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Learner Pathway Analysis: An Approach for Evaluating STEM Persistence in Learning Ecosystems

Seth Corrigan, Maggie Dahn, Mizuko Ito, Kylie Peppler
University of California, Irvine, scorrig1@uci.edu, dahnm@uci.edu, mizukoi@uci.edu, kpeppler@uci.edu

Abstract: Learning ecosystems provide children and youth with opportunities to explore STEM and non-STEM topics across in-school and out-of-school (OST) settings. Supporting learners in navigating the opportunities available to them across their local learning ecosystems is critical to ensuring learners can effectively investigate their interests. To do so, we introduce Learner Pathway Analysis (LPA), a Design-Based Research approach that operationalizes a pathways heuristic to evaluate STEM learning ecosystems. Building on patient pathway analysis in healthcare and other fields, LPA assists in longitudinal tracking of individual participation and transitions across programs. We illustrate the approach with TGR Foundation's afterschool programs, showing how LPA reveals patterns of enrollment, continuity, and transitions. By combining conceptual framing, principled measurement, and practical tracking tools, LPA provides a framework for evidence-informed design and coordination of connected, interest-driven STEM learning opportunities.

Introduction

STEM learning ecosystems encompass a network of formal classrooms, afterschool programs, community organizations, and home environments, offering learners multiple pathways to explore and develop their interests (Bevan et al., 2015; Falk & Dierking, 2018). While these ecosystems present rich opportunities, they also create challenges: learners must navigate diverse programs, topics, and transitions, often without consistent guidance or feedback about the alignment between their interests and available opportunities (NRC, 2015).

To address these challenges, we adopt a pathways heuristic grounded in ecological learning theories (Barron, 2006; Bronfenbrenner, 1994) and connected learning principles (Ito et al., 2013). Connected learning emphasizes linking personal interests, supportive relationships, and opportunities for academic and civic engagement, centering youth in their educational trajectories and connecting their passions to learning and career pathways (Ito et al., 2020). However, existing evaluation frameworks rarely capture learners' multi-context trajectories, limiting insights into how social relationships, programs, and ecosystems collectively shape STEM engagement (Stephens, 2016; Maul et al., 2017).

We introduce Learner Pathway Analysis (LPA) as an approach to operationalize the pathways heuristic, providing a structured method for tracking learners' transitions across STEM and non-STEM experiences, identifying gaps in opportunity, and diagnosing misalignments between learner interests and program offerings. This paper presents the Design-Based Research process for developing LPA, describes the framework's conceptual and operational metrics, and demonstrates its application in a case study with TGR Foundation (TGR), a nonprofit organization that partners with a network of providers to deliver STEM and college readiness programs. By examining enrollment patterns, continuity, and transitions, we illustrate how LPA provides actionable insights for fostering equitable, interest-driven STEM learning pathways across connected learning ecosystems. The findings have implications for strengthening organizational strategies, systematically connecting youth interests to program offerings, and contributing to theoretical frameworks for studying and assessing these outcomes.

Background

Connected learning and designing ecosystems to support STEM learning

Our general approach to STEM learning is rooted in an ecosystems view that prioritizes connected learning (Ito et al., 2020). Connected learning is an educational framework that emphasizes linking students' personal interests, supportive relationships, and opportunities for academic and civic engagement to create meaningful learning experiences. Rooted in the understanding that learning is most effective when it is relevant and socially connected, connected learning envisions environments where young people can explore their passions while developing critical skills. High-quality learning ecosystems that build on these principles are inclusive, adaptable, and responsive to the diverse needs of learners, providing opportunities for them to thrive academically and socially. These ecosystems leverage technology, mentorship, and community resources to bridge gaps between informal and formal learning spaces, fostering collaboration and creativity.

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Barriers to learners' discovery and enrollment in relevant out-of-school programs can stem from limited resources, restricted access, or breakdowns in organizational capacity to *coordinate*, *broker*, or *make learning visible* between programs and settings (Ito et al., 2020). *Coordination* refers to the processes through which organizations build shared infrastructure—exchanging information and resources, establishing common standards, and cultivating mutual agreements (Augustine et al., 2021). *Brokering*, in contrast, involves systems-level practices where individuals or teams develop interorganizational relationships to connect young people to educational and career opportunities (Akiva et al., 2020). Additionally, organizations can strengthen engagement by *making learning visible* across settings through networked infrastructures such as online affinity networks, digital badges (Pitt et al., 2019), or learner portfolios.

