



D&S learning continuity matrix: A novel framework for visually monitoring learner progression in technology-mediated higher education

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Abstract

Learning continuity advocates the uninterrupted advancement of knowledge, enabling students to consistently build on their learning abilities in pursuit of their academic objectives. The research proposed the newly developed D&S Matrix and D&S Scale of Learning Continuity, along with their validation, as a groundbreaking effort to visually monitor learners' progress in higher education. Prospective cohort research, EFA, box-and-whisker plots, and data analytics were used in this study to monitor the cyclical development of students. Data were collected from Higher Educational Institutions across different parts of the globe. An experimental study was conducted to observe how a group of higher education students transferred from one cohort to another and to evaluate their learning gains. The findings demonstrate encouraging results in monitoring the incremental development of learners, both at the individual and group levels, across dimensions such as maturity, rote, traditional, and induced characteristics. Acquiring deep understanding, expertise, and lasting memory of scholarly material is a crucial component of research in the technology-mediated learning space. The advent of remote learning and disruptions to conventional classroom instruction necessitate preserving learning continuity to avert adverse effects on students' academic achievements. This will have a substantial influence on the future undertakings of educational policymakers.

Keywords: Cohort study, Experimental research, Learning continuity research, Learning continuity, Learning gain, Learner Matrix, D&S Scale.

Citation | Chakraborty, S., Mukherjee, D., Jena, L. K., & Islam, M. (2026). D&S learning continuity matrix: A novel framework for visually monitoring learner progression in technology-mediated higher education. *Journal of Education and E-Learning Research*, 13(3), 22–37. 10.20448/jeelr.v13i3.8884

History:

Received: 30 March 2026

Revised: 25 May 2026

Accepted: 12 June 2026

Published: 29 June 2026

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Publisher: Asian Online Journal Publishing Group

Funding: This study received no external funding.

Institutional Review Board Statement: This study was approved by the Agartala Government Medical College, India under protocol number [F.TU/DOMB/Research/2022], dated 30-08-2022. Informed verbal consent was obtained from all participants and all data were anonymized to protect participants' confidentiality.

Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Competing Interests: The authors declare that they have no competing interests.

Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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Contribution of this paper to the literature

This study advances learning analytics by introducing the D&S Learning Continuity Matrix and the validated D&S Scale to track learner progression. It reconceptualizes learner typologies as dynamic rather than fixed and offers practical insights for personalized learning, early risk identification, and technology-mediated higher education policy and instructional design.

1. Introduction

The measurement of learning gain among learners has always been considered an essential factor for communities working in the learning domain. With the popularity of hybrid and self-paced learning, students enjoy the freedom to select the required reading materials and carry out the assignments in a manner most suited to their own needs (El Bachari, Abelwahed, & El Adnani, 2011). Learning or competence gain is the difference between an individual's pre-training level and present performance in a given context, including individual development and a shift in knowledge, proficiency, and skills (McGrath, Guerin, Harte, Frearson, & Manville, 2015). By tracking students' digital footprints for learner profiling, the learning experience has improved, thanks to LMS maturity and advanced features like digital attendance, grading assignments, quizzes, and feedback (Teng & Wang, 2021). In many instances, the learning outcome measurement focuses on shallow, fleeting, and subjective feelings of impactful teaching rather than genuine learning over a learner's time and dedication to the content (Caspersen, Smeby, & Olaf Aamodt, 2017). Understanding the physiological and cognitive components of learning will require the application of modern technologies such as machine learning, Big Data, AI, AR, etc., in tandem with clinical monitoring in the form of electrodermal activity, eye tracking, and ECG (Papamitsiou, Pappas, Sharma, & Giannakos, 2020; Yadav, Salman, Goyal, & Choubey, 2012). Recent research casts doubt on the "one size fits all" approach taken by educators, who have traditionally believed that it is sufficient to classify students into similar categories for information sharing (Mahajan, Sodhi, & Mahajan, 2012). Flexibility and the use of assistive technology, which draw heavily from the Fourth Industrial Revolution (4.0), are two of the most critical aspects of Education 4.0. This, in turn, finally gives rise to the concept of learning continuity, which signifies continuing learning even when instructions are not available (Mostofa, Hasan, Mukherjee, Hoq, & Othman, 2022). Extending the idea further, Mukherjee and Hasan (2020) took a similar tack with their learner matrix, classifying students into one of four cohorts based on factors such as their level of participation in class, the responsibility they were given, and their openness to new ideas and instructional methods.

Although learning analytics and learner profiling are not new, the existing literature focuses on a number of gaps that are very much predominant and pertinent to be considered. To begin with, available models of tracking learner progress are not dynamic, longitudinal tracking, but generally limited to a fixed, single classification. Second, existing tools seldom consider the complexity of the characteristics of learners (behavioural, cognitive, and emotional) in combination, which are complex to measure. Third, an observable lack of tools for educators to monitor the cohort transition in real time is widespread. Fourth, there is not a lot of empirical validation of the frameworks tracking the progression of learners in various subjects and time scales. The current study fills these gaps by suggesting and confirming a dynamic matrix of learning continuity. Considering the above, the study aims to:

- i. Create and test the D&S Scale of Learning Continuity.
- ii. Suggest the D&S Learning Continuity Matrix based on visual checks of the learner development.
- iii. Empirically visualise the fluctuating status of the position of learners in a series of four cohorts over time.
- iv. Equip teachers with a useful resource in customised content delivery in relation to the learners.

The study is the first to try categorising students in the Higher Education setup, and its results lend credence to the hypothesis of Learning Continuity. Over four months, students' learning abilities were monitored using a newly developed matrix to determine whether their cognitive functions shifted in ways that facilitated learning. The findings demonstrate that the categorical deflection in the position of the learners in a class can be tracked, keeping certain factors under control, which ultimately facilitates more customised and relevant content dissemination from the part of the educators.

2. Literature Review

2.1. Theoretical Underpinning

Several advances in critiquing learning gain can be traced back to the pressing need for more effective indicators of teacher quality, which is especially true in the context of advanced countries where the government has designated this task as a "high priority" (Evans, Kandiko Howson, & Forsythe, 2018). Leiber (2019) emphasised that understanding the teaching process is also crucial for accurately measuring learning outcomes, since the two processes are inextricably linked and require equal attention to clarify the complex system. Changes in the student's learning processes and teachers' methods of communicating new information can be observed alongside the development of technology-mediated learning. Bawden (2001) observed the shifting pattern of people's interactions as a result of alterations in technology, which has led to the expansion of a diverse range of categories of learners. Competencies in conditional resilience, critical reasoning, agility, profound interaction, imagination, etc., are seen as a few inevitable pre-requisites that involve knowledge, abilities, attitude, and principles and will be useful in dealing with any critical issues that monopolise all aspects of modern life (Wagner, 2010). As a result, a current transformation is occurring in the pedagogical process whereby competencies and skills are being integrated alongside course content. This integration aims to equip learners with the tools they need to succeed in the job market and ultimately foster the development of active learning. John Dewey's theory of social constructivism challenges the conventional view of the teacher as the sole source of knowledge and the learner as a passive recipient (Scheer, Noweski, & Meinel, 2012). Instead, Dewey advocates for an approach to learning that emphasises active participation of the learner in the knowledge acquisition process (Dewey, 1933). Piaget (1977) took the constructivist approach one step further by adding a cognitive dimension, in which he argued against the idea that knowledge is automatically transmitted from instructor to student and instead advocated for the idea that knowledge is constructed by the learner via exposure to the world around them

(Amineh & Asl, 2015). While focusing on the environment from which learners gained knowledge, Vygotsky (1978) added the social and cultural dimensions to the constructivist approach and argued that learners acquired more knowledge from their more capable peers. The notion that cognitive development necessitates more than mere acquisition of knowledge but also involves a transformation in one's cognitive processes, leading to the emergence of a mature learner, is also espoused (Huang, 2002). The concept of learning continuity stems from assessing learners' engagement within a cohort using a design thinking approach. Practical and situational reasoning, as opposed to analytical and rationalist thinking, more often determines the specific problem-solving strategies in design thinking (Kröper, Fay, Lindberg, & Meinel, 2010). Design thinking also calls for creating these norms within the process rather than using external ones to judge the quality of design outputs. Razzouk and Shute (2012) provide an overview and synthesis of the existing literature on design thinking, aiming to elucidate its defining features and procedural components, differentiate between novice and expert practitioners, and explore its potential applications in educational contexts. To go even further in the realm of education, Gottlieb, Wagner, Wagner, and Chan (2017) used design thinking to create curricula for the area of healthcare education. The existing paper will also use the design thinking approach to conceptualise the learning continuity theory.

