Beyond Attendance: Measuring Cultural Participation Through Longitudinal Learning Records

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Abstract

This study develops a longitudinal measurement framework for evaluating cultural participation in public learning programs beyond simple attendance counts. The study is designed to track approximately 6,000 learners across 50 public cultural learning programs over three program cycles, generating around 72,000 attendance records, 18,000 assignment or activity-completion records, 9,500 feedback entries, 4,200 course-switching records, and 3,000 re-enrollment records. Instead of treating participation as a one-time enrollment outcome, the study measures repeated attendance, course persistence, voluntary return, project completion, learning pathway change, feedback engagement, and progression across different program levels. Quantitative methods include longitudinal data analysis, survival analysis, sequence analysis, latent transition analysis, growth curve modeling, and logistic regression to identify participation trajectories and dropout risks. Learners can be classified into profiles such as stable participants, intermittent participants, course-switching learners, one-time participants, and re-engaged learners. Main indicators include retention rate, return rate, average participation duration, course-switching frequency, completion continuity, and progression probability. The innovation of this study lies in redefining cultural participation as a dynamic learning process rather than a static attendance outcome, providing public institutions with a more accurate tool for evaluating learner continuity and program impact.

Keywords: longitudinal records; cultural participation; learning continuity; survival analysis; sequence analysis; public learning programs; learner progression; program evaluation

1. Introduction

Public cultural learning programs provide accessible opportunities for community members to participate in music, visual arts, dance, crafts, literature, heritage, and other forms of cultural and creative learning. These programs are commonly delivered through public cultural centers, libraries, museums, community institutions, and local education initiatives, and they are expected to support cultural participation, lifelong learning, social inclusion, and equitable access to educational resources. Recent research on public art education has further emphasized the importance of monitoring teaching quality while evaluating educational equity, indicating that participation opportunities alone are insufficient for determining whether public cultural education produces stable and equitable learning experiences [1]. In practice, however, program performance is still frequently assessed using enrollment, attendance, or total participation counts because these indicators are straightforward to collect and compare. Such aggregate measures provide useful information about program reach, but they reveal little about how individual learners actually participate over time. This limitation is important because cultural participation is not a single event but a process that may involve continued attendance, temporary interruption, course switching, repeated enrollment, progression to higher-level activities, or later return [2,3]. A learner who attends only one session may be counted in the same way as another learner who completes several courses and continues into a subsequent program cycle. Similarly, conventional attendance statistics cannot distinguish between learners who permanently withdraw and those who temporarily interrupt their participation before returning. These differences matter because sustained cultural engagement appears to generate different outcomes from occasional participation. Previous studies have associated regular participation in cultural and creative activities with stronger social connection, improved well-being, and reduced social isolation [4,5]. The benefits associated with one-time or highly irregular participation are often less stable, suggesting that the duration and continuity of engagement should be considered alongside overall participation volume.

Participation patterns are also shaped by substantial differences among learners and their social environments. Age, educational background, income, health status, place of residence, previous cultural experience, available time, and familiarity with cultural institutions can all influence whether an individual begins, continues, or returns to a program [6,7]. Consequently, formal openness does not necessarily produce sustained or equitable participation. Research on cultural inclusion has therefore called for broader indicators that capture continued involvement, movement among activities, and access to different levels of cultural provision rather than relying only on initial entry into programs [8,9]. Learners may discontinue participation because of competing work or family responsibilities, scheduling difficulties, poor course fit, limited instructional support, or discontinuities between introductory and advanced programs [10,11]. In other cases, leaving one course may not represent disengagement at all. A learner may transfer to another activity that better matches his or her interests, ability, schedule, or learning goals. Treating every course departure as dropout may therefore obscure meaningful differences between disengagement and adaptive movement within the cultural learning system. This issue is particularly relevant to public cultural learning because its organizational structure differs from that of conventional formal education. Public programs are often modular, short-term, voluntary, and organized in recurring cycles. Learners may enter without formal prerequisites, participate in several types of activities, stop temporarily, or return after a substantial interval. Progression is also less standardized than in schools or universities. Instead of following a prescribed curriculum, learners may move horizontally between artistic fields or vertically from introductory to more advanced programs. These characteristics make public cultural learning highly flexible, but they also make participation difficult to evaluate using conventional completion and dropout measures. A meaningful evaluation framework must therefore consider both persistence within a program and movement across programs and cycles. Studies conducted in China have examined several related dimensions of public cultural participation, including digital cultural services, cultural engagement among older adults, community learning, and the broader social value of cultural participation [12,13]. This literature has provided important evidence concerning access, participation motivation, service satisfaction, and differences between population groups. Nevertheless, much of the existing evidence is based on cross-sectional surveys, regional statistics, self-reported participation, or participation measured at a single point in time. These approaches are effective for identifying who participates and how participants evaluate cultural services, but they are less suitable for explaining how participation develops. They cannot easily identify whether an individual gradually disengages, temporarily pauses, changes courses, returns after withdrawal, or progresses through multiple levels of learning. As public cultural institutions increasingly maintain digital enrollment, attendance, activity, and feedback records, there is greater potential to move from aggregate participation statistics toward longitudinal analysis of individual learning trajectories.