Fostering interorganizational collaboration is essential for addressing learner needs and interests. When organizations work together to offer youth a wider array of choices, they create opportunities for stronger alignment between what learners want and what programs provide. Data systems that help program leaders analyze this alignment can reveal where opportunities are lacking and generate insights that inform both internal planning and external partnerships. Metrics derived from such data can further sustain learning ecosystems by identifying gaps between learner interests and existing programs, generating strategies to bridge those gaps, and guiding decisions about when and where to form collaborative relationships.

The utility of the pathways heuristic across fields

The pathway concept has proven valuable across multiple fields. In medicine, patient pathway analysis has improved care coordination between organizations, increased consistency in treatment, enhanced patient satisfaction, and optimized resource use (Denekere et al., 2012; Rotter et al., 2010; Vanhaecht et al., 2007). In career development, Savickas (2005) conceptualizes career paths as dynamic and individualized, shaped by personal interests, experiences, and transitions over time. These applications demonstrate how the pathway heuristic can systematically enhance outcomes through improved coordination, consistency, and resource optimization. We believe the pathway heuristic presents similar value for education, particularly in understanding how inter-organizational collaborations between afterschool programs, schools, and community-based organizations can enrich options and improve alignment between learners' STEM interests and available opportunities. While STEM interest and ability may be evenly distributed, opportunities to explore and learn STEM content are not, especially for youth in rural and economically disadvantaged communities (Bevan & Michalchik, 2013).

Design-Based Research (DBR) approach

To systematically design and refine ecosystem-level supports, our project adopts a Design-Based Research (DBR) framework. DBR offers a methodological approach for iteratively developing, testing, and improving interventions through cycles of design, implementation, data collection, analysis, and revision (Brown, 1992; Collins, 1992; Cobb et al., 2003). It is inherently collaborative, engaging researchers and practitioners in real-world contexts to address complex educational challenges while producing both practical solutions and theoretical insights. Within the DBR tradition, researchers and practitioners co-develop overarching *conjectures* about what contributes to desired outcomes (Sandoval, 2014). In our case, DBR guided the development, testing, and refinement of an evaluation framework that aligns with connected learning principles while maintaining high utility and ease of use for educational program staff. The framework's elements include the constructs to be measured, the associated metrics, the required processes and data, and the intended analyses. The research questions guiding the DBR process are: 1) What core constructs are most relevant for tracking learners' STEM learning opportunities across informal and formal settings? 2) What data are needed to support inferences about these constructs? 3) How can collected data be synthesized to inform the improvement and alignment of STEM learning opportunities with learners' interests?

Research context: TGR foundation

This study was conducted in partnership with the STEM Next 50 State Afterschool Network, a national initiative supporting the development of youths' interest and engagement in STEM across the United States. The network provides an ideal context for investigating our ecological approach to STEM learning, as many member organizations intentionally connect in-school and out-of-school opportunities to promote sustained STEM engagement. Within this network, we focused on TGR Foundation (TGR), based in Southern California, as an in-depth case. Since launching its STEM learning focus in 2001, TGR has developed a portfolio of afterschool and summer programs—including the TGR Learning Lab, career exploration initiatives, and youth golf programs—that together offer sustained exposure to STEM inquiry. Each year, TGR enrolls local middle and high school students in multi-week afterschool experiences and summer camps, while also partnering with school districts to

facilitate field trips and college readiness activities. TGR's capacity to collect and manage longitudinal participation data made it a strong site for co-developing and testing our Learner Pathway Analysis (LPA) framework. In the 2023-2024 school year, TGR Foundation was well-positioned to gather longitudinal data on learner enrollments within TGR programs. Their data from 29 unique learning experiences (16 of which included STEM content) from that year used a unique identifier for each learner enrolled in one or more of their programs. The identifier also included learner demographic information for grade and gender, as well as detailed information about learners' enrollments in TGR's after school experiences. The latter included the name of the learning experience, the learning content category of the experience(s), and the particular term it was offered. TGR Foundation implemented this design to follow youth participation in multiple STEM initiatives, both within and beyond their programs. The result was a data frame indexed by learners' unique ID, with subsequent columns for their gender, grade, fall term enrollment(s), winter term enrollments and spring term enrollments.