2.2. Understanding the Learning Continuity Model

The emergence of COVID-19 transformed the approach to teaching and learning, with a shift from conventional strategies to hybrid models. All such issues have resulted in a surge in interest in learning continuity, which was previously not widely discussed. In the process of teaching and learning, Mukherjee and Hasan (2020) developed a design thinking-based learner's matrix. Within this matrix, learners' engagement, temporal availability, and compatibility with other learners were considered. Additionally, empathy was emphasised as a crucial construct for student performance. The learners are classified into four distinct quadrants: induced learner, rote learner, traditional learner, and mature learner. Upon comparing it with the established Spencer and Spencer (1993) workplace competency model, it was found that several crucial attributes of superior performers closely align with those of learners. As a result, the Learning Continuity Model incorporates workplace skills, such as teamwork and cooperation, conceptual thinking, self-initiative, analytical thinking, willingness to learn, interpersonal understanding, etc. (Hsieh, Lin, & Lee, 2012). Although Mukherjee and Hasan (2020) proposed the first system of typology of learners in the context of the COVID-19 pandemic, their model did not consider the possibility of empirical validation or long-term tracking. In the same way, the workplace competency model as provided by Spencer and Spencer (1993) sheds light on what ought to be the desirable attributes of a learner, but says nothing about how the competencies are acquired in the long run. The current paper combines these strategies and integrates workplace competency frameworks with dynamic learner tracking.

Additionally, Russell and Rao (1940) Competency Matrix analyses faculty and student feedback on how different workplace competencies are covered in the classroom through activities like team projects, student presentations, conceptual thinking, independent study, etc (Ling, 2010). The aforementioned skill sets exhibit a degree of alignment with the learner characteristics identified in the literature. Under the learner's matrix, induced learners are those in the initial stage of learning, having just been introduced to the content in the session. They exhibit low adaptability to content engagement and tend to allocate limited time to the session. Meece and Jones (1996) considered induced learners as 'casual thinkers' as they did not approach any subject matter with the required level of gravity. In addition to the study mentioned earlier, Handelsman, Briggs, Sullivan, and Towler (2005) identified two additional constructs, namely "limited content involvement" and "restricted involvement among learners," in which learners abstain from engaging in effective peer-level interactions. Msimanga and Lelliott (2014) identified the phenomenon of "limited engagement" as a primary factor contributing to the reluctance of induced learners to pose inquiries during classroom instruction. In a similar vein, Trowler (2010) argued that the restricted commitment of time and effort towards the subject matter is a pivotal attribute of induced learners.

Rote learners exhibit active engagement with content and flexibility but may demonstrate a lower level of time dedication. Biggs (1996) has researched learners, examining the impact of ethnic, context-specific, and behavioural variables. He has opted to define rote learners as a particular type of learner called "memory-based learners". Contrary to this, Davis, Goldman, Perrier, Dent, and Harden (2005) highlighted rote learners' superior capacity for recall while noting a deficiency in critical thinking skills. Since obedience to authority figures, like teachers, has emerged as a defining feature of rote learners, Purdie, Hattie, and Douglas (1996) contended that this is because they are passive learners. Pratt, Kelly, and Wong (1999) assertion characterises rote learners as naive minds who prioritise acquiring knowledge directly from instructors over engaging in critical thinking.

Traditional learners often exhibit a limited capacity for self-directed learning and tend to rely heavily on classroom instruction. Despite investing significant amounts of time in their studies, their level of engagement with course material is typically lower than that of their peers. Stone (2019) has conducted substantial research on comprehending traditional learning patterns and has referred to them as parent-dependent. The individuals cited that the inability to cover study-related expenses is prevalent among a section of society consisting primarily of young, middle-aged, and unmarried individuals. However, it is worth noting that these factors may not be consistent across all regions and could vary significantly. Shor (2014) prefers to emphasise traditional students' dependence on instructors over other traits because they rely so much on them for information rather than other sources on the globe or other students.

On the other hand, McMillan and Cheney (1996) identified the limited inclination towards collaboration among conventional learners as a key contributing factor to their incapacity to function effectively in a collaborative setting. Due to the abovementioned characteristics, conventional students have restricted input into knowledge development and the assignment procedure Allin (2014). Isaac (1987) has observed that students exhibit reduced agency during classroom sessions, with teachers assuming a dominant role in all aspects. Such attitudes make them comparatively less powerless than their counterparts. The trait in question also affects a significant aspect of conventional learners, compelling them to avoid any academic contradiction and wholeheartedly accept the opinions of their instructors without incorporating their perspectives (Hargreaves, 2017).

The most desired learning cohort available comprises mature students who demonstrate a high degree of academic interest and greater time commitment. Individuals exhibit a propensity to participate in demanding and captivating activities, which motivate their self-improvement and feeling of achievement, leading (King, 1998) to classify them as individuals with elevated levels of commitment and satisfaction. Ruble and Frey (1991) contended that the assertion above is substantiated by the fact that mature learners exhibit a noteworthy attribute of enhanced proficiency. When coupled with greater knowledge and experience, this attribute increases the capacity for effective communication and articulation (Dochy, De Rijdt, & Dyck, 2002). The level of motivation among learners is often regarded as a crucial factor in determining their ability to maintain their desired level of performance. Compared to their less mature counterparts, mature learners exhibit a relatively higher level of motivation (Marececk & Metee, 1972). According to Dodgson and Wood (1998) and Marshall and Nicolson (1991), individuals typically exhibit elevated levels of self-esteem and self-confidence, respectively. This, in turn, fosters a greater degree of consistency in their pursuit of knowledge, as noted by Hoskins, Newstead, and Dennis (1997). Mature learners have the conflicting qualities of being able to think critically (Facione & Facione, 1996) even when confronted with new challenges, as well as possessing a deeper level of empathy (Walker & Venker Weidenbenner, 2019), which, in turn, allows them to maintain their compassion even while doing so.

The critical literature review brings to light three important findings that motivate the proposed model: (a) the available typologies of learners are largely inactive; (b) no framework is available that can visually monitor cohort transitions; and (c) there is a lack of empirical validation of dynamic learner typology. These limitations are directly a theoretically established, empirically validated, and visually intuitive application for tracking learner progression.

2.3. Development and Validation of the Learning Continuity Model

The proposed learning continuity model has its foundation enshrined in the comprehensive examination of the relevant literature and the characteristics of various learning cohorts. The process of selecting the construct is typically informed by a comprehensive analysis of pertinent scholarly works, in conjunction with seeking guidance from specialists in the relevant field (DeVellis & Thorpe, 2021). According to Price (2016), the most important factor in any scale development activity is screening items from a list of prospective indicators. During the discourse on the collection of items in developing an instrument, Streiner, Norman, and Cairney (2015) identified five possible sources of ideas. These sources include engaging in discussions with the target population (in this instance, students and faculty), consulting established theories, conducting interviews with experts, and making clinical observations if appropriate. Following stakeholder discussions, the total number of items collected was significantly reduced by nearly half after the theory consultation. This reduction is an optimal scenario for developing an instrument that enhances internal consistency reliability, thereby supporting validity (Cripps, 2017; DeVellis & Thorpe, 2021). The study's psychometric tool aims to measure learners' behavioural, cognitive, and emotional dimensions to compare student participation between cohorts (Fredricks, Blumenfeld, & Paris, 2004). Following the preliminary screening, a group of specialists in clinical psychology, academic psychology, and anthropology was consulted to review and evaluate the instrument. Expert advice is often regarded as an effective means of obtaining a deeper understanding of scale items and mitigating various types of bias, such as cultural and confirmation biases (Ouimet, Bunnage, Carini, Kuh, & Kennedy, 2004). Additionally, the trilingual instrument created to address the linguistic heterogeneity of the students has been subjected to validation by language experts to mitigate any possible biases that could impact the scoring patterns of the participants (Hsu, 2016). The recommendations provided by the three groups of subject matter specialists have been compiled and are displayed in Table 1.

Table 1. Recommendations from subject specialists on the attributes of the learning continuity model.

