A Study on the Relationship between Domain Specific Self-Efficacy and Self-Regulation in E-learning Contexts

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Abstract
Self-regulation has been found to be integral to academic learning in traditional classroom environments. Social cognition theory highlights the significant relationships between academic self-efficacy, internet self-efficacy, and work experience in years on self-regulation in the context of traditional classroom learning. However, there is a lacuna in the literature on the significance of these relationships in the context of e-learning. The exponential growth of e-learning and changes in business environment necessitate a study to examine the effect on self-regulation in the context of e-learning. This research is based on a sample of 525 management students from a business school in South Asia. The findings highlight that academic and internet self-efficacy have a positive effect on self-regulation even in an e-learning environment. e-learning here refers to interactive online learning, in a university setting. The findings have significant implications for both theory and practice as they build on the existing literature. We suggest use of training-based interventions for promoting self-regulation which subsequently would facilitate higher e-learning efficacy.

Keywords: social cognition theory, e-learning, self-regulation, academic self-efficacy, internet self-efficacy, regression

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Self-regulation is integral to learning (Park & Kim, 2020; Usher & Schunk, 2018; Panadero et al., 2016; Zimmerman, 2008). "Self-regulation (or self-regulated learning) refers to self-generated thoughts, feelings, and actions that are planned and systematically adapted as needed to affect one's learning and motivation" (Schunk & Ertmer, 2000, p. 631). Self-regulation involves the process whereby learners engage in behaviors that help them achieve academic goals. While several studies have been conducted to understand self-regulation in greater depth, a majority of these have been centered around the traditional classroom set-up. In this research study we examine self-regulation in the context of e-learning. As a learner experiences the phenomena of learning differently in traditional and e-learning environments (Fadol et al., 2018), thus, there is an urgent need to assess self-regulation behavior in the context of e-learning (Gupta & Bamel, 2023). Such research will build on the existing literature as it examines self-regulation and the variables that are positively associated with self-regulation in the context of e-learning.

e-learning refers to the "use of information and communication technologies to enable access to online learning/teaching resources" (Rodrigues et al., 2019). Although e-learning is not a new phenomenon, the rapid advancement of technology (Tsekeris, 2018) has led to its inclusion in learning extensively. Proliferation of technological devices such as desktops, laptops, smartphones, and tablets facilitate a rapid rise in e-learning. The exponential increase in acceptance and implementation of e-learning programs globally (Arbaugh, 2016; Cavanagh et al., 2020) is also an outcome of changes in the business environment, such as prevalence of knowledge workers (Capestro & Kinkel, 2020), gig work (Wood et al., 2019), and unforeseen events such as the COVID-19 pandemic (Zhao et al., 2020). Such environmental phenomena require individuals to learn new skills with greater agility (Sessa & London, 2015; Kruchoski, 2016). e-learning provides the necessary platform and flexibility through customization of cost, functionality, content, pace, pedagogy, and environment, which facilitates learning with greater agility (Kunzia & Elis, 2014; Jahnke et al., 2020).

Extant literature posits that learning that take place in an online environment is influenced by relationship between constructs such as academic self-efficacy, internet self-efficacy, work experience in years, and self-regulation (Bandura, 1986, 2019; Zhang & Galletta, 2014; Bradley et al., 2017). Thereby, the theoretical framework presented in this research paper examines in detail the relationships between above-mentioned constructs in the context of e-learning.

In this research paper we invoke social cognition theory (Bandura, 1977; 1986; 2019) to study individual learning behaviors in the context of e-learning. The extant literature from social cognition theory encapsulates several studies on the delineated constructs in the context of traditional classroom learning (Schunk & DiBenedetto, 2020; Kimiagari & Baei, 2022; Shkëmbi & Treska, 2023). Further, the literature also examines social cognition theory in the context of impact of technology on learning, (Barnard et al., 2009; Bandura, 2019; Al-Fraihat & Sinclair, 2020). We call on social cognition theory to examine the delineated constructs; that is, academic self-efficacy, internet self-efficacy, experience in years, and self-regulation in the context of e-learning.

Empirical studies confirm self-regulation is an essential construct for success in e-learning (Barnard et al., 2009; Bradley et al., 2017; Kimiagari & Baei, 2022) yet few studies have looked at the relationship between domain specific self-efficacy, such as academic self-efficacy, internet self-efficacy, and experience in years on self-regulation in the context of e-learning. Such research is mandated as self-regulation has been deeply researched and accepted as an essential construct for achieving superior learning outcomes in traditional classroom environment. We now need to examine the significance of self-regulation in e-learning environment so as to develop mechanisms for higher e-learning efficacy.

