

MAIN-TRACK PERSISTENCE AND PLATFORM ENGAGEMENT OF INCLUSIVE LEARNERS IN AN INTENSIVE PEER-TO-PEER CODING ENVIRONMENT

Ibrogimova Nodira

Senior Lecturer at International Digital University

ORCID: 0000-0003-1749-6957

E-mail: nodira.ibrogimova@gmail.com

Abstract

This study examines main-track persistence and platform engagement among inclusive learners after entry into the Digital Engineering School (DES), Tashkent main track. The empirical analysis uses six main-track cohort rosters dated 16 May 2026 and platform profile exports for the inclusive learner population. Thirteen inclusive learners appeared in the main-track rosters; three were recorded as deactivated and ten as active, producing a deactivation rate of 23.1%. Among non-inclusive learners in the corresponding cohorts, 195 of 1,184 were deactivated (16.5%). Fisher's exact test showed no statistically significant aggregate difference ($p = 0.46$). Within the inclusive group, learners who passed the pool had a median cumulative XP of 4,162 compared with 0 XP among those who did not; Mann–Whitney $U = 117$, two-sided $p = 0.00009$, with complete rank separation. Completed and failed project counts also differed. The findings show that main-track persistence, platform engagement and administrative exit status represent distinct dimensions of learner trajectory and should not be collapsed into a single indicator of inclusion.

Keywords

inclusive learners; main-track persistence; platform engagement; peer-to-peer education; learning analytics; learning trajectories

Introduction

Educational access, progression and persistence are related but distinct outcomes. A learner who successfully enters a programme may remain active, temporarily disengage or leave for reasons that are not captured by an admission measure. This distinction is particularly important in intensive peer-to-peer coding environments, where learning is represented through project completion, peer review and platform activity rather than conventional classroom attendance and grades.

Recent research on coding bootcamp pedagogy emphasizes the importance of hands-on learning and peer interaction in making coding meaningful to learners (Tarling et al., 2023). Peer feedback research also indicates that the educational value of feedback depends on the nature of learner engagement, including explanation, revision and constructive participation (Wu & Schunn, 2023). A broad synthesis of online peer feedback similarly concludes that learner characteristics, environmental conditions, feedback design and technology jointly shape engagement and learning outcomes (Kerman et al., 2024). These findings make persistence and platform engagement particularly relevant outcomes in a tutor-less learning model.

At the same time, platform-generated indicators require careful interpretation. Learning analytics can help institutions examine retention and inclusion, but data traces do not automatically explain the experience of learners with disabilities or other marginalized groups (Khalil et al., 2024). CAST's UDL Guidelines 3.0 emphasize accessible interaction, multiple forms of communication and learner agency (CAST, 2024), reinforcing the need to distinguish observable platform activity from the broader experience of participation.

The present study therefore addresses two connected questions after learners reach the DES main track: whether inclusive learners show a different aggregate deactivation rate from non-inclusive peers, and how platform engagement differs within the inclusive group according to pool outcome. This focus is intentionally different from the first

thesis on pool-to-main-track transition. Here, the outcome is persistence and engagement after entry rather than selection-stage progression.

Materials and methods

A quantitative observational design was applied. The persistence analysis used six main-track cohort rosters exported on 16 May 2026. Platform profile exports were available for the inclusive learner population. The individual learner was the unit of analysis. One learner had two profile files because of repeated pool attempts; these records were reconciled to a single canonical person-level profile to avoid duplicate representation.

Main-track persistence was operationalized using the administrative status recorded in cohort rosters: active student or deactivated student. The comparison was restricted to cohorts containing at least one inclusive learner. Inclusive and non-inclusive deactivation proportions were compared using Fisher's exact test because inclusive cell counts were small. Cohort-level values were retained descriptively to avoid concealing heterogeneity behind the aggregate rate.

Platform engagement was examined within the inclusive group using cumulative experience points (XP), completed projects and failed projects extracted from profile exports. Learners who passed the pool were compared with those who did not using the Mann–Whitney U test. Rank-biserial correlation was used as an effect-size measure for XP. These variables were interpreted descriptively because XP is accumulated through project activity and is therefore structurally related to progression.

The analysis also treated administrative deactivation cautiously. A deactivated status indicates that a learner is no longer recorded as active at the snapshot date, but it does not by itself identify the reason for departure. Where campus notes documented a voluntary employment-related exit, that information was retained in interpretation. This

distinction is important for avoiding the assumption that every deactivation represents academic failure.

Results

Thirteen inclusive learners appeared in the main-track rosters dated 16 May 2026. Three were recorded as deactivated and ten as active, producing an inclusive deactivation rate of 23.1%. Among non-inclusive learners in the corresponding cohorts, 195 of 1,184 were deactivated, a rate of 16.5%. Fisher's exact test yielded $p = 0.46$. Thus, the available snapshot did not show a statistically significant aggregate difference in main-track deactivation.

Cohort-level patterns were heterogeneous. In cohort 24_12, both inclusive learners remained active. In cohort 25_04, three of four inclusive learners were recorded as deactivated (75.0%), compared with 48.5% among non-inclusive learners. In cohort 25_08, all five inclusive learners represented in the status table remained active, while the non-inclusive deactivation rate was 8.3%. Cohorts 25_12 and 26_03 each contained one inclusive learner and recorded no inclusive deactivation.

Campus notes provided an important qualification: two of the three deactivated inclusive learners in cohort 25_04 had found employment and left voluntarily. The administrative category therefore combined at least one positive post-programme outcome with other forms of departure. This makes deactivation an imperfect proxy for educational failure and illustrates why exit destination should be recorded separately from activity status.