Type of learner	Attributes	Views from the panel of Clinical Psychologists	Views from the panel of Academic Psychologists	Views from the panel of academic anthropologists	Whether considered for the final model
Matured	Higher Involvement	May be included	May be included	May be included	Included
Matured	Higher Satisfaction	May be included	May be included	May be included	Included
Matured	Higher Motivation	May be included	May be included	May be included	Included
Matured	Higher Self-esteem	May be included	May be reframed	May be reframed	Included
Matured	Higher Self-confidence	May be included	May be reframed	May be reframed	Included
Matured	Higher Consistency	May be included	May be included	May be included	Included
Matured	Higher Skill	May not be included	May not be included	May not be included	Discarded after discussion with the experts
Matured	Higher ability to articulate	May be included	May be included	May be included	Included
Matured	Critical Thinker	May be included	May be included	May be included	Included
Matured	Higher empathy	May be included	May be included	May be included	Included
Rote	Memory-Based Learner	May be included	May be included	May be included	Included
Rote	Shallow Thinker	May be included	May be included	May be included	Included
Rote	Passive Learner	May be included	May be reframed	May be reframed	Included

Type of learner	Attributes	Views from the panel of Clinical Psychologists	Views from the panel of Academic Psychologists	Views from the panel of academic anthropologists	Whether considered for the final model
Rote	Higher recall ability	May not be included	May be included	May be included	Discarded after discussion with the experts.
Rote	Cultural Learner	May be included	May be included	May be included	Included
Traditional	Parent Reliant	May be included	May not be included	May not be included	Discarded after discussion with the experts.
Traditional	Teacher Reliant	May be included	May not be included	May not be included	Discarded after discussion with the experts.
Traditional	Restricted Collusion	May be included	May be included	May be included	Included
Traditional	Limited Authority	May be included	May be included	May be included	Included
Traditional	Limited Power	May be included	May be included	May be included	Included
Traditional	Limited Contradiction	May be included	May be included	May be included	Included
Induced	Limited Time	May be included	May be included	May be included	Included
Induced	Limited Effort	May be included	May be included	May be included	Included
Induced	Limited Engagement	May be included	May be included	May be included	Included
Induced	Limited Content Involvement	May be included	May be included	May be included	Included
Induced	Limited participation	May be included	May be included	May be included	Included
Induced	Casual Thinker	May be included	May be included	May be included	Included

Based on a comprehensive analysis, a final model has been developed that excludes four initial attributes: "Higher skill" for mature learners, "Higher recalling ability" for rote learners, and the "Parent reliant" and "Teacher reliant" attributes for traditional learners. The learning continuity model is shown below.

The extensive analysis of the literature leads to the following assertion in the form of the following hypotheses.

H₁: Any student exhibits the characteristics of all four cohorts.

H₂: Any student may be in a different learning state for different subjects.

H₃: No student can remain permanently in a learning state all the time.

The literature review also provides an exhaustive list of learner attributes for the four categories: Traditional, rote, induced, and matured. On that basis, the following research model has been proposed, as shown in Figure 1, which presents the basic learning abilities in the D&S Learner Matrix.

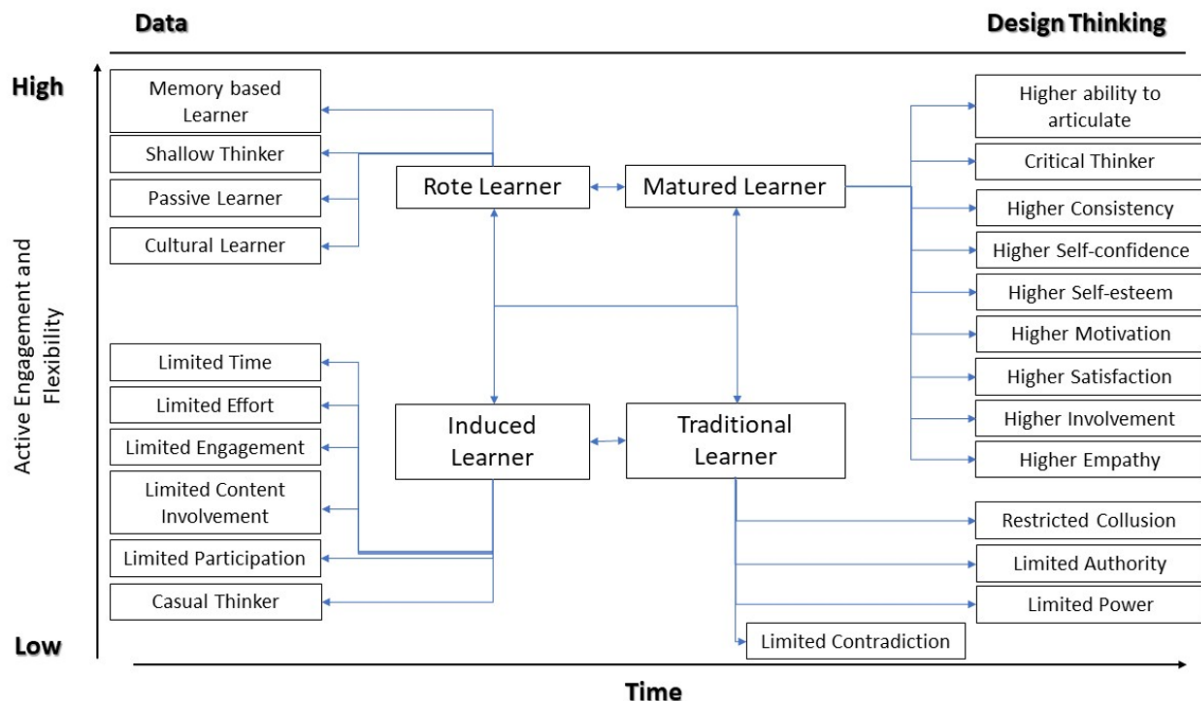


Figure 1. The D&S learning continuity matrix.

It is relevant to note that the model posits that the placement of learners within a given cohort is not fixed and that learners may transition from one quadrant to another in accordance with the progression of the curriculum. Furthermore, the model posits that no learner exhibits an absolute level of proficiency in all subjects, such as maturity or rote memorisation. Instead, learners' positions will shift gradually as their knowledge is enhanced. As a result, the present study could be framed by the following research inquiry.

RQ: Does the learner's position remain static in a learning continuity model?

2.4. Developing A Weighted Average Model

In the realm of research instrument design, the use of a weighted average model stands as a meritorious asset, particularly in scenarios where the components under scrutiny exhibit varying degrees of significance (Fletcher et al., 2014). Within the purview of numerous research endeavours, the same level of importance is not uniformly attributed to all variables or constituents under investigation (Richardson, Maeda, Lv, & Caskurlu, 2017). It is a commonplace occurrence that certain variables exert a more pronounced influence on the research outcomes or objectives than their counterparts. In light of this, researchers are afforded the capability to employ a weighted average model, thereby enabling them to impart distinct weightings to individual variables by their relative significance within the comprehensive analytical framework (Yu & Zhang, 2015).

The significance of integrating a weighted average model into the design of research instruments resides in its capacity to consider the significance of variables, augment precision, mitigate bias, and tailor the instrument to align with the distinct requirements of a research endeavour (Chen & Dubinsky, 2003). It empowers researchers to deliberate on data collection and analysis with a heightened degree of nuance and information, culminating in research outcomes characterised by greater accuracy and value.

A panel of eight experts in psychology and learning/education was invited to examine the scale's items. They have been asked to rate each item from the cohort of Mature Learner, Rote Learner, Traditional Learner, and Induced Learner based on four terms, namely.

- Essential Characteristic – 1.
- Desirable Characteristic – 2.
- Acclaimable Characteristic – 3.
- Best Case Characteristic – 4.

The Kendall's W test is also used here as it serves as a statistical metric for assessing the extent of agreement or concordance among multiple raters or observers when assigning rankings to a set of items (Landis & Koch, 1977). Its utility is particularly evident in situations where the data follows an ordinal scale, signifying a meaningful order in the measurements, albeit with non-uniform intervals between them, which goes perfectly with this case. The results are shown in Table 2, where the value of Kendall's W test statistic is 0.329, suggesting a moderate level of agreement in the rankings. The Chi-square value of 52.984 with 7 degrees of freedom is statistically significant at a p-value of less than 0.001, leading to the rejection of the null hypothesis, indicating no agreement among the rankings. As a result, it can be inferred that there is a statistically significant correlation between the rankings given by various experts or raters. It is pertinent to comment here that Kendall's W test is not the ideal test to measure the specific factors causing variations among the observers; rather, it focuses on identifying discrepancies in the observations of the experts of the identical dataset.

Table 2. Kendall's W test result.

Test Statistics	
N	23
Kendall's W ^a	0.329
Chi-Square	52.984
df	7
Asymp. Sig.	0.000

Note: a. Kendall's Coefficient of Concordance.

The understanding of the Kendall's W test statistic depends on the number of judges or assessors involved in the ranking. A value like 0.329 might be considered strong evidence of agreement when there are only a few judges or raters, but the same value might be considered less convincing proof of agreement when a larger number of judges or raters is involved in the process (Gearhart, Booth, Sedivec, & Schauer, 2013).

After a series of discussions and explanations, the report was prepared based on expert feedback. Table 3 illustrates the weights of each item, which were calculated and presented below.

Table 3. The weights of each item are based on experts' feedback.

