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Analysing the Key Enablers of Students' Readiness for Online Learning: An Interpretive Structural Modeling Approach

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ABSTRACT

Education has undergone a paradigm shift due to the COVID-19 outbreak declared as a pandemic by the WHO in 2020. The current research attempts to identify the key factors which enable students' readiness for online learning (SROL). The Interpretive Structural Modelling (ISM) approach is used to draw contextual relationships among the enablers of SROL and these are further clustered using Matrix of Cross-impact Multiplications (MICMAC) analysis. Personality traits like 'Open to experience', 'Agreeableness' and 'Extraversion' emerged as driving enablers while; several factors like academic performance, prior exposure to online classes, self-efficacy in online settings, learner control, self-directed learning and motivation for learning emerged as linkage enablers which would ultimately affect the 'willingness for future exposure to online classes'. The understanding of these enablers can help instructors to customize their online course delivery and counsel students based on their levels of readiness for online learning.

Keywords: *Distance education; online learning; Big Five Personality traits; Cognitive Flexibility; ISM; MICMAC*

INTRODUCTION

Voogt (2008) has pointed out that Information and Communication Technology (ICT) is changing our society from an industrial society to an information or knowledge society. From the array of Learning Theories available in the literature, 21st Century Skills summarizes the need to develop certain skills in students to ensure their success in school and life. Among a set of skills proposed by this theory, digital literacy, adaptability and flexibility, and initiative and self-direction are explored in the current study. While many academic institutions were already exploring blended learning, online learning, distance learning, many others had chosen to retain the status quo. However, the COVID-19 (Novel Coronavirus) pandemic has compelled the academic institutions to conduct classes in an online mode. This would entail a paradigm shift in the teaching-learning process.

Ravenscroft (2001) very rightly indicates that electronic learning (e-learning) is not a recent phenomenon, with its roots dating back to the 1950s. However, the growth of e-learning has not been linear in this duration. Many technologies and corresponding pedagogies have entered and exited in these years. Hence, the question addressed is whether the conventional class strategies can be used for online teaching as well or it requires a different design. In conclusion, Ravenscroft states that newer technologies allow teachers to re-think learning and instruction. Hence, the recent past has seen the emergence of methodologies which link learning to system designs. Experts also recommend that ICT skills cannot be taken as a separate set of skills, but they can be imparted by integrating its various roles in the curriculum design (Voogt & Roblin, 2010).

Theoretical Background

The current research is based on the Person-Environment Fit Theory. Person characteristics may include an individual's biological or psychological needs, values, goals, abilities, or personality, while environmental characteristics could include intrinsic and extrinsic rewards, demands of a job or role, cultural values, or characteristics of other individuals and collectives in the person's social environment (French et al., 1982). Person–environment fit theory focuses on the degree to which individual and environmental characteristics match, whereby the individual not only influences his or her environment, but the environment also affects the individual (Dawis,1992; Muchinsky et al., 1987). The absence of such a fit between person and environment may result in stress, while a good fit may improve the outcomes. Feldman, Ethington and Smart (2001) have used this theory in the academic context and studied the relationship between personality of college students and their choice of major. They found that a fit between personality and environment led to positive outcomes like satisfaction and commitment and hence, had repercussions on stability of these students. A similar philosophy has been applied in the current research wherein personality is linked to students' readiness for learning in an online environment. The contention is that certain personality traits are better fit for the online learning environment. However, the extension of this logic that a good fit should result in satisfaction; is not a scope of the current study.

On similar lines, in Information management, the Cognitive Fit Theory designed by Vessey and Galletta (1991) is used. This theory basically proposes that if the task characteristics correspond to the format in which information is presented, then it may lead to superior task performance by an individual. Although the theory started with simple information acquisition, it was also extended to complex tasks. So, if problem-solving is done with a cognitive fit, it would lead to effective and efficient problem-solving performance. Thus, in the context of this study if the structure is well understood by the students, they would present more readiness for learning, else the students need to possess cognitive flexibility. Pawlowska, Westerman, Bergman and Huelsman (2014) note that student personality is a consistent predictor of student satisfaction, while the classroom environment is a consistent predictor of performance. Further, the interplay between student personality and classroom environment had significant influence on satisfaction and performance.

Hence, considering the current situation which has forced the academic institutions to drive all their systems online involuntarily, in most cases and looking at the underlying theories, the current research attempts to look at this shift from the perspective of the students; by first identifying and exploring the enabling factors which affect the students' readiness for online learning. To this extent, the objectives of the current study are:

- To identify the key enablers which affect the students' readiness for online learning.
- To develop a contextual relationship amongst the identified enablers to adjudge the students' readiness for online learning and subsequently try and maximize the same.

LITERATURE REVIEW

This section gives an overview on the three major constructs of the study, namely, online education, personality, and online learning readiness. The various connotations of online education, its evolution, and its repercussions in terms of benefits and limitations are discussed in detail. Taking cue from the underlying theories discussed in the introduction, personality emerged as a major construct for identifying the enablers. Hence, the construct of personality and the Big Five Personality model have been reviewed with the help of past studies. Since the study aims to identify the key enablers for students' readiness in an online setting, the concept of online learning readiness is also explored with the help of literature.

Online Education – Evolution and Significance

Online education has experienced significant growth since the 1990s (Gallagher, 2002; Perreault, 2004). Moreover, online learning has become another important format for course delivery in higher education (Allen & Seaman, 2007; Schrum & Hong, 2002). The use of the Internet in higher education (teaching, learning and assessment) has grown at an exponential rate (OECD, 2010).

Various definitions of online education are available from the literature ranging from the most simple wherein online education has been described as learning based on the Internet (Urdan and

Weggen, 2000; Wentling et al., 2000; Bakia et al., 2012; Harasim, 2012) to the ones where online education is seen as an innovative approach using web-based pedagogical tools, while providing benefits of remote place and asynchronous time for the learner (Khan, 2005; Zhu, McKnight, and Edwards, 2009).

Online education advocates have highlighted several benefits of online education over time, such as:

- Online education being flexible and affordable gives a chance to many people to achieve certain qualifications, which otherwise would not have been possible (Carr, 2000; Mayes et al., 2011).
- Online learning environment facilitates content and knowledge sharing across a diverse group of people (Crook, 2008).
- Online learning environments can differentiate themselves based on their design, technical infrastructure, and use of pedagogical tools (Pillay et al., 2007).