Research in adult education and learning analytics provides several methodological approaches that may be useful for this purpose. Studies of educational dropout have shown that withdrawal is often not an isolated decision but the outcome of a process involving repeated absence, incomplete learning activities, changing work or family demands, declining engagement, or poor alignment between learners and courses [14,15]. Survival analysis is particularly useful for examining this process because it estimates not only whether withdrawal occurs but also when it occurs and how different learner or program characteristics influence the risk of leaving over time [16,17]. This temporal perspective is important for public cultural programs, where withdrawal after an introductory session may require a different intervention from withdrawal near the end of a course. Longitudinal and growth models can further examine whether engagement strengthens, weakens, or remains stable across repeated courses or program cycles [18,19]. Sequence-based methods provide another way to understand participation beyond isolated outcomes. Sequence analysis can represent a learner's complete participation history as a series of states, such as attendance, absence, completion, switching, interruption, and return, and can then identify recurring types of learning trajectories [20]. This approach is particularly relevant to public cultural learning because two learners with the same final completion status may have followed very different paths. One may have participated consistently, while another may have experienced repeated interruptions before eventually completing the program. Latent transition analysis provides a complementary perspective by estimating movement between underlying participation states, such as stable engagement, intermittent participation, disengagement, and re-engagement

[21,22]. Together, these approaches allow participation to be conceptualized as a dynamic process rather than a fixed individual characteristic. Despite their potential, longitudinal, survival, sequence, and transition methods have been used primarily in formal schooling, higher education, adult education, and online learning environments. Their application to public cultural learning remains limited. Existing cultural participation research rarely combines detailed administrative records across multiple programs and repeated program cycles. Studies that do follow participants over time often focus on a single institution, a relatively small sample, or a short observation period. Several conceptual limitations also remain. Course switching is frequently grouped together with withdrawal even though switching may represent successful adjustment toward a more appropriate learning pathway. Re-enrollment is commonly treated as a binary outcome without considering the length of interruption or the participation history preceding a learner's return. Progression is similarly difficult to identify when analysis is restricted to individual courses rather than the broader program system. As a result, existing measures may underestimate the complexity of participation and provide limited guidance about when and why learners disengage, return, or move between learning opportunities. A more comprehensive longitudinal framework is therefore needed to connect program access and educational equity with the actual continuity of learning. High enrollment can coexist with substantial early withdrawal, and apparently equal access can coexist with large differences in persistence, return, and progression among learner groups. From an equity perspective, the question is not only whether different groups can enter public cultural programs but also whether they have comparable opportunities to remain involved, find suitable courses, return after interruption, and advance within the program system. This perspective extends evaluations of public cultural education from the availability of learning opportunities toward the stability and development of participation itself. It also complements existing efforts to evaluate teaching quality and educational equity in public art education [23,24] by providing longitudinal evidence on what happens to learners after initial enrollment.