Sl.	Items	Wt.
1	Higher Involvement in Matured Learner (M_HI)	2.625
2	Higher Satisfaction in Matured Learner (M_HS)	1.875
3	Higher Motivation in Matured Learner (M_HM)	2.875
4	Higher Self-esteem in Matured Learner (M_HSE)	2.000
5	Higher Self-Confidence in Matured Learner (M_HSC)	2.125
6	Higher Consistency in Matured Learner (M_HC)	3.250
7	Higher Ability to Articulate in Matured Learner (M_HAA)	2.750
8	Critical Thinking in Matured Learner (M_CT)	3.000
9	Higher Empathy in Matured Learner (M_HE)	2.000
10	Memory-Based Learner in Rote Learner (R_MBL)	2.250
11	Shallow Thinking in Rote Learner (R_ST)	2.375
12	Passive Learning in Rote Learner (R_PL)	2.250
13	Cultural or Sequential Learning in Rote Learner (R_CL)	1.625
14	Restricted Collusion or Collaboration in Traditional Learner (T_RC)	2.500
15	Limited Authority in Traditional Learner (T_LA)	2.625
16	Limited Power in Traditional Learner (T_LP)	1.750
17	Limited Contradiction in Traditional Learner (T_LC)	1.875
18	Limited Time Dedication in Induced Learner (I_LT)	2.875
19	Limited Effort in Induced Learner (I_LE)	2.625
20	Limited Class Engagement in Induced Learner (I LENG)	2.500
21	Limited Content Involvement in Induced Learner (I_LC)	2.375
22	Limited Participation in Induced Learner (I_LP)	2.250
23	Casual Thinking in Induced Learner (I_CT)	2.750

2.5. Sampling Design

Determining the sample size is regarded as one of the most important components of any study. The confidence interval approach will be used in this work to calculate the sample size (Daniel, 1999; Naing, Winn, & Rusli, 2006). The following are the precise formulas and sample size:

$$n = \{Z^2 * P * (1-P)\} / d^2$$

Where n = Desired sample size.

Z = Z score for 95% confidence, which is 1.96.

P = Expected prevalence, which is 50%, i.e., 0.5.

d = Standard deviation or precision, which is 0.05.

Therefore, the minimum sample size for infinite population is $n = \{(1.96)^2 * (0.5) * (1-0.5)\} / (0.05)^2 = 385$.

The data will be collected from different HEIs, and participants will be learners.

2.6. Dataset

The research used a multi-stage design of the survey with three different datasets.

Pilot Study Sample (n=31): The first pilot study involved a convenience sample of 31 undergraduate students of Tripura University to evaluate the clarity and understandability of the instrument. The participants were aged between 19-24 years (M=21.2, SD=1.4), with 16 females and 15 males.

Exploratory Factor Analysis Sample (n=642): After the pilot study, 642 students from 22 Higher Education Institutions in India and Bangladesh participated in the data collection of data. The sample was utilised only for Exploratory Factor Analysis (EFA) and instrument validation. Inclusion criteria included full answers to each of the 23 scale items and participation in a degree program at the time of data gathering (December 2022 - March 2023).

Longitudinal Cohort Sample (n=4291): The primary sample used in the study comprised 4291 students followed over four months. This data was utilised to analyse the prospective cohort and to produce Box-Whiskers plots. This was broken down by institution, as shown in Table 4.

During the pilot study, sixty first-year university postgraduate students were selected. The experimental study involved the collection of data over four months, commencing in December 2022 and concluding in March 2023. The final analysis included data from 31 participants, as the remaining individuals did not adhere to the prescribed protocols deemed necessary for the study. The examination of the gathered data was conducted in accordance with the following protocols.

- i. Only student responses received between December 2022 and March 2023 were used in the analysis.
- ii. Any student who did not submit their data between December 2022 and March 2023 had their responses disregarded.
- iii. Information from students who withdrew from conventional classroom settings was ignored.
- iv. Data from students who switched majors throughout the study period were discarded.

The participants for the study were selected from a specified subset of the same population to achieve the desired results. On the other hand, students were invited to participate in the research voluntarily. They were given a certain amount of time to provide their feedback. The participants in the 642 EFA were a subset of the larger longitudinal sample of 4,291. In particular, EFA was performed on data gathered in the first month (December 2022) from 642 participants randomly selected and who completed the entire instrument. The rest of the participants (3,649) were not involved in the factor analysis; the longitudinal analysis included all of them, but not all of them took all the items to be chosen, and some had no follow-up data.

The same experiment was conducted with students from different institutions and specialities following the successful conclusion of the pilot study. The research process encompassed courses in management, engineering, medicine and paramedicine, general degree programs, agriculture, and veterinary science.

Table 4. The details regarding the institution from which the data has been collected.

Name of the institution	Name of the department	Name of the Course	Total number of responses received
Tripura University	Department of Business Management	Master's in Business Administration	62
Holy Cross College	Department of Commerce	Bachelor of Commerce	58
	Department of Sociology	Bachelor of Sociology	32
	Department of English	Bachelor of English	121
	Department of Management	Bachelor of Business Administration	49
Shanto-Mariam University of Creative Technology, Dhaka	Department of Management	Bachelor of Business Administration	213
Assam University	Department of Commerce	Master's in commerce	29
Maharaja Bir Bikram University	Department of Physics	Bachelor of Science	224
	Department of Commerce	Bachelor of Commerce	287
	Department of Education	Bachelor of Arts	311
Bir Bikram Memorial College	Department of Commerce	Bachelor of Commerce	182
	Department of English	Bachelor of Arts	138
East-West University, Dhaka	Department of Library Science	BISLM & MISLM	241
Indian Institute of Information Technology	Department of Computer Science and Engineering	Bachelor of Technology (CSE)	58
National Institute of Technology	Department of Computer Science and Engineering	Bachelor of Technology (CSE)	46
Bhawan's Tripura College of Science and Technology	Department of Information Technology	Bachelor of IT	44
	Department of Lab Technology	Bachelor of LT	53
	Department of Commerce	Bachelor of Business Administration	57

Name of the institution	Name of the department	Name of the Course	Total number of responses received
Tripura College of Agriculture	Department of Agriculture	Bachelor of Science in Agriculture	272
Tripura Government College of Veterinary Science	Department of Veterinary Science	Bachelor of Science in Veterinary	168
Jamia Millia Islamia	Department of Commerce	Bachelor of Commerce	79
G. L Bajaj Institute of Management and Research	Department of Business Management	Post Graduate Diploma in Management	163
Sharada University	Department of Business Management	Master's in Business Administration	238
Tripura Institute of Paramedical Science	Department of Lab Technology	Bachelor's in Medical Laboratory Technology	102
	Department of Physiotherapy	Bachelor's in Physiotherapy	114
	Department of Optometry	Bachelor's in Optometry	92
	Department of Hospital Management	Bachelor's in Hospital Management	76
	Department of OTT	Bachelor's in Operation Theatre Technology	116
Government Medical College	Department of Medicine	MBBS	217
Government General Degree Colleges	Department of Science	Bachelor of Science	148
	Department of Commerce	Bachelor of Commerce	172
	Department of Arts	Bachelor of Arts	129
Total			4291

3. Methodology

The study was conducted in a sequential mixed way encompassing four phases in a chain fashion.

- Phase 1: Instrument Development (Item generation → Weighted average modelling → Expert review).
- Phase 2: Instrument validation (Pilot testing → EFA → Reliability assessment).
- Phase 3: Longitudinal Tracking (Prospective cohort design → Month-wise data collection → Box-Whiskers visualisation).
- Phase 4: Personal analysis (Radar charts → Cohort-wise performance → Prescriptive recommendations).

These four phases are combined as follows: EFA will determine the factor structure and validity of the instrument; the prospective cohort design will give a timeline on how to track these aspects; weighted average modelling will be used to provide the appropriate weighting of the items on the basis of expertise input; and data visualisation (box plots, radar charts, line graphs) will transform the results of the analysis into practical implications of the educator. This integration guarantees that both methodological decisions will have a clear purpose to fulfil and will contribute to the overall aim of the research, namely, to track the learner progression.

3.1. Exploratory Factor Analysis (EFA)

The study used Data Analytics and Factor Analysis to develop the instrument and assess reliability.

The exploratory factor analysis (EFA) assesses the suitability of the data, involves factor extraction using principal component analysis (PCA), applies factor rotation via the Varimax Rotation Method, and facilitates factor interpretation.

3.2. Prospective Cohort Study

Prospective cohort studies are a type of observational study wherein a cohort of individuals is identified and thereafter monitored over a period of time to observe the progression of a specific outcome of interest. The selection of the cohort is contingent upon how susceptible they are to a particular aspect of interest and is widely used in health-related research (Song & Chung, 2010). Prospective studies are conducted to investigate phenomena or events that occur in the future, starting from the current time. As argued by Benson and Hartz (2017), prospective studies offer the advantage of being developed with specialised data collection methods, allowing for a tailored approach to gathering exposure data, perhaps resulting in a higher level of comprehensiveness.