Despite the benefits, several online and distance education courses are failing to meet quality standards set by institutions (Garrett, 2004; Oliver, 2005). This may be because the online learning environment varies substantially from the traditional classroom situation, especially with respect to learner's motivation, satisfaction and interaction (Bignoux and Sund, 2018). Selim (2005) identified the critical success factors of e-learning: instructor's attitude towards control of the technology; instructor's teaching style; learners' motivation and technical competency; learners' interactive collaboration; e-learning course content and structure; ease of on-campus Internet access; effectiveness of information technology infrastructure; and organizational support of e-learning activities. Readiness is a powerful factor in successful e-learning implementation (Mosadegh et al., 2011). The readiness of learners must be considered in the move to online learning, and it can be unwise for universities to impose online learning on students without first addressing their needs and concerns (Oliver, 2001).

Personality

Personality is an extremely well-researched construct from the psychological domain. However, the influence of personality attributes of learners has not received much attention (Bhagat et al., 2019). The definitions of personality have evolved over time. While the earlier definitions have focused more on personality being a unique internal trait which could predict an individual's behavior (Allport, 1961; Child, 1968), the more recent definitions opine that the personality traits also account for differences in behavior across time and context (McFerran, Aquino and Duffy, 2010; Zafar and Meenakshi, 2012). Quercia, Kosinski, Stillwell, and Crowcroft (2011) stated that the individuals' real world actions, taste and behaviors have been found significantly connected to their personalities. Further, in the context of B-school students, a study by Bhatt and Bhatt (2018) revealed that personality profiling of students can help in understanding their ethical proposition and thereby, also help the school administrators and mentors to give proper advice.

Of the numerous personality assessment models available in the psychology literature, the Big Five Personality model, the Myers-Briggs Type Personality Indicator, Type A/Type B personality theory are quite popular. For the present study, we would focus on the Big Five personality model, as literature suggests this model to be the most popular in research related to business/ management as well as academics. Also, it was found that although the model is composed of only five traits of personality, its values scale does consider the complexity of personality (Judge & Ilies, 2002; Otaibi & Moharib, 2012).

The Big-Five framework is a hierarchical model of personality traits with five broad factors, which constitute personality at the broadest level of abstraction: namely, Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Two things need to be noted in the context of the Big-Five Model: (i) each person has all five traits in different levels of tendency (Patrick, 2011) and (ii) the personality structure as measured is denoted as a point on the continuum of each of the five bipolar dimensions, which contributes to the interpersonal differences.

Online Learning Readiness (OLR)

Readiness is extremely important in the education-instruction process and is a significant input for the learning-teaching system (Bloom, 1995). The early definitions of OLR spoke about an individual's psychological and mental ability to experience the new mode of learning (Choucri et al., 2003; Kaur & Abas, 2004; Borotis & Poulymenakou, 2004; So & Swatman, 2006). However, later definitions by Pillay et al., 2007; Tang & Lim, 2013 have suggested various aspects linked to OLR like students' preference, confidence and competence, and ability to engage in independent learning.

Summary

While online education may not be a new phenomenon, it requires readiness of the educational institutions as well as the stakeholders to invest time and other resources so as to make online learning an enriching experience. Moreover, personality which has been linked to various other constructs like career choice as well as success, job satisfaction, leadership style, organizational citizenship behavior can also be explored in the context of student readiness and effective learning in an online environment.

Research Context

The education sector has experienced a tremendous shift because of an unforeseen calamity, namely, the COVID-19 pandemic which has spared no country. The occurrence of the pandemic was so sudden that it caught many schools and colleges unaware and unprepared. However, teaching all courses at all levels in an online format is the need of the hour. Hence, capturing whether students are receptive and ready for the shift from didactic learning to virtual learning was of interest to us as researchers as well as stakeholders of the teaching fraternity. The research would help in identifying the factors which affect the students' receptivity and readiness for learning online, which could be explored further for a more satisfying learning experience among students.

Moreover, there are certainly various programs which run in virtual formats or blended formats. However, in a developing country like India, the value placed on such programs is on the lower side. This is evident from the results of the All India Survey on Higher Education for the period 2018-2019 that distance enrolment constitutes only about 10.62% of the total enrolment in higher education. On the other hand, a study by KPMG (India) and Google (2017) revealed that the online education industry in India would grow by 8 folds by 2021. The major reasons highlighted for this growth were the need for reskilling and online certifications, supplementary learning for primary and secondary level school students, alternative to traditional higher education, test preparation and learning of non-academic subjects.

Hence, it is crucial to analyze the factors facilitating students' readiness for online learning and also, to provide, all stakeholders, a roadmap for a successful and enhanced online learning environment. In the literature studies integrating ISM technique with MICMAC analysis to investigate the factors affecting outcome of a project or to propose a framework for successful implementation or adoption of strategies. Agrawal et al. (2020) analyzed the factors influencing the e-learning process using ISM and MICMAC analysis. Desingh & Baskaran (2021) employed ISM-MICMAC approach to analyze the barriers to IoT adoption in the healthcare supply chain.

Therefore, the research context is selected for the following reasons:

- There exist contradictions between the current enrolment rate and the research trends as mentioned above.
- While previous studies on online learning chose only a few variables (Watjatrakul, 2016; Cazan & Schiopca, 2014) here a comprehensive list of enablers has been identified to make the research more holistic in nature.
- The methodological approach used in previous studies (Cohen & Baruth, 2017; Schniederjans & Kim, 2005; Shih et al., 2013) inclined towards Correlation and Regression Analysis between online learning readiness and personality, while the current study tries to establish linkages between the enablers of online learning readiness via the ISM approach.
- Further, readiness is a powerful factor in successful e-learning implementation (Mosadegh et al., 2011). Hence, this research can be used as a steppingstone for studying the efficacy of online teaching-learning.

RESEARCH METHODOLOGY

This section includes the research methodology, description of the key enablers for students' readiness for online learning identified in the literature and discussion with experts, application of the ISM model on the identified enablers and finally clustering the enablers with the help of MICMAC analysis.

In the growing stage of any research field, use of techniques such as statistical analysis and hypothesis testing allows identification and understanding of the relevant constructs and interrelationship among the variables. Quantitative methods allow for detailed investigation, testing and validation of these relationships. Moreover, statistical techniques such as structural equation modelling permits testing of the established models/theories, and they assist in development of the initial model (Khan & Rahman, 2015). Online education, specifically in the current pandemic scenario, is crucial for the future of the younger generation. The concept of online learning and various factors affecting the students' readiness for online learning need to be explored and investigated. Therefore, interpretive structural modelling (ISM) and the quantitative approach, are found suitable for this study.