Against this background, the present study aims to develop a longitudinal framework for examining participation trajectories in public cultural learning. Approximately 6,000 learners participating in 50 public cultural learning programs are followed across three program cycles using administrative records of attendance, activity completion, learner feedback, course switching, re-enrollment, and progression. Survival analysis is applied to identify the timing of withdrawal and the learner- and program-level factors associated with dropout risk. Sequence analysis is used to identify recurring learning pathways across courses and cycles, while latent transition analysis examines movement between stable, intermittent, disengaged, and re-engaged participation states. Growth models estimate changes in participation across program cycles, and logistic regression evaluates the factors associated with completion, return, and progression. By integrating these methods, the study distinguishes temporary interruption from persistent dropout and separates course switching from complete disengagement. The study contributes to public cultural education research by shifting the unit of analysis from isolated attendance events to longitudinal learning trajectories. This makes it possible to identify not only how many people participate but also how participation is sustained, interrupted, redirected, and restored over time. The resulting framework can provide a more precise basis for evaluating program continuity and educational equity, particularly by revealing whether particular learner groups face higher risks of early withdrawal or lower probabilities of re-engagement and progression. At the institutional level, the findings can support decisions concerning course scheduling, learner support, program transitions, capacity allocation, and follow-up interventions. At the policy level, they can help public cultural institutions move beyond enrollment-oriented performance indicators toward evaluation systems that account for sustained participation, learner mobility, and long-term engagement. In this way, public cultural learning can be evaluated not simply according to how many residents enter a program, but according to whether learners are able to develop stable, flexible, and continuing pathways of cultural participation.

2. Materials and Methods

2.1 Sample and Study Setting

The study followed about 6,000 learners from 50 public cultural learning programs over three program cycles. The programs were offered by cultural centers, libraries, museums, community colleges, and local learning centers. They covered music, visual arts, dance, crafts, literature, heritage, and other cultural activities. Programs were selected by subject area, course level, class size, and delivery site. Learners were included when they joined at least one activity in the first cycle and had a valid code that could be tracked across later cycles. Staff accounts, test records, duplicate profiles, and learners without valid activity records were removed. The dataset included about 72,000 attendance records, 18,000 activity-completion records, 9,500 feedback entries, 4,200 course-switching records, and 3,000 re-enrollment records. Learner age, gender, education, previous cultural experience, program type, course level, and delivery mode were also recorded.

2.2 Study Design and Comparison Groups

A three-cycle cohort design was used to examine changes in cultural participation over time. The 50 programs were divided into two groups according to course structure. Twenty-five programs offered linked levels from beginner to advanced study. The other 25 programs offered separate courses without a clear route to the next level. Programs were matched by subject area, class size, course length, fee level, and weekly teaching hours. Learners in linked programs had more chances to continue, change levels, or return through a planned course route. Learners in separate programs had to choose a new course without a fixed pathway. The two groups were compared in terms of retention, return, course switching, and progression. Random assignment was not used because the course structures were already in place before data collection.

2.3 Measurement and Quality Control

Participation was measured through repeated attendance, course completion, voluntary return, project completion, course switching, feedback activity, and movement to higher course levels. Retention was defined as continued participation until the end of a program cycle. Return was recorded when a learner enrolled in a later cycle after completing or leaving an earlier course. Course switching was recorded when a learner moved to another subject or level within the same cycle. Progression was recorded when a learner entered a higher-level course in the same subject area. Attendance and completion data were taken from program records. Feedback activity included submitted comments, surveys, and course reviews. All institutions used the same coding guide and variable definitions. Learner codes were checked across cycles, duplicate entries were removed, and records with impossible dates were reviewed. Ten percent of the records were compared with local class lists. Two researchers checked the course-switching and progression codes independently. Agreement was accepted when Cohen's kappa was above 0.80.

2.4 Data Processing and Model Formulation

Attendance, completion, feedback, switching, and re-enrollment records were linked through anonymous learner and program codes. Records were sorted by date to form a full participation path for each learner. Missing attendance dates were checked against course schedules before removal. Participation duration was measured from the first recorded activity to the final activity or withdrawal date. A continuity index was calculated as follows:

$$CI_i=\frac{A_i+C_i+R_i+P_i}{4}$$

where CI_i is the continuity score for learner i, A_i is the attendance score, C_i is the completion score, R_i is the return score, and P_i is the progression score. Each part was converted to a value between 0 and 1. Dropout risk was estimated with a Cox proportional hazards model:

$$hi(t)=h0(t)exp(\beta1X1i+\beta2X2i+\cdots+\beta kXki)$$

where $h_i(t)$ is the dropout risk for learner i at time t, $h_0(t)$ is the baseline risk, and X_{ki}represents learner, course, and program factors.