3.3. The Box-Whiskers Plot

The Box-Whiskers Plot approach has been utilised to understand and visually represent the longitudinal data obtained by the instrument. There were three methodological reasons for choosing the Box-Whiskers Plot for longitudinal tracking. First, box plots can represent changes in distributional patterns over time, with measures of central tendency (median), distribution (interquartile range), and the spread of outliers (whiskers). Second, box plots are insensitive to extreme values as opposed to means and standard deviations, which is imperative given that in the context of education, extreme scores can reflect actual learning disparities and not an error in measuring (Tukey, 1977). Third, box plots would allow comparison of several cohorts (Matured, Rote, Traditional, Induced) across several time points and would help visually identify patterns of transitions. Such a method has been effectively applied in the past longitudinal educational experiments (Li et al., 2022; Salkind, 2010).

3.4. Data Analytics

A plethora of data visualisation technologies is already available to present data in an easily comprehensible format, enabling faster decision-making. Every instrument has its unique features and limitations that must not be overlooked. A line chart and a radar chart were employed as data visualisation tools to compare the learner's performance with the class and to provide a learner-specific prescriptive solution.

3.5. Sampling Procedure

Stratified purposive sampling was used. Some of the strata were defined by: (a) institution type (central university, state university, private university, technical institute, medical college); (b) discipline (management, engineering, medicine, sciences, humanities, agriculture, veterinary); and (c) level of the program (undergraduate, postgraduate). Institutions in each stratum were selected based of availability and willingness to participate. Afterwards, invitations to take part were made to all students who were enrolled in the target courses within the course of the study.

3.6. Data Collection Process

Four-time stamps (T1: December 2022, T2: January 2023, T3: February 2023, T4: March 2023) were used to collect the data. Participants were asked to complete the 23-item D&S Scale of Learning Continuity online (via Google Forms) or on paper if they had a poor internet connection. The duration of the surveys was about 15-20 minutes. Two weekly reminders were completed in order to maximise the response rates.

3.7. Experiments and Results

The inferences are reported across three segments, corresponding to the three datasets mentioned in the Data section.

- Pilot study results (n=31) - instrument clarity.
- Factor analysis results (n=642) - scale validation.
- Longitudinal tracking results (n=4,291) - cohort transitions and individual learner progression.

Generally, a Cronbach's alpha coefficient exceeding 0.7 is commonly regarded as satisfactory in research, indicating a substantial level of internal consistency among the scale or questionnaire items (Nunnally & Bernstein, 1994). In the context of the current investigation, the observed Cronbach's alpha value of 0.857 is deemed acceptable.

To initiate the process of factor analysis, it is advisable to commence by conducting the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sample adequacy to ascertain the suitability of the dataset for factor analysis. These tests provide evidence in support of the adequacy of the sample for exploratory factor analysis (EFA). It is desirable to obtain a KMO score exceeding 0.5 (in this study, a score of 0.878 was obtained) and to observe a significance level below 0.05 for Bartlett's test of sphericity, as recommended by Kaiser (1974) and Williams, Hartman, and Cavazotte (2010).

Utilising Principal Component Analysis (PCA) by Kaiser's Criterion (also known as the Eigenvalue Criterion or Total Variance Explained - TVE) serves the purpose of identifying the minimum number of factors required for unrotated factor extraction. In this process, only factors with eigenvalues exceeding one are retained in the framework of Exploratory Factor Analysis (EFA), as this represents a critical criterion, as acknowledged in the works of Jöreskog, Olsson, and Wallentin (2016); Pallant (2011); Thompson (2004), and Verma (2014).

The initial phase of unrotated factor extraction can become intricate when multiple factors exhibit significant associations with a substantial number of variables, a phenomenon commonly referred to as cross-loadings. To address this complexity, Kaiser (1958) varimax approach was applied to diminish the number of variables displaying high factor loadings, thereby promoting orthogonal relationships among variables (Kaiser, 1958; Thompson, 2004). Variables with loading values below the threshold of 0.5 were excluded from further analysis. It is noteworthy that each variable in this study exhibited a Cronbach's alpha coefficient surpassing the established threshold of 0.7, signifying their suitability for evaluating the constructs under investigation (Lavrakas, 2008). Table 5 presents the Rotated component matrix and reliability coefficients (EFA sample, n=642).

Table 5. Rotated component matrix and reliability coefficients (EFA sample, n=642).

Variables	Factor Loading	Cronbach ($\alpha=0.752$)
M_HI	0.622	0.740
M_HS	0.789	0.735
M_HM	0.664	0.737
M_HSE	0.458	0.743
M_HSC	0.642	0.737
M_SC	0.505	0.741
M_HAA	0.558	0.737
M_CT	0.557	0.742
M_HE	0.532	0.738
R_MBL	0.372	0.736
R_ST	0.404	0.735
R_PL	0.591	0.736
R_CL	0.487	0.738
T_RC	0.446	0.746
T_LA	0.425	0.749
T_LP	0.489	0.749
T_LC	0.328	0.739
I_LT	0.410	0.742
I_LE	0.469	0.753
I_LENG	0.588	0.758
I_LC	0.588	0.756
I_LP	0.577	0.759
I_CT	0.628	0.758

Factor loadings and internal consistency of all items, based on 642 observations, are acceptable, with a stable measurement structure characterised by moderate to strong loadings. The Cronbach's alpha of 0.752 is acceptable

and above the threshold of 0.70. The Cronbach's alpha, if item deleted values remain close to the overall alpha, suggests that no item disproportionately weakens reliability. Hence, items with factor loading below 0.5 were retained, as these items capture conceptually important dimensions that are essential for content validity. This is supported by Item Response Theory (Cai, Choi, Hansen, & Harrell, 2016) that it is not necessary to have equal loading of all items.

3.8. Group Performance of One Group of Learners

At the study's outset, the participants were directed to provide their responses on a seven-point Likert Scale consisting of twenty-three items after one month from the beginning of the academic term. The initial data point was obtained on December 13th, 2022. A Box-Whiskers Plot has been generated from the students' responses, as shown in Figure 2.

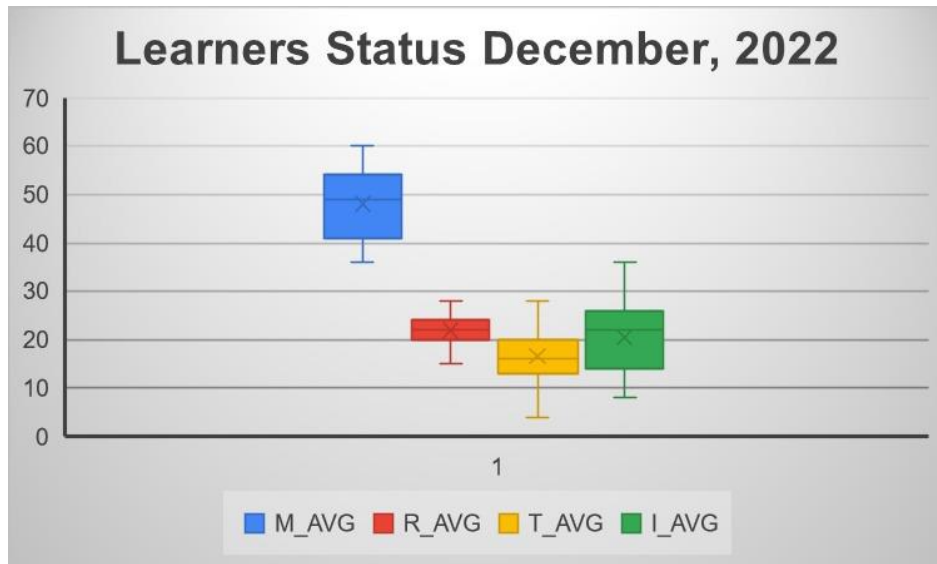


Figure 2. The cohort-wise position of the learners in December 2022.

Note: M_AVG – Average performance of Matured Learners, R_AVG - Average performance of Rote Learners, T_AVG - Average performance of Traditional Learners & I_AVG - Average performance of Induced Learners.

