced engaging pedagogical elements that differ meaningfully from business-as-usual teaching, where practical experimentation remains limited despite the presence of activity-oriented material in textbooks.

Participation rates were substantial in both treatment arms. Among surveyed students in treatment schools, 55% of MSL students reported attending at least half of the sessions (three or more out of six), compared to 46% of LoB students. Approximately 27% of MSL students and 35% of LoB students reported attending no sessions, reflecting common implementation realities in rural public schools, where advance communication about visit schedules was not always effective. Importantly, attendance on the survey day itself does not differ between treatment and control schools. These participation patterns are relevant for interpreting our intent-to-treat estimates: the main results capture average effects across all students in treatment schools, regardless of individual attendance.

5.2 Mobile Science Lab: Effects on Human Capital

We estimate specification 1 and report intent-to-treat (ITT) effects in standard deviation units. All outcomes are standardized using the control group mean and standard deviation.

Personal Factors. Table 2 reports effects on five personal dimensions: curiosity, self-confidence, perceived barriers to education, educational aspirations, and self-efficacy. The intervention produces consistent improvements across these outcomes. Against a control mean normalized to zero, curiosity increases by 0.18 sd and self-confidence by 0.16 sd. Perceived barriers, capturing economic constraints, social norms, and self-doubt, decline by 0.23 sd, representing a substantial reduction relative to the control distribution. Educational aspirations improve by 0.15 sd. Self-efficacy increases by 0.085 sd but remains marginally insignificant.

These magnitudes are economically meaningful and comparable to behavioral interventions targeting socio-emotional skills in similar contexts (Alan et al., 2019; Alan and Mumcu, 2024). The intervention's capacity to shift personal factors provides causal evidence that experiential pedagogy can reshape motivational orientations in low-capacity settings. Several mechanisms likely contribute. Hands-on experimentation activates curiosity through direct engagement with scientific phenomena, a process that may trigger dopaminergic reward pathways shown to enhance motivation and memory consolidation (Gruber et al., 2014). Repeated success in conducting experiments builds self-confidence by demonstrating competence and mastery. The student-centered approach, positioning learners as active investigators rather than passive recipients, may reduce perceived barriers by fostering a sense of agency and control over learning outcomes, consistent with self-determination theory showing that autonomy-supportive environments enhance intrinsic motivation (Ryan and Deci, 2000).

Engagement Factors. Table 3 presents treatment effects on academic engagement, measured at two levels: science-specific engagement and broader school engagement. Against a control mean normalized to zero, interest in science increases by 0.18 sd. Perceived understanding of the science teacher improves by 0.16 sd. Self-assessed performance in science rises by 0.15 sd but remains marginally insignificant. Complementing these classroom-based measures, Appendix Table A.38 shows that time spent studying science outside of school increases by 0.22 sd, indicating effects extend beyond formal instruction into students' independent learning activities.

Broader school engagement also improves. Against a control mean normalized to zero, enjoyment of school increases by 0.18 sd, and classroom participation across all subjects improves by 0.17 sd. However, we observe no effect on student-reported attendance over the past week. The control mean is 3.3 days attended, indicating relatively low attendance at endline. The survey was administered shortly before final examinations, a period during which attendance typically declines across schools as students prepare independently or reduce regular classroom attendance. In this context, the absence of a treatment effect likely reflects timing-related and structural constraints

rather than a failure of the intervention to engage students. When attendance is already depressed during examination periods, even highly engaging pedagogy may not translate into additional days physically present at school. The pattern therefore suggests that the intervention operates primarily on the intensive margin, improving attention, participation, and affect conditional on attendance, rather than on the extensive margin of days attended. Structural factors common in rural settings, including examination timing, household responsibilities, and economic constraints, may continue to bind attendance decisions even as classroom engagement improves.

The pattern of results points to two complementary channels. First, improvements in personal factors, particularly curiosity and self-confidence, appear to make students more favorably disposed toward learning generally. Second, the pedagogy itself introduces new participation norms that carry over beyond science. In Indian public schools, instruction typically emphasizes covering the prescribed grade-level syllabus over student-centered engagement, with pedagogy dominated by teacher-centered instruction, rote learning, and limited opportunities for student questioning and active participation (Banerjee et al., 2017; Brinkmann, 2015). The MSL intervention disrupts this norm by creating an environment where curiosity is legitimized and participation expected. Because attendance remains unchanged while participation increases, these gains reflect intensive rather than extensive engagement: the intervention shifts how students interact with instruction, not merely time in school. This behavioral shift appears portable: students who learn to ask questions and engage actively in science carry these habits to other subjects, explaining broad-based engagement improvements.

Performance. We examine performance using three complementary measures: state-administered standardized tests, customized conceptual assessments, and a creativity task.

State-administered tests. Table 4 reports subject-specific treatment effects using administrative data from the Nipun Assessment Test, covering the full universe of students enrolled in the sampled grades. Outcomes are standardized relative to the control group. The MSL intervention generates sizeable gains across all subjects: science scores increase by 0.28 sd, mathematics by 0.34 sd, English by 0.32 sd, and Hindi by 0.22 sd. These effects are economically meaningful and precisely estimated. We report estimates using the full universe of enrolled students rather than restricting to matched survey–administrative records in order to avoid potential bias arising from name-matching errors.[14]

The breadth of these gains is notable. Although the intervention was delivered through science instruction, improvements extend meaningfully to mathematics and language. This pattern is consistent with foundational accounts of epistemic curiosity. In Berlyne (1954) framework, curiosity is a knowledge-oriented drive triggered by novelty, complexity, and cognitive conflict. When

[14]The Nipun Assessment framework links test records to official enrollment data to reduce "ghost enrollment." Results are similar in magnitude and significance when restricting to matched survey–administrative observations; available upon request.

learners encounter discrepancies between expectations and outcomes, they experience informational incongruity that motivates exploratory behavior aimed at resolving that tension. Loewenstein (1994) formalizes this intuition in the information-gap model, in which curiosity arises when individuals perceive a gap between what they know and what they would like to know, generating an intrinsic incentive to seek information. Both perspectives emphasize that curiosity alters the learner's orientation toward information more generally, not merely toward the specific stimulus that triggered it.

The design of the MSL intervention deliberately introduces such informational gaps. Students are encouraged to generate predictions, observe unexpected outcomes through hands-on experimentation, and reconcile conflicting explanations. These pedagogical moments increase the salience of missing knowledge and invite active resolution. If curiosity shifts students into a more exploratory and attentive learning state, then its effects need not remain confined to science content. Evidence from neuroscience suggests that states of heightened curiosity are associated with stronger encoding and memory consolidation, including for material encountered incidentally during the same learning episode (Gruber et al., 2014). From this perspective, curiosity may operate less as a subject-specific input and more as a learning-state amplifier that raises receptivity to instruction across domains. Consistent with this interpretation, Alan and Mumcu (2024) document cross-subject spillovers from curiosity-enhancing pedagogy in a large-scale Turkish intervention, with gains extending beyond science and persisting over time.

The fact that mathematics and English gains are comparable to, and in the case of mathematics exceed, science gains suggests that the intervention shifted students' overall engagement with academic tasks rather than simply improving mastery of specific science content. An alternative, though not mutually exclusive, interpretation is that because the Nipun assessment integrates multiple subjects within a single testing session, heightened engagement during science sections may have carried over mechanically into subsequent mathematics and language sections through improved test-taking performance. These two interpretations carry different implications: the curiosity channel reflects a genuine human capital effect, whereas the test-taking channel reflects a within-session artifact. Our design does not permit a formal discrimination between them, and we note this as a limitation in interpreting the cross-subject gains. Taken together, the administrative results are consistent with a mechanism in which curiosity, understood as a response to perceived knowledge gaps and cognitive conflict, reshapes students' learning states in ways that generate broad improvements in measured achievement, though the precise channel through which non-science gains arise remains an open question.

Survey-based assessments. Table 5 examines performance on customized tests designed to capture conceptual understanding beyond standardized state assessments. Against a control mean of zero, we find no significant treatment effects on rote-based questions, application-based questions,

overall conceptual scores, or on the creativity task measuring divergent thinking. These null effects stand in contrast to the substantial gains of 0.22–0.34 sd observed on state-administered tests and therefore require interpretation.

The absence of detectable effects on conceptual and creativity measures is not necessarily inconsistent with the curiosity-based mechanism discussed above. In Berlyne (1954) account, curiosity is fundamentally a drive to reduce cognitive conflict or informational incongruity, with exploratory behavior directed toward resolving uncertainty. Loewenstein (1994) similarly emphasizes that curiosity is strongest when a knowledge gap is salient and perceived as tractable. In both frameworks, the immediate consequence of curiosity is increased information-seeking and attention to available cues. Neuroscientific evidence further suggests that heightened curiosity strengthens memory consolidation for material encountered during these states (Gruber et al., 2014). Together, these perspectives imply that curiosity may first manifest in improved engagement and retention of curricular content. By contrast, the higher-order conceptual synthesis and cognitive flexibility captured by our customized assessments likely require more sustained cycles of explanation, abstraction, and integration across contexts. Our survey instruments, designed by the research team to probe deeper analytical reasoning, proved substantially more demanding than the content students typically encountered in their classrooms.

The timing of assessments may also be informative. State examinations were administered in December 2022, when intervention activities were still fresh and classroom engagement was likely at its peak, while our customized survey tests were conducted two to three months later in February–March 2023. If curiosity-induced engagement naturally diminishes without continued reinforcement, as Berlyne's framework suggests since exploratory drive requires ongoing novelty and cognitive conflict to persist, the state exams may have captured students at a more favorable moment for demonstrating intervention effects, particularly for demanding conceptual material that extends beyond standard curricula. While curiosity may create favorable conditions for learning, the transformation of underlying cognitive structures typically depends on repeated practice and extended reinforcement. In this sense, the intervention may have shifted students into a more engaged and attentive learning mode, sufficient to improve performance on standardized tests that reward retention and procedural fluency, without yet altering deeper reasoning skills within the study horizon. Alan and Mumcu (2024) document precisely this temporal pattern: their curiosity-enhancing pedagogy generated immediate gains on standardized assessments, with effects on knowledge retention persisting and even strengthening three years post-intervention, suggesting that curiosity's cognitive benefits accumulate gradually rather than appearing immediately in more demanding conceptual measures.

The divergence between administrative and customized assessments therefore helps delineate the scope of the intervention's impact. The results suggest that the program raised attention,

engagement, and memory for curricular material, but that more complex cognitive transformations may require longer exposure or complementary instructional supports. Rather than contradicting the curiosity mechanism, the pattern underscores its likely temporal and developmental limits within the time-frame of the study.

Non-cognitive Outcomes. Beyond academic performance, we examine whether the intervention affects broader non-cognitive dimensions outside the classroom. Table 6 reports treatment effects on sociability, proxied by the number of friends, and on the Big Five personality traits: extroversion, agreeableness, conscientiousness, emotional stability, and openness. All outcomes are standardized relative to the control group. We find no statistically significant impacts on sociability or on four of the five personality dimensions. The only exception is a small negative effect on conscientiousness. While modest in magnitude, this estimate warrants interpretation. One plausible explanation is that the intervention's emphasis on questioning, experimentation, and active participation altered students' perceptions of routine adherence. Conscientiousness captures traits related to self-discipline, orderliness, and conformity to established routines; greater classroom spontaneity and encouragement of inquiry may have been perceived as a departure from these routines, resulting in slightly lower self-reported conscientiousness.[15]

Taken together, the pattern of results suggests that the intervention shifts education-specific beliefs and behaviors, namely curiosity, confidence, aspirations, and engagement, without meaningfully altering broader socio-emotional traits that are typically understood to be more stable over time. This distinction aligns with evidence that core personality dimensions are relatively resistant to short-run interventions (Heckman and Kautz, 2012), whereas context-specific motivational beliefs and classroom behaviors are more malleable. In this sense, the intervention operates primarily through targeted shifts in how students relate to learning, rather than through broader transformations in underlying personality structure.

Summary. The MSL intervention generates consistent gains along the experiential learning pathway articulated in our conceptual framework. It increases curiosity, confidence, aspirations, and classroom participation; these shifts in student-level engagement are accompanied by substantial improvements in state-administered test scores across subjects. At the same time, the intervention does not alter teachers' instructional practices, does not move more conceptually demanding cognitive outcomes, and does not meaningfully affect broader personality traits.

This pattern is internally coherent. Experiential pedagogy appears to activate motivation and attention, improving procedural learning and performance on curriculum-aligned assessments in the short run. However, deeper analytical reasoning and stable personality traits remain unchanged, suggesting that short-run exposure is insufficient to transform higher-order cognitive skills or enduring socio-emotional dimensions. The results therefore point to both the promise and the limits

[15]This interpretation should be treated cautiously. The effect is small and not accompanied by systematic changes in other personality traits.

of standalone experiential interventions in low-capacity public school systems: they can meaningfully shift how students relate to learning and improve measurable achievement, but sustained structural inputs may be required to convert these gains into deeper cognitive transformation.

5.3 Lab on Bike: Effects on Human Capital

We estimate specification 1 and report ITT effects in standard-deviation units, standardized using the control-group mean and standard deviation.

Personal Factors. Table A.4 reports effects on curiosity, self-confidence, perceived barriers to education, educational aspirations, and self-efficacy. In sharp contrast to the MSL findings, LOB produces no discernible improvements across any dimension. Point estimates are small and statistically insignificant: curiosity (−0.019), self-confidence (0.024), aspirations (0.016), self-efficacy (−0.048), and barriers (0.046). The conceptual framework predicts that motivational shifts require threshold levels of cumulative exposure; below the threshold, epistemic incongruity is insufficient to sustain exploratory drive (Berlyne, 1954; Loewenstein, 1994). With half the monthly instructional time and a single instructor, LOB falls systematically short of this threshold on average.

Engagement Factors. Table A.5 presents treatment effects on engagement. No significant improvements emerge: science interest (0.021), self-perceived performance (−0.069), understanding of the science teacher (−0.068), school enjoyment (−0.010), and the composite engagement index (−0.046) are all near zero. Appendix Table A.39 further shows that LOB reduces time spent on science and other subjects at tuition by 0.34 sd and 0.35 sd respectively, with no compensating gains in home study time, suggesting that the intervention did not shift students' independent learning behaviors outside the classroom. The only statistically significant result in the engagement table is a negative effect on self-reported attendance (−0.298), which is mechanical: endline surveys in LOB schools were conducted closer to final examinations in March, a period when attendance declines across schools regardless of treatment. Without the intensity and novelty of the MSL format, LOB appears unable to shift either the affective or behavioral dimensions of student engagement on average.

Performance. We examine performance using three complementary measures: state-administered standardized tests, customized conceptual assessments, and a creativity task.

State-administered tests. Table A.6 reports subject-specific ITT effects from the Nipun Assessment Test for all 10,289 enrolled students.[16] Point estimates are positive across subjects, namely total (0.21), science (0.12), mathematics (0.14), and Hindi (0.13), but none is statistically significant. English (0.27) is marginally significant at the 10 percent level; we interpret this cautiously as a possible mechanical spillover from faster science-section completion rather than

[16]We were able to match only 4,929 surveyed students to the administrative records; results using the matched sample are similar and available on request.

genuine English learning, given the absence of significant effects in the focal subject.

Survey-based assessments. Table A.7 shows null effects on the researcher-administered science test (0.032), its rote and application sub-scores (0.030 and 0.000), and the divergent-thinking creativity task (−0.136). Intent to choose the science stream is also unchanged (0.026). These results corroborate the administrative score findings: LOB did not generate meaningful learning gains at the level of average ITT effects.

Non-Cognitive Outcomes. Table A.8 reports treatment effects on sociability and the Big Five personality traits. Consistent with the null pattern elsewhere, we find no significant impacts on any dimension except agreeableness (−0.119, $p < 0.05$).[17] The remaining traits, namely extraversion, conscientiousness, emotional stability, and openness, as well as the number of friends, are unaffected.

Summary. LOB produces uniformly small, largely insignificant effects across personal factors, engagement, test scores, and non-cognitive outcomes. Both treatment arms delivered the same curriculum through the same pedagogical sequence; the differences were staffing intensity (one instructor versus three), monthly exposure (two hours versus four), and delivery salience. The absence of average effects in LOB, alongside meaningful gains among students who completed all six sessions (Tables A.9–A.11), points to intensity thresholds as the central mechanism. In low-capacity public school systems, delivering experiential pedagogy at a scale sufficient to sustain novelty and cognitive engagement is necessary, not merely beneficial, for the motivational pathway to activate.

5.4 Are there Spillovers on Regular Teachers?

A natural concern is whether the intervention affected regular classroom instruction, either by crowding out teaching effort or by generating positive spillovers through instructor demonstration effects—given that Agastya instructors modeled inquiry-based methods in the same school environment. Tables A.12 and A.13 examine this by estimating treatment effects on six dimensions of science teachers' self-reported pedagogical practices: instilling belief in students' abilities, instilling motivation, promoting critical thinking, use of science experiments, use of alternative examples, and use of digital equipment. Across all six dimensions and both arms, estimated coefficients are small and statistically insignificant. We find no evidence that MSL or LOB altered how regular science teachers instructed their classes. This null result is informative: it indicates that the intervention operated directly through students' learning experiences during Agastya sessions rather than by transforming the regular instructional environment. While the limited teacher-level sample—45 science teachers in MSL schools and 59 in LOB schools—constrains statistical power, these null results should be interpreted as ruling out large effects on teaching practice rather than effects of any

[17] We again obtain a negative effect on agreeableness. As discussed above for MSL, the intervention's emphasis on questioning and peer debate may lead students to perceive themselves as less deferential, reducing self-reported agreeableness.

magnitude. The consistency of near-zero estimates across all six dimensions nevertheless provides reassurance that instructor demonstration effects were not a primary channel. The achievement and engagement gains documented above therefore reflect student-level responses to the intervention itself, not downstream changes in teacher behavior.

5.5 Mechanisms: Evidence from Heterogeneity

The conceptual framework posits that discovery-based pedagogy affects learning through two margins: (i) immediate attention and encoding during instructional exposure, and (ii) shifts in motivational states induced by sustained informational gaps. The heterogeneity results provide evidence on these comparative statics. Taken together, the patterns admit a parsimonious interpretation in which two functionally distinct channels operate. The first is motivational–epistemic: repeated exposure shifts curiosity, confidence, and engagement. The second is direct and cognitive: heightened attention during sessions improves encoding and short-run content retention. The evidence suggests that these channels differ in their sensitivity to delivery intensity, pedagogical inputs, and baseline student characteristics. Because session attendance is endogenous, the within-arm dose–response patterns we discuss below are descriptive; we interpret them as broadly consistent with the framework rather than as causal estimates. The primary causal evidence that intensity shapes effectiveness comes from the randomized contrast between MSL and LOB.

Exposure gradients. The framework suggests that motivational responses may require sufficiently repeated exposure to generate persistent informational gaps, whereas attention responds contemporaneously to instructional novelty. The dose–response patterns are consistent with this interpretation. For MSL, gains in personal factors and engagement emerge only after five to six sessions, with improvements of 0.15–0.25 sd in curiosity, self-confidence, aspirations, and classroom engagement, and little movement at lower exposure levels (Tables 7 and 8). By contrast, survey-based test performance does not display a comparable gradient (Table 9), suggesting that content acquisition responds more immediately to exposure rather than requiring cumulative activation.

