Learner Performance and Preference Meter for Better Career Guidance and Holistic Growth

Nilay M. Vaidya and Kanubhai K. Patel

Abstract One of the biggest challenges for higher educational institutes is to increase the placement ratio. Another challenge is to increase the holistic development of the students. Looking at the global requirement, the companies require people not only excellent in the domain knowledge but required excellent in the soft skill too. Finding and predicting the performance factor of the student may help in improving the system and also give an indication to improve pedagogy being offered to students. Many tutoring systems and continuous evaluation patterns adopted by many institutes help in improving the performance of a student. As the trend changes toward holistic development of the students, focus is also upon the soft skills measurement factor. This encouraged us to have a model that helps predicting the holistic performance of a student based on the continuous evaluation as well as performance indicator of a student in other activities too. A gray-based decision-making theory helps assessing the required parameters that find the continuous performance measurement of a learner for each aspect. The multi-attribute situation decision-making theory helps in improving the criticality of the information system by recognizing the sensitivity of the criteria.

Keywords Employability · Grey decision-making · Multi-attribute situation decision-making · Tutoring system

1 Introduction and Related Work

With the revolution in the global market and the rapid development in Information Technology (IT) around, many companies started demanding the candidates with the good technical skill as well as soft skills. Soft skill development becomes one of the important components in good institutes nowadays. Institutes have started applying the different modules to build the soft skill measure among students. But

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the challenge is to have a performance factor analysis that may help in combining the result of technical as well as soft skill measure to identify the holistic measure of the student. Now the biggest challenge is to find (i) basic competency of a student at entry time [1], (ii) continuous internal evaluation, and (iii) preferences and outcome in other activities. Entry time basic competency skill identification can be done by considering basic criteria like age, area, previous qualification, family background (parent's qualification), score in the last competitive exam and others. Model already been developed using Multi-Criteria Decision-Making theory (Multi-Objective Grey Situation Decision-Making Theory) that identifies basic entry time competency level of a student [1].

Major task then is to track the continuous internal evaluation [3, 6] and the preference of the learner for the holistic personality development measure. The task is to measure the holistic flavor or holistic factor of the student during the study period. According to the survey the best way to find the performance measure is to calibrate the performance indicators. To provide better effect measure, multi-criteria (multi-attribute grey) decision-making theory helps in finding the performance indicator after comparing the effect measure in the same environment. Finding or evaluating the intellectual ability and improving it becomes challenge in the current environment. The objective of our study is to find the preference meter and performance meter of the student to increase the employability factor.

2 Proposed Model

As shown the Fig. 1, key dimensions are Assessee (Learner/Student), Assessment System, and Global recruiters. The key aspect is to improve the intellectuality, awareness of core ethics, and to have more social touch that leads toward the understanding of the social quotient.

Decision-making process takes a number of steps: (i) problem identification, (ii) preference building, (iii) assessing substitutes, and (iv) finding best substitute option (Simon 1977; Keendy and Raidda 1993; Kleindorfer, Kunreuther, and Schoemaker 1993). In the decision-making process we focus upon the decision science and operation research rather than focusing upon the thinking or end user's research. So we can say the problem objective is to make use of prescriptive and normative analysis rather than descriptive analysis.

The problem we focus on considers the alternative criteria with performance rating; and not on the single criteria. This encourages in finding multiple criteria with alternative weights depending on the preferences, outcomes, and corelation among the criteria to be taken into consideration while finding the effective result. Expert agent helps in improving the implicit knowledge of the learner as well as provides the conditional content to the learners. The system helps in identifying the effectiveness and likeliness of the user and provides the content as well as selects the pedagogy accordingly [2]. Many agents nowadays are designed and implemented that helps in identifying the interest and basic understanding of the user to produce