The diagram illustrates the academic achievement of different learning cohorts. In particular, M_AVG denotes the performance of Matured Learners, R_AVG represents Rote Learners, T_AVG signifies Traditional Learners, and I_AVG indicates Induced Learners. The maximum marks threshold for Matured Learners is 60, while Rote Learners, Traditional Learners, and Induced Learners have respective marks limits of 28, 28, and 36. The minimum thresholds for individuals classified as Matured, Rote, Traditional, and Induced learners are 36, 15, 4, and 8, respectively. The interquartile range values for the various learning cohorts are as follows: 13 for the Mature Learners, 4 for the Rote Learners, 7 for the Traditional Learners, and 12 for the Induced Learners. It signifies the maximum number of respondents belonging to the cohort of Matured Learners, followed by Induced Learners, Traditional Learners, and Rote Learners.

The data, when collected after one month from the same group of learners, gives a different picture, which is confirmed in Figure 3.

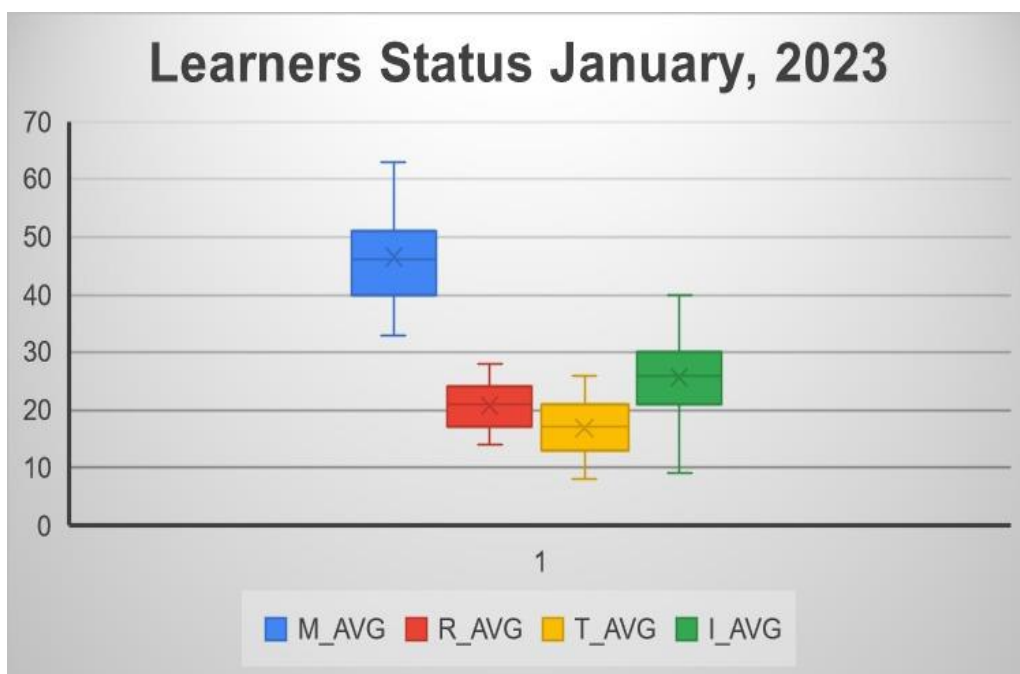


Figure 3. The cohort-wise position of the learners in January 2023.

The scoring ceiling for mature learners is 63, whereas Rote, Traditional, and Induced Learners are subject to distinct upper limits of 28, 26, and 40 marks, respectively. The minimum thresholds required for individuals categorized as Matured, Rote, Traditional, and Induced learners are 33, 14, 8, and 9, respectively. The interquartile range values for the different learning cohorts are reported as follows: 11 for the Mature Learners, 7 for the Rote

Learners, 8 for the Traditional Learners, and 9 for the Induced Learners. After two months and having attended lectures delivered by the faculty, the learners began to transition away from their initial stance.

The data collected after spending three months of the academic session and with the same group of learners showed some significant shifts, as seen in Figure 4.

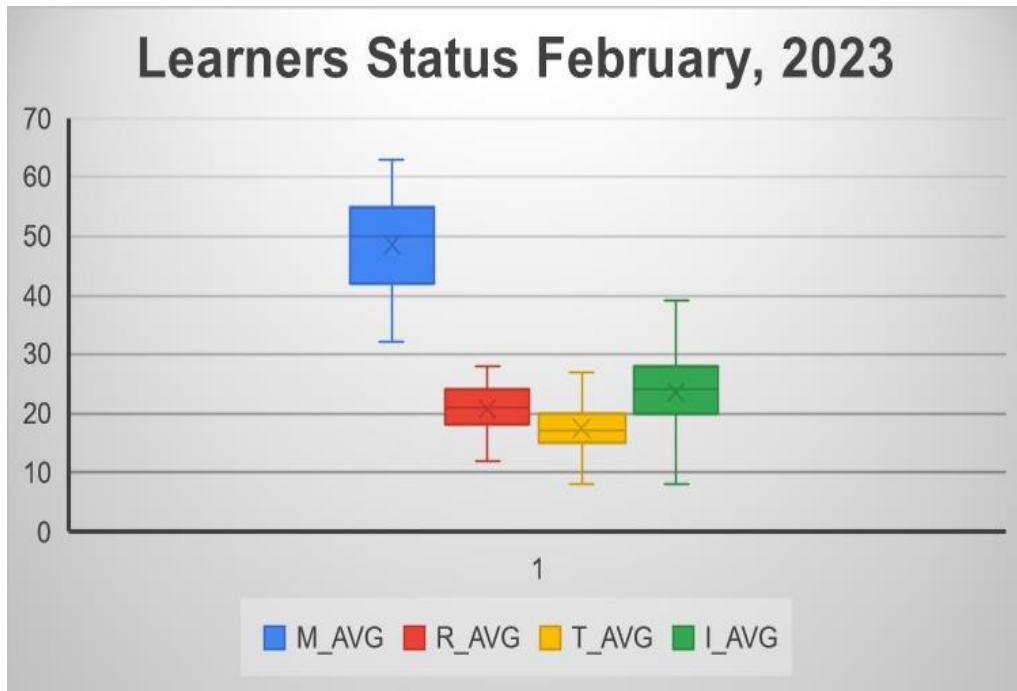


Figure 4. The cohort-wise position of the learners in February 2023.

The study reports distinct upper limits for the scoring ceiling across types of learners. Matured Learners have a scoring ceiling of 63, while Rote Learners, Traditional Learners, and Induced Learners have upper limits of 28, 27, and 39 marks, respectively. The minimum thresholds required for each learning category are 32, 12, 8, and 8, respectively. The interquartile range values for the different learning cohorts are 13 for Matured Learners, 6 for Rote Learners, 5 for Traditional Learners, and 8 for Induced Learners. The study indicates that the gradual influx of knowledge among learners over three months resulted in a greater number of Matured Learners followed by Induced Learners, Rote Learners, and Traditional Learners. Additionally, the study suggests that learners from other cohorts are migrating towards the Mature Learning cohort, which is a positive indicator of Learning Gain among the targeted learners.

This final dataset was gathered during March, 2023 to assess the ongoing process of learners' positional transition. It is relevant to note that the data was gathered immediately before the commencement of the semester examination. The specifics are depicted in Figure 5.

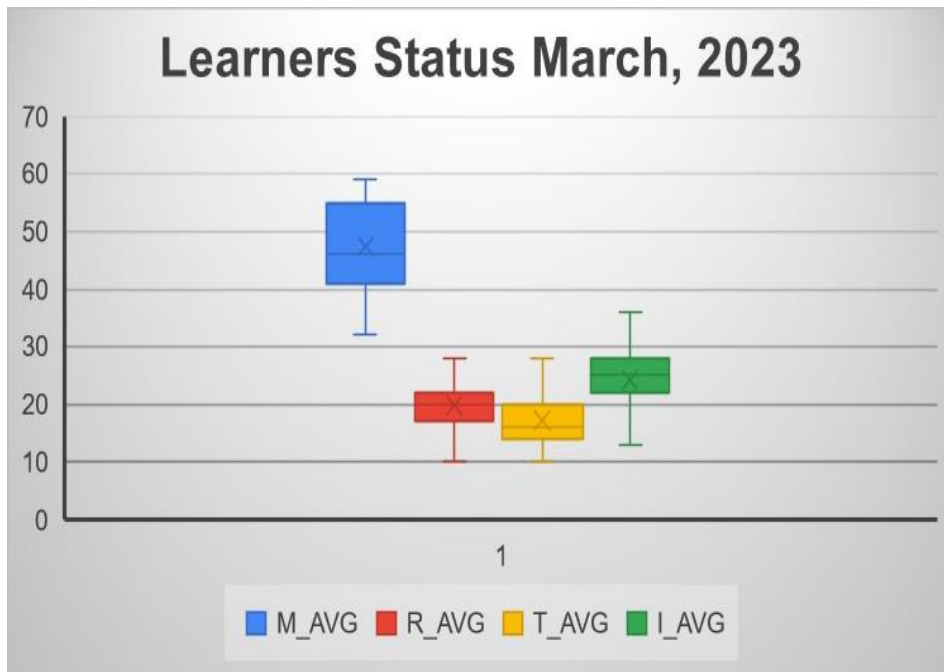


Figure 5. The cohort-wise position of the learners in March 2023.