Research participants

Focusing on TGR's afterschool experiences, we use TGR's enrollment data for the 2023-2024 school year across the fall and spring terms. The data also includes student demographics (grade and gender [self-identified]), program details (experience names, content categories), and seasonal enrollment categories (fall, winter, spring). Student enrollment counts by grade and gender are presented in Table 1.

Table 1

TGR Afterschool Enrollment Data for the Fall and Spring Terms 2023-2024.

	Fall (2023)		Spring (2024)	
GradeLevel	Female	Male	Female	Male
6	0 (0.00%)	0 (0.00%)	5 (2.54%)	32 (16.24%)
7	33 (17.19%)	65 (33.85%)	35 (17.77%)	53 (26.90%)
8	10 (5.21%)	22 (11.46%)	16 (8.12%)	29 (14.72%)
9	9 (4.69%)	12 (6.25%)	4 (2.03%)	6 (3.05%)
10	6 (3.13%)	16 (8.33%)	1 (0.51%)	8 (4.06%)
11	3 (1.56%)	10 (5.21%)	3 (1.52%)	3 (1.52%)
12	3 (1.56%)	3 (1.56%)	1 (0.51%)	1 (0.51%)
Total	64	128	65	132

Data and analytical techniques

Our collaborative work with TGR Foundation focused on design and iteration of measures for tracking the movement of learners within and between STEM programs and STEM career exploration programs. We also conducted collaborative work to record their efforts over time to build and sustain collaborative arrangements with schools, businesses and other community-based organizations as means to enriching learners' experiences and opportunities learning STEM and pursuing STEM careers. We also conducted semi-structured interviews with key members of each organization and gathered feedback on iterated drafts of the survey tools used in our DBR effort.

Team members' notes from the semi-structured interviews and survey review sessions for the study were reviewed to identify needs and limitations presented by our collaborative partners that were relevant to design decisions for the resulting instruments. Data reported by each of the partners using the iterations of the survey were analyzed using R (R Core team, 2021). Analyses descriptives and proportions, emphasizing calculation of odds of learners' transitions from and to STEM experiences. Core visualizations included investigation and development of several types of flow diagrams (Harris, 2000), in particular Sankey diagrams, in an effort to provide easy-to-use summaries of learners' transitions.

Principled measure design

Our approach draws from traditions of principled measurement design, which emphasize the systematic and iterative development of assessment tools within a theory-driven framework. Evidence-Centered Design (Mislevy et al., 2003) and the BEAR Assessment System (Wilson, 2023) both provide methodological scaffolds for defining the construct of interest, identifying sources of evidence, and determining rules for interpreting that evidence. Within the Design-Based Research process, we adapted these principles to develop measures for informal STEM

learning contexts. Iterative co-design cycles with partner organizations resulted in instruments for assessing three core outcomes: (1) *Program enrollment patterns*—including transitions between STEM and non-STEM activities over time; (2) *Alignment between learner interests and available STEM opportunities*; and (3) *Inter-organizational collaboration*—the extent to which partnerships expand access to enriched STEM learning resources.

These outcomes informed the evolving structure of the Learner Pathway Analysis (LPA) framework: To start, we designed a lightweight individual tracking system enabling partner organizations to record student-level data with minimal burden. Built as a shared online spreadsheet tool, the system used preconfigured unique identifiers to link each learner's record across programs and time. Organizations documented demographic information (grade and gender), program characteristics, and term-by-term enrollment, producing a de-identified dataset that could be merged for analysis. This instrument emphasized flexibility and scalability—local sites could adapt the tool to their internal workflows while maintaining consistency in key fields for cross-site comparison.