The LOB patterns further inform this interpretation. Rather than a smooth gradient, LOB exhibits a sharp pattern: effects at one to four sessions are null or negative, while students completing all six sessions experience gains of approximately 0.24–0.26 sd across curiosity, self-confidence, and test performance (Tables A.9, A.10, and A.11). These within-arm patterns, while descriptive, are consistent with the theoretical prediction that per-session intensity shapes the cumulative exposure required for motivational responses to materialize. The randomized contrast between arms reinforces this interpretation: higher-intensity delivery generates broad average effects, while lower-intensity delivery produces gains only among students with the highest cumulative exposure.

Pedagogical features. The framework also predicts that instructional components that increase

informational incongruity should affect both attention and motivation, whereas components that primarily structure classroom interaction should operate mainly through motivation. Student-reported salience aligns with this distinction. Among MSL students, those valuing hands-on experiments exhibit gains of 0.20–0.30 sd in personal factors and 0.15–0.18 sd in test performance (Tables A.14, A.15, and A.16), consistent with experiments raising both informational surprise and attentional focus. Valuing instructional style predicts improvements in personal factors but not in test performance (Tables A.16 and A.28), consistent with a predominantly motivational channel. Real-life examples display null or negative associations across both arms (Tables A.14, A.16, A.26, and A.28), suggesting that increased familiarity may reduce informational incongruity without strengthening either margin. Because salience measures are endogenous, these patterns should be interpreted as consistent with, rather than causal proof of, channel differentiation.

Background heterogeneity. The framework further implies that motivational responses depend on sufficient prior knowledge to render informational gaps salient, whereas attentional responses may be strongest among students lacking alternative instructional inputs. The background heterogeneity results align with these predictions. For MSL, neither wealth nor baseline achievement moderates effects (Tables A.17, A.18, A.19, A.23, A.24, and A.25), consistent with high-intensity delivery substituting for household learning complements and cognitive scaffolding. For LOB, lower-asset students experience larger test gains (0.19 sd on the survey-based test), while lower-ability students exhibit weaker or negative interactions (Tables A.29, A.30, A.31, A.35, A.36, and A.37). Under lower-intensity delivery, cognitive gains concentrate among students lacking home inputs, whereas motivational shifts appear to require baseline knowledge sufficient to generate meaningful informational gaps. Gender heterogeneity does not map cleanly onto either channel: MSL performance gains are somewhat larger for boys while LOB engagement gains are somewhat larger for girls, but neither pattern admits a clear mechanism interpretation (Tables A.20, A.21, A.22, A.32, A.33, and A.34).

Synthesis. Across exposure gradients, pedagogical salience, and student background, the heterogeneity patterns are broadly consistent with the comparative statics of the conceptual framework. High-intensity discovery-based instruction is associated with both immediate encoding effects and cumulative motivational shifts. Lower-intensity delivery is associated primarily with short-run content retention, with motivational responses emerging only among students with the highest cumulative exposure. The interpretation consistent with mediation, namely that improvements in personal factors feed into engagement, which in turn supports achievement, is suggested by the sequential pattern of effects across outcome families and the differential response to pedagogical components, though a formal causal decomposition of these pathways lies beyond what our design can establish. While we do not directly observe attention or informational conflict, the systematic differences in outcome domains across arms and the consistency of patterns across multiple

heterogeneity dimensions provide internally coherent evidence that discovery-based pedagogy operates through at least two functionally distinct mechanisms.

5.6 Robustness of the Main Results

Social Desirability Bias. To assess whether the estimated treatment effects on self-reported outcomes are driven by differential tendencies toward socially desirable responding, we re-estimate all specifications controlling for an individual-level social desirability bias (SDB) index, constructed using the short-form Marlowe–Crowne Social Desirability Scale (see Appendix Section D.4). Appendix Table B.1 reports results for MSL effects on personal factors (curiosity, self-confidence, perceived barriers, aspirations, and self-efficacy), Table B.2 for engagement outcomes (science interest, perceived performance, teacher understanding, school enjoyment, engagement index, and attendance), and Table B.3 for non-cognitive measures (number of friends and Big Five personality traits). The corresponding results for the LoB sample are reported in Tables B.4, B.5, and B.6, respectively.

As expected, the SDB index enters significantly across most self-reported outcomes, consistent with students with a higher propensity for socially desirable responding reporting more favorable attitudinal and motivational outcomes; it enters negatively and significantly for perceived barriers to education, reflecting a tendency to underreport constraints. Crucially, however, the inclusion of the SDB index leaves the MSL treatment coefficients on personal factors, engagement, and non-cognitive outcomes essentially unchanged in both magnitude and statistical significance. This stability indicates that the estimated effects are not driven by differential response tendencies across treatment and control groups.

For the LoB sample, treatment effects on personal factors and most engagement and non-cognitive outcomes remain small and statistically insignificant after controlling for SDB. The significant negative effects on attendance and agreeableness observed in the baseline specifications persist as well, confirming that these patterns are not artifacts of socially desirable responding. Taken together, these results suggest that social desirability bias does not meaningfully confound our estimates.

6 Benchmarking Effect Sizes

How does MSL compare to rigorously tested alternatives? Table 10 situates our estimates within the broader literature on education interventions in developing countries, drawing on both cognitive and non-cognitive outcomes where available. Three comparisons are instructive: MSL against India-based benchmarks, against the inquiry-based science literature, and against interventions that similarly target non-cognitive dimensions.

Academic gains in context. MSL's test score gains of 0.34 sd in mathematics, 0.32 sd in English, 0.28 sd in science, and 0.22 sd in Hindi place it in the mid-to-upper range of school-based interventions tested in comparable settings. Banerjee et al. (2007) find 0.14–0.28 sd from remedial tutoring and 0.35–0.47 sd from computer-assisted learning in urban India; MSL's mathematics gain matches the upper end of remedial tutoring but extends across all tested subjects without targeting foundational gaps. Muralidharan et al. (2019) report 0.37 sd in math and 0.23 sd in Hindi from technology-aided afterschool instruction in Delhi, with IV estimates reaching 0.60 sd and 0.39 sd, likely at lower per-student cost given that platform economics favor digital delivery at scale. MSL's gains are also substantially larger than the 0.12 sd from de Barros et al. (2024)'s activity-based mathematics instruction at $7.40 per student annually; as we show below, MSL's direct delivery cost of $5.56 per student is lower, making it more cost-effective on both dimensions simultaneously. The most demanding benchmark is Nourani et al. (2025), who report gains of 0.49–0.83 sd across cognitive dimensions from a teacher-transformation model in Uganda, substantially exceeding MSL's effects, though that intervention operates through deep restructuring of regular classroom teaching rather than supplementary student-facing delivery.

Within the inquiry-based science literature, MSL's 0.28 sd science gain sits within the range from historical meta-analyses, namely 0.26 sd (Shymansky et al., 1990), 0.31 sd (Weinstein et al., 1982), and 0.35 sd (Bredderman, 1983), but below more recent estimates of 0.50 sd (Furtak et al., 2012) and 0.65 sd (Schroeder et al., 2007). The gap is unsurprising: recent meta-analyses disproportionately draw on small, tightly controlled experiments, whereas MSL operates across 27 treatment schools in a low-resource public system. Cross-regional evidence from Bando et al. (2019), pooling ten RCTs from Latin America, shows that short-run effects of 0.14 sd (science) and 0.18 sd (math) compound to 0.23 sd and 0.39 sd after four years. MSL's short-run gains of 0.28–0.34 sd exceed those early benchmarks, suggesting potentially larger long-run returns, though follow-up data are needed to confirm this.

The breadth advantage. The more notable feature of MSL is not the magnitude of its academic gains but their breadth. Most interventions in Table 10 target test scores alone. MSL simultaneously shifts curiosity (+0.18 sd), self-confidence (+0.16 sd), educational aspirations (+0.15 sd), and perceived barriers (−0.23 sd), alongside engagement improvements of 0.17–0.18 sd across affective and behavioral dimensions. The nearest comparator on non-cognitive outcomes is Alan and Mumcu (2024), whose teacher-delivered curiosity curriculum in Turkey yields 0.075 sd in science and 0.11 sd in curiosity at $3.47 per student, substantially cheaper but with effects concentrated on curiosity and knowledge retention, without the broader shifts in aspirations, engagement, and achievement across subjects that MSL produces. Breadth matters for the value calculation: Kautz and Zanoni (2014) find that the OneGoal program increased college enrollment by 10–20 percentage points and reduced male arrests by five percentage points, with 15–30% of these effects mediated through non-cognitive

skills. To the extent that MSL's improvements in curiosity, aspirations, and engagement similarly translate into durable changes in academic effort and attainment, cost-effectiveness ratios based on test scores alone will understate MSL's true returns.

Cost-effectiveness. Delivery cost data from Agastya International Foundation allow us to compute per-student costs directly. The MSL model costs Rs 75 per child per school visit and the LoB model Rs 60, translating to Rs 450 and Rs 360 per student annually, approximately $5.56 and $4.44 at the prevailing exchange rate (Rs 81 per USD).[18] Using the Banerjee et al. (2007) benchmark of 3.01 sd per $100, MSL achieves approximately 5.1 sd per $100 on science and 6.2 sd per $100 on mathematics, 1.7 to 2.0 times more cost-effective than remedial tutoring on academic outcomes alone. For context, Duflo et al. (2015) find 34.78 sd per $100 from contract teacher programs in Kenya, while Duflo et al. (2024) achieve average gains of ∼0.10 sd at $126–161 per student across four scalable Kenyan interventions. MSL's $5.56 places it well below those costs at substantially larger effect sizes. Relative to Alan and Mumcu (2024)'s curiosity curriculum at $3.47 per student, MSL costs modestly more while generating effects roughly 3.7 times larger in science and substantially broader in scope. Cross-regional evidence from Bando et al. (2019) further suggests short-run estimates understate long-run cost-effectiveness: the cost per 0.10 sd gain falls from $18 / $17.90 (math/science) to $8.40 / $10.90 as four-year returns are taken into account.

In sum, MSL occupies a credible position on academic effect sizes and, at $5.56 per student per year, performs favorably on cost-effectiveness relative to comparable interventions. The key open question is persistence: whether the non-cognitive gains in curiosity, aspirations, and engagement documented here translate into durable improvements in educational trajectories and labor market outcomes beyond what test scores alone predict. Establishing this through follow-up data collection would substantially strengthen the case for large-scale adoption.

7 Conclusion

This study contributes to the longstanding debate on how best to strengthen education in systems where conventional inputs—better infrastructure, more teachers, or higher salaries—are difficult to provide and slow to take effect (Chaudhury et al., 2006; Glewwe et al., 2020; Glewwe and Muralidharan, 2016). By focusing on the design of pedagogy rather than the scale of resources, it highlights that even in under-resourced schools, children's orientation toward learning can be shifted in ways that matter for future trajectories. The results underscore the idea, central to recent work in economics and psychology, that curiosity, self-efficacy, and related non-cognitive traits are not

[18] These figures reflect direct Agastya delivery costs: instructor salaries, portable equipment, and transport. They exclude curriculum development amortization, government coordination costs, and the opportunity cost of displaced school periods, and therefore represent a lower bound on full economic cost.

fixed endowments but can be cultivated through deliberate experiences in the classroom (Alan and Mumcu, 2024; Deming, 2017; Gruber et al., 2014; Heckman and Mosso, 2014).

Two broader lessons emerge. First, pedagogy is not a peripheral concern: how material is presented and practiced can shape students' motivation, perseverance, and confidence as much as the content itself. The evidence here resonates with programs that empower adolescents through targeted roles and peer dynamics (Alan and Kubilay, 2025), and with experimental approaches that have restructured classroom routines to unlock learning at scale (Banerjee et al., 2016; Duflo et al., 2012; Muralidharan et al., 2019). Second, intensity is indispensable. The temptation to dilute interventions for cost or logistical reasons is strong, but the contrast between MSL and LOB cautions that doing so risks undermining effectiveness altogether—a point with relevance well beyond science instruction. A lower-intensity version of the same curriculum, delivered by a single instructor for half the monthly exposure, generated limited average effects, suggesting that the pedagogical design and the intensity with which it is delivered are jointly necessary conditions for impact.

Seen through a wider lens, the findings add to a body of evidence that calls for moving beyond a narrow preoccupation with test scores toward cultivating multidimensional human capital. As labor markets increasingly reward adaptability, problem-solving, and socio-emotional skills (Deming, 2017), the case for educational policy that foregrounds curiosity and engagement becomes stronger. In low-capacity environments, where the promise of infrastructure and staffing reforms often lies far in the future, discovery-based pedagogy implemented with continuity offers a credible and immediate pathway. More than an incremental fix, it reflects a broader reorientation of what schools can do: provide not just knowledge, but the dispositions and skills that enable children to keep learning, adapt to change, and participate fully in economic and civic life.

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Figures

Figure 1: Contextual Model of Students' Engagement

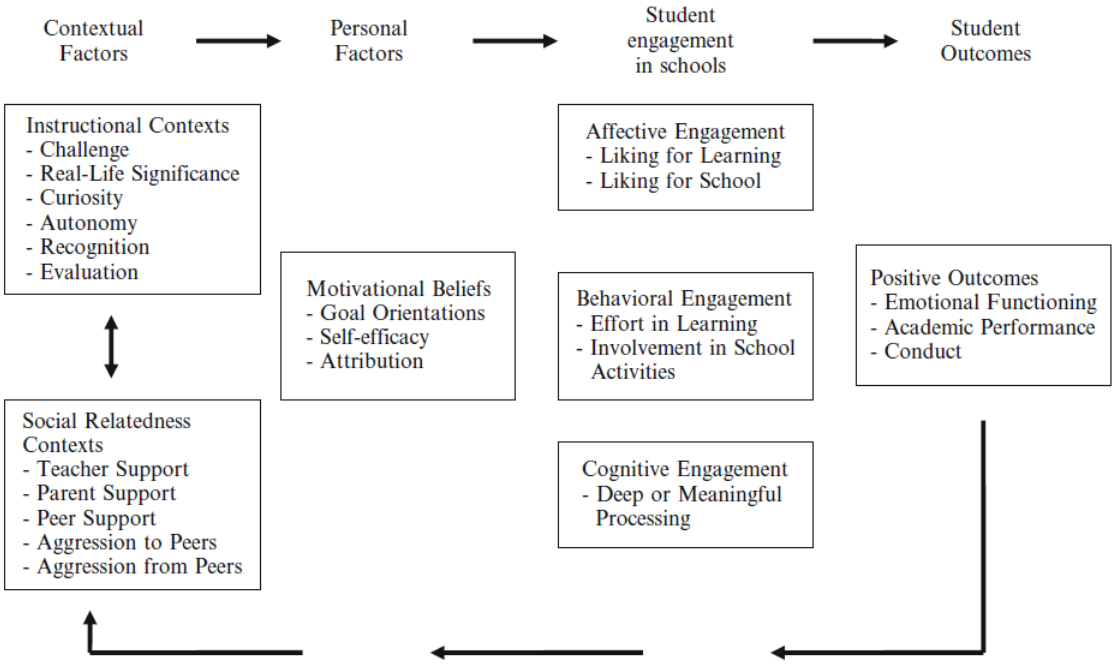
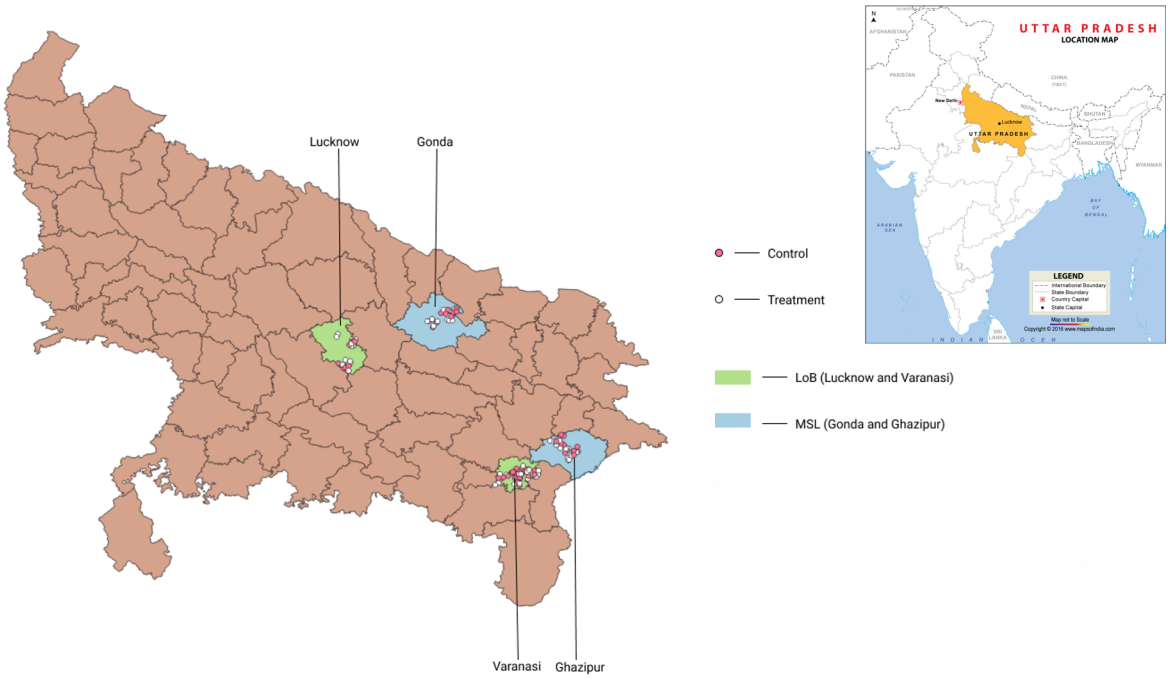


Fig. 19.1 A contextual model for student engagement

Notes: The figure shows a simple diagram of students' model of engagement, borrowed from Lam et al. (2012), p. 406.

Figure 2: Spatial Coverage of the Intervention in Uttar Pradesh



Notes: The figure shows the spatial coverage of our intervention in the districts of Ghazipur, Gonda, Lucknow, and Varanasi in Uttar Pradesh.