As the objective of this research study is to examine the relationships of domain-specific self-efficacy; that is academic self-efficacy, internet self-efficacy, and years of experience on self-regulation when learning takes place in e-learning environment; to address these research objectives, the below research questions have been posed:

(a) What is the relationship between academic self-efficacy and self-regulation in an e-learning context?
(b) What is the relationship between internet self-efficacy and self-regulation in an e-learning context?
(c) What is the relationship between work experience years and self-regulation in an e-learning context?

These research questions will help to build on the existing literature in the context of e-learning. The findings will add to both theory and practice. The research questions help to examine relationships that, if true, will augment the relevance of self-efficacy and self-regulation in the context of e-learning. Self-efficacy and self-regulation hold an integral place in classroom learning. Thus, we seek to examine these constructs in the e-learning context. Further, we examine experience to understand its effect on self-regulation (Endedijk & Cuyvers, 2022). This association highlights to teachers and trainers the need to develop training interventions to supplement self-regulation behaviors, as the literature from social cognition theory affirms a greater need for self-regulation in e-learning environment. Also, an empirical examination of the above-mentioned relationships will act as a guideline on the dependency of self-regulation with each predictor. Such a guideline can be used as a measure by teachers and trainers in their pedagogy to attain higher e-learning efficacy (Bradley et al., 2017; Duchatelet & Donche, 2019; Blau et al., 2020).

Theoretical Framework and Hypothesis

In this research paper we refer to social cognition theory (SCT) (Bandura, 1986; Zimmerman et al., 2008; 2009; 2017; Usher & Schunk, 2018; Schunk & DiBenedetto, 2020) as a foundation to discuss the theoretical framework and present the conceptual model. Social cognition theory is based on a model that emphasizes reciprocal relationships between a person's cognition, behaviors, and the environment (Bandura, 1986). Thus, it is a relevant framework to examine the variables in the backdrop of environmental changes such as rise in e-learning and need for agile learning as discussed above. Also, social cognition theory provides the mechanisms to assess the impact of technology on learning (Barnard et al., 2009; Bandura, 2019). This allows for an examination of the study constructs in the context of e-learning. The flow of this section is as follows. First, we define and discuss the study constructs and then we discuss their interrelationships, which leads us to our hypotheses.

Self-Efficacy

Self-efficacy is defined as "beliefs in one's capabilities to organize and execute the course of action required to produce given attainments" (Bandura, 1977, p. 3). Self-efficacy in cognition can be achieved via the four elements as detailed in social cognition theory (Bandura, 1977). These four elements are personal mastery, which entails developing knowledge, skills, and abilities; vicarious learning; which refers to gaining confidence by observing another person do the same task; verbal persuasion, which points to developing conviction by listening; and emotional arousal, referring to getting energized (Bandura, 1977; 1986).

Social cognition theory also explains the significance of domain-related forms of self-efficacy. Domain specific self-efficacy such as academic self-efficacy or internet self-efficacy can have a differentiated influence on learning (Bandura, 2006). Such differentiation helps to emphasize greater specificity in attaining superior learning outcomes.

Academic Self-Efficacy

Academic self-efficacy can be defined as the "conviction that one can successfully execute behaviors which can result in superior academic outcomes" (Bandura, 1977, p. 193). Individuals who demonstrate high academic self-efficacy are able to self-regulate their learning more effectively (Bandura, 2006), and thereby academic self-efficacy has a higher positive correlation with positive learning outcomes (Schunk & Ertmer, 2012). Empirical studies confirm academic self-efficacy is positively related with outcomes even when learning takes place in e-learning environment (Moreno & Cavazotte et al., 2017). This postulation is also supported by the literature in self-efficacy theory that confirms that the "positive relationship between strength of an individual's self-efficacy and probability of successful performance is virtually identical for the similar and the dissimilar tasks at 84% for an individual" (Bandura, 1977; 2006).

Internet Self-Efficacy

Internet self-efficacy refers to "confidence and comfort an individual has in working on the internet. Internet refers to the level of comfort with computers or digital devices, as well as the ability to navigate the nuances of online communication over the internet" (LaRose & Eastin, 2004). Research confirms that training and past experience in using the internet increases internet self-efficacy. Individuals with high internet self-efficacy readily adopt self-regulation, leading to a higher positive association with learning outcomes even in e-learning environments (LaRose & Eastin, 2004; Paraskeva et al., 2009; Landrum, 2020).