During the first phase of instrument design, the research team identified major challenges in collecting consistent, individual-level enrollment data—namely, limited infrastructure, inconsistent data practices, and high staff turnover at local sites. In the second phase, the team worked iteratively with participants to develop a generalized system for tracking individual learner enrollments within and across organizations, designed for ease of local implementation. The resulting instrument (Table 2) was an editable online spreadsheet with preformatted fields and unique learner identifiers.

Table 2

Excerpt of Survey Instrument

1a	Your first name:				
1b	Your last name:				
1c	Role:		If 'other', please describe:		
2	Are you answering this survey for more than one site? (Y/N) (If yes, please complete the worksheet for each site.)				
3	Org. name:				
4a.	State:				
4b.	Site Name				
5	Please list the names of the programs that you are reporting on at this site:		Was/Is the program STEM or Comp Sci related?	Please describe the content focus of this program.	
5a	Name Program 01	*Sample Name*			
5b	Name Program 02				
5c	Name Program 03				
Please enter the student names here. These will not be shared outside of the organization.	*Please add IDs as needed.*	Please record the students' current grade (Spring 2024) and gender.	Please indicate the programs students were enrolled in during the **2022-2023 Year**	Please indicate the programs students enrolled in during the current 2023-2024 Year	

The survey asked organizations to describe their programs and identify enrolled learners, shifting focus from aggregate counts to individual-level data needed to track transitions over time. Each learner was linked to a unique ID and associated with gender and grade level. Organizations could record names and demographics locally, then upload de-identified versions for analysis. The instrument also captured program names and locations, indexing enrollments to specific experiences. For sites unable to collect individual-level data, an alternative aggregate version was provided. The refined phase two instrument (Table 2) was then implemented across participating organizations.

Learner Pathway Analysis (LPA): Concepts and metrics

With the data in hand outlined above, Table 3 details the expansion of the Learner Pathway Analysis framework, which expanded to nine core concepts and associated metrics across three broader categories over the course of the study (see Table 3). The *STEM programming* category aids practitioners and researchers in characterizing opportunities to investigate and learn STEM afforded by programs or organizations. STEM coverage points to the extent to which a program's offerings include opportunities to investigate or learn STEM content. Depth of STEM coverage indicates the number of unique STEM-focused experiences offered by a program, with the idea that when more unique experiences are offered within a particular branch of STEM, students have greater opportunity to investigate that content in depth. Breadth of STEM coverage indicates the proportion of STEM disciplines treated in a given term within the program, relying on the Higher Education Research Institute taxonomy (HERI, n.d.). The *student states-traits* category introduces student-level constructs relevant to understanding enrollment choices. Multiple measures of student traits are included. This category is useful for gauging alignment between STEM opportunities in students' environments and their social and psychological characteristics, whether slow-changing traits or dynamic states like engagement. The *student behaviors* category includes five concepts characterizing student enrollment behaviors. STEM enrollment indicates the proportion of students enrolled in STEM-focused experiences at a program or organization. Pathway delay defines the span of time between STEM enrollments for a given student. STEM re-enrollment provides a term for describing student persistence in STEM investigation and learning. The two transition concepts characterize when and how often students initiate STEM involvement and when they attrite or break their STEM involvement within a program or organization. Together, these metrics offer an empirical lens for describing how learners navigate ecosystems of opportunity and where gaps or bottlenecks emerge.

Table 3

Learning Pathway Analysis Framework Core Metrics

Category	**LPA Concepts**	**Definition**
STEM Programming	STEM Coverage	The proportion of all experiences that focus on STEM content made available through the given program, organization, or inter-organizational collaboration.
	Depth of STEM Coverage	The count of unique experiences offered within the four areas of STEM for a given term by a program, organization or collaboration.
	Breadth of STEM Coverage	The proportion of STEM disciplines treated in experiences offered in a given term, defined with regard to the taxonomy developed by the Higher Education Research Institute.
Student States/Traits	STEM Seeking	The proportion of students in a program or organization who indicate interest in STEM.
Student Behaviors	STEM Enrollment	The proportion of students enrolled in one or more STEM experiences in a specified term through a given program, organization, or inter-organizational collaboration.
	Pathway Delay	The length of time between STEM enrollments during a student's participation in an afterschool program.
	STEM Re-Enrollment	The odds of students transitioning from STEM experiences in one term to additional STEM experiences in a subsequent, consecutive term.
	Transitions to STEM	The odds that students will enroll in one or more STEM experiences after not having enrolled in a STEM experience the prior term.
	Transition from STEM	The odds that students will go on to enroll in one or more non-STEM experiences after having enrolled in at least one STEM experience the prior term.