Tables

Table 1: Comparison of Mobile Science Lab and Lab on Bike Interventions

Features	**Mobile Science Lab**	**Lab on Bike**
Mode of Delivery	Van with science kits	Bike carrying science kits
Instructor Team	3 instructors + 1 driver	1 instructor
Instructor Responsibility	2 sessions per visit	3 sessions over 2 days
Instructor Quality	Same	Same
Session Time (Hrs)	2	2
Number of Sessions per student	2	1
Instruction Time (monthly)	4 hours	2 hours
Increase in Instruction Time	4%	2%

Table 2: Impact of the Mobile Science Lab on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
MSL	0.179**	0.157*	-0.231***	0.145***	0.082
	(0.077)	(0.081)	(0.068)	(0.051)	(0.051)
Family-wise error rate p-value	[0.001]	[0.000]	[0.001]	[0.000]	[0.001]
False discovery rate p-value	[0.024]	[0.059]	[0.001]	[0.006]	[0.112]
Randomization inference p-value	[0.040]	[0.074]	[0.007]	[0.016]	[0.113]
Control mean	0.000	0.000	0.000	0.000	0.000
Observations	5,750	5,750	5,750	5,386	4,994
R-squared	0.029	0.026	0.027	0.037	0.011
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports the impact of the Mobile Science Lab (MSL) treatment on student personal factors using endline survey data. The analysis sample includes 5,750 students across 55 schools (27 treatment and 28 control schools) in Uttar Pradesh. All dependent variables are normalized indices with mean zero and standard deviation one in the control group. The explanatory variable is a binary indicator for schools assigned to receive the MSL treatment. All specifications include block fixed effects (corresponding to the stratification used in randomization) and school-level controls for baseline characteristics. Column (1) reports treatment effects on the curiosity index, measured using the Hindi Epistemic Curiosity Scale. Column (2) reports effects on the self-confidence index. Column (3) reports effects on the self-perceived barriers to education index (negative coefficients indicate reduction in perceived barriers). Column (4) reports effects on educational goal aspirations. Column (5) reports effects on the self-efficacy index. Robust standard errors clustered at the school level are reported in parentheses. We report three sets of adjusted p-values to account for multiple hypothesis testing: family-wise error rate (FWER) p-values in square brackets using the Romano-Wolf stepdown procedure, false discovery rate (FDR) q-values using the Benjamini-Hochberg procedure, and randomization inference p-values based on 10,000 permutations of the treatment assignment. The sample size varies across columns due to missing responses on specific survey modules. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table 3: Impact of Mobile Science Lab on Engagement Factors

	Science interest	Performance in science	Understand science teacher	Enjoy school	Engagement index	Attendance
	(1)	(2)	(3)	(4)	(5)	(6)
MSL	0.182***	0.147	0.155*	0.184***	0.171**	-0.103
	(0.063)	(0.091)	(0.081)	(0.066)	(0.081)	(0.120)
Family-wise error rate p-value	[0.001]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
False discovery rate p-value	[0.006]	[0.112]	[0.060]	[0.008]	[0.039]	[0.394]
Randomization inference p-value	[0.023]	[0.135]	[0.091]	[0.023]	[0.079]	[0.395]
Control mean	0.000	0.000	0.000	0.000	0.000	3.340
Observations	5,750	5,750	5,750	5,296	5,750	5,019
R^2	0.030	0.029	0.034	0.022	0.028	0.021
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55	55

Notes: This table reports the impact of the Mobile Science Lab (MSL) treatment on student engagement and school participation using endline survey data. The analysis sample includes 5,750 students across 55 schools (27 treatment and 28 control schools) in Uttar Pradesh. All dependent variables except attendance are normalized indices with mean zero and standard deviation one in the control group. The explanatory variable is a binary indicator for schools assigned to receive the MSL treatment. All specifications include block fixed effects (corresponding to the stratification used in randomization) and school-level controls for baseline characteristics. Column (1) reports treatment effects on the science interest index, measuring students' curiosity and motivation toward science subjects. Column (2) reports effects on self-perceived performance in science, capturing students' assessment of their own science abilities. Column (3) reports effects on students' understanding of their science teacher, measuring clarity of instruction and pedagogical effectiveness. Column (4) reports effects on students' enjoyment of attending school, a general measure of school engagement. Column (5) reports effects on the composite engagement index, aggregating multiple dimensions of active participation in school activities. Column (6) reports effects on school attendance, measured as the number of days attended in the reference period (control mean: 3.34 days). Robust standard errors clustered at the school level are reported in parentheses. We report three sets of adjusted p-values to account for multiple hypothesis testing: family-wise error rate (FWER) p-values in square brackets using the Romano-Wolf stepdown procedure, false discovery rate (FDR) q-values using the Benjamini-Hochberg procedure, and randomization inference p-values based on 10,000 permutations of the treatment assignment. The sample size varies across columns due to missing responses on specific survey modules. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table 4: Impact of Mobile Science Lab on Students' Administrative Test Scores

	Aggregate	Science	Maths	English	Hindi
	(1)	(2)	(3)	(4)	(5)
MSL	0.375**	0.281**	0.342***	0.324**	0.218*
	(0.144)	(0.120)	(0.118)	(0.129)	(0.129)
Control mean	0.000	0.000	0.000	0.000	0.000
Observations	7,899	7,899	7,899	7,899	7,899
R-squared	0.205	0.179	0.150	0.153	0.172
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Grade fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports the impact of the Mobile Science Lab (MSL) treatment on students' performance in school-administered examinations using administrative test score data. The analysis sample includes 7,899 students across 55 schools (27 treatment and 28 control schools) in Uttar Pradesh. All dependent variables are normalized test scores with mean zero and standard deviation one in the control group, derived from school-conducted examinations in four core subjects. The explanatory variable is a binary indicator for schools assigned to receive the MSL treatment. All specifications include block fixed effects (corresponding to the stratification used in randomization), grade fixed effects to account for differences across Grades 6–8, and school-level controls for baseline characteristics. Column (1) reports treatment effects on the composite aggregate score index, which combines performance across all four subjects. Column (2) reports effects on the science test score, the primary subject targeted by the MSL intervention. Column (3) reports effects on the mathematics test score, examining potential spillovers to a related STEM subject. Column (4) reports effects on the English test score. Column (5) reports effects on the Hindi test score. The larger sample size compared to survey-based outcomes reflects the availability of administrative records for all enrolled students rather than only surveyed students. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table 5: Impact of Mobile Science Lab on Student Performance

	Science Choice	Test	Rote	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
MSL	0.011	0.004	0.058	-0.036	-0.066
	(0.034)	(0.114)	(0.106)	(0.094)	(0.091)
Control mean	0.370	0.000	0.000	0.000	0.000
Observations	5,750	5,750	5,750	5,750	5,326
R-squared	0.009	0.053	0.068	0.033	0.282
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports the impact of the Mobile Science Lab (MSL) treatment on students' test score outcomes using data from researcher-administered assessments. The analysis sample includes 5,750 students across 55 schools (27 treatment and 28 control schools) in Uttar Pradesh. All test scores and creativity scores are normalized with mean zero and standard deviation one in the control group. The explanatory variable is a binary indicator for schools assigned to receive the MSL treatment. All specifications include block fixed effects (corresponding to the stratification used in randomization), school-level controls for baseline characteristics, and baseline values of the respective dependent variables as additional controls. Column (1) reports treatment effects on students' intent to choose science stream in further studies, measured as a binary indicator (control mean: 0.37, indicating 37% of control students intend to choose science). Column (2) reports effects on the overall science test score, aggregating performance across multiple assessment items. Column (3) reports effects on the rote learning component of the test score, capturing memorization-based knowledge. Column (4) reports effects on the application-based learning component, measuring students' ability to apply scientific concepts to novel problems. Column (5) reports effects on creativity score, assessed through open-ended tasks requiring divergent thinking and problem-solving. The smaller sample size in Column (5) reflects missing responses on the creativity assessment module. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table 6: Impact of Mobile Science Lab on Students' Non-Cognitive Measures

	Friends	Extraversion	Agreeableness	Conscientiousness	Emotional stability	Openness
	(1)	(2)	(3)	(4)	(5)	(6)
MSL	-0.118	-0.221	-0.102	-0.277**	-0.133	-0.177
	(0.137)	(0.155)	(0.128)	(0.120)	(0.118)	(0.126)
Control mean	4.330	4.360	4.490	4.650	4.740	4.470
Observations	5,750	5,166	5,167	5,169	5,168	5,169
R-squared	0.080	0.021	0.024	0.026	0.019	0.022
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55	55

Notes: This table reports the impact of the Mobile Science Lab (MSL) treatment on students' non-cognitive measures using endline survey data. The analysis sample includes 5,750 students across 55 schools (27 treatment and 28 control schools) in Uttar Pradesh. All dependent variables are measured on their original scales rather than normalized indices. The explanatory variable is a binary indicator for schools assigned to receive the MSL treatment. All specifications include block fixed effects (corresponding to the stratification used in randomization) and school-level controls for baseline characteristics. Column (1) reports treatment effects on the number of friends reported by students, with baseline values of the dependent variable included as a control. Columns (2)–(6) report effects on the Big Five personality traits: Column (2) reports effects on extraversion, measuring sociability and assertiveness. Column (3) reports effects on agreeableness, capturing cooperation and compassion. Column (4) reports effects on conscientiousness, measuring organization and dependability. Column (5) reports effects on emotional stability (reverse-scored neuroticism), assessing calmness and emotional regulation. Column (6) reports effects on openness to experience, measuring curiosity and appreciation for novel ideas. The Big Five personality measures are assessed using standard personality inventory items adapted for the study context. Control means indicate the average levels in the control group, measured on the original response scales. The sample size varies across columns due to missing responses on specific personality inventory modules. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table 7: Dose–Response Effects of the Mobile Science Lab on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
MSL × Sessions = 0	-0.303**	-0.172	-0.228**	0.092	-0.039
	(0.116)	(0.107)	(0.101)	(0.158)	(0.188)
MSL × Sessions = 1	0.029	-0.059	-0.213**	0.120	0.124*
	(0.119)	(0.121)	(0.104)	(0.079)	(0.073)
MSL × Sessions = 2	0.092	-0.008	-0.253***	0.088	-0.060
	(0.085)	(0.097)	(0.088)	(0.091)	(0.087)
MSL × Sessions = 3	0.059	0.117	-0.166	-0.038	-0.160
	(0.099)	(0.119)	(0.100)	(0.123)	(0.123)
MSL × Sessions = 4	0.115	0.149	-0.221*	0.078	0.208**
	(0.126)	(0.107)	(0.132)	(0.085)	(0.081)
MSL × Sessions = 5	0.340***	0.302***	-0.364***	0.272***	0.163
	(0.100)	(0.109)	(0.115)	(0.082)	(0.111)
MSL × Sessions = 6	0.308***	0.275***	-0.225**	0.238***	0.142**
	(0.078)	(0.096)	(0.085)	(0.053)	(0.064)
Control mean	-0.000	0.000	-0.000	-0.000	0.000
Observations	5,750	5,750	5,750	5,386	4,994
R^2	0.039	0.036	0.029	0.043	0.018
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects by participation intensity in the Mobile Science Lab (MSL) intervention using endline survey data from 5,750 students across 55 schools (27 treatment and 28 control schools). The explanatory variables interact a school-level indicator for assignment to MSL with the number of sessions attended by each student (0 to 6 sessions), following specification 2. The omitted category is students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. All specifications include block fixed effects corresponding to the stratification used in randomization and school-level baseline controls. Column (1) reports effects on the curiosity index. Column (2) reports effects on the self-confidence index. Column (3) reports effects on the self-perceived education barriers index. Column (4) reports effects on students' goals and aspirations to study further. Column (5) reports effects on the self-efficacy index. Robust standard errors clustered at the school level are reported in parentheses. The sample size varies across columns due to missing responses on specific survey modules. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table 8: Dose–Response Effects of the Mobile Science Lab on Engagement Factors

	Science interest	Performance in science	Understand science teacher	Engagement index
	(1)	(2)	(3)	(4)
MSL × Sessions = 0	-0.352**	-0.365**	-0.308*	-0.327**
	(0.149)	(0.155)	(0.175)	(0.132)
MSL × Sessions = 1	0.042	-0.078	0.014	-0.008
	(0.115)	(0.112)	(0.120)	(0.128)
MSL × Sessions = 2	0.094	0.033	-0.035	0.077
	(0.093)	(0.099)	(0.098)	(0.100)
MSL × Sessions = 3	-0.081	0.063	0.015	0.034
	(0.134)	(0.119)	(0.105)	(0.104)
MSL × Sessions = 4	0.031	0.148	0.083	0.155
	(0.087)	(0.120)	(0.117)	(0.113)
MSL × Sessions = 5	0.392***	0.242**	0.333***	0.305***
	(0.086)	(0.110)	(0.100)	(0.108)
MSL × Sessions = 6	0.387***	0.305***	0.299***	0.314***
	(0.064)	(0.101)	(0.083)	(0.087)
Control mean	0.000	0.000	-0.000	-0.000
Observations	5,750	5,750	5,750	5,750
R^2	0.052	0.041	0.046	0.039
Block fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55

Notes: This table reports heterogeneous treatment effects by participation intensity in the Mobile Science Lab (MSL) intervention on engagement-related outcomes using endline survey data from 5,750 students across 55 schools. The explanatory variables interact a school-level indicator for assignment to MSL with the number of sessions attended by each student (0 to 6 sessions), following specification 2. The omitted category is students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. All specifications include block fixed effects corresponding to the stratification used in randomization and school-level baseline controls. Column (1) reports effects on the science interest index. Column (2) reports effects on self-perceived performance in science. Column (3) reports effects on students' understanding of the science teacher. Column (4) reports effects on the composite engagement index. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table 9: Dose–Response Effects of the Mobile Science Lab on Student Performance

	Science Choice	Test score	Rote	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
MSL × Sessions = 0	-0.127**	-0.219	-0.187	-0.166	-0.214**
	(0.062)	(0.157)	(0.133)	(0.162)	(0.098)
MSL × Sessions = 1	0.026	0.002	0.081	-0.081	0.044
	(0.050)	(0.139)	(0.114)	(0.132)	(0.106)
MSL × Sessions = 2	-0.002	-0.028	0.028	-0.055	-0.005
	(0.046)	(0.110)	(0.105)	(0.097)	(0.122)
MSL × Sessions = 3	-0.008	-0.145	-0.038	-0.165	-0.144
	(0.053)	(0.130)	(0.133)	(0.118)	(0.091)
MSL × Sessions = 4	0.027	-0.081	0.029	-0.162	-0.143
	(0.050)	(0.131)	(0.119)	(0.134)	(0.108)
MSL × Sessions = 5	0.007	0.150	0.197	0.100	-0.079
	(0.041)	(0.126)	(0.120)	(0.113)	(0.098)
MSL × Sessions = 6	0.044	0.120	0.099	0.097	-0.009
	(0.042)	(0.148)	(0.128)	(0.124)	(0.105)
Control mean	0.370	0.000	-0.000	-0.000	-0.000
Observations	5,750	5,750	5,750	5,750	5,326
R^2	0.012	0.063	0.073	0.042	0.285
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects by participation intensity in the Mobile Science Lab (MSL) intervention on student performance outcomes using endline survey data. The explanatory variables interact the MSL treatment indicator with the number of sessions attended (0 to 6 sessions), following specification 2. The omitted category is control schools. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Column (1) reports effects on an indicator for choosing the science stream in the future. Column (2) reports effects on the survey-based science test score. Columns (3) and (4) report effects on the rote and application-based components of the test, respectively. Column (5) reports effects on the creativity score. Robust standard errors clustered at the school level are reported in parentheses. The sample size varies across columns due to missing responses on specific modules. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table 10: Benchmarking MSL Effect Sizes Against Education Interventions

Study	Context	Intervention	Effect Size (sd)	Cost-Effectiveness
Panel A: Mobile Science Lab (Current Study)				
MSL	Uttar Pradesh, India (Grades 6–8)	Mobile science laboratories; experiential pedagogy	Math 0.34; English 0.32; Science 0.28; Hindi 0.22; Curiosity 0.16; Self-confidence 0.18; Aspirations 0.15	Rs 75/child/visit × 6 = Rs 450/yr ($5.56); **5.1–6.2 sd per $100**
LoB	Uttar Pradesh, India (Grades 6–8)	Lower-intensity mobile science; single instructor	Avg. ITT null; full-complier survey test: 0.26[†]	Rs 60/child/visit × 6 = Rs 360/yr ($4.44)
Panel B: India-Based Comparisons				
Banerjee et al. (2007)	Urban India, primary	Remedial tutoring; Computer-assisted learning	Remedial 0.14–0.28; CAL 0.35–0.47	3.01 sd per $100
Muralidharan et al. (2019)	Delhi, Grades 6–9 (4.5 months)	Technology-aided after-school instruction	Math 0.37 (ITT), 0.60 (IV); Hindi 0.23 (ITT), 0.39 (IV)	Lower cost per unit learning than govt. provision
de Barros et al. (2024)	India (13 months)	Activity-based math + teacher training	0.12 (lower-order skills)	$7.40 per student per year
Nourani et al. (2025)	Uganda	Learning to teach by learning to learn	Recall 0.49; Understanding 0.54; Reasoning 0.83; Creativity 0.79	Not reported
Panel C: International Comparisons				
Duflo et al. (2015)	Kenya, rural primary	Extra contract teacher; smaller pupil-teacher ratios	0.24 (literacy, math)	34.78 sd per $100
Duflo et al. (2024)	Ghana (500 schools; 4 interventions)	Remedial pull-out; after-school; smaller classes; tracking	Average ~0.10; High fidelity ~0.40	$126–161 initially; ~$21 at scale; 0.06–0.11 sd/$100 (0.36 at scale)
Panel D: Meta-Analyses of Inquiry-Based Science				
Furtak et al. (2012)	Meta-analysis (37 studies, K–12)	Inquiry-based science	Mean 0.50	—
Schroeder et al. (2007)	Meta-analysis (12 studies, US)	Science teaching strategies	Mean 0.65	—
Weinstein et al. (1982)	Meta-analysis (151 studies)	Science curriculum effects	Mean 0.31	—
Bredderman (1983)	Meta-analysis (57 studies)	Activity-based elementary science	Mean 0.35	—
Shymansky et al. (1990)	Meta-analysis (136 studies)	Inquiry-based curricula	Mean 0.26	—
Panel E: Cross-Regional / Non-Cognitive Interventions				
Bando et al. (2019)	Latin America (10 RCTs, 4 countries)	Inquiry and problem-based pedagogy	Short-run: Sci 0.14, Math 0.18; 4-year: Sci 0.23, Math 0.39	$18 (math) / $17.9 (science); $8.4 / $10.9 per 0.10 sd (long-run)
Alan and Mumcu (2024)	Turkey (teacher-delivered)	Curiosity-nurturing curriculum	Science 0.075; Curiosity 0.11	$3.47 per student
Kautz and Zanoni (2014)	Chicago, US (high school)	OneGoal (non-cognitive skills focus)	+10–20 pp college enrollment; –5 pp arrests (male); 15–30% mediated via non-cognitive	Not reported

Notes: Effect sizes reported in standard deviations (sd) unless otherwise noted. ITT = intent-to-treat; IV = instrumental variables accounting for attendance. Cost-effectiveness ratios report sd gains per $100 spent where available. MSL = Mobile Science Lab; LoB = Lab on Bike; pp = percentage points; Sci = Science. MSL and LoB costs are direct delivery costs from Agastya International Foundation (Rs 75 and Rs 60 per child per school visit respectively), covering instructor salaries, equipment, and transport; converted at Rs 81/USD (August 2022–February 2023). These exclude curriculum development, government coordination, and opportunity costs of displaced school time, and represent a lower bound on full economic cost. MSL cost-effectiveness of 5.1–6.2 sd per $100 corresponds to science (0.28 sd) and mathematics (0.34 sd). [†]LoB full-complier estimate is descriptive and not causal. Bando et al. (2019) long-run effects measured at four-year follow-up. Duflo et al. (2024) reports ranges across four scalable interventions. Meta-analyses (Panel D) summarize mean reported effects across studies. Nourani et al. (2025) is an unpublished manuscript.