According to the study's findings, different types of students have varying upper limits on their potential scoring ceilings. The maximum possible score for Matured Learners is 59, while the maximum possible score for Rote Learners is 28, and the maximum possible score for Traditional Learners is 28, and for Induced Learners is 36, respectively. The relative minimum thresholds for each learner category are 32, 10, 10, and 13, respectively. Matured learners have an interquartile range of 14, Rote learners have a range of 5, Traditional learners have a range of 4, and Induced learners have a range of 6.

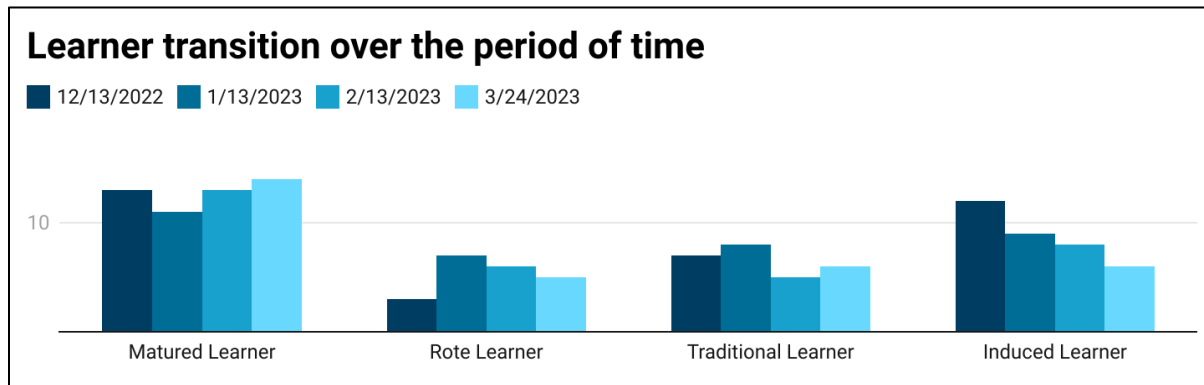


Figure 6. Learner's transition based on the Learning Continuity Model.

The data obtained from a meticulous analysis depicted in Figure 6 indicates a gradual increase in the number of Mature Learners, while all other cohorts exhibit a declining trend. In light of the increasing prevalence of remote learning and the consequent disruptions to conventional classroom instruction, it is imperative to preserve learning continuity to avert any adverse effects on students' academic achievements (Staddon, 2020). The gradual rise in the number of mature learners provides instructors with assurance that knowledge is being disseminated to all levels, thereby ensuring the efficacy of the Learning Continuity Model. According to the findings of the study, the cumulative accumulation of new information among students over four months led to a bigger proportion of Matured Learners, who were then followed by Induced Learners, Rote Learners, and Traditional Learners. According to the findings of the study, the course of studies effectively disseminated knowledge among students, leading to a significant increase in the number of students who possess a sophisticated comprehension of the subject matter. This, in turn, resulted in a substantial shift of learners from comparable groups.

While exploring the possible reasons, the following inference can be drawn:

The interquartile range of the initiation stage data suggests that there are more mature learners in the class than induced, traditional, or rote learners.

After the first month of a new school year, the number of mature learners and induced learners decreased significantly, while the number of rote and traditional learners increased. This is likely due to the introduction of new topics in the classroom, which caused students to feel less confident in their understanding of the material. As a result, they resorted to rote memorisation and regurgitation of facts, rather than engaging in deeper learning.

Here are some possible reasons why students might show limited authority over the content and mug up more:

- The new topics are too difficult for them to understand.
- They are not being given enough opportunities to practice what they are learning.
- They are not being given enough feedback on their work.
- They are not being challenged enough.
- They are not interested in the material.

After spending two months with the newly introduced content, learners have shown significant progress and transitioned more toward the mature segment. This is evident from the decreasing trend in the number of rote, traditional, and induced learners.

There are several possible reasons for this positive trend. First, learners may have had more time to adjust to the new material. Second, they may have received more support from their teachers and peers. Third, they may have become more engaged with the learning process.

After spending three months with the content, there is a significant increase in the number of mature learners and a gradual decrease in the number of rote, traditional, and induced learners. This indicates that learners are becoming more engaged in the classroom and are making progress in their learning.

Several factors could be contributing to this positive trend. For example, learners may benefit from the following:

- Effective teaching methods: Teachers may be using a variety of effective teaching methods, such as active learning, cooperative learning, and project-based learning. These methods can help learners to be more engaged in the learning process and to develop a deeper understanding of the content.
- Engaging content: The content may be engaging and relevant to learners' interests. This can help learners to be more motivated to learn and to retain the information that they are learning.
- Positive classroom environment: The classroom environment may be positive and conducive for the learners to feel comfortable taking risks and asking questions.

3.9. Individual Performance Assessment of Learners from the Same Group

The evaluation of a learner's performance on an individual basis is of utmost importance as it provides a comprehensive understanding of their progress in learning. For the sake of confidentiality, the names of the learners have been masked and marked as 'Learner – I/ Learner – II'. To facilitate the study, the report cards of two students belonging to the same class have been provided below:

The graphs (Figure 7) show that the learner – I falls in all the cohorts, and her change in performance can be tracked. These graphs allow observation and analysis of the learner's performance changes over a four-month data collection period. When comparing the graphs of learner II (Figure 8) with those of learner I, it becomes evident that learner I demonstrate superior performance in comparison to her counterpart.

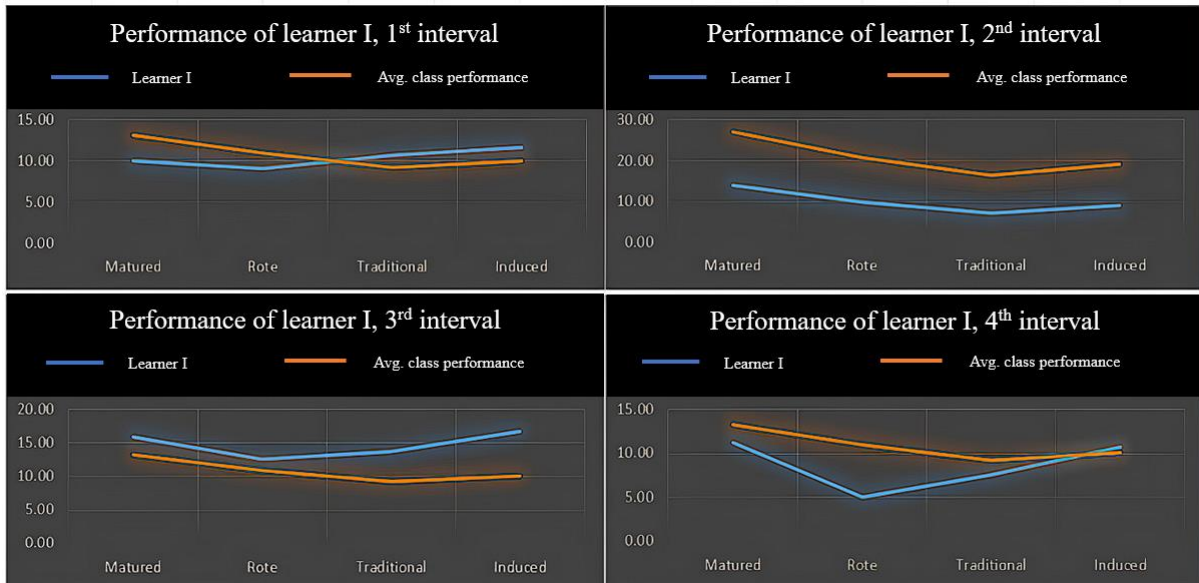


Figure 7. Individual Learner – I progression and the average class performance.