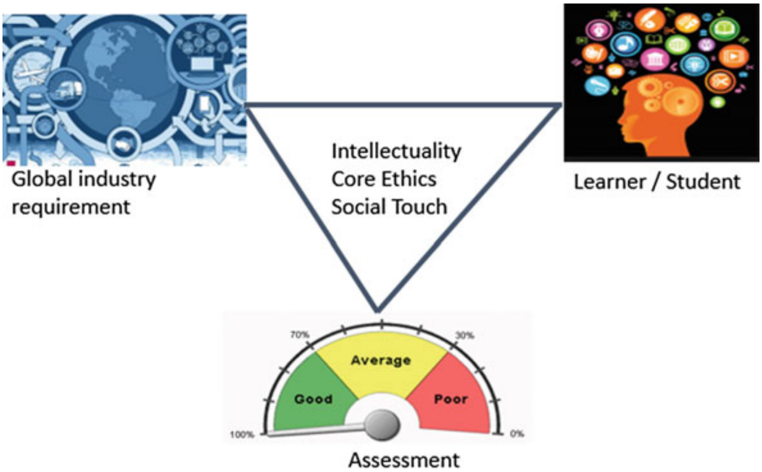

Fig. 1 Overall working of the model

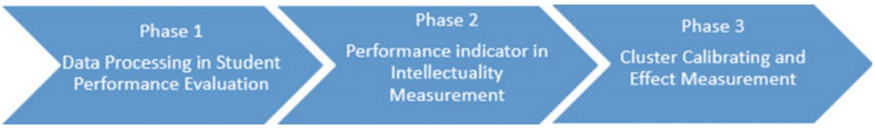

Fig. 2 Phases identified for the working model

the content. Now the challenge is to find the performance meter of the learner using an alternative approach that helps in giving the effective measure of the learner that helps tutor in knowing the exact indicator of the learner in the given cluster. This also helps in finding the performance matrix for the cluster that gives better indicator of the learner by calibrating the effect measures within the cluster.

Three-phase performance indicator meter identified that uses different criteria to generate the effect measures as shown in Fig. 2.

2.1 Phase 1

Data processing to evaluate the learning effectiveness in the domain knowledge using information systems by applying Multi-Objective Grey Situation Decision-Making theory. This makes the information system more adaptive by flavoring the intelligent agent onto it. The working flow is shown in Fig. 3.

The processing model collects and investigates data for the future prospecting that can be further utilized by alternative phase that helps in calibrating the multiple user effective measure grade. This phase also uses exploratory model that helps in

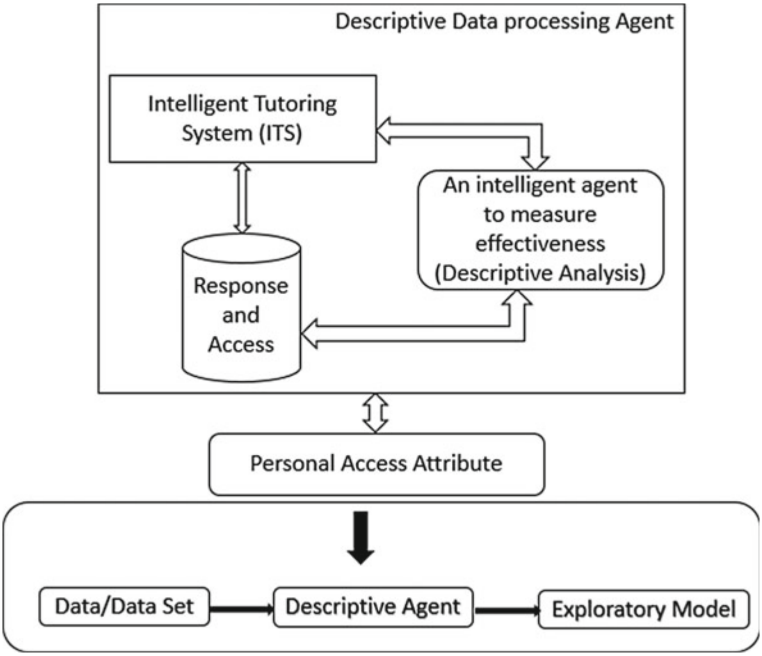

Fig. 3 Working of the internal evaluation model

identifying the correct learning pedagogy that suits the learning style and offers services accordingly.