Online Appendix

for

Science on the Move: How Experiential Pedagogy Shapes Human Capital

Nitin Kumar Bharti Samreen Malik Abhiroop Mukhopadhyay Nishith Prakash

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Table A.1: Pre-Treatment Balance in School Infrastructure: Mobile Science Lab (MSL), 2020

	Control Schools		MSL Schools		
Variable	N	Mean (SE)	N	Mean (SE)	Diff. (MSL – Control)
	(1)	(2)	(3)	(4)	(5)
Total enrollment (Grades 6–8)	28	131.68 (11.89)	27	151.74 (9.27)	20.06
Female enrollment share	28	0.51 (0.01)	27	0.49 (0.01)	-0.01
Scheduled Caste enrollment share	28	0.29 (0.03)	27	0.25 (0.03)	-0.04
Other Backward Class enrollment share	28	0.58 (0.04)	27	0.58 (0.04)	0.00
Total teachers	28	7.71 (0.76)	27	7.63 (0.76)	-0.08
Student–teacher ratio (Grades 6–8)	28	25.88 (4.60)	27	26.14 (3.31)	0.26
Female teachers share	28	0.41 (0.06)	27	0.41 (0.05)	0.00
Teachers with graduate degree or higher	28	6.89 (0.69)	27	7.22 (0.74)	0.33
Non-teaching staff	28	0.61 (0.35)	27	0.67 (0.32)	0.06
Dummy for school boundary wall	28	0.54 (0.10)	27	0.74 (0.09)	0.21
Dummy for school boundary wall (concrete)	28	0.46 (0.10)	27	0.74 (0.09)	0.28**
Number of buildings	28	2.54 (0.62)	27	2.48 (0.53)	-0.05
Number of buildings (concrete)	28	2.36 (0.60)	27	2.30 (0.53)	-0.06
Number of toilets for boys	28	1.46 (0.17)	27	1.41 (0.14)	-0.06
Number of toilets for girls	28	1.61 (0.17)	27	1.37 (0.11)	-0.24
Toilets (per student)	28	0.03 (0.00)	27	0.02 (0.00)	-0.01*
Number of classrooms	28	7.75 (0.82)	27	8.15 (0.88)	0.40
Number of classrooms (in good condition)	28	5.82 (0.75)	27	5.82 (0.77)	0.01
Dummy for school playground	28	0.75 (0.08)	27	0.78 (0.08)	0.03
Dummy for school with electricity	28	0.93 (0.05)	27	0.82 (0.08)	-0.11
Dummy for medical checkup facility	28	0.36 (0.09)	27	0.30 (0.09)	-0.06
Free textbooks distributed (per student)	28	0.61 (0.10)	27	0.57 (0.09)	-0.04
Free uniforms distributed (per student)	28	0.48 (0.09)	27	0.57 (0.09)	0.09
School Infrastructure Index	28	0.00 (0.19)	27	-0.47 (0.24)	-0.47

Notes: This table reports pre-intervention balance in school-level characteristics for the Mobile Science Lab (MSL) intervention using administrative data from UDISE (2020), which were used for stratification and randomization. The analysis sample includes 27 treatment and 28 control schools; three schools that declined participation after randomization are excluded. All variables are measured at the school level prior to treatment. Reported values are means with standard errors in parentheses. Column (5) reports differences in means between treatment and control schools based on two-sided *t*-tests. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.2: Pre-Treatment Balance in School-Level Characteristics: Lab on Bike (LoB), 2020

	Control Schools		LoB Schools		
Variable	N	Mean (SE)	N	Mean (SE)	Diff. (LoB – Control)
	(1)	(2)	(3)	(4)	(5)
Total enrollment (Grades 6–8)	36	140.31 (9.58)	41	142.32 (7.05)	2.01
Female enrollment share	36	0.49 (0.02)	41	0.49 (0.01)	0.00
Scheduled Caste enrollment share	36	0.36 (0.03)	41	0.42 (0.03)	0.05
Other Backward Class enrollment share	36	0.57 (0.03)	41	0.54 (0.03)	-0.03
Total teachers	36	7.58 (0.79)	41	9.61 (0.71)	2.03*
Student–teacher ratio (Grades 6–8)	36	22.50 (1.73)	41	18.25 (1.61)	-4.25*
Female teachers share	36	0.64 (0.05)	41	0.64 (0.04)	0.00
Teachers with graduate degree or higher	36	6.89 (0.75)	41	8.93 (0.66)	2.04**
Non-teaching staff	36	1.17 (0.55)	41	2.39 (0.71)	1.22
Dummy for school boundary wall	36	0.83 (0.06)	41	0.83 (0.06)	0.00
Dummy for school boundary wall (concrete)	36	0.83 (0.06)	41	0.81 (0.06)	-0.03
Number of buildings	36	2.58 (0.49)	41	3.12 (0.41)	0.54
Number of buildings (concrete)	36	2.50 (0.43)	41	3.05 (0.41)	0.55
Number of toilets for boys	36	1.58 (0.14)	41	2.12 (0.22)	0.54*
Number of toilets for girls	36	1.78 (0.16)	41	2.27 (0.20)	0.49*
Toilets (per student)	35	0.03 (0.00)	41	0.03 (0.00)	0.01
Number of classrooms	36	6.81 (0.78)	41	7.66 (0.76)	0.85
Number of classrooms (in good condition)	36	5.94 (0.79)	41	6.07 (0.80)	0.13
Dummy for school playground	36	0.72 (0.08)	41	0.73 (0.07)	0.01
Dummy for school with electricity	36	0.86 (0.06)	41	0.95 (0.03)	0.09
Dummy for medical checkup facility	36	0.47 (0.08)	41	0.59 (0.08)	0.11
Free textbooks distributed (per student)	36	0.84 (0.06)	41	0.89 (0.04)	0.05
Free uniforms distributed (per student)	36	0.79 (0.07)	41	0.87 (0.05)	0.08
School Infrastructure Index	35	-0.03 (0.17)	41	0.14 (0.18)	0.17

Notes: This table reports pre-intervention balance in school-level characteristics for the Lab on Bike (LoB) intervention using administrative data from UDISE (2020), which were used for stratification and randomization. The analysis sample includes 41 treatment and 36 control schools; one school that declined participation after randomization is excluded. All variables are measured at baseline. Reported values are means with standard errors in parentheses. Column (5) reports differences in means between treatment and control schools based on two-sided *t*-tests. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.3: Student-Level Characteristics by Intervention Type

	Lab on Bike (LoB)		Mobile Science Lab (MSL)	
Variable	N	Mean (SE)	N	Mean (SE)
Female	8,453	0.53 (0.01)	5,750	0.53 (0.01)
Grade 6	8,453	0.39 (0.01)	5,750	0.38 (0.01)
Grade 7	8,453	0.32 (0.01)	5,750	0.35 (0.01)
Grade 8	8,453	0.28 (0.01)	5,750	0.27 (0.01)
Student age (years)	8,453	12.81 (0.02)	5,750	12.69 (0.02)
Father's education (years)	8,453	8.39 (0.04)	5,750	8.64 (0.05)
Mother's education (years)	8,453	7.13 (0.04)	5,750	7.02 (0.06)
Employment (agriculture) share	8,453	0.27 (0.01)	5,750	0.37 (0.01)
Employment (self-employed) share	8,453	0.21 (0.00)	5,750	0.20 (0.01)
Employment (salaried) share	8,453	0.10 (0.00)	5,750	0.12 (0.00)
Employment (other) share	8,453	0.42 (0.01)	5,750	0.31 (0.01)
Household wealth index	8,453	2.86 (0.02)	5,750	2.85 (0.02)
Household size	8,453	6.84 (0.03)	5,750	7.19 (0.04)

Notes: This table reports student-level descriptive statistics for the main analysis sample collected post-randomization. Columns (1)–(2) correspond to students enrolled in Lab on Bike (LoB) schools, and Columns (3)–(4) correspond to students enrolled in Mobile Science Lab (MSL) schools. Reported values are means with standard errors in parentheses. Employment categories refer to the father's primary occupation. The household wealth index is a standardized asset-based measure. No statistical tests are reported, as the table is intended to summarize baseline characteristics rather than assess treatment–control balance.

Table A.4: Impact of the Lab on Bike on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
LoB	-0.019	0.024	0.046	0.016	-0.048
	(0.057)	(0.060)	(0.037)	(0.047)	(0.047)
Control mean	0.000	0.000	0.000	0.010	-0.000
Observations	8,453	8,453	8,453	7,708	7,069
R-squared	0.013	0.018	0.020	0.011	0.005
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: This table reports the impact of the Lab on Bike (LoB) treatment on student personal factors using endline survey data. The analysis sample includes students across 76 schools. All dependent variables are normalized indices with mean zero and standard deviation one in the control group. The explanatory variable is a binary indicator for schools assigned to receive the LoB treatment. All specifications include block fixed effects corresponding to the stratified randomization design and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels based on unadjusted t-tests.

Table A.5: Impact of the Lab on Bike on Engagement Factors

	Science interest	Performance in science	Understand science teacher	Enjoy school	Engagement index	Attendance
	(1)	(2)	(3)	(4)	(5)	(6)
LoB	0.021	-0.069	-0.068	-0.010	-0.046	-0.298***
	(0.061)	(0.058)	(0.057)	(0.052)	(0.056)	(0.089)
Control mean	0.000	0.000	0.000	0.000	0.000	0.000
Observations	8,453	8,453	8,453	7,433	8,453	7,331
R-squared	0.010	0.020	0.014	0.013	0.018	0.024
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76	76

Notes: This table reports the impact of the Lab on Bike (LoB) treatment on student engagement outcomes using endline survey data. The analysis sample includes students across 76 schools. All dependent variables are normalized indices with mean zero and standard deviation one in the control group. The explanatory variable is a binary indicator for schools assigned to receive the LoB treatment. All specifications include block fixed effects corresponding to the stratified randomization design and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.6: Impact of the Lab on Bike on Administrative Test Scores

	Total	Science	Maths	English	Hindi
	(1)	(2)	(3)	(4)	(5)
LoB	0.212	0.117	0.143	0.271*	0.134
	(0.128)	(0.109)	(0.116)	(0.145)	(0.107)
Control mean	0.000	0.000	0.000	0.000	0.000
Observations	10,289	10,289	10,289	10,289	10,289
R-squared	0.276	0.266	0.212	0.171	0.254
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Grade fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	72	72	72	72	72

Notes: This table reports the impact of the Lab on Bike (LoB) treatment on administrative test scores using school-conducted examinations. The analysis sample includes 10,289 students across 72 schools. All dependent variables are normalized to have mean zero and standard deviation one in the control group. The explanatory variable is a binary indicator for schools assigned to receive the LoB treatment. All specifications include block fixed effects corresponding to the stratified randomization design, grade fixed effects, and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.7: Impact of the Lab on Bike on Student Performance

	Science choice	Test score	Rote score	Application score	Creativity
	(1)	(2)	(3)	(4)	(5)
LoB	0.026	0.032	0.030	0.000	-0.136
	(0.026)	(0.087)	(0.070)	(0.077)	(0.098)
Control mean	0.360	0.000	0.000	0.000	0.000
Observations	8,453	8,453	8,453	8,453	7,641
R-squared	0.008	0.070	0.055	0.043	0.108
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: This table reports the impact of the Lab on Bike (LoB) treatment on student academic outcomes using endline survey data. The dependent variable in Column (1) is an indicator for intent to choose science in further studies. Columns (2)–(5) report normalized measures of science test score, share of rote learning score, share of application-based learning score, and creativity score, respectively (mean zero and sd one in the control group). All specifications include the baseline value of the corresponding dependent variable, block fixed effects corresponding to the stratified randomization design, and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.8: Impact of the Lab on Bike on Non-cognitive Measures

	Friends	Extraversion	Agreeableness	Conscientiousness	Emotional stability	Openness
	(1)	(2)	(3)	(4)	(5)	(6)
LoB	-0.013	-0.072	-0.119**	-0.074	-0.079	-0.094
	(0.141)	(0.070)	(0.053)	(0.070)	(0.074)	(0.059)
Control mean	4.080	0.000	0.000	0.000	0.000	-0.000
Observations	8,453	7,561	7,560	7,557	7,558	7,559
R-squared	0.031	0.025	0.033	0.039	0.047	0.039
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76	76

Notes: This table reports the impact of the Lab on Bike (LoB) treatment on non-cognitive outcomes using endline survey data. Column (1) reports the number of friends. Columns (2)–(6) report normalized measures of the Big Five personality traits: extraversion, agreeableness, conscientiousness, emotional stability, and openness (mean zero and sd one in the control group). The explanatory variable is a binary indicator for schools assigned to receive the LoB treatment. All specifications include block fixed effects corresponding to the stratified randomization design and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels based on unadjusted t-tests.

Table A.9: Dose-Response Effects of Lab on Bike on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
LoB × Sessions = 0	-0.053	0.060	0.062	-0.241**	-0.292**
	(0.097)	(0.093)	(0.096)	(0.115)	(0.117)
LoB × Sessions = 1	-0.088	-0.037	0.091*	-0.021	-0.134**
	(0.079)	(0.077)	(0.049)	(0.063)	(0.057)
LoB × Sessions = 2	-0.134	-0.068	0.130**	-0.097	-0.156**
	(0.085)	(0.087)	(0.056)	(0.082)	(0.066)
LoB × Sessions = 3	-0.200**	-0.180**	0.180***	-0.049	-0.113*
	(0.079)	(0.079)	(0.054)	(0.057)	(0.062)
LoB × Sessions = 4	-0.114	-0.057	0.049	0.013	-0.035
	(0.075)	(0.088)	(0.069)	(0.070)	(0.078)
LoB × Sessions = 5	0.048	0.065	-0.099*	0.166***	0.103
	(0.074)	(0.086)	(0.059)	(0.062)	(0.066)
LoB × Sessions = 6	0.243***	0.258***	-0.131**	0.166***	0.092
	(0.067)	(0.066)	(0.056)	(0.049)	(0.055)
Control mean	0.00	0.00	0.00	0.01	0.00
Observations	8,453	8,453	8,453	7,708	7,069
R^2	0.026	0.030	0.029	0.019	0.012
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: This table reports heterogeneous treatment effects of the Learning on Bus (LoB) intervention by student participation intensity. The explanatory variables are indicators for the number of sessions attended interacted with the LoB treatment assignment, following specification 2. The omitted category is students in control schools. Columns (1)–(5) report effects on the curiosity index, self-confidence index, self-perceived barriers to education index, goal/aspiration to study in the future, and self-efficacy index, respectively. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.10: Dose–Response Effects of the Lab on Bike on Engagement Factors

	Science interest	Performance in science	Understand science teacher	Engagement index
	(1)	(2)	(3)	(4)
LoB × Sessions = 0	-0.039	0.040	-0.069	-0.021
	(0.101)	(0.083)	(0.096)	(0.096)
LoB × Sessions = 1	0.017	-0.167**	-0.080	-0.093
	(0.076)	(0.079)	(0.073)	(0.070)
LoB × Sessions = 2	-0.128*	-0.195**	-0.177**	-0.181**
	(0.071)	(0.080)	(0.075)	(0.090)
LoB × Sessions = 3	-0.149**	-0.203***	-0.248***	-0.229***
	(0.073)	(0.075)	(0.078)	(0.080)
LoB × Sessions = 4	-0.044	-0.093	-0.152*	-0.194**
	(0.075)	(0.074)	(0.078)	(0.079)
LoB × Sessions = 5	0.060	-0.047	0.007	-0.039
	(0.077)	(0.089)	(0.076)	(0.085)
LoB × Sessions = 6	0.289***	0.154**	0.159**	0.251***
	(0.076)	(0.066)	(0.071)	(0.062)
Control mean	0.00	0.00	0.00	0.00
Observations	8,453	8,453	8,453	8,453
R^2	0.024	0.030	0.026	0.034
Block fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76

Notes: This table reports heterogeneous treatment effects of the Learning on Bus (LoB) intervention by student participation intensity. The explanatory variables are indicators for the number of sessions attended interacted with the LoB treatment assignment, following specification 2. The omitted category is students in control schools. Columns (1)–(4) report effects on the science interest index, perceived performance in science, understanding of the science teacher, and the engagement index, respectively. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.11: Dose–Response Effects of the Lab on Bike on Student Performance

	Science Choice	Test Score	Rote Score	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
LoB × Sessions = 0	-0.035	-0.101	-0.035	-0.154	-0.315**
	(0.055)	(0.125)	(0.128)	(0.102)	(0.125)
LoB × Sessions = 1	0.033	0.063	0.076	0.026	-0.125
	(0.031)	(0.086)	(0.072)	(0.081)	(0.103)
LoB × Sessions = 2	-0.040	-0.098	-0.025	-0.155*	-0.132
	(0.033)	(0.093)	(0.079)	(0.082)	(0.113)
LoB × Sessions = 3	-0.005	0.056	0.045	0.024	-0.157
	(0.032)	(0.108)	(0.090)	(0.101)	(0.112)
LoB × Sessions = 4	-0.030	-0.089	-0.028	-0.136	-0.245**
	(0.037)	(0.109)	(0.095)	(0.098)	(0.109)
LoB × Sessions = 5	0.051	0.051	0.048	0.003	-0.080
	(0.036)	(0.109)	(0.108)	(0.098)	(0.121)
LoB × Sessions = 6	0.143***	0.262**	0.156*	0.242**	0.021
	(0.036)	(0.107)	(0.085)	(0.102)	(0.115)
Control mean	0.36	0.00	-0.00	0.00	0.00
Observations	8,453	8,453	8,453	8,453	7,641
R^2	0.021	0.084	0.061	0.057	0.117
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: This table reports heterogeneous treatment effects of the Learning on Bus (LoB) intervention by student participation intensity. The explanatory variables are indicators for the number of sessions attended interacted with the LoB treatment assignment, following specification 2. The omitted category is students in control schools. Column (1) reports effects on an indicator for choosing the science stream in the future. Column (2) reports effects on the survey-based science test score. Columns (3) and (4) report effects on the rote and application-based components of the test, respectively. Column (5) reports effects on the creativity score. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.12: Did the Mobile Science Lab Change Teachers' Instructional Practices?

	Instill belief	Instill motivation	Instill critical thinking	Use science experiments	Use other examples	Use digital
	(1)	(2)	(3)	(4)	(5)	(6)
MSL	-0.115	-0.028	0.274	-0.134	-0.297	0.050
	(0.213)	(0.249)	(0.222)	(0.245)	(0.244)	(0.187)
Control mean	0.61	0.50	0.22	0.39	0.33	0.17
Observations	45	45	45	45	45	45
R^2	0.471	0.252	0.609	0.524	0.545	0.617
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
School-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	43	43	43	43	43	43

Notes: This table reports the impact of the Mobile Science Lab (MSL) intervention on science teachers' pedagogical practices. The unit of observation is the science teacher. The key independent variable is an indicator for schools assigned to receive the MSL treatment, estimated using specification 1. All regressions include block fixed effects corresponding to the randomization strata and baseline school-level controls. Robust standard errors clustered at the school level are reported in parentheses. Dependent variables measure teacher-reported instructional practices: instilling belief in students' abilities (column 1), instilling motivation (column 2), promoting critical thinking (column 3), use of science experiments (column 4), use of alternative examples to clarify concepts (column 5), and use of digital equipment in instruction (column 6). Control means are reported for reference. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.13: Did the Lab on Bike Change Teachers' Instructional Practices?