In this study, initially faculties and students from different education fields such as management studies, engineering and technology, pharmacy, law, commerce, and science were contacted in person to explain the purpose of this study and to obtain their views and their experiences in the online learning and teaching process. After discussion, a total of 8 experts comprising 3 members of faculty with more than 10 years of teaching experience using online platforms and 5 students currently pursuing their post-graduate and under-graduate studies using online teaching-learning platforms, agreed to participate in this study. The entire study was conducted in the Indian context with the experts hailing mainly from the cities of Ahmedabad and Mumbai. Naveed *et al.* (2017) studied barriers of E-learning education with a team of five decision makers using the ISM methodology, while Ahmad *et al.* (2018) employed the ISM technique for analyzing critical success factors for sustainability and performance improvement in e-learning with a team of four decision makers. Therefore, in this research, a team of eight decision makers was devised to analyze the enablers of students' readiness for online learning.

The contextual relationship among the enablers of Students' Readiness for Online Learning is examined using the Interpretive Structural Modeling (ISM) approach. Enablers for online learning were analyzed earlier using statistical tools but, there exists no study which attempts to develop the structural relationship among enablers of students' readiness for online learning. Hence, this research can be seen as the first attempt to fill this gap by analyzing interrelationship between the enablers of online learning and classifying them into various categories using MICMAC (*Matrices* d'*Impacts Croises Multiplication* Appliqué a un *Classement*) analysis.

Figure 1 below illustrates the methodology followed in this research.

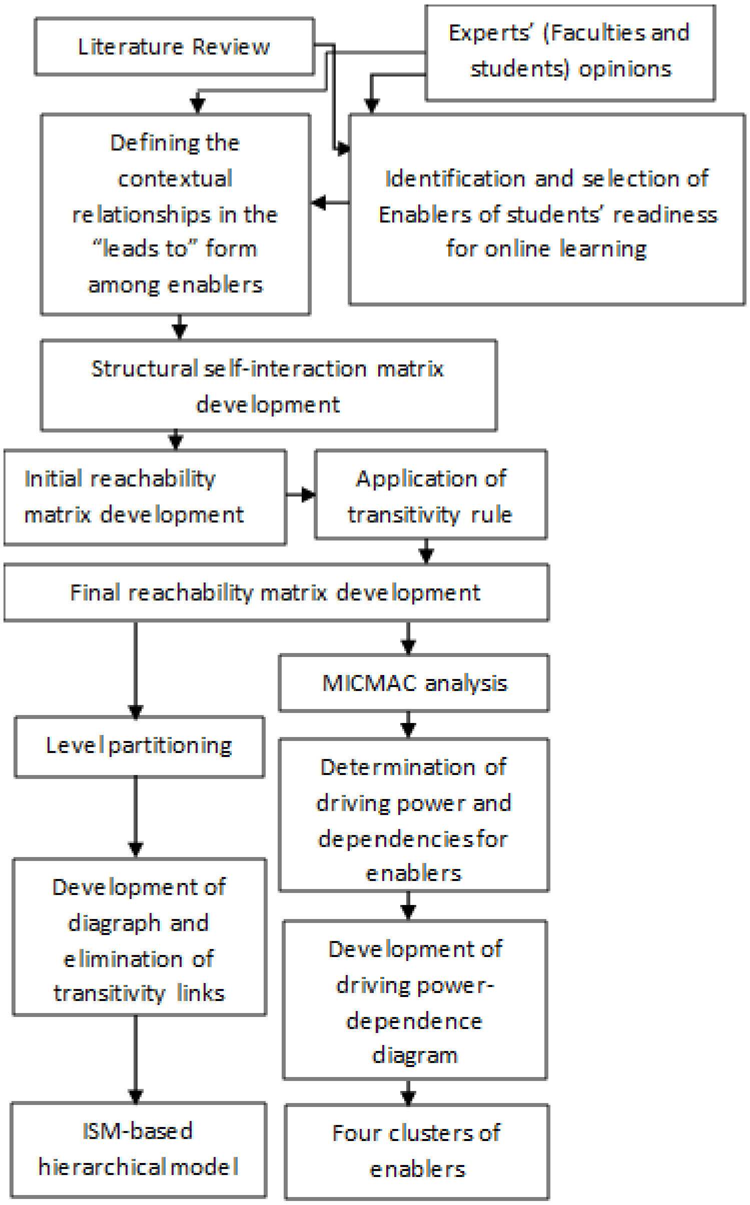

Figure 1. Research Methodology

Enablers of students' readiness for online learning are identified through a comprehensive review of contemporary literature (see Table 1) and academic experts' opinion. For conducting this literature review, keywords such as 'online learning', 'student readiness', 'personality traits', 'cognitive flexibility' were used in a database including Scopus, EBSCO, and Google Scholar. The paper abstracts were reviewed for initial screening and the most relevant papers were selected for detailed review. A hierarchical structure for analyzing the structural relationship among enablers has been devised using the ISM approach and a classification of enablers into four clusters using

MICMAC analysis. The literature reviewed to identify the key enablers of student readiness for online learning are presented in Table 1 below.

Table 1: *Identified Key Enablers of Students' Readiness for Online Learning based on review of contemporary literature*

S. No.	Enabler	Studied in the context of	Methodological Approach	Region	Author(s) with publication year	Journal
1	Extraversion (EX)	Adoption and use of technology	Correlation, Regression, Cluster Analysis	Israel	Cohen & Baruth, 2017	Computers in Human Behavior
2	Neuroticism (NE)	Students' perceptions towards online learning	Hierarchical regression	Taiwan	Bhagat, Wu, & Chang, 2019	Australasian Journal of Educational Technology
3	Openness to experience (OE)	Students' intentions to adopt online learning	Structural Equation Modelling Analysis	Thailand	Watjatrakul, 2016	Interactive Technology and Smart Education
4	Agreeablenes s (AG)	Academic performance across studies	Regression		Schniederjans, & Kim, 2005	Decision Sciences Journal of Innovative Education
5	Conscientious ness (CO)	Student satisfaction with online courses and motivation	Correlation, Regression	Taiwan	Shih, Chen, Chen, & Wey, 2013	Procedia – Social and Behavioral Sciences
6	Cognitive Flexibility (CF)	Exploration of online sources, engagement with peers and instructors online, and monitoring the success of self-learning	Correlation, Regression	USA	Schommer-Aikins & Easter, 2018	Journal of Business and Educational Leadership
7	Computer/Int ernet self-efficacy (ISE)	Student Engagement	Hierarchical Regression	Greece	Pellas (2014)	Computers in Human Behavior
8	Self-directed learning (SDL)	Characteristics of online learners	Based on literature review	NA	Dabbagh (2007)	Contemporary Issues in Technology and Teacher Education