Self-Regulation

Self-regulation is an integral aspect of social cognition theory. Self-regulated learning can be defined as, "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment" (Pintrich, 2005, p. 453). Learners who engage in self-regulation believe that learning is a systematic process and learning outcomes can be controlled. Thus, they take responsibility for their learning by engaging in self-regulatory strategies (Pintrich, 2005; Park & Kim, 2020).

Self-regulation delineates the strategies that individuals consciously adopt to achieve their goals (Schunk & DiBenedetto, 2020). Self-regulation strategies can broadly be classified into three categories: behavioral, which involves self-observation; environmental, which involves adjusting environmental conditions; and covert, which involves adjusting cognitive and affective states (Zimmerman & Kitsantas, 2005). Some key self-regulation strategies are planning and organizing, resisting distractions, making environment more conducive to learning, monitoring self-behavior, self-reflection, managing resources such as time and effort, taking interests in tasks and having a self-improvement mindset (Kizilcec et al., 2016; Panadero, 2016; 2017).

There are several models in the literature to study the conceptualization of self-regulation construct. One of the most popular and comprehensive models used in academic research is the three-phase cyclical model by Zimmerman (Panadero & Tapia, 2014; Panadero, 2017; Zimmerman et al., 2017). As each phase reinforces the next phase leading to a self-sustaining cyclical process, there exists a spiral effect leading to more effective outcomes (Zimmerman & Moylan, 2009, p. 304). Each phase in the self-regulation cyclical model is influenced by the environment as detailed in the self-cognition theory. Self-regulation approaches adopted by an individual equips to regulate both skill and will behaviors which provides a comprehensive learning environment and leads to more effective learning (Schunk, 2012).

The first phase, forethought, provides for a platform on which to perform. The second phase, performance, explains how learning influences cognition and affect. The third phase, self-reflection, provides evaluative feedback for the learners. Theorists state that self-regulated learners are driven by motives of self-efficacy and further self-efficacy and self-regulation reinforce each other (Bandura, 1977; 2005; Schunk & Estmer, 2012; Valverde-Berrocoso, 2020).

Self-Regulation & e-learning

Empirical literature confirms the study of self-regulation becomes more relevant in e-learning environment (Paraskeva et al*.,* 2009; Broadbent et al*.,* 2021). In e-learning, self-regulation mechanisms are not a "nice to have": they are a required behavioral strength to achieve better outcomes (Santhanam et al*.,* 2008; Sharp & Sharp, 2016). During e-learning the need for self-direction and self-motivation is much more as the interaction is through a technology platform. As self-regulation behavior of individuals increases individuals set more challenging goals. This can lead to more effective e-learning (Zhao & Ye, 2020).

Self-Efficacy & Self-Regulation

Learning outcomes can be measured statistically to investigate the magnitude of change among constructs. For instance, in an empirical study, the correlation between prior grades and subsequent grades was found to be $r = .23$. However, when self-efficacy mediates this relationship, the actual correlation was $r = .56$; displaying an increase of 26% in predicted correlation (Zimmerman et al., 1992). Clearly self-efficacy can positively affect academic learning outcomes. Further, "the positive relationship between strength of self-efficacy and probability of successful performance is virtually identical for the similar and the dissimilar threats at 84%" (Bandura, 1977). Thus, we present our case; that self-efficacy can positively affect academic learning outcomes in all learning environments; traditional and e-learning (Bandura, 1977; Zimmerman et al., 1992; 2009; Pintrich, 2005).

Extant literature from social cognition theory also highlights that self-efficacy and self-regulation reinforce each other (Schunk & Ertmer, 2012). Individuals who demonstrate these behaviors develop the impetus to achieve superior learning outcomes in both traditional and e-learning environments (Bandura, 1977; Usher & Schunk, 2018). The behavioral mechanisms inherent in self-efficacy and self-regulation reinforce and nurture cognitive growth that facilitates learning (Bradley & Browne, 2017; Schunk & DiBenedetto, 2020). Self-regulated learners have higher motivation, they display more proactive behaviors towards goal achievement and set more challenging goals that enables learning efficacy in any environment (Yen et al., 2016; Usher & Schunk, 2018; Chopra & Madan, 2021). Thus, the author proposes hypothesis 1 and hypothesis 2 as below:

H1: Academic self-efficacy will be positively associated with self-regulation in e-learning environment.
H2: Internet self-efficacy will be positively associated with self-regulation in e-learning environment.