	Instill belief	Instill motivation	Instill critical thinking	Use science experiments	Use other examples	Use digital
	(1)	(2)	(3)	(4)	(5)	(6)
LoB	0.022	0.134	0.085	0.039	-0.035	0.067
	(0.065)	(0.080)	(0.068)	(0.081)	(0.077)	(0.079)
Control mean	3.55	3.34	3.30	3.26	3.27	3.15
Observations	59	59	59	59	59	59
R^2	0.762	0.594	0.805	0.699	0.794	0.803
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
School-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76	76

Notes: This table reports the impact of the Lab on Bike (LoB) intervention on science teachers' pedagogical practices. The unit of observation is the science teacher. The key independent variable is an indicator for schools assigned to receive the LoB treatment, estimated using specification 1. All regressions include block fixed effects corresponding to the randomization strata and baseline school-level controls. Robust standard errors clustered at the school level are reported in parentheses. Dependent variables measure teacher-reported instructional practices: instilling belief in students' abilities (column 1), instilling motivation (column 2), promoting critical thinking (column 3), use of science experiments (column 4), use of alternative examples to clarify concepts (column 5), and use of digital equipment in instruction (column 6). Control means are reported for reference. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.14: Heterogeneous Effects by Student-Reported Components of the Mobile Science Lab on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
MSL × Like nothing	0.135	0.224	-0.154*	-0.030	0.120
	(0.116)	(0.155)	(0.080)	(0.083)	(0.118)
MSL × Group activity	0.060	0.013	-0.110	0.056	0.118
	(0.079)	(0.079)	(0.080)	(0.064)	(0.088)
MSL × Science experiment	0.287***	0.194***	-0.246***	0.270***	0.197***
	(0.051)	(0.055)	(0.057)	(0.048)	(0.062)
MSL × Real life engagement	-0.121*	-0.025	0.066	-0.058	-0.179*
	(0.064)	(0.067)	(0.078)	(0.077)	(0.100)
MSL × Freedom to express	0.017	0.014	-0.057	0.002	0.060
	(0.077)	(0.067)	(0.076)	(0.061)	(0.056)
MSL × Instructional style	0.231***	0.145**	-0.324***	0.076	0.039
	(0.061)	(0.067)	(0.067)	(0.056)	(0.074)
Control mean	-0.00	0.00	-0.00	-0.00	0.00
Observations	5,523	5,523	5,523	5,202	4,832
R^2	0.045	0.034	0.039	0.049	0.021
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects by the components of the Mobile Science Lab (MSL) intervention that students reported liking. The explanatory variables interact the MSL treatment indicator with indicators for the specific components students reported enjoying: liking nothing, group activity, science experiments, real-life examples, freedom to express, and instructional style, following specification 2. The omitted category is students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(5) report treatment effects on the curiosity index, self-confidence index, self-perceived education barriers index, goals and aspirations to study further, and self-efficacy index, respectively. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.15: Heterogeneous Effects by Student-Reported Components of the Mobile Science Lab on Engagement Factors

	Science interest	Performance in science	Understanding science teacher	Engagement index
	(1)	(2)	(3)	(4)
MSL × Like nothing	0.087	0.019	0.229**	0.139
	(0.126)	(0.141)	(0.090)	(0.122)
MSL × Group activity	0.126	0.097	0.075	0.051
	(0.083)	(0.076)	(0.070)	(0.092)
MSL × Science experiment	0.297***	0.216***	0.242***	0.290***
	(0.050)	(0.055)	(0.053)	(0.054)
MSL × Real life engagement	-0.105	-0.055	-0.119	-0.152**
	(0.068)	(0.064)	(0.074)	(0.068)
MSL × Freedom to express	0.068	-0.029	0.020	0.060
	(0.066)	(0.086)	(0.087)	(0.066)
MSL × Instructional style	0.237***	0.165**	0.211***	0.236***
	(0.050)	(0.080)	(0.071)	(0.066)
Control mean	0.00	0.00	-0.00	-0.00
Observations	5,523	5,523	5,523	5,523
R^2	0.047	0.039	0.047	0.047
Block fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55

Notes: This table reports heterogeneous treatment effects by the components of the Mobile Science Lab (MSL) intervention that students reported liking on engagement-related outcomes. The explanatory variables interact the MSL treatment indicator with indicators for the specific components students reported enjoying—liking nothing, group activity, science experiments, real-life examples, freedom to express, and instructional style—following specification 2. The omitted category is students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(4) report treatment effects on the science interest index, self-perceived performance in science, understanding of the science teacher, and the composite engagement index, respectively. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.16: Heterogeneous Effects by Student-Reported Components of the Mobile Science Lab on Student Performance

	Science Choice	Test score	Rote	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
MSL × Like nothing	-0.110**	-0.170	-0.137	-0.109	-0.216**
	(0.052)	(0.132)	(0.110)	(0.129)	(0.105)
MSL × Group activity	0.051	0.024	0.055	-0.020	0.038
	(0.037)	(0.089)	(0.080)	(0.100)	(0.060)
MSL × Science Experiment	0.091***	0.184*	0.238**	0.083	0.066
	(0.027)	(0.096)	(0.098)	(0.075)	(0.067)
MSL × Real Life Engagement	-0.168***	-0.147*	-0.136*	-0.113	-0.271***
	(0.032)	(0.084)	(0.073)	(0.088)	(0.064)
MSL × Freedom to express	-0.009	-0.027	-0.105	0.063	-0.089
	(0.027)	(0.076)	(0.079)	(0.070)	(0.071)
MSL × Instructional style	0.018	0.185**	0.147**	0.164*	0.028
	(0.037)	(0.084)	(0.070)	(0.091)	(0.062)
Control mean	0.00	0.00	0.00	-0.00	-0.00
Observations	5,523	5,523	5,523	5,523	5,154
R^2	0.026	0.063	0.080	0.037	0.282
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects by the components of the Mobile Science Lab (MSL) intervention that students reported liking on test-based outcomes. The explanatory variables interact the MSL treatment indicator with indicators for the specific components students reported enjoying—liking nothing, group activity, science experiments, real-life examples, freedom to express, and instructional style—following specification 2. The omitted category is students in control schools. Columns (1)–(5) report treatment effects on an indicator for choosing the science stream in the future, the survey-based science test score, the rote component of the test, the application-based component of the test, and the creativity score, respectively. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.17: Heterogeneous Effects of the Mobile Science Lab by Household Wealth on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
MSL	0.186**	0.171*	-0.261***	0.158***	0.112*
	(0.078)	(0.086)	(0.068)	(0.054)	(0.056)
Low asset dummy	-0.026	-0.001	0.061	-0.084*	-0.071
	(0.035)	(0.040)	(0.047)	(0.045)	(0.044)
MSL × Low asset dummy	-0.021	-0.040	0.085	-0.039	-0.089
	(0.049)	(0.058)	(0.063)	(0.056)	(0.063)
Control mean	0.00	0.00	0.00	0.01	0.00
Observations	5,750	5,750	5,750	5,386	4,994
R^2	0.029	0.027	0.030	0.039	0.014
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Mobile Science Lab (MSL) intervention by household wealth status. The main explanatory variable interacts the MSL treatment indicator with a low-asset dummy (equal to one for households below the median wealth level), following specification 3. The omitted category is students in control schools from above-median wealth households. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(5) report treatment effects on the curiosity index, self-confidence index, self-perceived education barriers index, goals and aspirations to study further, and self-efficacy index, respectively. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.18: Heterogeneous Effects of the Mobile Science Lab by Household Wealth on Engagement Factors

	Science interest	Performance in science	Understanding science teacher	Engagement index
	(1)	(2)	(3)	(4)
MSL	0.191***	0.167*	0.176**	0.192**
	(0.065)	(0.093)	(0.082)	(0.082)
Low asset dummy	-0.086**	-0.029	-0.051	-0.005
	(0.039)	(0.036)	(0.045)	(0.037)
MSL × Low asset dummy	-0.029	-0.060	-0.060	-0.061
	(0.060)	(0.051)	(0.062)	(0.049)
Control mean	0.00	-0.00	-0.00	0.00
Observations	5,750	5,750	5,750	5,750
R^2	0.033	0.030	0.035	0.029
Block fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Mobile Science Lab (MSL) intervention on engagement-related outcomes by household wealth status. The explanatory variables include the MSL treatment indicator, a low-asset dummy (below median household wealth), and their interaction, following specification 3. The omitted category is students in control schools from above-median wealth households. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(4) report treatment effects on the science interest index, self-perceived performance in science, understanding of the science teacher, and the composite engagement index, respectively. All specifications include block fixed effects and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.19: Heterogeneous Effects of the Mobile Science Lab by Household Wealth on Student Performance

	Science Choice	Test score	Rote	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
MSL	0.013	-0.018	0.051	-0.057	-0.083
	(0.038)	(0.123)	(0.115)	(0.102)	(0.096)
Low Asset	-0.027	-0.199***	-0.168***	-0.147***	-0.127***
	(0.021)	(0.045)	(0.042)	(0.048)	(0.042)
MSL × Low Asset	-0.006	0.061	0.015	0.062	0.052
	(0.033)	(0.070)	(0.059)	(0.076)	(0.057)
Control mean	0.37	0.00	-0.00	-0.00	-0.00
Observations	5,750	5,750	5,750	5,750	5,326
R^2	0.010	0.059	0.073	0.034	0.283
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Mobile Science Lab (MSL) intervention on student performance outcomes by household wealth status. The explanatory variables include the MSL treatment indicator, a low-asset dummy (equal to one for households below the median wealth level), and their interaction, following specification 3. The omitted category is students in control schools from above-median wealth households. Column (1) reports effects on an indicator for choosing the science stream in the future. Column (2) reports effects on the survey-based science test score. Columns (3) and (4) report effects on the rote and application-based components of the test, respectively. Column (5) reports effects on the creativity score. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.20: Heterogeneous Effects of the Mobile Science Lab by Gender on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
MSL	0.166**	0.160*	-0.245***	0.214***	0.149**
	(0.080)	(0.082)	(0.074)	(0.072)	(0.065)
Female	0.058	0.066	-0.024	0.137***	0.053
	(0.057)	(0.062)	(0.053)	(0.049)	(0.045)
MSL × Female	0.021	-0.009	0.025	-0.131*	-0.125*
	(0.080)	(0.078)	(0.072)	(0.072)	(0.072)
Control mean	0.00	0.00	0.00	0.01	0.00
Observations	5,750	5,750	5,750	5,386	4,994
R^2	0.030	0.027	0.027	0.039	0.012
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Mobile Science Lab (MSL) intervention by gender. The explanatory variables include the MSL treatment indicator, a female dummy, and their interaction, following specification 3. The omitted category is male students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(5) report treatment effects on the curiosity index, self-confidence index, self-perceived education barriers index, goals and aspirations to study further, and self-efficacy index, respectively. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.21: Heterogeneous Effects of the Mobile Science Lab by Gender on Engagement Factors

	Science interest	Performance in science	Understand science teacher	Engagement index
	(1)	(2)	(3)	(4)
MSL	0.197**	0.146	0.138*	0.171**
	(0.075)	(0.087)	(0.081)	(0.078)
Female	0.062	0.101	0.067	0.070
	(0.053)	(0.064)	(0.052)	(0.060)
MSL × Female	-0.030	-0.002	0.028	-0.002
	(0.068)	(0.077)	(0.078)	(0.076)
Control mean	0.00	-0.00	-0.00	0.00
Observations	5,750	5,750	5,750	5,750
R^2	0.031	0.032	0.035	0.029
Block fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Mobile Science Lab (MSL) intervention on engagement-related outcomes by gender. The explanatory variables include the MSL treatment indicator, a female dummy, and their interaction, following specification 3. The omitted category is male students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(4) report treatment effects on the science interest index, self-perceived performance in science, understanding of the science teacher, and the composite engagement index, respectively. All specifications include block fixed effects and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.22: Heterogeneous Effects of the Mobile Science Lab by Gender on Student Performance

	Science Choice	Test score	Rote	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
MSL	0.001	0.088	0.133	0.035	-0.005
	(0.036)	(0.119)	(0.116)	(0.093)	(0.101)
Female	-0.004	0.139***	0.131***	0.107**	0.127**
	(0.017)	(0.051)	(0.045)	(0.048)	(0.053)
MSL × Female	0.019	-0.158**	-0.143*	-0.132*	-0.111
	(0.028)	(0.074)	(0.072)	(0.076)	(0.075)
Control mean	0.37	0.00	-0.00	-0.00	-0.00
Observations	5,750	5,750	5,750	5,750	5,326
R^2	0.009	0.054	0.069	0.032	0.282
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Mobile Science Lab (MSL) intervention on student performance outcomes by gender. The explanatory variables include the MSL treatment indicator, a female dummy, and their interaction, following specification 3. The omitted category is male students in control schools. Column (1) reports effects on an indicator for choosing the science stream in the future. Column (2) reports effects on the survey-based science test score. Columns (3) and (4) report effects on the rote and application-based components of the test, respectively. Column (5) reports effects on the creativity score. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.23: Heterogeneous Effects of the Mobile Science Lab by Student Ability on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
MSL	0.249***	0.226***	-0.228***	0.168***	0.070
	(0.076)	(0.083)	(0.069)	(0.058)	(0.065)
Low ability dummy	-0.070	-0.029	0.081	-0.090*	-0.074
	(0.065)	(0.072)	(0.051)	(0.045)	(0.047)
MSL × Low ability dummy	-0.099	-0.130	0.013	-0.054	0.064
	(0.089)	(0.087)	(0.081)	(0.068)	(0.090)
Control mean	0.00	0.00	0.00	0.01	0.00
Observations	4,518	4,518	4,518	4,269	3,981
R^2	0.041	0.032	0.029	0.042	0.015
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Mobile Science Lab (MSL) intervention by baseline student ability. The explanatory variables include the MSL treatment indicator, a low-ability dummy (equal to one for students scoring below the median on the survey-based test), and their interaction, following specification 3. The omitted category is higher-ability students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(5) report treatment effects on the curiosity index, self-confidence index, self-perceived education barriers index, goals and aspirations to study further, and self-efficacy index, respectively. All specifications include block fixed effects and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.24: Heterogeneous Effects of the Mobile Science Lab by Student Ability on Engagement Factors

	Science interest	Performance in science	Understanding science teacher	Engagement index
	(1)	(2)	(3)	(4)
MSL	0.215***	0.223**	0.191**	0.242***
	(0.076)	(0.089)	(0.083)	(0.086)
Low ability dummy	-0.108	-0.122*	-0.149**	-0.050
	(0.073)	(0.068)	(0.068)	(0.066)
MSL × Low ability dummy	-0.011	-0.101	-0.046	-0.107
	(0.111)	(0.093)	(0.096)	(0.092)
Control mean	0.00	-0.00	-0.00	0.00
Observations	4,518	4,518	4,518	4,518
R^2	0.039	0.046	0.047	0.036
Block fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Mobile Science Lab (MSL) intervention on engagement-related outcomes by baseline student ability. The explanatory variables include the MSL treatment indicator, a low-ability dummy (below median survey-based test score), and their interaction, following specification 3. The omitted category is higher-ability students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(4) report treatment effects on the science interest index, self-perceived performance in science, understanding of the science teacher, and the composite engagement index, respectively. All specifications include block fixed effects and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.25: Heterogeneous Effects of the Mobile Science Lab by Student Ability on Student Performance

	Science Choice	Test score	Rote	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
MSL	0.047	0.037	0.122	-0.050	-0.131
	(0.039)	(0.152)	(0.140)	(0.123)	(0.127)
Low Ability	-0.035	-0.143	-0.097	-0.148*	-0.133
	(0.032)	(0.088)	(0.073)	(0.082)	(0.085)
MSL × Low Ability	-0.011	-0.090	-0.149	0.014	0.054
	(0.044)	(0.125)	(0.117)	(0.114)	(0.111)
Control mean	0.36	0.04	0.04	0.02	0.03
Observations	4,518	4,518	4,518	4,518	4,518
R^2	0.011	0.065	0.082	0.035	0.319
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Mobile Science Lab (MSL) intervention on student performance outcomes by baseline ability. The explanatory variables include the MSL treatment indicator, a low-ability dummy (equal to one for students scoring below the median on the survey-based test), and their interaction, following specification 3. The omitted category is higher-ability students in control schools. Column (1) reports effects on an indicator for choosing the science stream in the future. Column (2) reports effects on the survey-based science test score. Columns (3) and (4) report effects on the rote and application-based components of the test, respectively. Column (5) reports effects on the creativity score. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.26: Heterogeneous Effects by Student-Reported Components of the Lab on Bike on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
LoB × Like nothing	0.092	0.270**	0.059	-0.057	-0.105
	(0.122)	(0.114)	(0.082)	(0.074)	(0.079)
LoB × Group activity	0.109	0.131*	-0.087	0.079	0.094
	(0.068)	(0.074)	(0.059)	(0.059)	(0.063)
LoB × Science experiment	0.131***	0.046	-0.115***	0.166***	0.060
	(0.046)	(0.050)	(0.036)	(0.036)	(0.041)
LoB × Real-life examples	-0.194***	-0.103*	0.164***	-0.216***	-0.199***
	(0.055)	(0.054)	(0.059)	(0.060)	(0.060)
LoB × Freedom to express	0.032	0.023	-0.092**	-0.004	0.029
	(0.037)	(0.043)	(0.044)	(0.046)	(0.039)
LoB × Instructional style	0.285***	0.362***	-0.105**	0.171***	0.015
	(0.045)	(0.052)	(0.051)	(0.041)	(0.059)
Control mean	0.00	0.00	0.00	-0.00	0.00
Observations	8,015	8,015	8,015	7,352	6,755
R^2	0.027	0.035	0.026	0.023	0.009
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: This table reports heterogeneous treatment effects by the components of the Lab on Bike (LoB) intervention that students reported liking. The explanatory variables interact the LoB treatment indicator with indicators for the specific components students reported enjoying: liking nothing, group activity, science experiments, real-life examples, freedom to express, and instructional style, following specification 2. The omitted category is students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(5) report treatment effects on curiosity, self-confidence, perceived education barriers, goals and aspirations to study further, and self-efficacy, respectively. All specifications include block fixed effects and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.27: Heterogeneous Effects by Student-Reported Components of the Lab on Bike on Engagement Factors

	Science interest	Performance in science	Understanding science teacher	Engagement index
	(1)	(2)	(3)	(4)
LoB × Like nothing	-0.047	0.064	-0.039	0.020
	(0.093)	(0.110)	(0.098)	(0.090)
LoB × Group activity	0.088	0.139**	0.078	0.058
	(0.060)	(0.067)	(0.059)	(0.057)
LoB × Science experiment	0.215***	0.045	0.090*	0.106**
	(0.048)	(0.050)	(0.048)	(0.045)
LoB × Real-life examples	-0.218***	-0.167***	-0.277***	-0.278***
	(0.059)	(0.054)	(0.060)	(0.054)
LoB × Freedom to express	-0.011	-0.016	-0.014	-0.005
	(0.056)	(0.045)	(0.045)	(0.044)
LoB × Instructional style	0.210***	0.249***	0.231***	0.290***
	(0.044)	(0.043)	(0.044)	(0.047)
Control mean	-0.00	-0.00	0.00	-0.00
Observations	8,015	8,015	8,015	8,015
R^2	0.027	0.030	0.026	0.033
Block fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76