2.5 Statistical Analysis

Descriptive statistics were used to summarize participation across the three cycles. Kaplan–Meier curves compared time to dropout between linked and separate programs. Cox regression tested the effects of learner background, course type, attendance gaps, feedback activity, and program structure on dropout risk. Sequence analysis grouped learners by the order of attendance, absence, course switching, completion, and return. Latent transition analysis was used to measure movement among stable, intermittent, one-time, course-switching, and re-engaged groups. Growth curve models examined changes in attendance, completion, and continuity across cycles. Logistic regression tested the factors related to re-enrollment and progression. Standard errors were adjusted for learners grouped within programs and institutions. Results were reported as hazard ratios, odds ratios, model coefficients, 95% confidence intervals, and ppp-values. Statistical significance was set at $p<0.05$.

3. Results and Discussion

3.1 Participation Patterns across Program Cycles

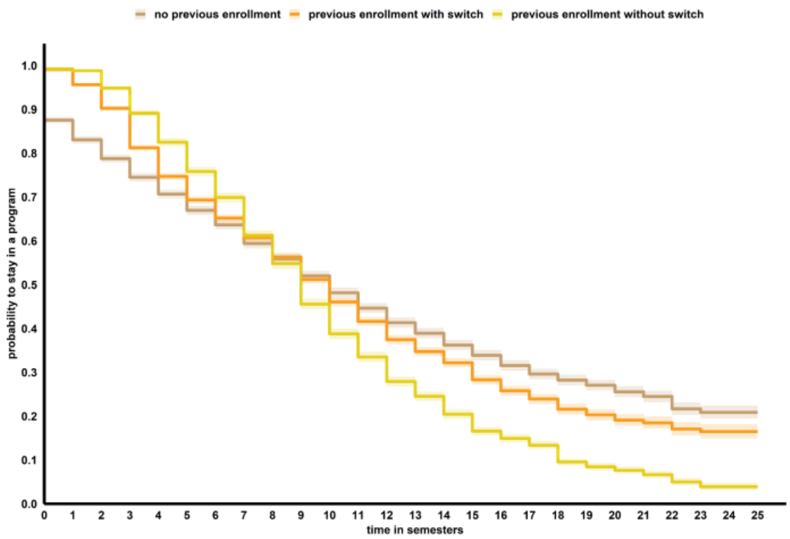
After invalid and duplicate records were removed, 5,842 learners remained in the analysis. Sequence analysis identified five main participation patterns. Stable participants made up 30.8% of the sample. They attended regularly, completed most activities, and remained enrolled across all three cycles. Intermittent participants accounted for 23.5% and showed several short attendance gaps. One-time participants represented 19.6% and usually left after the first cycle. Course-switching learners accounted for 15.8%, while re-engaged learners made up 10.3%. As shown in Fig. 1, stable participants remained active across the full study period. Intermittent and re-engaged learners moved between active and inactive periods. These patterns cannot be identified from total attendance alone. Two learners may record the same number of visits but follow very different learning paths [25,26]. Zhang et al. (2025) also found that sequence plots can separate regular activity, early decline, and irregular participation. Mulenga et al. (2025) showed that sequence analysis can group learners by the order of their actions rather than by total activity. The present results extend this method to public cultural learning. They show that participation should be measured through both the timing and order of learning activities.

Fig. 1. Participation patterns of five learner groups across three cycles.

3.2 Retention and Dropout Timing

The overall retention rate was 79.1% at the end of the first cycle, 67.4% at the end of the second cycle, and 57.9% at the end of the third cycle. Retention was higher in linked programs than in stand-alone programs at each stage. The estimated probability of remaining active after three cycles was 0.65 in linked programs and 0.45 in stand-alone programs. The Kaplan–Meier curves in Fig. 2 show that dropout risk was highest during the first six weeks. A second decline occurred between program cycles, when learners had to decide whether to enroll again. The Cox model showed that linked course routes reduced dropout risk by 31% (HR = 0.69, 95% CI: 0.62–

0.77, p<0.001). Completion of the first project also reduced the risk (HR = 0.59, 95% CI: 0.53–0.66, p<0.001). In contrast, two consecutive attendance gaps increased dropout risk (HR = 1.79, 95% CI: 1.61–1.99, p<0.001). Learners who received feedback during the first four weeks were also less likely to leave. Xiong et al (2026) used Kaplan–Meier and Cox models to show that dropout depends on both time and enrollment history. The present results identify the gap between program cycles as another high-risk period [27,28]. Early project support and clear links to the next course may therefore reduce dropout more effectively than general reminders near the end of a program.