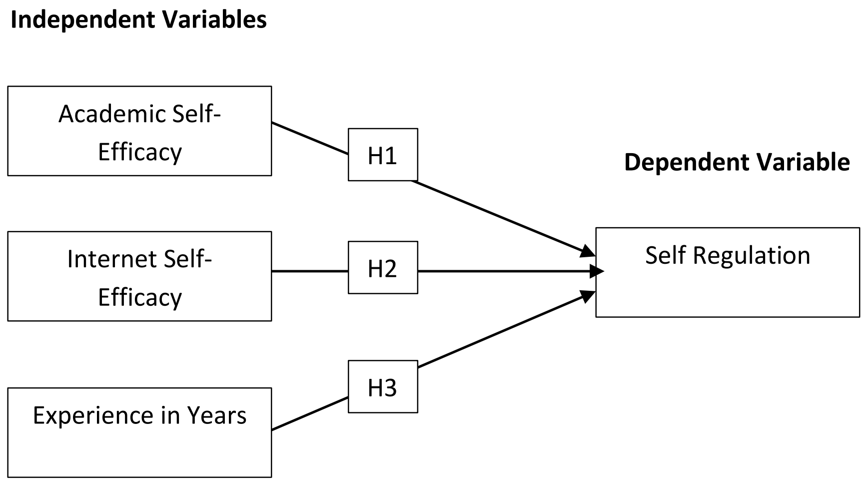
Experience in Years

Literature states the number of years an individual spends working can have a positive influence on e-learning outcomes (Landrum, 2020). While working, individuals develop their skills in using the internet and computer as well as other communication skills and ability to handle unknown situations. An individual's self-efficacy and self-regulation improve from experience. Every time an individual executes these approaches he builds on his confidence; this sets the stage for superior learning next time. Further, past experience helps an individual to overcome any unique challenges during e-learning (Bandura, 1977). Experienced individuals are more likely to have a peer group with whom they can communicate and extend help as and when needed. This ensures that learning can continue to take place without any barriers (Zimmerman & Kitsantas, 2005; Lim, 2020). Past experience also provides individuals with the skills to plan and organize their day to meet their learning needs and pick an environment or location that is most conducive for learning. Thus, the author proposes hypothesis 3 as below:

H3: Experience will be positively associated with self-regulation in an e-learning environment.

Figure 1 presents the conceptual model graphically. The conceptual model presented below has been laid out as follows: academic self-efficacy, internet self-efficacy, and experience in years are the three independent variables and self-regulation is the dependent variable. The relationships between these variables are examined in the context of e-learning. Academic self-efficacy is relevant for academic learning (Bandura, 2006). Internet self-efficacy is relevant in the context of learning in e-learning environment (Landrum, 2020). Experience in years is also related with self-regulation positively (Tseng & Yeh, 2019). The dependent construct self-regulation is critical as it is considered an essential element for success of e-learning (Valverde-Berrocoso, 2020; Broadbent et al., 2021).

Figure 1
Conceptual Model



Method

This paper uses the statistical technique of multiple regression to examine the empirical relationships among the constructs. As multiple regression methodology allows for the conceptual model to have one dependent variable and many independent variables it is a robust technique for the presented conceptual model (Wolters & Benzon, 2013; Sujatha et al., 2023). The known values of the independent variables simultaneously help to predict the unknown values of dependent variables. The effect of each independent variable is distinctly analyzed. SPSS (version 20) was used to carry out the analysis of the data.

Sampling and Sample

The data was collected from a diverse postgraduate student population of a premier business school in Southeast Asia using simple random sampling technique. Confidentiality of all respondents has been maintained. The self-report survey had 40 questions and took about 8 minutes to complete. Data has been collected on demographics such as gender and area of specialization. The data was collected from a sample of 570 postgraduate management students. Forty-five responses were nullified in data clean-up due to missing values; 525 complete responses have been considered for analysis. Thus, the accepted response rate is 92%. Of the total 525 participants, 70% were male and 30% were female. Table 1a captures demographic details of the sample data in tabular form.