Notes: This table reports heterogeneous treatment effects by the components of the Lab on Bike (LoB) intervention that students reported liking. The explanatory variables interact the LoB treatment indicator with indicators for the specific components students reported enjoying: liking nothing, group activity, science experiments, real-life examples, freedom to express, and instructional style, following specification 2. The omitted category is students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(4) report treatment effects on science interest, perceived performance in science, understanding of the science teacher, and engagement, respectively. All specifications include block fixed effects and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.28: Heterogeneous Effects by Student-Reported Components of the Lab on Bike on Student Performance

	Science choice	Test score	Rote	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
LoB × Like nothing	-0.114***	-0.094	-0.107	-0.031	-0.309***
	(0.037)	(0.108)	(0.089)	(0.111)	(0.092)
LoB × Group activity	0.057**	0.242***	0.232***	0.169**	0.050
	(0.026)	(0.068)	(0.069)	(0.067)	(0.078)
LoB × Science experiment	0.127***	0.131*	0.119**	0.068	0.047
	(0.024)	(0.071)	(0.058)	(0.069)	(0.072)
LoB × Real-life examples	-0.076***	-0.065	-0.031	-0.070	-0.203***
	(0.028)	(0.069)	(0.064)	(0.069)	(0.068)
LoB × Freedom to express	-0.011	0.098	0.075	0.074	-0.038
	(0.024)	(0.067)	(0.060)	(0.068)	(0.072)
LoB × Instructional style	-0.019	0.097	0.032	0.119*	-0.112*
	(0.025)	(0.064)	(0.055)	(0.068)	(0.060)
Control mean	0.36	0.00	-0.00	0.00	0.00
Observations	8,015	8,015	8,015	8,015	7,297
R^2	0.025	0.079	0.060	0.048	0.112
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: This table reports heterogeneous treatment effects by the components of the Lab on Bike (LoB) intervention that students reported liking on test-based outcomes. The explanatory variables interact the LoB treatment indicator with indicators for the specific components students reported enjoying—liking nothing, group activity, science experiments, real-life examples, freedom to express, and instructional style—following specification 2. The omitted category is students in control schools. Columns (1)–(5) report treatment effects on an indicator for choosing the science stream in the future, the survey-based science test score, the rote component of the test, the application-based component of the test, and the creativity score, respectively. All specifications include block fixed effects corresponding to the randomization strata and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.29: Heterogeneous Effects of the Lab-on-Bike by Household Wealth on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
LoB	-0.044	0.023	0.063	-0.002	-0.033
	(0.055)	(0.062)	(0.039)	(0.047)	(0.053)
Low asset dummy	-0.148***	-0.053	0.105**	-0.140***	-0.049
	(0.037)	(0.034)	(0.042)	(0.035)	(0.042)
LoB × Low asset dummy	0.059	-0.004	-0.041	0.040	-0.050
	(0.054)	(0.046)	(0.055)	(0.055)	(0.055)
Control mean	0.00	0.00	0.00	-0.00	0.00
Observations	8,453	8,453	8,453	7,708	7,069
R^2	0.017	0.019	0.021	0.014	0.006
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Lab-on-Bike (LoB) intervention by household wealth status. The main explanatory variable interacts the LoB treatment indicator with a low-asset dummy (equal to one for households below the median wealth level), following specification 3. The omitted category is students in control schools from above-median wealth households. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(5) report treatment effects on the curiosity index, self-confidence index, self-perceived education barriers index, goals and aspirations to study further, and self-efficacy index, respectively. All specifications include block fixed effects and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.30: Heterogeneous Effects of the Lab-on-Bike by Household Wealth on Engagement Factors

	Science interest	Performance in science	Understanding science teacher	Engagement index
	(1)	(2)	(3)	(4)
LoB	0.000	-0.086	-0.090	-0.068
	(0.060)	(0.054)	(0.056)	(0.057)
Low asset dummy	-0.119***	-0.104**	-0.137***	-0.097***
	(0.036)	(0.040)	(0.041)	(0.035)
LoB × Low asset dummy	0.051	0.040	0.052	0.056
	(0.053)	(0.052)	(0.055)	(0.052)
Control mean	-0.00	-0.00	0.00	-0.00
Observations	8,453	8,453	8,453	8,453
R^2	0.012	0.022	0.017	0.019
Block fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55

Notes: This table reports heterogeneous treatment effects of the Lab-on-Bike (LoB) intervention by household wealth status. The main explanatory variable interacts the LoB treatment indicator with a low-asset dummy (equal to one for households below the median wealth level), following specification 3. The omitted category is students in control schools from above-median wealth households. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(4) report treatment effects on the science interest index, self-perceived performance in science, understanding of the science teacher, and the overall engagement index, respectively. All specifications include block fixed effects and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.31: Heterogeneous Effects of the Lab-on-Bike by Household Wealth on Student Performance

	Science Choice	Test Score	Rote Score	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
LoB	0.021	-0.037	-0.028	-0.060	-0.166
	(0.028)	(0.091)	(0.070)	(0.083)	(0.104)
Low asset dummy	-0.068***	-0.224***	-0.170***	-0.196***	-0.182***
	(0.018)	(0.043)	(0.031)	(0.046)	(0.046)
LoB × Low asset dummy	0.007	0.186***	0.161***	0.165**	0.084
	(0.028)	(0.060)	(0.050)	(0.065)	(0.058)
Control mean	0.36	0.00	-0.00	0.00	0.00
Observations	8,453	8,453	8,453	8,453	7,641
R^2	0.012	0.075	0.058	0.047	0.113
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: Robust standard errors clustered at the school level are reported in parentheses. The main explanatory variable interacts the LoB treatment indicator with a low-asset dummy (equal to one for households below the median wealth level), following specification 3. The omitted category is students in control schools from above-median wealth households. Test outcomes are standardized to have mean zero and standard deviation one in the control group. Science choice is a binary indicator equal to one if the student reports intending to pursue the science stream in the future. All specifications include block fixed effects and school-level baseline controls. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.32: Heterogeneous Effects of the Lab-on-Bike by Gender on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
LoB	-0.040	-0.010	0.106**	-0.006	-0.067
	(0.074)	(0.081)	(0.049)	(0.053)	(0.063)
Female	0.053	0.048	-0.009	0.037	0.010
	(0.054)	(0.055)	(0.043)	(0.051)	(0.048)
LoB × Female	0.039	0.066	-0.114**	0.041	0.036
	(0.073)	(0.080)	(0.056)	(0.068)	(0.069)
Control mean	0.00	0.00	0.00	-0.00	0.00
Observations	8,453	8,453	8,453	7,708	7,069
R^2	0.015	0.020	0.022	0.012	0.005
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: Robust standard errors clustered at the school level are reported in parentheses. The main explanatory variable interacts the LoB treatment indicator with a female dummy, following specification 3. The omitted category is male students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(5) report treatment effects on the curiosity index, self-confidence index, self-perceived education barriers index, goals and aspirations to study further, and self-efficacy index. All specifications include block fixed effects and school-level baseline controls. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.33: Heterogeneous Effects of the Lab-on-Bike by Gender on Engagement Factors

	Science interest	Performance in science	Understanding science teacher	Engagement index
	(1)	(2)	(3)	(4)
LoB	-0.013	-0.092	-0.089	-0.134*
	(0.074)	(0.069)	(0.074)	(0.071)
Female	0.015	0.037	0.085	0.034
	(0.056)	(0.052)	(0.054)	(0.064)
LoB × Female	0.063	0.042	0.040	0.168**
	(0.074)	(0.070)	(0.074)	(0.079)
Control mean	-0.00	-0.00	0.00	-0.00
Observations	8,453	8,453	8,453	8,453
R^2	0.011	0.021	0.017	0.024
Block fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76

Notes: Robust standard errors clustered at the school level are reported in parentheses. The main explanatory variable interacts the LoB treatment indicator with a female dummy, following specification 3. The omitted category is male students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(4) report treatment effects on science interest, perceived performance in science, understanding of the science teacher, and the overall engagement index. All specifications include block fixed effects and school-level baseline controls. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.34: Heterogeneous Effects of the Lab-on-Bike by Gender on Student Performance

	Science Choice	Test Score	Rote	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
LoB	0.011	0.013	0.007	-0.008	-0.071
	(0.031)	(0.090)	(0.070)	(0.087)	(0.099)
Female	-0.036	0.068	0.030	0.057	0.172***
	(0.022)	(0.056)	(0.046)	(0.061)	(0.055)
LoB × Female	0.029	0.034	0.044	0.015	-0.120
	(0.030)	(0.069)	(0.058)	(0.076)	(0.075)
Control mean	0.36	0.00	-0.00	0.00	0.00
Observations	8,453	8,453	8,453	8,453	7,641
R^2	0.009	0.071	0.055	0.044	0.113
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: Robust standard errors clustered at the school level are reported in parentheses. The main explanatory variable interacts the LoB treatment indicator with a female dummy, following specification 3. The omitted category is male students in control schools. Survey-based test outcomes are standardized to have mean zero and standard deviation one in the control group. Science choice is a binary indicator equal to one if the student reports intending to pursue the science stream in the future. All specifications include block fixed effects and school-level baseline controls. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.35: Heterogeneous Effects of the Lab-on-Bike by Student Ability on Personal Factors

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
LoB	-0.074	0.013	0.041	0.014	-0.090
	(0.066)	(0.075)	(0.052)	(0.056)	(0.059)
Low ability	-0.247***	-0.213***	0.016	-0.096**	-0.128***
	(0.064)	(0.063)	(0.049)	(0.037)	(0.047)
LoB × Low ability	0.069	0.060	0.106*	-0.086	0.045
	(0.078)	(0.080)	(0.058)	(0.064)	(0.070)
Control mean	0.06	0.02	-0.06	0.07	0.03
Observations	6,147	6,147	6,147	5,667	5,211
R^2	0.025	0.025	0.023	0.018	0.011
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: Robust standard errors clustered at the school level are reported in parentheses. The main explanatory variable interacts the LoB treatment indicator with a low-ability dummy (equal to one for students scoring below the median on the baseline survey-based test), following specification 3. The omitted category is high-ability students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(5) report treatment effects on the curiosity index, self-confidence index, self-perceived education barriers index, goals and aspirations to study further, and self-efficacy index. All specifications include block fixed effects and school-level baseline controls. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.36: Heterogeneous Effects of the Lab-on-Bike by Student Ability on Engagement Factors

	Science interest	Performance in science	Understanding science teacher	Engagement index
	(1)	(2)	(3)	(4)
LoB	-0.012	-0.101	-0.123*	-0.092
	(0.070)	(0.061)	(0.064)	(0.068)
Low ability	-0.253***	-0.253***	-0.248***	-0.228***
	(0.053)	(0.055)	(0.054)	(0.056)
LoB × Low ability	0.024	0.083	0.080	0.083
	(0.070)	(0.068)	(0.072)	(0.072)
Control mean	0.04	0.03	0.04	0.04
Observations	6,147	6,147	6,147	6,147
R^2	0.030	0.033	0.032	0.027
Block fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76

Notes: Robust standard errors clustered at the school level are reported in parentheses. The main explanatory variable interacts the LoB treatment indicator with a low-ability dummy (equal to one for students scoring below the median on the baseline survey-based test), following specification 3. The omitted category is high-ability students in control schools. All dependent variables are standardized indices with mean zero and standard deviation one in the control group. Columns (1)–(4) report treatment effects on science interest, perceived performance in science, understanding of the science teacher, and the overall engagement index. All specifications include block fixed effects and school-level baseline controls. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.37: Heterogeneous Effects of the Lab-on-Bike by Student Ability on Student Performance

	Science Choice	Test Score	Rote	Application	Creativity
	(1)	(2)	(3)	(4)	(5)
LoB	0.030	-0.010	0.023	-0.062	-0.080
	(0.030)	(0.099)	(0.074)	(0.099)	(0.111)
Low ability	-0.028	-0.119*	-0.061	-0.125*	-0.096
	(0.021)	(0.063)	(0.060)	(0.070)	(0.075)
LoB × Low ability	-0.037	-0.080	-0.131*	0.000	-0.178*
	(0.031)	(0.087)	(0.073)	(0.098)	(0.103)
Control mean	0.38	0.10	0.09	0.07	0.02
Observations	6,147	6,147	6,147	6,147	6,147
R^2	0.013	0.077	0.060	0.049	0.130
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: Robust standard errors clustered at the school level are reported in parentheses. The main explanatory variable interacts the LoB treatment indicator with a low-ability dummy (equal to one for students scoring below the median on the baseline survey-based test), following specification 3. The omitted category is high-ability students in control schools. All survey-based test outcomes are standardized to have mean zero and standard deviation one in the control group. Science choice is a binary indicator equal to one if the student reports intending to pursue the science stream in the future. All specifications include block fixed effects and school-level baseline controls. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels.

Table A.38: Impact of Mobile Science Lab on Weekly Study Time

	Science Tuition	Science Home	Mathematics Tuition	Mathematics Home	Other Tuition	Other Home
	(1)	(2)	(3)	(4)	(5)	(6)
MSL	-0.066	0.232*	-0.062	0.095	-0.122	0.180*
	(0.161)	(0.127)	(0.161)	(0.119)	(0.179)	(0.097)
Observations	4,638	4,927	4,484	5,219	4,712	5,082
R^2	0.025	0.013	0.027	0.014	0.028	0.015
Control mean	2.43	2.68	2.43	2.89	2.74	3.42
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55	55

Notes: This table reports the impact of the Mobile Science Lab (MSL) treatment on weekly study time using endline survey data. The dependent variables measure hours devoted per week to studying science, mathematics, and other subjects, separately for tuition and home study. The explanatory variable is a binary indicator for schools assigned to receive the MSL treatment. All specifications include block fixed effects (corresponding to the stratification used in randomization) and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. The sample size varies across columns due to missing responses on specific study-time modules. ***, **, * denote statistical significance at 1, 5, and 10 percent levels based on unadjusted p-values from standard t-tests.

Table A.39: Impact of the Lab on Bike on Weekly Study Time

	Science Tuition	Science Home	Mathematics Tuition	Mathematics Home	Other Tuition	Other Home
	(1)	(2)	(3)	(4)	(5)	(6)
LoB	-0.342**	0.087	-0.231	0.098	-0.352**	0.019
	(0.142)	(0.117)	(0.150)	(0.141)	(0.169)	(0.119)
Observations	6,773	7,053	6,368	7,623	6,828	7,228
R^2	0.091	0.010	0.094	0.019	0.093	0.014
Control mean	2.42	2.82	2.50	3.07	2.76	3.52
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76	76

Notes: This table reports the impact of the Lab on Bike (LoB) treatment on weekly study time using endline survey data. The dependent variables measure hours devoted per week to studying science, mathematics, and other subjects, separately for tuition and home study. The explanatory variable is a binary indicator for schools assigned to receive the LoB treatment. All specifications include block fixed effects (corresponding to the stratification used in randomization) and school-level baseline controls. Robust standard errors clustered at the school level are reported in parentheses. The sample size varies across columns due to missing responses on specific study-time modules. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

B Robustness Tables

Table B.1: Impact of the Mobile Science Lab on Personal Factors: Robustness to Social Desirability Bias

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
MSL	0.196**	0.171**	-0.241***	0.158***	0.090*
	(0.077)	(0.081)	(0.069)	(0.050)	(0.052)
SDB	0.133***	0.109***	-0.080***	0.102***	0.075***
	(0.020)	(0.020)	(0.020)	(0.011)	(0.015)
Control mean	0.000	0.000	0.000	0.000	0.000
Observations	5,750	5,750	5,750	5,386	4,994
R-squared	0.050	0.041	0.035	0.050	0.017
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Social desirability control	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55

Notes: This table replicates the baseline personal factors analysis controlling for social desirability bias (SDB), measured using the short-form Marlowe–Crowne Social Desirability Scale (see Appendix Section D.4). The sample includes 5,750 students across 55 schools (27 treatment, 28 control) in Uttar Pradesh. All dependent variables are normalized indices with mean zero and standard deviation one in the control group. The explanatory variable is a binary indicator for MSL treatment assignment. All specifications include block fixed effects and school-level controls for baseline characteristics. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table B.2: Impact of the Mobile Science Lab on Engagement Factors: Robustness to Social Desirability Bias

	Science interest	Performance in science	Understand science teacher	Enjoy school	Engagement index	Attendance
	(1)	(2)	(3)	(4)	(5)	(6)
MSL	0.199***	0.161*	0.173**	0.199***	0.189**	-0.102
	(0.061)	(0.090)	(0.079)	(0.066)	(0.080)	(0.119)
SDB	0.140***	0.118***	0.143***	0.121***	0.143***	0.005
	(0.018)	(0.020)	(0.018)	(0.018)	(0.020)	(0.035)
Control mean	0.000	0.000	0.000	0.000	0.000	3.340
Observations	5,750	5,750	5,750	5,296	5,750	5,019
R-squared	0.054	0.046	0.059	0.041	0.053	0.021
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Social desirability control	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55	55

Notes: This table replicates the baseline student engagement analysis controlling for social desirability bias (SDB), measured using the short-form Marlowe–Crowne Social Desirability Scale (see Appendix Section D.4). The sample includes 5,750 students across 55 schools (27 treatment, 28 control) in Uttar Pradesh. All dependent variables are normalized indices with mean zero and standard deviation one in the control group, except Column (6) which reports attendance in levels. The explanatory variable is a binary indicator for MSL treatment assignment. All specifications include block fixed effects and school-level controls for baseline characteristics. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table B.3: Impact of the Mobile Science Lab on Non-Cognitive Measures: Robustness to Social Desirability Bias

	Friends	Extraversion	Agreeableness	Conscientiousness	Emotional Stability	Openness
	(1)	(2)	(3)	(4)	(5)	(6)
MSL	-0.116	-0.217	-0.105	-0.269**	-0.132	-0.176
	(0.145)	(0.156)	(0.128)	(0.118)	(0.118)	(0.126)
SDB	0.135***	0.046	-0.032	0.092**	0.006	0.008
	(0.038)	(0.033)	(0.027)	(0.036)	(0.028)	(0.026)
Control mean	4.350	4.360	4.490	4.650	4.740	4.470
Observations	5,145	5,166	5,167	5,169	5,168	5,169
R-squared	0.092	0.022	0.024	0.030	0.019	0.022
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Social desirability control	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	55	55	55	55	55	55

Notes: This table replicates the baseline non-cognitive measures analysis controlling for social desirability bias (SDB), measured using the short-form Marlowe–Crowne Social Desirability Scale (see Appendix Section D.4). The sample includes 5,750 students across 55 schools (27 treatment, 28 control) in Uttar Pradesh. All dependent variables are normalized indices with mean zero and standard deviation one in the control group. The explanatory variable is a binary indicator for MSL treatment assignment. Columns (2)–(6) report Big Five personality measures: extraversion, agreeableness, conscientiousness, emotional stability, and openness. All specifications include block fixed effects and school-level controls for baseline characteristics. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table B.4: Impact of the Lab on Bike on Personal Factors: Robustness to Social Desirability Bias

