Relationship between factors that contribute to student success in the e-learning environment

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Abstract. *This qualitative research study identifies and investigates the relationship between key factors influencing student success in e-learning environments. It emphasizes the importance of identifying key factors to enhance educational practices and student outcomes. By applying Interpretive Structural Modelling (ISM) to factors already identified as crucial in previous literature, this research reveals the interdependencies and impact levels among factors such as faculty guidance, resource availability, and continuous assessment. The analysis, supported by Structural-Self Interaction Matrix (SSIM) and MICMAC diagram highlights that 10 of 12 factors are interconnected and therefore depend on each other, that is, the change of one factor affects the others. Low attendance was identified as a factor that depends on all other factors.*

Keywords. E-learning, Interpretive Structural Modelling, ISM, student performance, student success

1 Introduction

Ensuring quality and enhancing student performance in the e-learning context had become key factors in monitoring the progress of student attributes. Tracking student performance was not merely about collecting data on students but served as a mechanism for evaluating learning and adjusting teaching materials and methods to develop students' full potential. E-learning systems like Moodle typically collected large amounts of data that needed to be analysed. However, it was very challenging to isolate the precise factors that required special attention. Raw data was often used to predict students' test results or various forms of assessments, but it was less commonly used to identify factors or behavioural patterns (Chen, 2023) that needed attention to identify students who required additional support or to further enhance successful practices and encourage the continuous improvement of the educational process (Kumar, 2021).

By using different factors such as students' historical performance and behaviour, and studying the relationship between these factors and grades, it was possible to form a prediction model to assess students' learning effectiveness and then infer future student performance. This provided a crucial basis for academic warnings, adjustment of teaching strategies, optimisation of educational resource allocation, and personalised customisation of learning plans for students (Yan, 2022). Monitoring student performance was important not only for students but also for teachers and broader educational institutions such as universities. To improve learning success and evaluate the effectiveness of educational methods, it was essential to understand the social, cognitive, and behavioural aspects of students, enabling teachers to enhance their teaching by adapting to the individual needs of students, and educational institutions to assess and improve the effectiveness of their programmes by predicting academic success and adjusting the curriculum according to industry requirements (Kuna & Prasad, 2019).

In this paper, we focused on the factors identified in the study proposed by Bharadi & Awasthi (2022), specifically those marked as having a positive or negative impact on student performance, to examine whether and how these factors affected their success. For this purpose, Interpretive Structural Modelling (ISM) was used. The method was interpretive in that the group's judgement decided whether and how items were related; it was structural in that, based on the relationship, an overall structure was extracted from the complex set of items; and it was modelling in that the specific relationships and overall structure were portrayed in a diagram model (Sage, 1977).

2 Research objectives and methodology

The aim of this research is:

- To identify how selected factors contribute to student performance.

- To determine the relationships between those factors.

And to answer the following research question:

RQ: In what way do the identified factors contribute to student success?

Interpretive Structural Modeling (ISM) is a computer-aided method for developing graphical representations of system composition and structure (Attri et al., 2013). ISM not only aided in understanding the relative relationship between the critical success factors but also helped to build their interdependence while implementing sustainability (Sreenivasan et al., 2023). When a problem was identified within a system, the first step involved identifying all relevant elements or factors that were part of the system being studied. Having decided on the factor set and the contextual relation, a Structural Self-Interaction Matrix (SSIM) was developed based on a pairwise comparison of factors (Attri et al., 2013). The SSIM was vital in ISM as it systematically captured and represented the direct relationships between elements within a system. This matrix served as the foundation for constructing the reachability matrix, which in turn allowed for the hierarchical structuring of elements, enabling the identification of key drivers and dependencies within complex systems. Once transitivity embedding was complete, a matrix model was obtained. This allowed for the partitioning of elements and the extraction of the structural model known as ISM (Agarwal et al., 2007).