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TGR's pathway analysis

In this section we present a small subset of the findings made possible by the pathway analysis for TGR's 2023-2024 afterschool program. The dataset included 192 unique middle school and high school students in grades 6-12 attending TGR's afterschool experiences in fall 2023, and 197 attending in spring 2024. Female students represented approximately one-third of the enrollment across both terms. TGR has several afterschool programs and experiences that they offer, and only those students enrolled in their afterschool STEM program are represented here.

STEM programming

A total of 29 experiences were made available to high school students across the fall and spring terms. Of the experiences, 50% in the fall and then 36% in the spring, were STEM-focused, covering diverse science, technology, and engineering topics but lacking representation in mathematics.

STEM Coverage. These STEM topics encompassed 75% of the taxonomy categories in the taxonomy developed by the Higher Education Research Institute (HERI). Among the 18 unique experiences offered for the fall term, nine were STEM-focused, resulting in a STEM coverage value of 0.50. In the 2023-2024 spring term, the STEM focus value was 0.36 with four out of 11 of the experiences offered focusing on STEM content. The same data point can be reported for other terms and other content types. Alternatively, the percentage of experiences focused on individual STEM domains can be calculated (e.g., experiences that focus on computer science, biology, chemistry or physics) (see Table 4).

Depth of STEM Coverage. Recognizing that hybrid experiences are common, programs can categorize each by its primary focus or add categories for hybrid cases. Ideally, this indicator would reflect increasing skill or knowledge levels, similar to academic prerequisites, though this proved impractical in informal education. In TGR Foundation's afterschool program, students averaged 3.0 unique STEM experiences in the fall (SD = 1.0), with most in Science and none in Mathematics. In the spring, the average dropped to 2.33 (SD = 1.53), again concentrated in Science and none in Mathematics.

Table 4

TGR's depth of STEM coverage for 2023-2024

Term	Science	Technology	Engineering	Math	STEM	Non-STEM	TOTAL
Fall 2023	4	3	2	0	9	9	18
Spring 2024	4	1	2	0	7	4	11

Breadth of STEM Coverage. For TGR's 2023-2024 year, it offered a total of nine unique STEM experiences in the fall and four in the spring. After categorizing each of the experiences in one of the eight HERI STEM disciplines (e.g., agriculture/natural resources, engineering, health professions), the value for its breadth of TGR's after school STEM coverage for the fall was 0.750, where a value of 1.0 would mean that all categories were represented. The spring value for breadth of coverage was 0.625, a drop in the percentage of the categories of STEM content when compared to the fall.

Student states/traits

STEM Seeking. Because this metric inherits measured values resulting from another instrument (e.g., a survey instrument used to gauge STEM interest) the value this metric takes on is dependent on the particular interest survey used and the given cut-point for "high-interest." In the case of TGR Foundation's after school program, staff have recently begun linking students' self reported STEM interest using a survey developed in-house. But at the time of writing, that data had not linked that data to student enrollments.

Student behaviors

STEM Enrollment. For the fall of the 2023-2024 year, TGR Foundation had a total of n = 192 students enrolled in its afterschool programs. Out of that total, 116 (60.73%) of its afterschool students enrolled in one or more STEM experiences (Table 5). In the spring of the same year, the figure was similar with 67.01% (132) of students enrolled in STEM experiences out of a total of n = 197.