9	Learner Control (in an online context) (LC)	Student's task performance	Two way full factorial model anova	Taiwan	Wang & Beasley (2002)	Journal of Educational Multimedia and Hypermedia
10	Motivation for Learning (in an online context) (ML)	Cognitive engagement and academic performance	Paired Sample t test (Quantitative) and Qualitative	USA	Patricia (2020)	International Journal of Educational Research Open
11	Online Communication Self-efficacy (OCSE)	Academic Performance and multi-tasking behavior in online and traditional setting	Structural Equation Modeling – Mediated Moderation	NA	Alghamdi, Karpinski, Lepp, & Barkley (2019)	Computers in Human Behavior
12	Age (A)	Distance learners' academic achievement	Multiple Regression Analysis	NA	Thurmond, Wambach, Connors, & Frey (2002)	American Journal of Distance Education
13	Highest Academic Qualification (HAC)	Preference for online courses	Correlation, Regression	USA	Keller & Karau (2013)	Computers in Human Behavior
14	Academic Performance (AP)	Success in online course	Correlation, Regression	USA	Wojciechowski & Bierlein Palmer (2005)	The Online Journal of Distance Education Administration
15	Prior exposure to online class (PE)	Development of new learning, motivation and self-evaluation of learning	Factor Analysis	USA and Australia	Smith, Murphy, & Mahoney (2003)	Distance Education
16	Duration of prior exposure (DPE)	*Introduced in the current study by the authors*				
17	Willingness for future exposure to online classes (in duration terms) (WFE)	*Introduced in the current study by the authors*				

Enablers

This section describes the key enablers of students' readiness for online learning as identified from literature.

Extraversion (EX)

Extraversion refers to the individual's degree of interpersonal skills, friendliness, warmth, assertiveness, activist, thrill-seeking, and positive emotions (Watson & Clark, 1997). Pavalache and Cocorada (2014) note that extroverts may appreciate collaborative working in online contexts and may also use games to learn. However, if such an ambience is not available, they may be disinterested in studying online. Hills and Argyle (2003) observe that the usage of the Internet is lower for extraverts, however, their social media usage is higher (Wang et. al, 2012). Hence, given the dichotomous online behavior of extroverts, their linkage to SROL is explored in the current study.

Neuroticism (NE)

Neuroticism depicts the emotional stability of the individual and the degree to which he exhibits self-control (Emmons et al., 1985). People with a higher degree of neuroticism may experience greater stress as well as anger and frustration and neurotic individuals may get trapped in negative spirals because of their inclination to put themselves into situations that foster negative effects. Watjatrakul (2016) reported that students who are more neurotic avoid stress from learning in a situation that they are not familiar with. Hence, as online learning is as good as treading on unfamiliar grounds for students, neuroticism is being studied for its linkage to SROL.

Openness to experience (OE)

Openness to experience describes the individual's intellectual curiosity, creativity and interest in new experiences or new ideas in various fields (McCrae,1996). As a matter of fact, people scoring high on this dimension of personality are unsatisfied with the routine life (Barrick & Mount, 1991). Zhang (2003) found that openness significantly predicted the deep approach to learning. Moreover, students who rated high on this trait were observed to succeed in academic performance in online classes. Hence, given that online learning is a radical shift from the traditional learning, openness to experience maybe a significant driver of SROL.

Agreeableness (AG)

Agreeableness describes a person's interpersonal behavior such as sympathetic, cooperative, kindness, thoughtfulness, and helpfulness (Graziano & Eisenberg, 1997). People with a dominant agreeable trait do well in jobs that involve considerable interpersonal interaction (McElroy et al., 2007). Poropat (2009) conducted a meta-analysis and found that agreeableness was significantly related with academic performance across studies. Hence, as agreeable people like to interact with others on a continuous basis, which may not be easily available in online learning context, the role of this factor in SROL may have to be analysed.

Conscientiousness (CO)

Conscientiousness depicts the ability to control impulsive behavior, exhibit self-discipline, competence and exhibit an achievement oriented behavior and hence, set targets for themselves (Patrick, 2011). Costa and McCrae (1992) describe conscientious individuals as people who tend to push towards their goals, show self-control, and act dutifully. Conscientiousness as a personality trait is a significant predictor of motivation and satisfaction among students according to Shih et al., (2013) and hence, it makes sense to study its role as an enabler of SROL.

Cognitive Flexibility (CF)

Cognitive flexibility, while cannot be termed as intelligence, refers to shifting of the mindset contingent on the situation at hand. Hence, it is deemed as an important element of intelligence. Cognitive scientists tend to agree that the ability to alternate between processing types is a key determinant of cognitive flexibility (Diamond, 2013; Evans & Stanovich, 2013). A study by Schommer-Aikins and Easter (2018) reported that higher cognitive flexibility resulted in better exploration of online sources, engagement with peers and instructors online, and monitoring the success of self-learning. Thus, in the current situation in which the COVID-19 pandemic has mandated that classes be conducted online, cognitive flexibility which indicates an individual's ability to shift through different styles of learning shall play an important role in determining online learning readiness as well as academic performance in students.

Computer/Internet self-efficacy (ISE)

Self-efficacy is defined as an individual's beliefs and expectations in his/her capability to perform a task (Bandura et al., 1996). Hence, taking the former as the base, when an individual is confident of using computers or the Internet, the same can be termed as computer or Internet self-efficacy. While Internet self-efficacy could refer to the behavior associated with the usage of the Internet; computer self-efficacy refers to the set-up and maintenance of computers (Hung et al., 2010).

Self-directed learning (SDL)

Self-directed learning readiness is defined as "the degree the individual possesses the attitudes, abilities and personality characteristics necessary for self-directed learning" (Wiley 1983, p.182). SDL puts the onus of learning on the individual starting right from identifying the learning needs, designing of learning objectives, determining the appropriate material resources, and learning strategies, and using appropriate evaluation methods (Knowles, 1975). Albelbisi and Yusop (2019) explain that learners who are highly self-regulated exhibit effective positive motivation and self-efficacy concerning their learning processes. Hence, this also became a base for selecting motivation and self-efficacy as probable enablers.