As mentioned in the previous section, factors selected for the ISM are taken from Bhardi & Asasthi (2022). The authors, based on a literature review, identified 33 potential independent variables that could influence student performance in an e-learning environment. After a more detailed analysis, the following factors were identified as having either positive or negative impact on student performance (Bhardi & Asasthi, 2022):

1) Trained Faculty guidance
2) Resource Availability (Labs, Library etc)
3) Continuous Assessment (Tests) During Course
4) Student's focus on career and self-grooming
5) Use of New Educational Tools and Techniques in Teaching (Smartboards, Portals etc)
6) Prior in-depth knowledge about current subjects (Prerequisites)
7) Score/Performance in Prior Course
8) Extra-Curricular Activities Participation
9) Social Media Platforms utilization
10) Peer Pressure
11) Parent's involvement in student's study
12) Low Attendance.

As presented by Bhardi & Asasthi (2022), in the e-learning context, factors 1-7 had a positive impact on student’s performance, while factors 8-12 provided a negative impact. It was also found that those factors had different impacts on a student's educational performance. For example, Trained Faculty Guidance and the Use of New Educational Tools and Techniques (like smartboards and online portals) are critical in delivering effective and engaging online education. On the other hand, external factors such as Peer Pressure or Parent’s involvement in student’s study may also impact student’s performance, but not to such an extent. It can also be noted that the factors the authors consider positive are related to the teaching process (teaching staff, resources, assessments, student career development, new educational technologies...) while the factors identified by the authors as having a negative impact on student performance are related to external factors (extracurricular activities, social media use, peer pressure, parental involvement...).

3 Participants and data collection

To identify the correct relationships between the individual factors, it was necessary to ensure understanding and seriousness when completing the SSIM matrix. To this end, efforts were made to avoid undergraduate students, as they could not reflect on those factors since they do not have adequate experience and consequently, cannot develop proper attitudes towards different factors influencing their study. Therefore, postgraduate students were deemed more representative for identifying relevant factors in the SSIM analysis, as they already possess certain research knowledge, and some have even experience working with other students. Additionally, all postgraduate students have completed their master’s degree, which allows them to assess better which factors more or less influence student success. In contrast, first-year students often lack sufficient experience in theoretical and practical research aspects, which could lead to more superficial or inaccurate results. For this purpose, a task was prepared in the LMS Moodle, which the students downloaded to their computers and then re-uploaded to the Moodle system once completed. To ensure students had enough time to complete the task, the deadline for submitting the task was set to 2 days, which aimed to ensure accurate and honest responses. A total of 17 SSIM matrices were completed, with 17 students participating in the research. The SSIM matrix factors refer to the 12 factors previously mentioned, which were identified by Bhardi & Asasthi (2022) as factors that can significantly influence student performance within an e-learning environment.

4 The ISM procedure

The procedure started with identification and analysis of relationships and interactions between different factors identified as important for student success in previous literature. The relationships between factors established by the participant's responses were presented using a standard ISM notation:
V: factor i will assist to reach factor j;
A: factor j will assist to reach factor i;
X: factor i and j will assist to reach each other;
O: factors j and i are unrelated (Pramod & Banwet, 2010).

Using the ISM notation described above, a SSIM was generated (Table 1) where the relationships between factors are represented in terms of rows (i) and columns (j) along with their respective connections. After the students expressed the degree of connection between the two factors (using standard ISM notation symbols), their responses were compared, and the most common values were selected using the mode function. The final SSIM table is based on the mode function, meaning that for each value at the intersection of (i) row and (j) column the most frequent value was used. The final SSIM is presented in Table 1 where factors from 1-12 present independent variables mentioned before.

Table 1. SSIM

Factors	**(j)**	**12**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
(i)													
1		O	O	O	O	V	X	O	X	X	X	X	1
2		V	O	O	O	X	X	O	X	V	V	1	
3		V	O	O	O	O	X	A	X	V	1		
4		O	O	O	O	X	A	X	X	1			
5		O	O	O	X	O	O	O	1				
6		V	O	O	O	O	A	1					
7		V	O	O	O	X	1						
8		V	O	A	X	1							
9		V	O	X	1								
10		V	O	1									
11		O	1										
12		1											