Table 5

STEM Enrollment for 2023-2024 School Year

	Fall 2024	Spring 2024

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	Non STEM Enrollment	STEM Enrollment	Total	Non STEM Enrollment	STEM Enrollment	Total
Female	32 (50.0%)	32 (50.0%)	64 (100.0%)	30 (46.15%)	35 (53.85%)	65 (100.00%)
Male	43 (33.86%)	84 (66.14%)	127 (100.00%)	35 (26.52%)	97 (73.48%)	132 (100.00%)
All	75 (39.27%)	116 (60.73%)	191 (100%)	65 (32.99%)	132 (67.01%)	197 (100%)

Pathway Delay. Because the enrollment data for this report covers only two terms, we were not able to calculate this metric. Once the data is updated and analyzed for enrollments in the current year, it may be possible to start tracking pathway delay with enrollments for fall and spring 2024.

STEM Re-Enrollment. Re-enrollment rates in STEM experiences were similarly encouraging but also showed room for growth. Overall, the odds of re-enrollment were 1.06 (95% CI [0.67, 1.68]), with higher rates for female students compared to male students. In fall 2023, TGR Foundation had n = 72 afterschool students enrolled in one or more STEM experiences. From that group, 37 went on to enroll in one or more STEM experiences in the following spring. The re-enrollment rate for male students was 0.424, 95% CI [0.424, 0.265], making the re-enrollment rate for female students 1.4 times higher with a value of 0.600, 95% CI [0.293, 0.193]. Importantly, the computed values for STEM re-enrollment for TGR's afterschool experiences across the 2023-2024 year only account for students who enrolled again in experiences at the Foundation. They do not account for students who enrolled in STEM experiences elsewhere, including in school or other afterschool activities not tracked in this report.

Transitions to STEM. Students attending both fall and spring terms were more than twice as likely to transition into STEM experiences than transition away from them. TGR afterschool had n = 75 students who were only enrolled in non-STEM experiences in the fall. Of that total, sixteen (16) students transitioned to enroll in one or more STEM experiences in the fall. The odds of transitioning from non-STEM only, to one or more STEM enrollments was 0.271 95% CI [0.156, 0.471].

Transitions from STEM. As given in Table 6, during the 2023-2024 year at TGR, the odds that students would transition from one or more STEM enrollments in the fall to non-STEM enrollments-only, in the spring were 0.125, 95% CI [0.059, 0.261]. Similarly, the odds of the STEM-Fall group achieving the outcome of not enrolling at all in the spring were 0.600, 95% CI [0.372, 0.967]. Taken together, these kinds of metrics can be used to compare year over year, program iterations to one another, and other forms of metrics to track change over time.

Subgroup Transitions. Because TGR Foundation also records learners' self-reported gender, the odds of transitioning to STEM and the odds of transitioning from STEM across the fall and spring can be calculated. There were 32 female learners enrolled in only non-STEM experiences in the fall 2023, and 9 of them went on to one or more STEM classes in the spring. The odds of making that transition to STEM for females were 0.391, 95% CI [0.181,0.846]. In the same year, there were 43 male learners enrolled in only non-STEM experiences in the fall, and 7 of them went on to one or more STEM experiences in the spring. The odds of the transition for males was smaller than that for females, 0.194, 95% CI [0.865, 0.437], making females twice as likely to transition from non-STEM experiences to one or more STEM experiences. Considering the experience of learners transitioning from STEM, from-STEM transition was 1.6 times more likely for females than it was for males. The from-STEM transition value was 0.063 [CI 0.026, 0.156] for male learners. It was 0.103 [CI 0.032, 0.340] for females.

Sankey diagrams: Sample visualizations

In addition to the analysis framework, visual forms can help summarize the complex information captured by the pathway heuristic. One useful type is the *flow diagram*, a directed graph that depicts pathways between related events such as courses or activities (Harris, 2000). *Sankey diagrams*—a subset of flow diagrams—use nodes and arcs to visualize transitions, such as students moving from one course or domain to another. Figure 1 shows a Sankey diagram summarizing TGR's student enrollment transitions from fall to spring (2023–2024) by content type, highlighting in blue those who began in the arts. In Sankey diagrams, node size and arc width represent the number of students, allowing for quick comparison of transitions over time (e.g., an arc for 20 students is twice as thick as one for 10). When nodes are vertically stacked and organized by time steps, the diagram is called an *alluvial diagram*. This form enables comparison across multiple time points but requires individual-level data, not just aggregated counts.