Platform engagement produced a clearer within-inclusive separation. Learners who passed the pool had a median cumulative XP of 4,162, whereas learners who did not pass had a median of 0 XP. The Mann–Whitney U statistic was 117 (two-sided $p = 0.00009$), with rank-biserial $r = -1.00$. Mean completed projects were 2.85 among

passers compared with 0.22 among non-passers ($p = 0.00025$). Mean failed projects were 0.08 among passers and 3.78 among non-passers ($p = 0.00134$).

Table 1. Platform engagement indicators within the inclusive group

Indicator	Pool pass group	No-pass group	Statistical result
Cumulative XP (median)	4,162	0	$U = 117$; $p = 0.00009$; $r = -1.00$
Completed projects (mean)	2.85	0.22	$p = 0.00025$
Failed projects (mean)	0.08	3.78	$p = 0.00134$

Source: Calculated from the inclusive learner platform-profile dataset used in the study.

Discussion

The persistence results differ from the earlier pool-to-main-track transition pattern. Among learners who had already reached the main track, the aggregate difference in deactivation between inclusive and non-inclusive groups was not statistically significant. This should not be interpreted as proof of equivalence, because the inclusive sample is small. Rather, the result indicates that the available snapshot does not provide statistical evidence of a group difference in main-track deactivation.

The contrast between cohorts 25_04 and 25_08 demonstrates why aggregate statistics require contextual interpretation. Cohort-level variation may reflect differences in learner composition, timing, organizational practice or other unmeasured factors. The administrative data cannot determine which explanation is correct. Prinsloo et al. (2024) describe learning analytics as part of a broader data ecology, a perspective that is relevant here because platform status gains meaning only when combined with contextual information.

The XP and project indicators show strong differences within the inclusive group, but they should not be treated as causal predictors. XP is generated through project activity, and project completion is itself part of progression. Consequently, the observed separation partly reflects the programme's internal logic. The indicators are useful for describing trajectories, not for claiming that XP independently causes successful progression.

Recent peer-feedback research helps explain why engagement should be treated as multidimensional. Wu and Schunn (2023) distinguish passive, active and constructive forms of engagement and show that different feedback activities provide different learning opportunities. Kerman et al. (2024) similarly emphasize the interaction between learner characteristics, environment, feedback design and technology. In a peer-to-peer coding environment, the quantity of platform activity therefore cannot fully represent the quality or accessibility of peer interaction.

For inclusive learners, this distinction is especially relevant. CAST (2024) emphasizes multiple means of interaction, expression and communication, while Khalil et al. (2024) show that learning analytics has potential to support inclusion but remains underdeveloped for disability-focused analysis. The DES data demonstrate why these perspectives matter: an active/deactivated status and an XP total can describe what is recorded on the platform, but they cannot directly measure communication accessibility, belonging, informal accommodation or the reasons behind each learner's decisions.

The study has several limitations. The inclusive population is small, the analysis covers one campus, and main-track status is observed at a single snapshot date. Comparable individual-level XP and project trajectories were not available for non-inclusive learners, preventing a direct cross-group engagement comparison. The platform's deactivation category also conflates different exit pathways. These

limitations support a cautious interpretation and strengthen the case for longitudinal tracking and qualitative interviews.

Conclusion

At the 16 May 2026 snapshot, main-track deactivation among inclusive learners was not statistically different from that of non-inclusive peers, although cohort-level outcomes varied substantially. Within the inclusive group, XP and project indicators clearly differentiated learners who passed the pool from those who did not, but these measures are descriptive and closely tied to the programme's progression structure.

The findings demonstrate the importance of measuring transition, persistence, platform engagement and exit destination separately. More precise exit coding would distinguish voluntary employment-related departure from other forms of deactivation, while longitudinal platform records across learner groups would permit stronger trajectory analysis. Accessible qualitative inquiry is also needed to explain how peer interaction, communication and informal support shape the experiences represented only indirectly in administrative telemetry.

References

1. CAST. (2024). Universal Design for Learning Guidelines version 3.0. CAST. <https://udlguidelines.cast.org>
2. Khalil, M., Slade, S., & Prinsloo, P. (2024). Learning analytics in support of inclusiveness and disabled students: A systematic review. *Journal of Computing in Higher Education*, 36, 202–219. <https://doi.org/10.1007/s12528-023-09363-4>
3. Kerman, N. T., Banihashem, S. K., Karami, M., Er, E., van Ginkel, S., & Noroozi, O. (2024). Online peer feedback in higher education: A synthesis of the literature. *Education and Information Technologies*, 29, 763–813. <https://doi.org/10.1007/s10639-023-12273-8>

4. Tarling, G., Melro, A., Kleine Staarman, J., & Fujita, T. (2023). Making coding meaningful: University students' perceptions of bootcamp pedagogies. *Pedagogies: An International Journal*, 18(4), 578–595. <https://doi.org/10.1080/1554480X.2022.2077338>
5. Wu, Y., & Schunn, C. D. (2023). Passive, active, and constructive engagement with peer feedback: A revised model of learning from peer feedback. *Contemporary Educational Psychology*, 73, 102160. <https://doi.org/10.1016/j.cedpsych.2023.102160>
6. Prinsloo, P., Khalil, M., & Slade, S. (2024). Learning analytics as data ecology: A tentative proposal. *Journal of Computing in Higher Education*, 36, 154–182. <https://doi.org/10.1007/s12528-023-09355-4>