4.1 Reachability matrix

The next stage in the ISM methodology involved creating an initial reachability matrix from the SSIM. This process entailed transforming the SSIM into the Initial Reachability Matrix (IRM) by replacing the four symbols (V, A, X, and O) with 1s or 0s. IRM is created by converting symbolic SSIM matrices into binary format using the ISM rules (Tabziri et al., 2010). The Initial Reachability Matrix is created from the SSIM by applying the following rules: if the SSIM entry is "V," the matrix entry is (1,0); if "A," it is (0,1); if "X," it is (1,1); and if "O," it is (0,0), where the pairs represent the direction of influence between the factors. With the mentioned guidelines, the initial reachability matrix was constructed. To address any gaps in the opinions gathered during the creation of the structural self-interaction matrix, 1* entries were added to ensure transitivity. Transitivity can be described as follows: if factor A leads to another factor B and if factor B leads to a third factor C, as per the rule of transitivity A leads to C also exists (George & Pramod., 2014). Once the transitivity concept had been applied as outlined, the Final Reachability Matrix (FRM) was obtained, and presented in Table 2. An example of transitivity is observed when Trained Faculty Guidance (factor 1) influences Resource Availability (factor 2), and Resource Availability (factor 2) influences Continuous Assessment (factor 3); therefore, Trained Faculty Guidance (factor 1) indirectly influences Continuous Assessment (factor 3) through Resource Availability (factor 2). This example presents that 1* would be placed at the intersection of Trained Faculty Guidance (1) and Continuous Assessment (3) in the Final Reachability Matrix, indicating that although there is no direct relationship between these two variables, there is an indirect influence established through Resource Availability (2).

Table 2. FRM

Factors	**(j)**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Driving power**
(i)														
1		1	1	1	1	1	1*	1	1	1*	1*	0	1*	11
2		1	1	1	1	1	1*	1	1	1*	1*	0	1	11
3		1	1*	1	1	1	1*	1	1*	1*	1*	0	1	11
4		1	1*	1*	1	1	1	1*	1	1*	1*	0	1*	11
5		1	1	1	1	1	1*	1*	1*	1	1*	0	1*	11
6		1*	1*	1	1	1*	1	1*	1*	1*	1*	0	1	11
7		1	1	1	1	1*	1	1	1	1*	1*	0	1	11
8		1*	1	1*	1	1*	1*	1	1	1	1*	0	1	11
9		1*	1*	1*	1*	1	1*	1*	1	1	1	0	1	11
10		1*	1*	1*	1*	1*	1*	1*	1	1	1	0	1	11
11		0	0	0	0	0	0	0	0	0	0	1	0	1
12		0	0	0	0	0	0	0	0	0	0	0	1	1
Dependence power		10	10	10	10	10	10	10	10	10	10	1	11	

From the FRM, reachability and antecedent sets were derived. The reachability set contained the factor itself and any other factors it might affect, while the antecedent set included the factor itself and any other factors that may affect it. The intersection of these sets was then determined for all factors, allowing for the identification of different factor levels. Factors where the reachability and intersection set match were placed at the top level of the ISM hierarchy. Top-level factors did not influence any factors above their level. Once identified, they were excluded from further consideration. This process was repeated to determine the next level of factors. In our example shown in Table 3, only 2 levels were detected which later will correspond to the levels of the diagram.

Table 3. Level Partitioning (LP)

Factor	Reachability Set	Antecedent Set	Intersection	Level
1	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2
2	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2
3	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2
4	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2
5	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2
6	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2
7	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2
8	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2
9	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2
10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2
11	11	11	11	1
12	12	1,2,3,4,5,6,7,8,9,10,12	12	1

5 Results

The Conical Matrix (CM) presented in Table 4. helped construct hierarchical linkages among factors and is a restructured version of the reachability matrix. It made the representation of direct and indirect relationships simpler by organising factors according to their degrees of influence. A more organised and perceptive examination of complex systems is made possible by this matrix rearrangement, which improves the clarity of factor interdependencies. In summary, driving power indicates how strongly a factor influences other factors, while dependence power shows how strongly is one factor influenced by other factors (Balaban, 2020).