At Risk

no previous enrollment	8217	6825	5895	4996	4084	3148	2386	1818	1349	981	585	348	123
previous enrollment with switch	13,580	12,987	10,340	7872	5879	3888	2485	1592	883	463	236	130	48
previous enrollment without switch	6861	6780	6116	5152	4095	2900	1957	1248	737	488	189	101	22

Fig.2. Retention rates in linked and stand-alone cultural programs across three cycles.

3.3 Course Switching and Return to Learning

A total of 4,086 course switches were recorded across the three cycles. Changes in subject accounted for 44.9% of these cases. Changes in course level accounted for 35.7%, while changes in time or location accounted for 19.4%. Learners who changed only the time or location had the highest later completion rate at 73.1%. The completion rate was 61.6% for learners who changed course level and 56.4% for those who changed subject. All three rates were higher than the rate among learners who left without choosing another course. This result shows that course switching should not always be treated as dropout. In many cases, learners changed courses to find a better match. The re-enrollment rate was 49.2% in linked programs and 31.8% in stand-alone programs (p<0.001). The median break before return was 10.6 weeks. Among returning learners, 42.5% returned to the same subject, 34.1% entered a related subject, and 23.4% selected a different cultural activity. Feedback submission before withdrawal increased the odds of later return (OR =

1.44, 95% CI: 1.25–1.66). Hong et al. (2026) found that sequence methods can identify changes between learning states that are hidden by final scores and average engagement values. The present results support this view. Course switching and return should therefore be included in cultural participation measures rather than treated as irregular or missing records.

3.4 Changes in Participation and Program Evaluation

The mean continuity score decreased from 0.67 in the first cycle to 0.62 in the third cycle. However, the growth model showed different trends across the five participation groups. The score for stable participants increased from 0.75 to 0.83. The score for intermittent participants decreased from 0.63 to 0.53. One-time participants showed a sharp decline after the first cycle. Re-engaged learners followed a different pattern. Their mean score fell from 0.61 to 0.29 during the inactive period and then rose to 0.69 after they returned. Completion of the first-cycle project increased the odds of re-enrollment (OR = 1.71, 95% CI: 1.49–1.96). Regular feedback activity increased the odds of progression to a higher course level (OR = 1.39, 95% CI: 1.20–1.61). Participation in a linked program also increased progression probability (OR = 1.61, 95% CI: 1.38–1.88). Age was not related to total participation time. However, older learners had longer attendance gaps and were more likely to return after a break. These results show that weekly attendance is not the only sign of long-term participation. Public institutions should assess retention, return, switching, completion, and progression together. Previous sequence-based studies also found that average scores can hide important differences in individual learning paths [29,30]. The proposed framework gives a fuller view of program performance. However, the study covered only three cycles and did not include cultural activities outside the selected programs. Longer follow-up periods and learner interviews are needed to explain why learners pause, change courses, or return.

4. Conclusion

This study found that cultural participation should be measured as a process over time rather than by attendance alone. Longitudinal records identified five learner groups: stable, intermittent, one-time, course-switching, and re-engaged participants. Linked programs had higher retention, lower dropout risk, and greater progression than stand-alone programs. Early project completion, regular feedback, and clear routes to the next course were also linked to continued participation and later return. Course switching did not always mean failure, because many learners completed another course after changing subject, level, time, or location. The study combines survival analysis, sequence analysis, latent transition analysis, growth models, and regression in one framework. This method measures attendance, completion, switching, return, and progression together. It can help public institutions identify dropout risk, support flexible learning paths, and plan connected course levels. However, the study covered only three program cycles and did not record cultural activities outside the selected programs. Administrative records also could not fully explain why learners left or returned. Future studies should use longer follow-up periods and include learner interviews to examine the reasons for pauses, course changes, and later participation.

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