	Curiosity	Self-confidence	Barriers to education	Aspiration	Self-efficacy
	(1)	(2)	(3)	(4)	(5)
LoB	-0.002	0.040	0.034	0.030	-0.037
	(0.052)	(0.055)	(0.036)	(0.045)	(0.043)
SDB	0.184***	0.169***	-0.132***	0.120***	0.103***
	(0.015)	(0.016)	(0.015)	(0.015)	(0.017)
Control mean	0.000	0.000	0.000	0.000	0.000
Observations	8,453	8,453	8,453	7,708	7,069
R-squared	0.055	0.054	0.042	0.030	0.019
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Social desirability control	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76

Notes: This table replicates the baseline personal factors analysis for the Lab on Bike (LoB) sample, controlling for social desirability bias (SDB), measured using the short-form Marlowe–Crowne Social Desirability Scale (see Appendix Section D.4). The sample includes 8,453 students across 76 schools in Uttar Pradesh. All dependent variables are normalized indices with mean zero and standard deviation one in the control group. The explanatory variable is a binary indicator for LoB treatment assignment. All specifications include block fixed effects and school-level controls for baseline characteristics. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table B.5: Impact of the Lab on Bike on Engagement Factors: Robustness to Social Desirability Bias

	Science interest	Performance in science	Understand science teacher	Enjoy school	Engagement index	Attendance
	(1)	(2)	(3)	(4)	(5)	(6)
LoB	0.037	-0.053	-0.051	0.010	-0.026	-0.289***
	(0.054)	(0.053)	(0.050)	(0.047)	(0.048)	(0.088)
SDB	0.175***	0.179***	0.179***	0.167***	0.215***	0.083***
	(0.014)	(0.017)	(0.016)	(0.012)	(0.014)	(0.026)
Control mean	0.000	0.000	0.000	0.000	0.000	3.310
Observations	8,453	8,453	8,453	7,433	8,453	7,331
R-squared	0.049	0.062	0.056	0.051	0.077	0.027
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Social desirability control	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76	76

Notes: This table replicates the baseline engagement analysis for the Lab on Bike (LoB) sample, controlling for social desirability bias (SDB), measured using the short-form Marlowe–Crowne Social Desirability Scale (see Appendix Section D.4). The sample includes 8,453 students across 76 schools in Uttar Pradesh. All dependent variables are normalized indices with mean zero and standard deviation one in the control group, except Column (6) which reports attendance in levels. The explanatory variable is a binary indicator for LoB treatment assignment. All specifications include block fixed effects and school-level controls for baseline characteristics. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table B.6: Impact of the Lab on Bike on Non-Cognitive Measures: Robustness to Social Desirability Bias

	Friends	Extraversion	Agreeableness	Conscientiousness	Emotional Stability	Openness
	(1)	(2)	(3)	(4)	(5)	(6)
LoB	0.009	-0.121	-0.195**	-0.126	-0.139	-0.167
	(0.155)	(0.125)	(0.086)	(0.122)	(0.124)	(0.103)
SDB	0.158***	0.054*	-0.020	0.038	-0.033	0.004
	(0.034)	(0.031)	(0.023)	(0.023)	(0.032)	(0.027)
Control mean	4.070	4.680	4.700	4.780	4.810	4.580
Observations	7,521	7,561	7,560	7,557	7,558	7,559
R-squared	0.046	0.026	0.033	0.039	0.048	0.039
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Social desirability control	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	76	76	76	76	76	76

Notes: This table replicates the baseline non-cognitive measures analysis for the Lab on Bike (LoB) sample, controlling for social desirability bias (SDB), measured using the short-form Marlowe–Crowne Social Desirability Scale (see Appendix Section D.4). The sample includes 8,453 students across 76 schools in Uttar Pradesh. All dependent variables are normalized indices with mean zero and standard deviation one in the control group. The explanatory variable is a binary indicator for LoB treatment assignment. Columns (2)–(6) report Big Five personality measures: extraversion, agreeableness, conscientiousness, emotional stability, and openness. All specifications include block fixed effects and school-level controls for baseline characteristics. Robust standard errors clustered at the school level are reported in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table B.7: Pre-Treatment Balance in School Infrastructure: Mobile Science Lab (MSL), 2020

	Control Schools		MSL Schools		
Variable	N	Mean (SE)	N	Mean (SE)	Diff. (MSL – Control)
	(1)	(2)	(3)	(4)	(5)
Total enrollment (Grades 6–8)	28	131.68 (11.89)	30	147.93 (8.70)	16.26
Female enrollment share	28	0.51 (0.01)	30	0.49 (0.01)	-0.01
Scheduled Caste enrollment share	28	0.29 (0.03)	30	0.26 (0.03)	-0.03
Other Backward Class enrollment share	28	0.58 (0.04)	30	0.57 (0.04)	0.01
Total teachers	28	7.71 (0.76)	30	7.50 (0.73)	-0.21
Student–teacher ratio (Grades 6–8)	28	25.88 (4.60)	30	26.01 (3.01)	0.13
Female teachers share	28	0.41 (0.06)	30	0.42 (0.05)	0.01
Teachers with graduate degree or higher	28	6.89 (0.69)	30	7.13 (0.71)	0.24
Teachers with graduate degree or higher (per student)	28	0.06 (0.01)	30	0.05 (0.01)	-0.00
Non-teaching staff	28	0.61 (0.35)	30	0.60 (0.29)	-0.00
Non-teaching staff (per student)	28	0.01 (0.00)	30	0.00 (0.00)	0.00
Dummy for school boundary wall	28	0.54 (0.10)	30	0.77 (0.09)	0.23*
Dummy for school boundary wall (concrete)	28	0.46 (0.10)	30	0.77 (0.08)	0.30**
Number of buildings	28	2.54 (0.62)	30	2.63 (0.52)	-0.01
Number of buildings (concrete)	28	2.36 (0.60)	30	2.40 (0.52)	-0.04
Number of toilets for boys	28	1.46 (0.17)	30	1.40 (0.13)	-0.06
Number of toilets for girls	28	1.61 (0.17)	30	1.38 (0.10)	-0.24
Toilets (per student)	28	0.03 (0.00)	30	0.02 (0.00)	-0.01*
Number of classrooms	28	7.75 (0.82)	30	8.00 (0.82)	0.25
Number of classrooms (in good condition)	28	5.82 (0.75)	30	5.73 (0.74)	-0.09
Dummy for school playground	28	0.75 (0.08)	30	0.73 (0.08)	-0.02
Dummy for school with electricity	28	0.93 (0.05)	30	0.80 (0.07)	-0.13
Dummy for medical checkup facility	28	0.36 (0.09)	30	0.30 (0.09)	-0.06
Free textbooks distributed (per student)	28	0.61 (0.10)	30	0.60 (0.08)	-0.00
Free uniforms distributed (per student)	28	0.48 (0.09)	30	0.60 (0.08)	0.13
School Infrastructure Index	28	0.00 (0.19)	30	-0.53 (0.23)	-0.53*

Notes: This table reports pre-intervention balance in school-level characteristics for the Mobile Science Lab (MSL) intervention using administrative data from UDISE (2020), which were used for stratification and randomization. The analysis sample includes the full original sample of 30 treatment and 28 control schools prior to any attrition. All variables are measured at the school level prior to treatment. The characteristics reported include enrollment and composition measures (total enrollment in Grades 6–8, female share, and caste composition), teacher characteristics (total number of teachers, share of female teachers, number of teachers with a graduate degree or higher, and non-teaching staff), and school infrastructure indicators (boundary walls, buildings and classrooms, toilet facilities, playgrounds, electricity, medical checkup facilities, and distribution of free textbooks and uniforms per student). The school infrastructure index aggregates indicators for boundary wall, playground, electricity, medical checkup facility, and library presence. Reported values are means with standard errors in parentheses. Column (5) reports differences in means between treatment and control schools, along with two-sided *t*-tests of equality of means. ***, **, * mean statistical significance at 1, 5, 10 percent levels.

Table B.8: Pre-Treatment Balance in School-Level Characteristics: Lab on Bike (LoB), 2020

	Control Schools		LoB Schools		
Variable	N	Mean (SE)	N	Mean (SE)	Diff. (LoB – Control)
	(1)	(2)	(3)	(4)	(5)
Total enrollment (Grades 6–8)	36	140.31 (9.58)	42	144.24 (7.15)	3.94
Female enrollment share	36	0.49 (0.02)	42	0.49 (0.01)	0.00
Scheduled Caste enrollment share	36	0.36 (0.03)	42	0.41 (0.03)	0.05
Other Backward Class enrollment share	36	0.57 (0.03)	42	0.54 (0.03)	-0.03
Total teachers	36	7.58 (0.79)	42	9.60 (0.69)	2.01*
Student–teacher ratio (Grades 6–8)	36	22.50 (1.73)	42	18.40 (1.58)	-4.09*
Female teachers share	36	0.64 (0.05)	42	0.65 (0.04)	0.00
Teachers with graduate degree or higher	36	6.89 (0.75)	42	8.91 (0.65)	2.02**
Teachers with graduate degree or higher (per student)	36	0.05 (0.00)	42	0.07 (0.00)	0.16**
Non-teaching staff	36	1.17 (0.55)	42	2.33 (0.69)	1.17
Dummy for school boundary wall	36	0.83 (0.06)	42	0.81 (0.06)	-0.02
Dummy for school boundary wall (concrete)	36	0.83 (0.06)	42	0.79 (0.06)	-0.05
Number of buildings	36	2.58 (0.49)	42	3.10 (0.40)	0.54
Number of buildings (concrete)	36	2.50 (0.43)	42	3.02 (0.40)	0.52
Number of toilets for boys	36	1.58 (0.14)	42	2.01 (0.22)	0.51*
Number of toilets for girls	36	1.78 (0.16)	42	2.24 (0.20)	0.46*
Toilets (per student)	35	0.03 (0.00)	42	0.03 (0.00)	0.01
Number of classrooms	36	6.81 (0.78)	42	7.69 (0.74)	0.86
Number of classrooms (in good condition)	36	5.94 (0.79)	42	6.14 (0.78)	0.20
Dummy for school playground	36	0.72 (0.08)	42	0.74 (0.07)	0.02
Dummy for school with electricity	36	0.86 (0.06)	42	0.95 (0.03)	0.09
Dummy for medical checkup facility	36	0.47 (0.08)	42	0.57 (0.07)	0.10
Free textbooks distributed (per student)	36	0.84 (0.06)	42	0.87 (0.04)	0.03
Free uniforms distributed (per student)	36	0.79 (0.07)	42	0.86 (0.05)	0.06
School Infrastructure Index	36	0.00 (0.17)	42	0.18 (0.18)	-0.18

Notes: This table reports pre-intervention balance in school-level characteristics for the Lab on Bike (LoB) intervention using administrative data from UDISE (2020), which were used for stratification and randomization. The analysis sample includes the full original sample of 42 treatment and 36 control schools prior to any attrition. All variables are measured at the school level prior to treatment. Enrollment refers to total enrollment in Grades 6–8. Caste shares correspond to the proportion of enrolled students belonging to Scheduled Castes and Other Backward Classes. Teacher characteristics include the total number of teachers, the share of female teachers, and the number of teachers with a graduate degree or higher. The student–teacher ratio is computed using enrollment and teacher counts for Grades 6–8. Infrastructure variables capture the presence and quality of school facilities, including buildings, classrooms, toilets, playgrounds, electricity, and medical checkup facilities, as well as the distribution of free textbooks and uniforms per student. Reported values are means with standard errors in parentheses. Column (5) reports differences in means between treatment and control schools, along with two-sided *t*-tests of equality of means. ***, **, * mean statistical significance at 1, 5, 10 percent levels.

C Pedagogical Design

The learning arc. Sessions open with a *super start*—a five- to seven-minute activity designed to provoke surprise before any explanation is offered. In a session on light, for example, students receive periscopes to explore prior to any discussion of reflection or angles.[19] The questions students generate are written on the blackboard and become the organizing thread of the lesson. This inversion—phenomenon before principle, observation before abstraction—is the structural mechanism through which the curriculum activates curiosity and establishes inquiry as the driver of learning (Alan and Mumcu, 2024; Nourani et al., 2025).

Experimentation and reasoning. Students work in groups of four to six. They predict outcomes before each experiment and articulate observations in their own words using action-oriented scientific verbs—*observe, compare, measure, classify, infer*. The predict-then-verify structure simultaneously deepens content understanding through the direct cognitive pathway and builds perceived competence and self-efficacy through the indirect motivational pathway (Bando et al., 2019; Fredricks et al., 2004). Every student conducts each experiment independently; the experience of completing a task successfully is intended to reinforce both mastery beliefs and persistence (Alan et al., 2019).

Synthesis and extension. Sessions conclude with a *super finish* in which the instructor uses concise "key message" charts to connect empirical observations to formal terminology, consolidating the session's conceptual content. Learning is extended through short "Do It Yourself" prompts encouraging home replication, accompanied by a brief story about a scientific discovery or scientist that illustrates creativity and perseverance.[20]

Curricular fit and monitoring. Topics are sequenced to reinforce material taught in regular classes, so experimental sessions serve as complements rather than substitutes for standard instruction, occupying a small fraction of total instructional time while serving as conceptual anchors. Instructors follow a standardized pedagogical script—*super start, inquiry, experimentation, synthesis*—while adapting examples and pacing to local context; formal lecturing and extended note-taking are avoided. These design choices reflect the autonomy-support lever: by minimizing didactic instruction and providing structured opportunities for peer dialogue and self-directed exploration, the curriculum reinforces students' sense of agency over learning (Reeve, 2012; Skinner and Pitzer, 2012). Agastya's internal monitoring system conducts random supervisory visits to verify adherence.

[19] Periscopes are uncommon in rural India and therefore serve as effective curiosity triggers.

[20] Each session typically includes one such story—real or imagined—integrated into the logical flow of the topic.

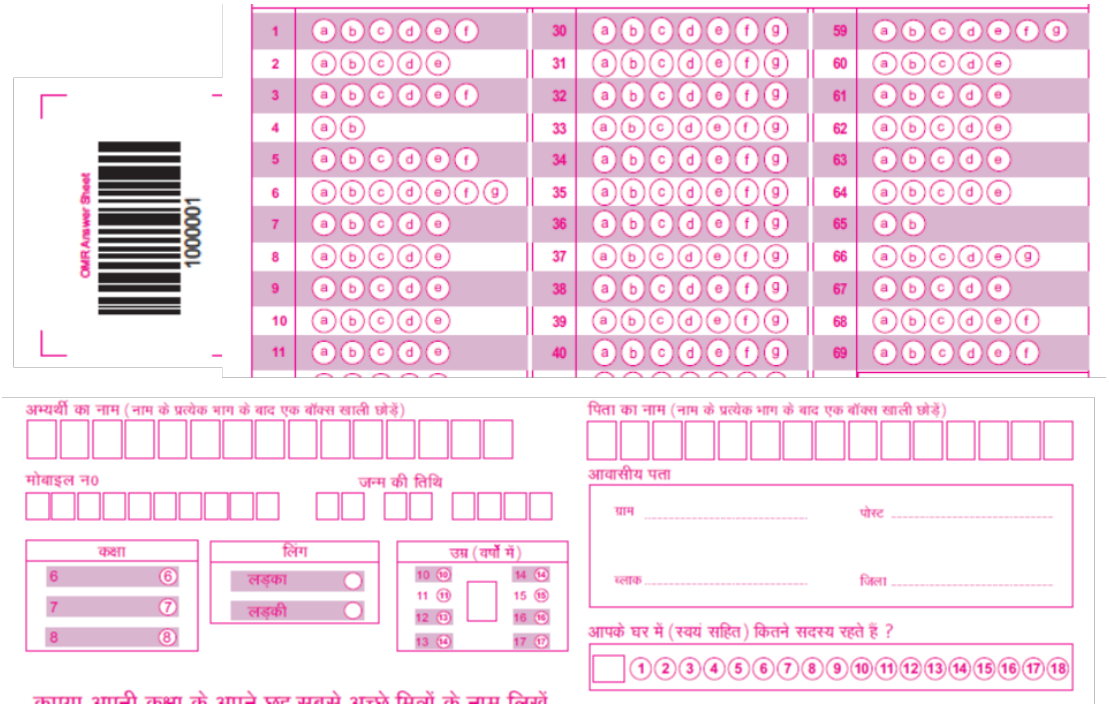
Dosage and learning dynamics. Because the intervention embeds substantive science content within experiential sessions, motivational and engagement shifts are likely to emerge gradually through repeated exposure rather than from any single session. Content learning may accumulate more directly with attendance, while shifts in competence beliefs and intrinsic motivation may require threshold levels of exposure before they materialize—implying that learning gains need not scale linearly with dosage. These dynamics are relevant for interpreting differences in effectiveness between the two delivery arms.

MSL versus LOB. Both arms deliver the same curriculum through the same pedagogical sequence. MSL operates from a mobile van with a team of instructors and achieves higher visit frequency; LOB delivers identical content through a single instructor traveling by motorbike. These logistical differences generate variation in cumulative exposure—the key margin of treatment intensity—without altering the underlying pedagogy (Table 1).

D Survey Instruments and Measures

D.1 Survey Response Format

Figure A.1: Sample Optical Mark Recognition (OMR) Response Sheet



Notes: This figure shows an example of the Optical Mark Recognition (OMR) response sheet used to record student answers in the endline survey. Students marked their responses directly on the sheet, which was subsequently scanned and digitized for analysis.

D.2 Endline Student Survey

The endline student survey was administered to students in Grades 6–8 after completion of the intervention. The survey consisted of multiple modules designed to capture students' educational inputs, attitudes toward science, non-cognitive skills, engagement, and household background. All questions were presented in multiple-choice format to ensure compatibility with OMR-based data collection. Below we describe the main modules of the survey. Question numbering refers to the original survey instrument.

Module A : Schooling History, Attendance, and Subject Preferences

This module collected information on grade repetition, recent school absenteeism, students' favorite subjects, availability of homework support at home, and engagement with science-related activities outside school, such as watching science programs or conducting experiments at home.

Q1. Last year you were in which class?

a) Class 5

b) Class 6

c) Class 7

d) Class 8

Q2. Have you ever repeated a grade in school?

a) Yes

b) No

c) Don't want to answer

Q3. Past week, how often were you absent from school?

a) Never

b) 1 day

c) 2 days

d) 3 days

e) 4 days

f) 5 days or full week

Q4. Have you ever done a science-based experiment?

a) Yes

b) No

c) I do not know what a science-based experiment is

Q5. What are your two most favorite subjects? *[Select 1 or 2]*

a) Hindi

b) Science

c) English

d) Maths

e) Social Science (history, geography, civics, etc.)