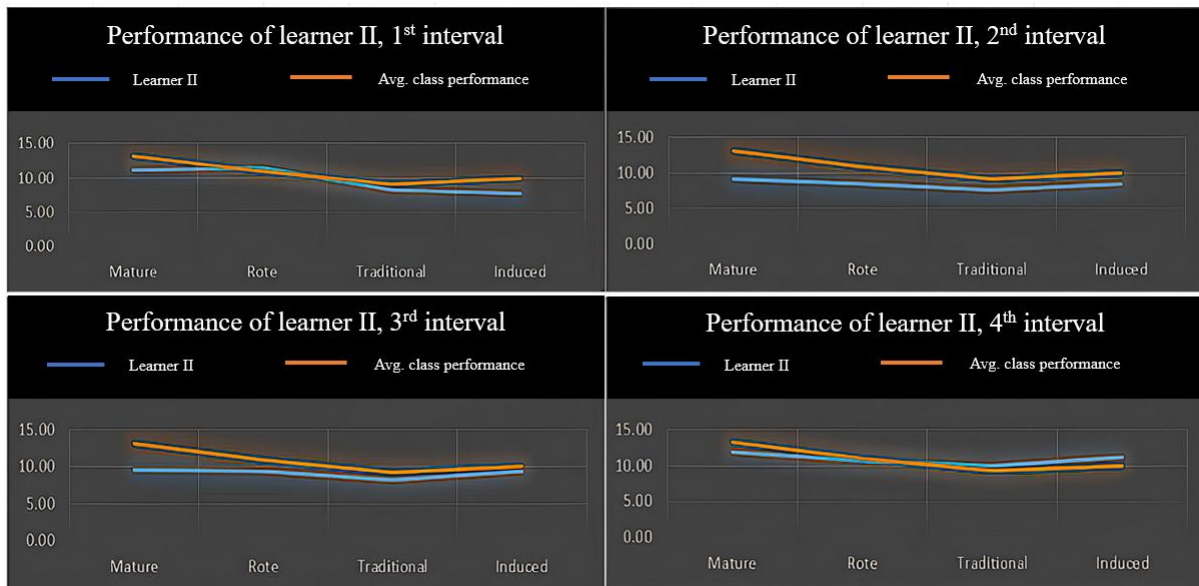


Figure 8. Individual Learner – II progression and the average class performance.

Focusing on the cohort-wise performance of the learners, Figure 9 provides a more comprehensive understanding of the performance of learner I. It shows the learner's maturity score is 12.74, while the class average maturity score is 13.18. The evidence indicates that the learner's level of maturity is lower than that of the class as a whole. The aforementioned metric assesses the extent to which the learner has cultivated the requisite competencies and expertise to achieve academic success. The learner's rote score is 9.13, while the class average is 10.93. This indicates a positive trend. This metric assesses the learner's ability to effectively memorise and subsequently retrieve knowledge. The learner's traditional score of 9.80 is slightly higher than the class average of 9.23. The aforementioned metric assesses the aptitude of the learner to acquire knowledge within the confines of a conventional educational environment. The learner's induced score is 12.04, exhibiting a marginal increase of nearly 2 points compared to the class average. This metric assesses the learner's proficiency in acquiring knowledge through self-directed and autonomous means.

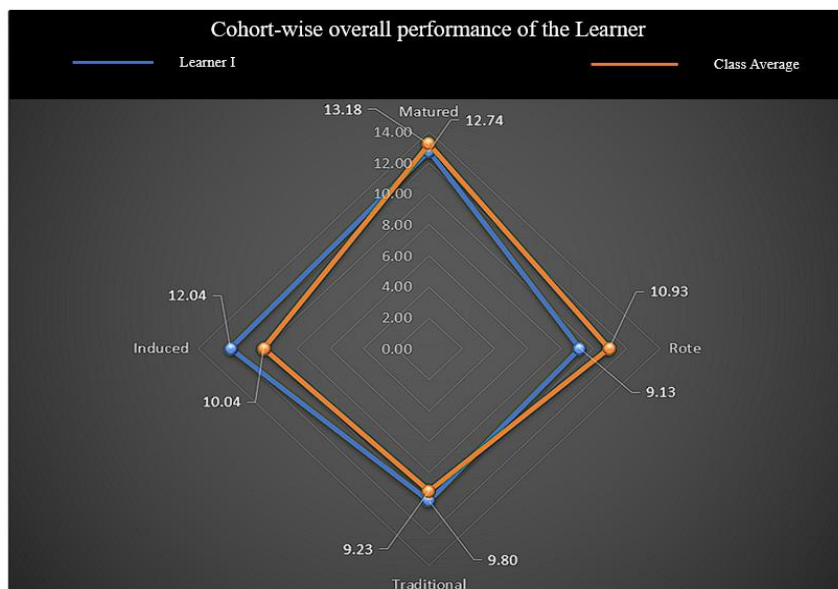


Figure 9. Cohort-wise performance of learner I.

However, when comparing the same with the performance of learner – II (may be seen in Figure 10), it can be concluded that the learner's maturity score is 10.44, while the class average maturity score is 13.18. The evidence indicates that the learner's level of maturity is substantially lower than that of the class as a whole. The aforementioned metric assesses the extent to which the learner has cultivated the requisite competencies and expertise to achieve academic success. The learner's rote score is 10.04 of 10.93. This situation is also alarming. This metric assesses the learner's ability to effectively memorise and subsequently retrieve knowledge. The learner's traditional score of 8.56 is also lower than the class average of 9.23. The aforementioned metric assesses the aptitude of the learner to acquire knowledge within the confines of a conventional educational environment. The learner's induced score is 9.20, which is also lower compared to the class average of 10.04. This metric assesses the learner's proficiency in acquiring knowledge through self-directed and autonomous means.

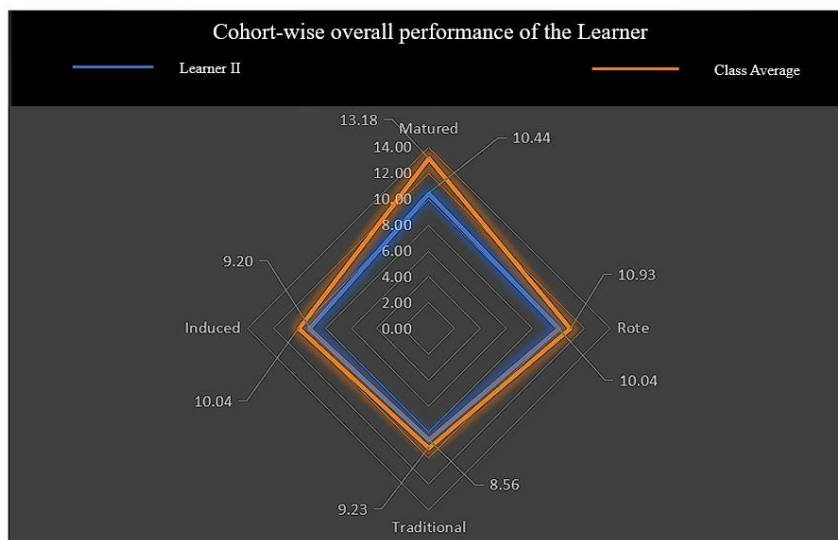


Figure 10. Cohort-wise performance of learner II.

4. Future Scope and Conclusion

Acknowledging and facilitating the distinctive educational requirements of learners is a crucial element in guaranteeing the uninterrupted provision of education. It is incumbent upon educators to recognise the unique learning styles of individual students and adapt instructional methods accordingly. The proposed approach ought to transcend conventional academic disciplines and encompass students with disabilities and those who may require supplementary assistance to attain their full potential. It is recommended that instructors participate in collaborative professional development activities to stay current with the latest learning strategies and tools. Additionally, it is important for instructors to regularly evaluate student progress to identify any necessary modifications that may better facilitate their learning. Educational institutions can foster inclusive learning environments that facilitate academic achievement for all students by acknowledging and meeting their distinct needs (Meinck, Fraillon, & Strietholt, 2022). The propagation and maintenance of learning continuity is reliant upon the essential components of collaboration and teamwork. In contemporary society, the process of acquiring knowledge extends beyond traditional educational settings and necessitates ongoing learning opportunities that transcend the boundaries of formal instruction. In the given context, the utilisation of collaboration and teamwork serves as a crucial avenue for disseminating knowledge and acquiring new insights. Collaborative learning facilitates the cultivation of interpersonal abilities and communication, which are crucial not only in academic endeavours but also in the realm of work. Moreover, collaborative projects and tasks involving teams foster a sense of accountability, responsibility, and mutual respect among the team members, thus creating an environment conducive to learning (Stone & Glover, 2021). The concept of lifelong learning pertains to the continuous attainment of knowledge or expertise by an individual throughout their lifespan. The interdependence of learning continuity and lifelong learning is noteworthy, as the existence of one is contingent upon the other, thus extending the idea of learning continuity research only to evolve as a theory of the relevant domain. The usefulness of the present theoretical components of learning continuity research seeks validation across the practice domains of tertiary education, offering a conclusive ability measurement matrix for students to aim for higher learning gain. Providing uninterrupted learning opportunities enables individuals to consistently acquire novel knowledge and enhance their pre-existing competencies, thereby promoting the cultivation of a lifelong learning disposition. The aforementioned mindset is distinguished by an inclination to acquire knowledge, proficiency in adapting to novel circumstances and obstacles, and a readiness to engage in autonomous learning.

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