2.2 *Phase 2*

Data processing with Multi-Objective Decision-Making (MODM) on the external environment and explicit feedback. This phase identifies several results as well as contributions of the assessee in terms of participation in the event or coordinating the event, competing in the several events, cracking or attempting the certification exams, feedback of the peer and the teacher or coordinator, and many more. Many of the criteria have fuzzy values and greyness associated with it. This fuzziness as well greyness needs to be evaluated in such a way that it helps in generating a better result. This leads to the normative analysis approach.

This phase also uses the scores of different aptitude tests being conducted by the internal evaluation information systems (phase 1). The scores are then being mapped with the criteria and also affect the weights associated with it.

General overall picture is shown in Fig. 4:

Each criterion has got the measuring scale from upper, lower, or central. The decision-making during the measurement of the performance factor includes four

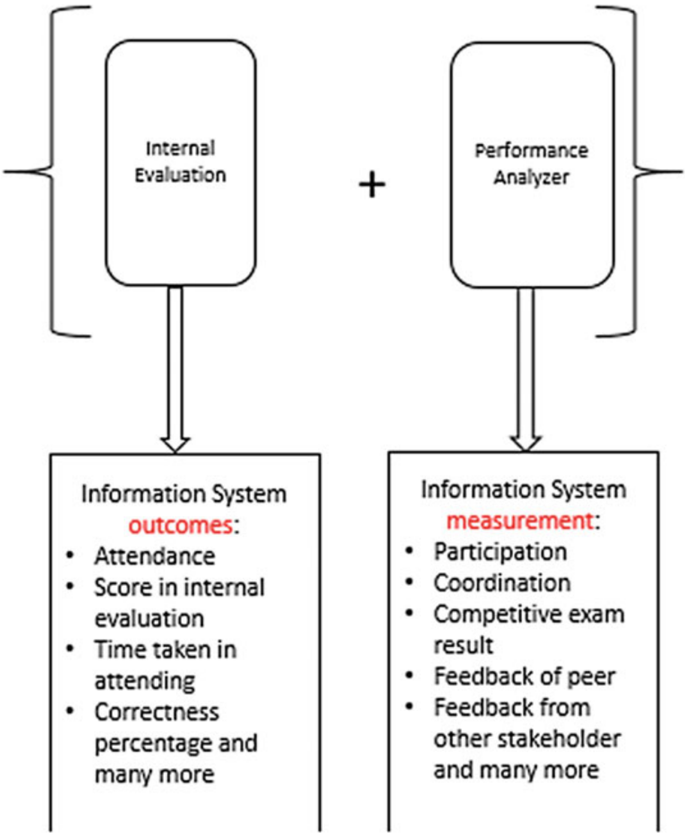

Fig. 4 Working of the continuous performance analyzer

major elements: (i) event, (ii) strategy, (iii) effect, and (iv) scale. In case of finding the performance factor of the student, here we considered the factors like participation in various curricular activities, co-curricular activities, certification exam cracked or appeared, events coordinated as head or member with team size and event type, direct as well as indirect feedback of the student from peer or teacher or counselor.

Depending upon the deviation factor of the criteria, the effect measure is classified into three levels: (i) upper, (ii) lower, and (iii) center. The criteria use of the effect measure is depended upon the deviation in size of the group, objective of the task, criticality defined for the task and many other criteria can be taken into consideration to have the effect measure for the criteria. To find the effect measure for different levels we need to fix the upper, lower, and central limits for the cluster to find the effect measures for the students. So the primary effect measure for the criteria with classified level as higher the better, i.e., upper level:

$$r_{ij} = \frac{u_{ij}}{u_{max}} \tag{1}$$

where u_{ij} is the actual effect measuring value and the u_{max} is the maximum data for the criteria $u_{ij} \leq u_{max} : r_{ij} \leq 1$. Similarly, for the effect measure with lower measure with the lower level:

$$r_{ij} = \frac{u_{min}}{u_{ij}} \tag{2}$$

where u_{ij} is the actual effect measuring value and the u_{min} is the minimum data for the criteria $u_{ij} \geq u_{min} : r_{ij} \geq 1$ [4, 5].