Q6. Is there someone at home who teaches you or helps you in doing homework? *[Multiple select allowed]*

a) Father

b) Mother

c) Elder brother

d) Elder sister

e) Others (uncle, aunt, grandparents, etc.)

f) No one helps

Q7. In my leisure time, I like . . . *[Multiple select allowed]*

a) Watching popular science channels on TV

b) Watching other science-related videos on television or through the internet

c) Reading science-related books or magazines (other than school book)

d) Conducting homemade science experiments

e) Having conversations with others about science

f) None of the above

Module B : Time Use and Study Inputs

Students reported the amount of time spent on household work, self-study, and private tuition. Subject-specific time use was elicited for science, mathematics, and other subjects, distinguishing between tuition-based study and independent study at home.

How many hours, on an average weekday, do you spend doing the following (in one day)?

Q8. Help family with household work or other types of work (e.g., agriculture, cooking, cleaning, caring for younger siblings or elders)

a) Almost no time in household work

b) Less than 1 hour

c) 1 to 2 hours

d) 2 to 3 hours

e) More than 3 hours

Q9. Study (do homework) outside of tuition and school per day?

a) Don't study at home

b) Less than 1 hour

c) 1 to 2 hours

d) 2 to 3 hours

e) More than 3 hours

Q10. Time spent per day on tuition (please do not add travel time)

a) Don't go for tuition *(if this, skip to Q18)*

b) Less than 1 hour

c) 1 to 2 hours

d) 2 to 3 hours

e) More than 3 hours

Last week, how many hours per day did you spend in private tuition for the following subjects?

Q11. Science **Q12.** Maths **Q13.** Other subjects

a) 0–2 hours

b) 2–4 hours

c) 4–6 hours

d) 6–8 hours

e) More than 8 hours

Last week, how many hours did you spend studying at home (do not include tuition time)?

Q14. Science **Q15.** Maths **Q16.** Other subjects

a) 0–2 hours

b) 2–4 hours

c) 4–6 hours

d) 6–8 hours

e) More than 8 hours

Module C : Educational Aspirations and Perceived Constraints

This module measured students' educational aspirations, perceived likelihood of completing higher education, intended subject streams, and perceived barriers to educational attainment, including financial constraints, family expectations, social identity, and self-confidence.

Questions related to what you think about yourself. Please select the best possible option. There is no right or wrong answer.

Q17. Thinking about your future education-wise, what objective do you intend to achieve?

a) Up to Class 8

b) Up to Class 10

c) Up to Class 12

d) Up to a university degree

Q18. Independently from your educational aim, but thinking about your abilities, do you think you could obtain a university degree?

a) Not at all

b) Very little

c) Somewhat

d) Very much

Q19. Thinking about your future education-wise, what subject do you intend to study in higher grades?

a) Science stream (science, maths-type courses)

b) Arts stream (English, history, geography-type courses)

c) Commerce stream (business, bookkeeping-type courses)

d) I have not made up my mind yet

e) Don't know

Do you think the following could be an obstacle in the achievement of your educational aim?

Q20. Economic resources **Q21.** Family needs and ideas **Q22.** Gender/caste prejudice **Q23.** Not feeling up to the standards

a) Very much

b) Somewhat

c) Very little

d) Not at all

Module D : Attitudes Toward Science Learning

Students rated their enjoyment of learning science, perceived relevance of science, and interest in conducting experiments using a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree).

How much do you agree with these statements about learning science?

Q24. I enjoy learning science.

Q25. Science teaches me how things in the world work.

Q26. I like to do science experiments.

Response scale (all items in this module):

a) Strongly Disagree

b) Disagree

c) Somewhat Disagree

d) Neither Agree Nor Disagree

e) Somewhat Agree

f) Agree

g) Strongly Agree

Module E : Perceptions of Science Instruction

This module captured students' perceptions of teaching quality, including clarity of instruction, responsiveness to questions, use of varied teaching methods, and willingness to re-explain concepts.

How much do you agree with these statements about your science lessons? (Same 7-point scale as Module D.)

Q27. My teacher is easy to understand.

Q28. My teacher has clear answers to my questions.

Q29. My teacher is good at explaining science.

Q30. My teacher does a variety of things (e.g., conducting small experiments, providing examples, etc.) to help us learn.

Q31. My teacher explains a topic again when we don't understand.

Module F : Academic Self-Concept in Science

Students reported their perceived ability and confidence in science, including beliefs about doing well in science, learning speed, perceived difficulty, and comfort asking questions.

How much do you agree with these statements about science? (Same 7-point scale as Module D.)

Q32. I usually do well in science.

Q33. I learn things quickly in science.

Q34. Science is harder for me than any other subject.

Q35. Science is not confusing for me.

Q36. I do not feel shy asking questions during my science class. *(Note: response scale is reversed in the original instrument relative to Q32–Q35; higher agreement = more confidence.)*

Module G : Household Background and Assets

This module collected information on parental education and occupation, sibling composition, housing characteristics, and ownership of household assets.

Q37. Father's primary occupation

a) Farming

b) Non-farm business (cloth shop, selling milk, etc.)

c) Self-employment (blacksmith, barber, etc.)

d) Government or private job

e) Unemployed/Retired

f) Other

Q38. Father's educational level **Q39.** Mother's educational level

a) No formal schooling

b) Up to Class 5

c) Up to Class 8

d) Up to Class 10

e) Up to Class 12

f) College or above

g) Don't know

Q40. Do you have any brother(s)/sister(s) studying in the same school as you?

a) Yes

b) No

Q41. In which class are your brother(s)/sister(s) studying? *[Multiple select allowed]*

a) Class 5 or less

b) Class 6

c) Class 7

d) Class 8

e) Above Class 8

f) Not applicable

Tell us about the house you are currently living in.

Q42. Number of rooms (having 4 walls; not including kitchen/bathroom/common living area)

a) 1

b) 2–3

c) 4–5

d) 6–7

e) More than 7

Q43. Main material of the roof

a) Pucca (concrete)

b) Semi-pucca (khappad/tin)

c) Kutcha

How many of the following items are there in your household?

Q44. Motor vehicles *[Multiple select allowed]*

a) Car/Jeep

b) Tractor

c) Motorcycle

d) Cycle

e) Nothing

Q45. Phone *[Multiple select allowed]*

a) Smartphone

b) Simple phone/landline

c) Nothing

d) Don't know

Q46. Television *[Multiple select allowed]*

a) Color TV

b) Black-and-white TV

c) No TV

Q47. Number of cattle (cow/buffalo)

a) 0

b) 1–2

c) 3–4

d) 5–6

e) More than 6

Module H : Mindset, Curiosity, and Non-Cognitive Skills

Standardized batteries were used to measure growth mindset, curiosity, self-confidence, and personality traits. These included fixed versus growth mindset items, anxiety-related items, a short Big Five personality battery, and components of a critical-thinking disposition scale.

Growth Mindset (Q48–Q50). *How much do you agree/disagree with the following? (5-point scale: Strongly Disagree to Strongly Agree)*

Q48. You have a certain amount of intelligence, and you can't really do much to change it.
Q49. Your intelligence is something about you that you can't change very much.
Q50. You can learn new things, but you can't really change your basic intelligence.

Anxiety Items (Q51–Q52). **Q51.** Even a small doubt can stop me from doing new things.
Q52. When I am unsure about anything, I get tensed.

Birth Order (Q53). **Q53.** Are you the first-born child to your parents?

a) Yes

b) No

Big Five Personality—10-Item Scale (Q54–Q63). *I see myself as . . . (7-point scale: Strongly Disagree to Strongly Agree)*

Q54. Extraverted, enthusiastic.
Q55. Critical, quarrelsome.
Q56. Dependable, self-disciplined.
Q57. Anxious, easily upset.
Q58. Open to new experiences, complex.
Q59. Reserved, quiet.
Q60. Sympathetic, warm.
Q61. Disorganized, careless.

Q62. Calm, emotionally stable.

Q63. Conventional, uncreative.

Curiosity—Critical-Thinking Disposition Scale (Q64–Q68). *(7-point scale: Strongly Disagree to Strongly Agree)*

Q64. I am curious because I try to find out what I don't know.

Q65. I like to learn how everything works.

Q66. I enjoy learning new things.

Q67. I don't care if I know more or less things. *(reverse-coded)*

Q68. I try to understand things as well as possible.

Self-Confidence—Critical-Thinking Disposition Scale (Q69–Q74). *(7-point scale: Strongly Disagree to Strongly Agree)*

Q69. I try to say what I think even if others think otherwise.

Q70. I am able to understand things by myself.

Q71. I trust what others think more than what I think. *(reverse-coded)*

Q72. I notice that I reason better and better.

Q73. I like learning something without the help of others.

Q74. Learning to think well is important in order to improve.

Module I : Program Exposure and Experience (Treatment Schools Only)

Students in treatment schools reported whether they attended Agastya-based sessions, the number of sessions attended, overall experience ratings, and which aspects they found most enjoyable or novel.

Q75. Did you attend any Agastya-based sessions?

a) Yes

b) No

Q76. How many sessions did you attend?

a) 1

b) 2

c) 3

d) 4

e) 5

f) 6

g) 7

Q77. Rate your experience during those sessions on average. *(5-point scale)*

a) Very good

b) Good

c) Okay, like any other class

d) Bad

e) Very bad

Q78. Which aspect(s) of the sessions did you enjoy the most?

a) Group activity

b) Science experiments

c) Real-life examples

d) Speaking up in the classroom

e) Teachers giving more time to speak in the classroom

f) Didn't enjoy

Q79. Do you want more such sessions?

a) Yes

b) No

Q80. Have you discussed these sessions with your parents, friends, or siblings?

a) Yes

b) No

Module J : Student Engagement and Effort

This module measured behavioral, emotional, and cognitive engagement in school, including enjoyment of school, effort in class, participation, attention, homework completion, and help-seeking behavior.

How much do you agree with the following statements? (Same 7-point scale as Module D.)

Q81. I enjoy going to school.
Q82. I work as hard as I can in class. *(vs. during science class)*
Q83. I try very hard to do well in school.
Q84. I participate in class discussions. *(vs. during science class)*
Q85. I pay attention in class. *(vs. during science class)*
Q86. I listen carefully in class. *(vs. during science class)*
Q87. I complete my homework on time. *(vs. science homework)*
Q88. I talk about science/maths outside of class.
Q89. I ask questions when I don't understand something in my readings or during lectures.
Q90. I study at home even when I don't have a test.
Q91. I read extra books to learn more about things we do in school.

Module K : Curriculum-Aligned Science Assessment (Grade-Specific)

The endline survey also included curriculum-aligned multiple-choice science questions separately for Grades 6, 7, and 8. Each grade-level assessment consisted of ten questions covering core concepts from the state syllabus, including physical sciences, life sciences, and environmental science.

Response Scales and Index Construction

Most survey items were recorded using ordered categorical response scales. Unless otherwise noted, higher values correspond to higher levels of the underlying construct.

Likert-Scale Items (Attitudes, Beliefs, and Engagement). Items measuring attitudes toward science, perceptions of instruction, academic self-concept, and student engagement were collected using Likert-type response scales ranging from four-point to seven-point (e.g., *strongly disagree* to *strongly agree*). For each construct, responses were coded numerically, standardized using the control-group mean and standard deviation, and averaged to form composite indices.

Non-Cognitive Skills. Growth mindset, curiosity, self-confidence, and personality traits were measured using short batteries adapted from established instruments. Growth mindset and curiosity

items used agreement-based Likert scales, while personality traits were elicited using the 10-item Big Five battery. Individual items were standardized and aggregated into domain-specific indices following standard practice.

Educational Aspirations and Perceived Constraints. Items capturing aspirations and perceived barriers to attainment were recorded on ordered categorical scales reflecting likelihood or agreement and analyzed both individually and as part of standardized indices.

Time Use and Study Inputs. Time-use measures were collected in categorical bins reflecting hours spent on study, tuition, and household work. These variables are used in their original categorical form or converted to approximate continuous measures using bin midpoints.

Program Exposure Measures. Program exposure and experience questions were asked only in treatment schools and recorded using categorical or ordered response options. These measures characterize participation intensity and engagement with the intervention rather than serving as identifying variation.

Curriculum-Aligned Science Questions. Grade-specific science questions were scored as binary indicators of correct responses and aggregated to form standardized test-score indices within each grade.

D.3 Teacher Survey

The teacher survey was administered to science teachers in both treatment and control schools to document baseline instructional environments, teaching practices, and pedagogical beliefs, and to examine whether the intervention influenced reported teaching behaviors. The survey was administered using a structured questionnaire with ordered categorical response options. Below we summarize the main modules and response scales. Question numbering refers to the original survey instrument.

Module A : Demographic and Educational Background

This module collected information on teachers' gender, age, highest level of education completed, field of study, and social category. These variables are used to describe the teacher sample and to assess balance across treatment and control schools.

Q1. Are you female or male?

a) Female

b) Male

Q2. How old are you? *[Write a number]* Years: _____

Q3. What is the highest level of formal education you have completed?

a) Below Graduate degree

b) Graduate

c) Post Graduate

d) Bachelors in Education (or equivalent degree)

e) Masters in Education (or equivalent degree)

f) Other professional courses for teaching (Diploma, etc.)

Q4. For the highest degree, what was your major?

a) Science

b) Arts

c) Business and Economics

d) Engineering and Computer Science

e) Education

f) Other

Q5. Which social category do you belong to?

a) General Class

b) Scheduled Caste/Scheduled Tribe

c) Other Backward Caste

d) Do not want to respond

Module B : Teaching Assignment and Experience

Teachers reported the grades and subjects they currently teach, years of experience as a science teacher, and whether teaching was their first career choice. These measures capture exposure to science instruction and accumulated teaching experience.

Q6. In the current school, which grades do you teach science lessons to? *[Multiple select allowed]*

a) Grade 6

b) Grade 7

c) Grade 8

d) Other than Grade 6, 7 and 8

Q7. Which other subjects (apart from science) do you teach?

a) English

b) Math

c) Hindi

d) Social Science

e) Other

Q8. How many years of work experience as a science teacher do you have, regardless of whether you worked full-time or part-time?

a) Less than 1 year

b) 1–2 years

c) 3–5 years

d) 5–7 years

e) More than 7 years

Q9. Was teaching your first choice as a career? *(A "career" is having a paid job that you regarded as likely to form your life's work.)*

a) Yes

b) No

Module C : Motivation for Entering Teaching

This module elicited teachers' motivations for choosing teaching as a profession, including job security, career stability, work–life balance considerations, intrinsic motivation related to working with children, and family influence.

Q10. Were any of the following factors influenced your decision to become a teacher? *[Multiple select allowed]*

i. Teaching offered a steady career path.

ii. Teaching was a secure job (reliable income).

iii. The teaching schedule (e.g., hours, holidays, part-time positions) fit with responsibilities in my personal life.

iv. Teaching allows me to influence the development of children and young people.

v. It is a respectable profession.

vi. I was inspired by my parents (or other close family member) to become teacher.

vii. None of the above.

viii. Other.

Module D : Teaching Practices and Self-Assessment

Teachers reported the extent to which they engage in specific instructional practices, including motivating students, encouraging critical thinking, using experiments, providing alternative explanations, and supporting learning with digital tools. Items (i)–(vi) use a 4-point scale (*Not at all* to *A lot*); items (vii)–(ix) use a 4-point agreement scale (*Agree a lot* to *Disagree a lot*).

Q11. In your teaching of Science, to what extent can you do the following?

Scale for items (i)–(vi): (a) Not at all (b) To some extent (c) Quite a bit (d) A lot

(i) Get students to believe they can do well in school work.
(ii) Motivate students who show low interest in school work.
(iii) Help students think critically.
(iv) Use science-related experiments as an alternative teaching methods.
(v) Provide an alternative explanation, for example when students are confused.
(vi) Support student learning through the use of digital technology (e.g., computers, tablets, projector).

Scale for items (vii)–(ix): (a) Agree a lot (b) Agree a little (c) Disagree a little (d) Disagree a lot

(vii) I am good at explaining science.
(viii) I do a variety of things (e.g., conducting small experiments, providing examples, etc.) to help my students learn.
(ix) I explain a topic again when my students don't understand.

Module E : Assessment Practices and Parent Interaction

This module collected information on the frequency of student assessments and the nature of interactions with parents, including participation in parent–teacher meetings and targeted outreach to parents of low-performing students.

Q12. How often do you conduct small tests to grade/mark/rank students?

a) Monthly 1 small test

b) 1 test in 2 months

c) 1 quarterly tests

d) 2 tests in a year (one half-yearly and one final)

Q13. How often do you meet with parents of students?

a) In a usual parents-teacher meeting

b) I sometimes call parents of student if he/she is not doing well academically (or otherwise)

c) We never have any parents-teachers meeting

Module F : Perceptions of Student Performance and Interest

Teachers rated students' performance and interest in science separately for Grades 6, 7, and 8 using ordered categorical scales. These measures capture teachers' perceptions of student engagement and learning and are analyzed descriptively or standardized where appropriate.

Performance ratings (Q14–Q16): applicable only if the teacher teaches the respective grade.

Q14. Grade 6 **Q15.** Grade 7 **Q16.** Grade 8 — How would you rate students' performance/knowledge in science?

a) Excellent

b) Very good

c) Good

d) Not so good

e) Students need to work a lot to improve the standard

Interest ratings (Q17–Q19): applicable only if the teacher teaches the respective grade.

Q17. Grade 6 **Q18.** Grade 7 **Q19.** Grade 8 — How would you rate students' interest toward science on average?

a) Very much

b) Somewhat

c) Very little

d) Not at all

Module G : Job Satisfaction

Teachers reported their overall level of job satisfaction using an ordered categorical scale. This measure is used descriptively and to assess whether the intervention affected reported satisfaction with teaching.

Q20. Are you satisfied with your job?

a) Not at all

b) To some extent

c) Quite a bit

d) A lot

Response Scales and Index Construction in Teacher Survey

Unless otherwise noted, teacher survey items were recorded using ordered categorical response scales, with higher values corresponding to higher levels of the underlying construct. For empirical analysis, selected items related to teaching practices and self-assessment (Module D) are standardized and aggregated into composite indices, while other measures are used individually for descriptive analysis and robustness checks.

D.4 Social Desirability Score

To assess respondents' tendency to provide socially desirable rather than truthful responses, we use a short-form version of the Marlowe–Crowne Social Desirability Scale originally developed by Crowne and Marlowe (1960) and subsequently adapted into reliable and valid short forms by Hays et al. (1989). The scale consists of 5 items and was administered as part of the student survey at the endline. Each item is presented as a statement with a 5-point true/false response scale. For each item, the extreme response corresponding to the socially desirable answer is coded as 1 and all other responses as 0. The social desirability score is constructed by summing the number of socially desirable responses across all items, yielding a total score ranging from 0 to 5. Higher scores indicate a greater tendency toward socially desirable responding, while lower scores indicate a lower propensity for social desirability bias. This measure is used in robustness analyses to assess whether estimated treatment effects on self-reported outcomes are sensitive to differential response tendencies across treatment and control groups.

Response scale (all items): (a) Definitely true (b) Mostly true (c) Don't know (d) Mostly false (e) Definitely false

i. I am always courteous even to people who are disagreeable.

ii. There have been occasions when I took advantage of someone.

iii. I sometimes try to get even rather than forgive and forget.

iv. I sometimes feel resentful when I don't get my way.

v. No matter who I'm talking to, I am always a good listener.