Table 4. Conical Matrix (CM)

F	(j)	11	12	1	2	3	4	5	6	7	8	9	10	DRP
(i)														
11		1	0	0	0	0	0	0	0	0	0	0	0	1
12		0	1	0	0	0	0	0	0	0	0	0	0	1
1		0	1*	1	1	1	1	1	1*	1	1	1*	1*	11
2		0	1	1	1	1	1	1	1*	1	1	1*	1*	11
3		0	1	1	1*	1	1	1	1*	1	1*	1*	1*	11
4		0	1*	1	1*	1*	1	1	1	1*	1	1*	1*	11
5		0	1*	1	1	1	1	1	1*	1*	1*	1	1*	11
6		0	1	1*	1*	1	1	1*	1	1*	1*	1*	1*	11
7		0	1	1	1	1	1	1*	1	1	1	1*	1*	11
8		0	1	1*	1	1*	1	1*	1*	1	1	1	1*	11
9		0	1	1*	1*	1*	1*	1	1*	1*	1	1	1	11
10		0	1	1*	1*	1*	1*	1*	1*	1*	1	1	1	11
DEP		1	11	10	10	10	10	10	10	10	10	10	10	
Level		1	1	2	2	2	2	2	2	2	2	2	2	

* DEP: Dependence Power; DRP: Driving Power; F: Factors

5.1 Classification of factors

To analyse and classify factors based on their driving power and dependence, a Matrics d'Impacts Croises-Multiplication Applique an Classment (MICMAC) diagram was constructed and presented in Fig. 1. The diagram categorizes factors into four main groups:

I. Autonomous factors: Have weak driving power and weak dependence.
II. Dependent factors: Have high dependence but weak driving power.
III. Linkage factors: Have both high driving power and dependence. These factors are considered unstable because any intervention on them affects other factors and triggers feedback effects on themselves (Balaban, 2020).
IV. Independent factors: Have strong driving power and weak dependence.

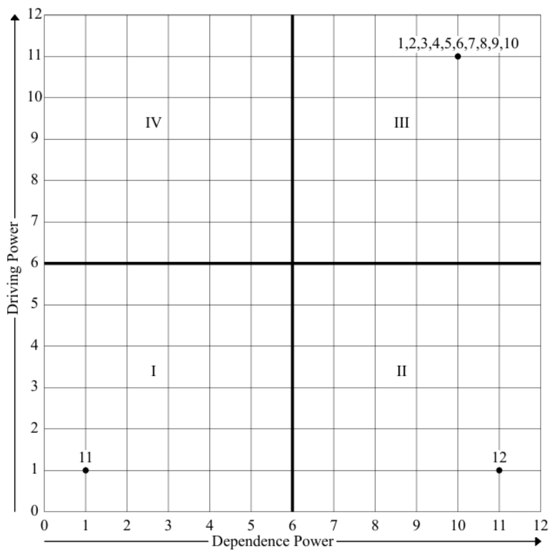

Figure 1. MICMAC diagram

As seen in Fig. 1, in the first quartile there was only a factor number 11 which had weak driving power and also weak dependence. This factor is called "Parent's involvement in student's study". This is also a factor with a negative impact on student performance divided by Bhardi & Asasthi (2022). It means that "Parent's involvement in student's study" does not heavily influence other factors, and also is not heavily influenced by other factors. Also, in the "Dependent factor" quartile, there was only one factor called "Low Attendance", which means that this factor has high dependence but weak driving power and was also one with a negative impact on student performance. This also means that this factor is very influenced by other factors but does not significantly influence other factors. The third quartile is a home of factors from 1 to 10. Those factors have both high driving power but also dependence. Those factors are very influenced by other factors in the system, but also very influence other factors: 1) Trained Faculty guidance 2) Resource Availability (Labs, Library etc), 3) Continuous Assessment (Tests) During Course, 4) Student's focus on career and self-grooming 5) Use of New Educational Tools and Techniques in Teaching (Smart boards, Portals etc) 6) Prior in-depth knowledge about current subjects (Prerequisites) 7) Score/Performance in Prior Course 8) Extra-Curricular Activities Participation 9) Social Media Platforms utilization 10) Peer Pressure. In comparison with the results of the authors Bhardi & Asasthi (2022), all our factors from 1 to 10 are highly dependent on each other, which does not align with the author's previous findings, and give an answer to our research question. Differences in research results may arise due to the different research contexts as well as the methodology, as the authors Bhardi & Asasthi (2022) did not use ISM. Additionally, our research was conducted with postgraduate respondents who had a slightly longer period to complete the matrix. Additionally, the factors identified as having a positive impact on student success by Bhardi & Asasthi (2022) are present in the 3rd quartile in this study and strongly influence each other. The same is true for factors 8-10, which have been identified as factors that negatively impact student success.