Learner Control (in an online context) (LC)

Learner control is defined as a process wherein a student gives direction to his/her self-learning. A study by Corbalan, Kester, & van Merriënboer (2008) has indicated some potential threats to learner control like; a lack of perception of control, making choices which may not be optimal and a high stress on learners' processing resources emanating from the number of choices available.

Motivation for Learning (in an online context) (ML)

Several studies (Deci & Ryan, 1985; Fairchild et al., 2005; Deci & Ryan, 2000) have identified motivation to have a significant impact on learners' attitudes and learning behavior. The cognitive and motivational variables interact with each other for learning to take place, and these two facets have been found to be inseparable (Pintrich & Schunk, 2002; Stefanou & Salisbury-Glennon, 2002). Study findings have indicated that technology and communication competencies are the key factors to enhance student satisfaction and retention, but motivation and presence in online learning are the key issues for student participation (Law et al., 2019; Widjaja, 2017)

Online Communication Self-efficacy (OCSE)

Since discussions and interactions between instructors and students are an important part of the teaching-learning process, these should be facilitated in the online mode as well and successful students should engage productively in these online discussions. It is obvious that students who have better online communication self-efficacy feel relatively comfortable in expressing themselves in writing (McVay, 2000, 2001; Roper, 2007). Some studies found that online communication facilitates the subjective well-being of college students (Ko & Kuo, 2009; Valenzuela et al., 2009). Hence, online communication self-efficacy can be considered as one of the factors affecting the learning process in online classes.

Age (A)

Several studies have observed the relationship between age and academic achievement of learners in the online mode and found that age does have a significant role to play (Thurmond, Wambach, and Connors, 2002; Maki and Maki, 2003; Wojciechowski and Palmer, 2005).

Highest Academic Qualification (HAC)

Online learning also seems to attract a larger proportion of first generation college students for their highest academic qualification (Athabasca University, 2006). Keller and Karau (2013) also found that within this category, undergraduates reported stronger preferences for online courses than did graduate students.

Academic Performance (AP)

Since teaching-learning processes can never be complete without a component of assessment and knowledge of where an individual stands, academic performance was also identified as a critical variable for the study. Studies by Maki and Maki (2003) and Wojciechowski and Palmer (2005) have found significant relationships between results of online business class and the students' overall grade point averages.

Prior exposure to online class (PE)

Smith, Murphy, and Mahoney (2003) observed that individuals who had previously taken online classes made use of past experiences in various ways to develop new learning. They were capable of setting their own goals; being motivated by intrinsic factors and were engaged in planning for strategies to evaluate and monitor their own learning. Hence, an individual who has been exposed to virtual learning may know what to expect and may be better prepared for online learning.

Duration of prior exposure (DPE)

Several studies (Cheng & Tsai, 2011; Paraskeva, Bouta, & Papagianni, 2008; Tseng & Tsai, 2010) have found that computer self-efficacy is higher for students that received previous training or had prior experience in computers before taking other distance learning courses. But distance learning courses can vary immensely in terms of duration. Hence, along with prior exposure to online classes, the factor of 'duration of prior exposure' was added in this study.

Willingness for future exposure to online classes (in duration terms) (WFE)

Hao (2016) in his study observed that the willingness of the students to participate in group learning activities was associated with readiness for flipped learning. Also, in the healthcare context willingness to communicate with a healthcare provider was associated with an individual's readiness for public health interventions (Taylor et al., 2004). Hence, willingness emerged to be an indicator of individual readiness. Thus, in our context, the willingness for future exposure to online classes has also been added to the list of enablers of students' readiness for online leaning.

Application of Interpretive Structural modeling (ISM)

The steps embraced for the application of the ISM approach in this study are as follows:

SSIM development

For developing SSIM, a team of eight experts was formed to establish the contextual relationships, in the "leads to" form, among 17 enablers of students' readiness for online learning. A series of symbols (shown in Table 2) were used to demonstrate the direction of relationship between two enablers (i and j). For example, if enabler i led to enabler j, it is represented in Table 3 with the symbol 'V'. If enabler j led to enabler i, the symbol A was used. If enablers i and j led to each other, it is represented by symbol 'X', while symbol 'O' is used if they are unrelated.

***Table 2**: Symbols for SSIM development*

Symbol	Direction of relationship	Conversion to develop initial reachability matrix	
		(i, j value)	(j, i value)
V	$i \longrightarrow j$	1	0
A	$i \longleftarrow j$	0	1
X	$i \longleftrightarrow j$	1	1
O	i and j - unrelated	0	0

Table 3 presents the Structural self-interaction matrix developed using the directional relationships established by the experts.

***Table 3:** Structural self-interaction matrix (SSIM) for enablers*

Variable	AP	HAC	A	WFE	DPE	PE	OCSE	ML	LC	SDL	ISE	CF	CO	AG	OE	NE
EX	O	O	O	O	O	O	V	V	O	O	O	V	O	X	X	O
NE	V	O	O	V	O	O	O	V	V	V	O	V	X	O	X	
OE	V	O	O	O	O	O	V	V	V	V	V	V	O	X		
AG	O	O	O	O	O	O	V	V	O	O	O	V	O			
CO	V	O	O	V	O	O	V	V	V	V	V	X				
CF	V	O	O	O	O	O	V	V	V	V	V					
ISE	A	A	A	V	A	A	V	X	V	X						
SDL	A	A	A	V	X	X	X	A	X							
LC	A	A	A	V	A	A	X	X								
ML	X	A	O	V	A	A	V									
OCSE	A	A	O	V	A	A										
PE	O	O	O	V	O											
DPE	O	O	O	V												
WFE	O	O	O													
A	O	V														
HAC	O															

Reachability matrix development

The initial reachability matrix (shown in Table 4) was developed by converting the symbols into appropriate binary numbers shown in Table 2. The final reachability matrix (shown Table 5) was derived by applying the transitivity rule. The transitivity rule suggests that if enabler i leads to enabler j and enabler j leads to enabler k, then it is deduced that enabler i also leads to enabler k. It was applied in the final reachability matrix by replacing '0' with '1' if this condition was satisfied and as such '1' is represented by an asterisk (*) mark. The driving power and dependence power of each enabler was calculated by adding all the '1' representations for each row and column respectively.