As there are several such objectives taken to find the performance meter, we need to find the comprehensive measure on the objectives, i.e., criteria defined which are called multi-objective situation decision-making. The effect measure for individual criteria for students need to be calculated as $s_{ij.}$ The decision factor then can be calculated as for the kth element as $\delta_i^{(k)}$ and the decision matrix which is prepared as

$$\begin{bmatrix} \frac{r_{11}^{(k)}}{s_{11}} \\ \frac{r_{21}^{(k)}}{s_{21}} \\ . \\ . \\ \frac{r_{n1}^{(k)}}{s_{n1}} \end{bmatrix} \tag{3}$$

Similarly, the comprehensive matrix then can be calculated as:

$$r_{ij}^{(\Sigma)} = \frac{1}{N} \sum_{k=1}^{n} r_{ij}^{(k)} \tag{4}$$

This comprehensive value being generated shall then be used to find the effectiveness of the student in the given environment. More the value is nearer to one more effective the result. The classification is shown in Fig. 5.

Every criterion has got the actual effect measure which is being calculated by the system once being inserted into the system. The greyness or fuzziness factors are converted into their equivalent crisp values before being processed by the algorithm. Each criterion has got the minimum effect measure or maximum effect measure or

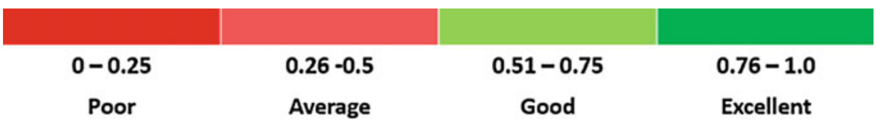

Fig. 5 Effect measure classification

Table 1 Sample data of students

	Participation in co-curricular events	μ1	Clearing any online course	μ2	Attending the workshop/seminar	μ3	Number of attempts to clear the aptitude test	μ4
S1	1	1	2	2	0	0	3	3
S2	4	4	5	5	1	1	1	1
The quantitative and qualitative assessment								

central effect measure depending upon the deviation factor of the activity/criteria. These models use few criteria which are single level, few are multilevel, few are multistage. But all are dynamic and required comparison at all the levels.

Problem solving by the multi-objective situation decision-making theory for sample criteria for two students: Considering sample four parameters to find the effect measure for a student by considering the participation in co-curricular events (upper limit measure—minimum four per year), clearing any online course (higher limit measure—minimum five as one per course/subject), attending the workshop/seminar (higher limit measure—minimum two per year), number of attempts to clear the aptitude test (lower limit measure—out of three attempts offered) (Table 1).

The effect measure for different parameters:

$$r_{ij}^{(1)} = \left[\frac{1}{4}, \frac{4}{4}\right], r_{ij}^{(2)} = \left[\frac{2}{5}, \frac{5}{5}\right], r_{ij}^{(3)} = \left[\frac{0}{2}, \frac{1}{2}\right], r_{ij}^{(4)} = \left[\frac{3}{3}, \frac{1}{3}\right]$$

And the comprehensive effect measure shall be

$$r_{ij}^{(\Sigma)} = \left[r_{11}^{(\Sigma)}, r_{12}^{(\Sigma)}\right] = [0.4125,\ 0.7075]$$

As discussed above the effect measures calculated above shows that the competitiveness of student S1 is average and S2 is good.

2.3 Phase 3

Extending the comprehensive measure by comparing the effect measures of each student and standardizing will give the comprehensive analysis factor. This helps in finding and comparing the performance factors as well as the preference factor of the batch. Applying the aggregation gives better understanding of an individual in the group of assessees. In the previous example, taking the average of two comprehensive effect measures shall give us the aggregate of [0.4125, 0.7075], which is 0.56 which indicates that the overall classification of the batch is "Good" as per the effect measure classification shown in Fig. 5.

3 Conclusion

As the biggest challenge is to increase the employability of the student and to increase the ration and to make the students competitive we need to continuously observe the performance of the student. The proposed solution keeps on observing their details and finds the effect measure at the regular interval. The counselor or teacher is able to find overall personality performance meter that helps them to take corrective actions to improve the employability of the students and their holistic growth.

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