5.2 Relationship between factors

The final step in ISM was creating the ISM diagram which was utilized to illustrate the complex relationships between factors within a system. Nodes in this directed graph represented factors, and the directed lines indicated the relative influence of each factor on other factors. The diagram facilitated identification of important factors and dependent factors by helping to see the hierarchical structure and interdependencies. It was created from the Conical Matrix shown in Table 4 and was presented in Fig. 2.

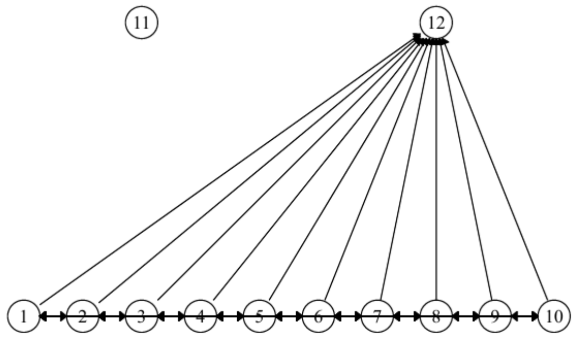

Figure 2. ISM diagram

6 Conclusion

The study has effectively employed Interpretive Structural Modelling (ISM) to analyse the factors impacting student performance in an educational setting. By utilizing the ISM methodology, we were able to systematically identify and understand the interrelationships among various factors that contribute to students' performance.

The results, encapsulated in the reachability and conical matrices, as well as the MICMAC diagram, provide a clear hierarchical structure and classification of these factors based on their driving and dependence power. Notably, the study highlights that most factors (1-10) have fallen into the third (Linkage) quadrant in which factors have both high driving power and dependence. These factors are considered unstable because any intervention on them affects other factors and triggers feedback effects on themselves (Balaban, 2020). Also, it can be concluded that factors: 1) Trained Faculty guidance 2) Resource Availability (Labs, Library etc), 3) Continuous Assessment (Tests) During Course, 4) Student's focus on career and self-grooming 5) Use of New Educational Tools and Techniques in Teaching (Smart boards, Portals etc) 6) Prior in-depth knowledge about current subjects (Prerequisites) 7) Score/Performance in Prior Course 8) Extra-Curricular Activities Participation 9) Social Media Platforms utilization 10) Peer Pressure depend on each other in a great extent, and any action on any of them can affect other factors.

On the other hand, 'Parent's involvement in student's study' emerged as an autonomous factor with weak driving and dependence power, while 'Low Attendance' was identified as a dependent factor, heavily influenced by other factors but exerting minimal influence itself.

The ISM diagram further illustrated the hierarchical and directional relationships among the factors, providing a visual representation that aids in comprehending the underlying dynamics. This model serves as a valuable tool for educators and administrators, enabling them to pinpoint key areas for intervention and strategic improvements.

In conclusion, it can be noted that by identifying the key drivers and dependencies, educational institutions can tailor their strategies to foster a more effective learning environment, thereby improving educational outcomes and addressing the specific needs of their student populations. Future research could expand on this study by incorporating a larger and more diverse sample size, exploring additional factors, and integrating longitudinal data to further validate and refine the ISM model. Along that, questions for future research could be, how do the key factors in the ISM model interact with each other and what long-term effects do they have on students' performance?

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