Table 4: *Initial Reachability Matrix*

	EX	NE	OE	AG	CO	CF	ISE	SDL	LC	ML	OCSE	PE	DPE	WFE	A	HAC	AP
EX	1	0	1	1	0	1	0	0	0	1	1	0	0	0	0	0	0
NE	0	1	1	0	1	1	0	1	1	1	0	0	0	1	0	0	1
OE	1	1	1	1	0	1	1	1	1	1	1	0	0	0	0	0	1
AG	1	0	1	1	0	1	0	0	0	1	1	0	0	0	0	0	0
CO	0	1	0	0	1	1	1	1	1	1	1	0	0	1	0	0	1
CF	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	1
ISE	0	0	0	0	0	0	1	0	1	1	1	0	0	1	0	0	0
SDL	0	0	0	0	0	0	1	1	1	0	1	1	1	1	0	0	0
LC	0	0	0	0	0	0	0	1	1	1	1	0	0	1	0	0	0
ML	0	0	0	0	0	0	1	1	1	1	1	0	0	1	0	0	1
OCSE	0	0	0	0	0	0	0	1	1	0	1	0	0	1	0	0	0
PE	0	0	0	0	0	0	1	1	1	1	1	1	0	1	0	0	0
DPE	0	0	0	0	0	0	1	1	1	1	1	0	1	1	0	0	0
WFE	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
A	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	0
HAC	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	1	0
AP	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	1

Table 5: *Final Reachability Matrix*

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	
	Enabler	**EX**	**NE**	**OE**	**AG**	**CO**	**CF**	**ISE**	**SDL**	**LC**	**ML**	**OCSE**	**PE**	**DPE**	**WFE**	**A**	**HAC**	**AP**	**Driving Power**
1	**EX**	1	1*	1	1	1*	1	1*	1*	1*	1	1	0	0	1*	0	0	1*	13
2	**NE**	1*	1	1	1*	1	1	1*	1	1	1	1*	1*	1*	1	0	0	1	15
3	**OE**	1	1	1	1	1*	1	1	1	1	1	1	1*	1*	1*	0	0	1	15
4	**AG**	1	1*	1	1	1*	1	1*	1*	1*	1	1	0	0	1*	0	0	1*	13
5	**CO**	0	1	1	0	1	1	1	1	1	1	1	1*	1*	1	0	0	1	13
6	**CF**	0	1*	0	0	1	1	1	1	1	1	1	1*	1*	1*	0	0	1	12
7	**ISE**	0	0	0	0	0	0	1	1	1	1	1	1*	1*	1	0	0	1*	9
8	**SDL**	0	0	0	0	0	0	1	1	1	1*	1	1	1	1	0	0	0	8
9	**LC**	0	0	0	0	0	0	1*	1	1	1	1	1*	1*	1	0	0	1*	9
10	**ML**	0	0	0	0	0	0	1	1	1	1	1	1*	1*	1	0	0	1	9
11	**OCSE**	0	0	0	0	0	0	1*	1	1	1*	1	1*	1*	1	0	0	0	8
12	**PE**	0	0	0	0	0	0	1	1	1	1	1	1	1*	1	0	0	1*	9
13	**DPE**	0	0	0	0	0	0	1	1	1	1	1	1*	1	1	0	0	1*	9
14	**WFE**	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
15	**A**	0	0	0	0	0	0	1	1	1	1*	1*	1*	1*	1*	1	1	0	10
16	**HAC**	0	0	0	0	0	0	1	1	1	1	1	1*	1*	1*	0	1	1*	10
17	**AP**	0	0	0	0	0	0	1	1	1	1	1	1*	1*	1*	0	0	1	9
	Dependence power	4	6	5	4	6	6	16	16	16	16	16	14	14	17	1	2	13	
***: transitivity application**																			

Level partitioning

To establish the hierarchy within the enablers, level partitioning was performed by identifying the reachability set and antecedent set for each enabler using the data in Table 5. Members of the reachability set for an enabler consist of the enabler itself along with other enablers which can be achieved by it, while the antecedent set consists of the enabler itself in addition to other enablers which may help in accomplishing it. Further, the intersection set for each enabler was identified by selecting the enablers which were common in the reachability set and the antecedent set. The level I enabler is one for which members in the reachability and intersection sets are identical in the first iteration. Once a level was assigned to the enablers, they were removed from the table for next stage iteration of level partitioning. In this study, the hierarchical structure is developed with five levels and are detailed in Table 6 below.

Table 6: *Level partitioning*

Enabler	Reachability Set	Antecedent Set	Intersection	Level
1	1,2,3,4,5,6,7,8,9,10,11,14,17	1,2,3,4	1,2,3,4	**V**
2	1,2,3,4,5,6,7,8,9,10,11,12,13,14,17	1,2,3,4,5,6	1,2,3,4,5,6	**IV**
3	1,2,3,4,5,6,7,8,9,10,11,12,13,14,17	1,2,3,4,5	1,2,3,4,5	**V**
4	1,2,3,4,5,6,7,8,9,10,11,14,17	1,2,3,4	1,2,3,4	**V**
5	2,3,5,6,7,8,9,10,11,12,13,14,17	1,2,3,4,5,6	2,3,5,6	**IV**
6	2,5,6,7,8,9,10,11,12,13,14,17	1,2,3,4,5,6	2,5,6	**IV**
7	7,8,9,10,11,12,13,14,17	1,2,3,4,5,6,7,8,9,10,11,12,13,15,16,17	7,8,9,10,11,12,13,17	**II**
8	7,8,9,10,11,12,13,14	1,2,3,4,5,6,7,8,9,10,11,12,13,15,16,17	7,8,9,10,11,12,13	**II**
9	7,8,9,10,11,12,13,14,17	1,2,3,4,5,6,7,8,9,10,11,12,13,15,16,17	7,8,9,10,11,12,13,17	**II**
10	7,8,9,10,11,12,13,14,17	1,2,3,4,5,6,7,8,9,10,11,12,13,15,16,17	7,8,9,10,11,12,13,17	**II**
11	7,8,9,10,11,12,13,14	1,2,3,4,5,6,7,8,9,10,11,12,13,15,16,17	7,8,9,10,11,12,13	**II**
12	7,8,9,10,11,12,13,14,17	2,3,5,6,7,8,9,10,11,12,13,15,16,17	7,8,9,10,11,12,13,17	**II**
13	7,8,9,10,11,12,13,14,17	2,3,5,6,7,8,9,10,11,12,13,15,16,17	7,8,9,10,11,12,13,17	**II**
14	14	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	14	**I**
15	7,8,9,10,11,12,13,14,15,16	15	15	**V**
16	7,8,9,10,11,12,13,14,16,17	15,16	16	**IV**
17	7,8,9,10,11,12,13,14,17	1,2,3,4,5,6,7,9,10,12,13,16, 17	7,9,10,12,13,17	**III**