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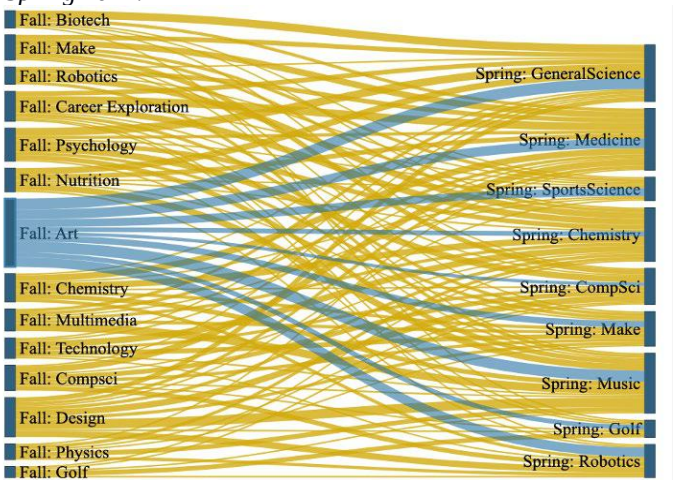
Figure 1

Sample Sankey Diagram Depicting the Volume of Students Transitioning from non-STEM Enrollments in Art in Fall 2023 to One or more STEM and/or Non-STEM Enrollments in Spring 2024.



Discussion

The TGR Foundation case highlights how implementing individual-level Learner Pathway Analysis (LPA) within a Design-Based Research framework can generate actionable insights about learners' engagement and transitions in STEM. By linking longitudinal participation data to visualization tools such as Sankey and alluvial diagrams, the analysis revealed how students—particularly female learners—move into and sustain participation in STEM experiences over time. These visualizations not only function as analytic tools but also as design artifacts that help practitioners view their programs as part of a larger ecosystem of interconnected learning opportunities. At the same time, the case revealed persistent challenges in using data to represent the full complexity of learning ecosystems. Staff turnover, decentralized record keeping, and the absence of interoperable data systems limited the completeness and comparability of records across programs. Addressing these challenges will require coordinated development of shared data standards, streamlined reporting processes, and lightweight digital infrastructures that can be realistically maintained by community-based organizations. Future design cycles will focus on co-developing and testing these coordination practices to balance local flexibility with ecosystem-wide visibility. Applying LPA at the organizational and ecosystem levels can strengthen coordination between in-school and out-of-school STEM programs by making patterns of participation and alignment visible. By identifying where learners' interests do not align with available opportunities, LPA could help program leaders form partnerships that bridge those gaps—ensuring, for instance, that learners introduced to STEM concepts after school have clear pathways to pursue them in the classroom. This data-driven approach encourages a holistic learning ecosystem in which both formal and informal settings contribute to sustained engagement and interest development. Because LPA integrates data on learner interests, participation, and transitions, it offers a shared evaluative language for educators, program leaders, and policymakers. For afterschool organizations in particular, it provides an evidence base for refining programming and improving equity in access to STEM opportunities. When learners' progress can be tracked across settings, the ecosystem becomes more responsive—able to adapt programming to real patterns of engagement rather than relying on isolated snapshots of participation.

Conclusion

This paper introduced Learner Pathway Analysis as a Design-Based Research approach for evaluating and improving STEM ecosystems. Analysis demonstrated how individual-level tracking can reveal meaningful patterns in enrollment, re-enrollment, and transitions across programs. The LPA framework's metrics on programming, learner states, and behaviors provide a structured means of identifying alignment gaps and coordination opportunities. Findings indicate that students were more than twice as likely to transition into STEM experiences as away from them, underscoring the role of well-designed afterschool programs in cultivating STEM interest. Yet the persistence of gender disparities and data coordination challenges reveals the ongoing need for equity-focused design and shared infrastructure. LPA offers a pathway toward evidence-informed ecosystem design that supports learners as they explore, deepen, and sustain interests across contexts. As educational ecosystems evolve, frameworks like LPA that combine theoretical coherence with practical utility will be essential for creating equitable, connected, and interest-driven opportunities for learners.

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