ISM model development

First, a digraph, connecting the enablers at different levels using interrelationships established in the final reachability matrix (Table 5), was developed. Further, a hierarchical structure, that is, an ISM model was deduced by removing the transitivity links and by replacing nodes with a corresponding enabler (Figure 2). It was observed that the factors 'Open to experience', 'Agreeableness' and 'Extraversion' are the most significant enablers for students' readiness for online learning since these are placed at the base of the ISM hierarchy. The three factors as mentioned are personality traits from the Big Five Personality Model. Individuals high on open to experience would like to break the routine, and hence, may view the shift from traditional learning to online learning as a new experience. Agreeableness is reflected in the way an individual is willing to cooperate and help others. Extraversion describes a person's social behavior, willingness to express opinions, and leadership. Extravert people usually seek out new opportunities and exciting life (Watson & Clark, 1997). Hence, these personality traits may play an important role in developing a student's mindset in preparing for online learning. The personality traits of an individual coupled with cognitive flexibility have an impact on academic performance as exhibited from the 2nd and 3rd level of the ISM based model. Parallel demographic factors like age which is linked to academic qualification also emerged as enablers. These then drive the enablers which focus on learning aspects of a student and student's efficacy in an online setting. These ultimately lead to student's willingness to attend online classes in the future which would impact the student's readiness for online learning.

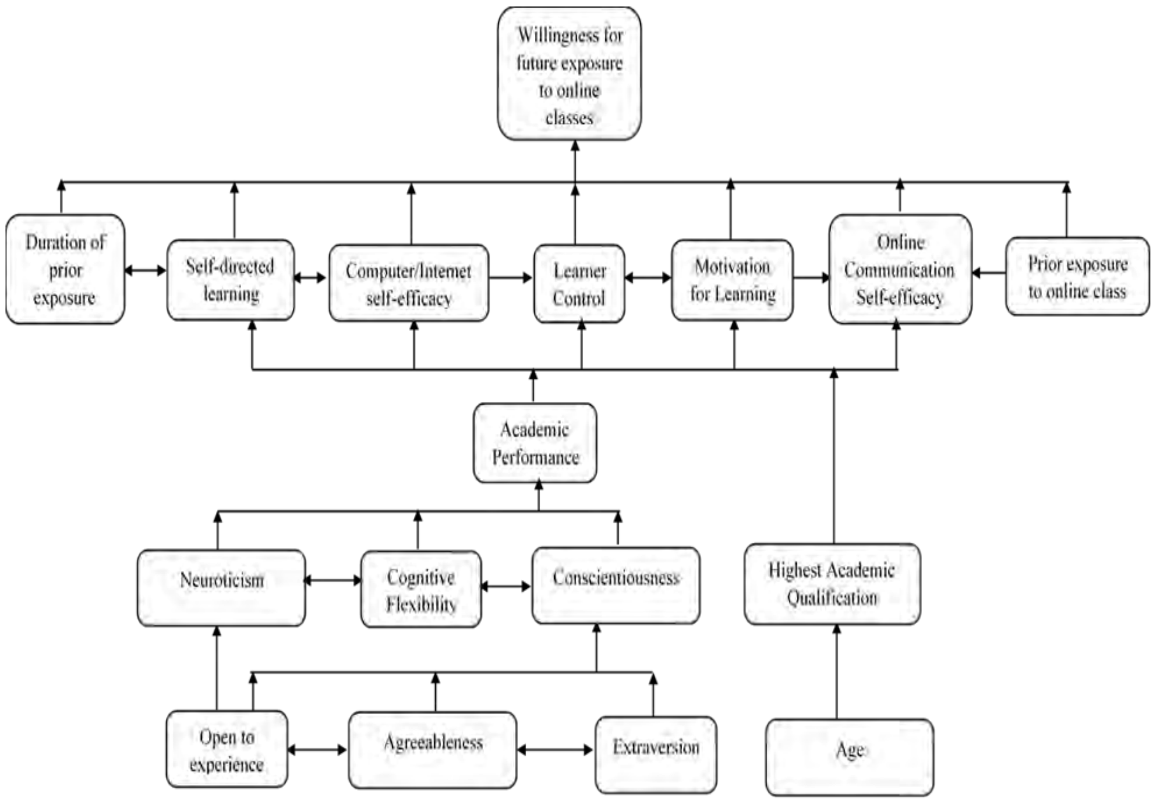

Figure 2: ISM model for enablers of students' readiness for online learning

MICMAC analysis

The purpose of the matrix of cross-impact multiplications applied to classification (MICMAC) analysis was to classify the enablers into four clusters using their driving power and dependence power obtained in the final reachability matrix (Table 5). Based on the MICMAC analysis, the enablers are classified into four clusters namely, autonomous enablers, dependent enablers, linkage enablers and independent enablers.

- The enablers classified as autonomous are those having weak driver and dependent power. In this study, no enabler falls in this category as seen in Figure 3 below.
- In the dependent cluster, the enablers with low driving power, but high dependence power are included. The enabler 'Willingness for future exposure to online classes' is classified in this category.
- The enablers having high driving power as well as high dependence power fall in the linkage cluster. Here, enablers such as 'Academic performance', 'Prior exposure to online class', 'Duration of prior exposure', 'Computer/Internet self-efficacy', 'Learner control', 'Motivation for learning', 'Self-directed learning', and 'Online Communication Self-efficacy' are identified as linkage enablers.

- As the enablers ‘Age’, ‘Highest academic qualification’, ‘Extraversion’, ‘Agreeableness’, ‘Open to experience’, ‘Neuroticism’, ‘Cognitive flexibility’ and ‘Conscientiousness’ are having high driving power and low dependence power, they are classified as driver enablers.

The enablers falling under the independent cluster are the key to affecting readiness in students for online learning. Academic institutions should give maximum attention to these factors during the teaching-learning process in an online setting. The dependent cluster includes one enabler and should be dealt as the coveted objectives for students’ learning process. Here, ‘Willingness for future exposure to online classes’ has lowest driving power and the highest dependence power and situated at the highest level of the ISM model. A total of eight enablers were identified in the linkage cluster. These enablers are unstable as any change to these enablers will impact other enablers and also have feedback on themselves. No enabler found place as an autonomous enabler. As argued by Kumar et al. (2016) and Thanki and Thakkar (2018), the driving enablers will lead to linkage enablers, and the driving cluster along with the linkage cluster will lead to dependent enablers so as to impact the level of readiness in students in an online learning context.

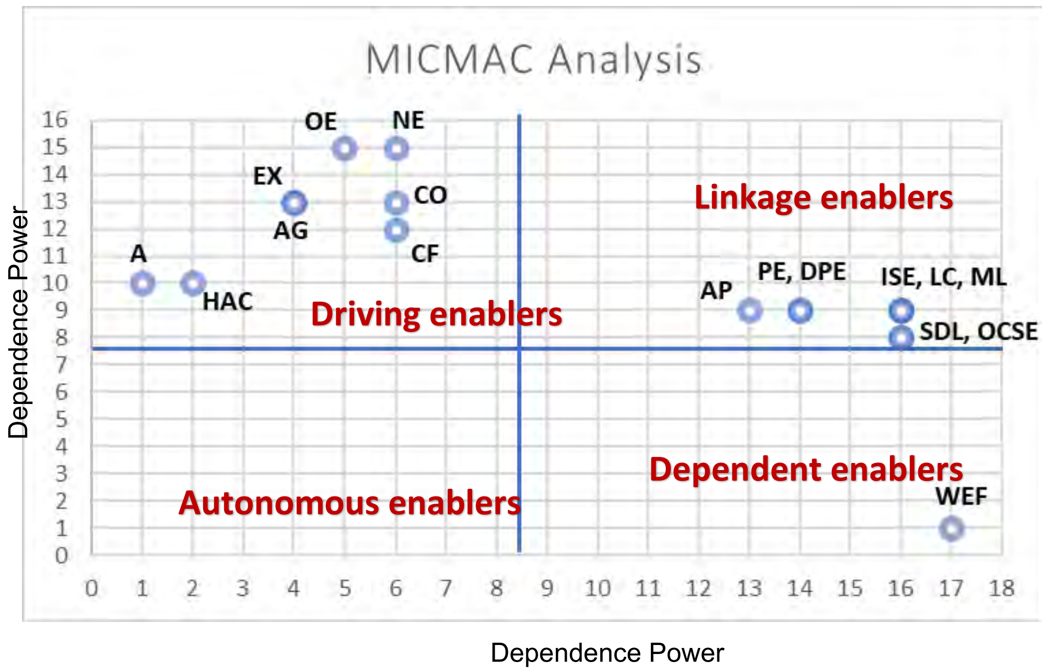

Figure 3: Clusters of enablers of students’ readiness for online learning

DISCUSSION

The results as depicted in Figure 2 post application of ISM can also be interpreted in terms of givens, means and ends as suggested by Anantatmula and Kanungo (2010). Applying this framework, the elements at the bottom can be considered as ‘givens’. Hence, in this case the personality traits of open to experience, agreeableness and extraversion along with age can be labelled as ‘givens’. Givens can be looked at a basic set of requirements which need to be in place so as to achieve the ends or the goals. The elements at the top, that is, willingness for future exposure to online classes is considered as the ‘end’. This forms the desired outcome to achieve students’ readiness for online learning. ‘Means’ are the elements which appear between the ‘givens’ and the ‘ends’. Hence, the set of elements at the 2nd, 3rd and 4th levels form the ‘means’.

These mainly comprise the other personality types, cognitive flexibility, academic qualification, academic performance, self-directed learning, learner control, motivation for learning, computer/internet self-efficacy, online communication self-efficacy and prior exposure to online classes. Some of the elements observed in the study are in alignment with a few of the six instructional strategies with high impact in online education, that is, high relevance between online instructional design and student learning and high quality participation from the students (Bao, 2020). In fact, a recent study by Walia et. al.,(2019) found seven components - student access to technology, their technology skills, lifestyle factors, teaching presence, cognitive presence, social presence, their skills and study habits, which affected a student's readiness for online learning. These are fundamentally similar to the 'means' observed in the current study.

The elements which are classified as 'means' can be controlled, manipulated or developed to form the link between the 'givens' and the 'ends'. It needs to be noted here that individuals differ in their behavior based on their personality type, but the results indicate that some personality types more significantly affect students' readiness in an online setting. However, whether these personality types act as enablers or inhibitors may have to be studied further. At the same time, some other elements such as cognitive flexibility, learning aspects and online efficacy can be clearly interpreted as enablers if they are stronger in an individual. The same may turn out to be inhibitors if not developed well. Similarly, prior exposure to online classes may also turn out to be an enabling factor.

CONCLUSION AND FUTURE SCOPE

This study examined the contextual relationship among the enablers of Students' Readiness for Online Learning using the interpretive structural modeling (ISM) approach. About seventeen enablers were identified from literature and based on discussion with the experts, the factors 'Open to experience', 'Agreeableness' and 'Extraversion' were found to be the most significant enablers for students' readiness for online learning; since these are placed at the base of the ISM hierarchy. These personality traits also showcased in the cluster of driving enablers as assessed by MICMAC analysis. Several factors such as academic performance, prior exposure to online classes, self-efficacy in online settings, and learner control emerged as linkage enablers which would ultimately affect the 'willingness for future exposure to online classes'. This end goal would ultimately result in developing or inhibiting readiness level of students' learning in online classes.

A study by Bubou and Job (2021) mentions the ever growing need to integrate e-learning platforms in formal as well as informal settings in the higher education sector due to the varied benefits offered by such ICT based learning. Hence, the understanding of these enablers can help higher education administrators and instructors classify students based on their levels of readiness for online learning and customize their online course delivery. Further, mentoring and counselling plays a crucial role in these conditions of uncertainty and shift from didactic teaching-learning practices. So, this study may also help mentors/counsellors to classify students based on their mindset for online learning and advise accordingly. This study also has potential to assist higher education policy makers in designing guidelines taking into consideration diverse groups of students, and the higher educational institutions can better prepare themselves in terms of online systems and processes.

Academics is a continuously evolving area; wherein newer pedagogies are explored for effective teaching-learning to take place. Online teaching-learning was in an introductory stage for most academic institutions and teacher and student groups at the time this study was conducted. However, as the pandemic situation extends and there is greater experimentation with online technologies by the teachers and students alike, the perceptions as presented here may change. Further, initially with the onset of the COVID-19 pandemic, online teaching-learning was projected as a stop-gap arrangement. However, with the passage of time, as this concept sets in as a long-term exercise, again, the perceptions of students may change. Hence, a longitudinal study of this kind may be conducted to study the comparative results. Further studies can also statistically validate the findings of this research work using structural equation modelling. Finally, further linkages of students' readiness for online learning and students' satisfaction or efficacy of online learning can also be explored.

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