Table 1a
Demographics of Sample Data

Variable		n	%
Gender	Male	369	70%
	Female	157	30%
PGDM Elective	Finance	315	59%
	Marketing	211	41%
	1–2	105	20%
Experience *(in years)*	3–4	368	70%
	5–6	53	10%

Instruments

Academic Self-Efficacy (ASE)

To examine the effect of academic self-efficacy on self-regulation, the "Self-Efficacy for Self-Regulated Learning" (SESR) scale by Albert Bandura was deployed (Bandura, 2006; Usher & Pajares, 2008). This is a 10-item unidimensional comparative scale with questions such as "Finish my homework assignments by deadlines," "Get myself to study when there are other interesting things to do," etc. Responses were measured as a percentage on a scale of 0 to 100. To allow for comparative analysis with other scales in this study the data was converted to a 5-point Likert-type response format having values ranging from strongly agree (5) to strongly disagree (1). Scale was verified for validity & reliability (Bandura, 2006).

Internet Self-Efficacy (ISE)

To examine the effect of internet self-efficacy on self-regulation, the General Internet self-efficacy (GISE) scale was used. GISE consists of the confidence to overcome basic challenges in working on the internet. This scale is based on the seminal work of Eastin and LaRose (2000). The GISE comprises three questions, such as "I feel confident in understanding terms/words related to Internet use" etc. The questions were presented in a 5-point Likert format with values ranging from strongly agree (5) to strongly disagree (1). The scale has been successfully deployed in Asia. GISE Scale demonstrates a Cronbach alpha of 0.90 (Schenk & Scheiko, 2011; Jokisch et al., 2020).

Self-Regulation (SR)

To examine self-regulation, the online self-regulation questionnaire the OSLQ scale was deployed (Barnard et al., 2009). The (OSLQ) is a 24-item scale with questions such as "I set standards for my assignments in online courses," "I allocate extra studying time for my online courses because I know it is time-demanding," "I summarize my learning in online courses to examine my understanding of what I have learned," etc. The questions were presented in a 5-point Likert format with values ranging from strongly agree (5) to strongly disagree (1). The OSLQ consists of six subscale constructs, which include environment structuring, goal setting, time management, help seeking, task strategies, and self-evaluation.

The existing research in e-learning has focused on using the motivated strategies for learning questionnaire (MSLQ) and the Metacognition Awareness Inventory (MAI). In this research paper, we used the (OSLQ) online self-regulation questionnaire to conduct this analysis. Unlike the MSLQ and MAI, the OSLQ has been tested in an e-learning environment and OLSQ is a more comprehensive construct to examine all self-regulation strategies (Jansen et al., 2017 Yen et al., 2016; Lim, 2020; Palalas & Wark, 2020). Also, the scale has been deployed successfully in Asia (Lim, 2020). The Cronbach alpha for subscales ranged from 0.85 to 0.92 (Barnard et al., 2009).

Experience in Years (EXP)

Each respondent was requested to share the years of work experience. The data was collected on a continuous scale with years of experience ranging from one to six years (Chawla & Sodhi, 2011).

Control Variables

The respondents' gender and business elective have been modelled as control variables in this study. Gender and business elective have been collated as ordinal variables (Chawla & Sodhi, 2011; Chopra & Madan, 2021)

Scale Reliability

Scale Cronbach alpha values confirm the internal consistency between items in a scale. All three scales were found to have a robust Cronbach alpha. An alpha of 0.7 and above is considered highly reliable (Chawla & Sodhi, 2011; Bonett & Wright, 2015).

Common Method Variance (CMV)

As this study used self-report instruments to collect data from respondents, common method variance CMV was a potential threat. "Most researchers agree that common method variance (i.e., variance that is attributable to the measurement method rather than to the constructs the measures represent) is a potential problem in behavioral research" (Podsakoff, 2003). In this paper, this threat was addressed at the point of data collection by adopting a two-pronged approach. First, data on independent and dependent variables was collected in no specific order by mixing the sequence of the scale questions. Second, unique IDs were used by each respondent to ensure complete anonymity and confidentiality of the data.

Results

Multiple liner regression was performed in SPSS on the data collated through the self-report surveys. The analysis of the data and results are presented in this section. Table 1b presents the descriptive statistics for the data.

Table 1b
Descriptive Statistics

					1	2	3
		N	Mean	Std. Dev		Correlation	
1	ASE_MEAN	524	3.43	0.578	1	0.274	0.075
2	ISE_MEAN	524	3.622	0.8648	0.274	1	0.380
3	EXP_MEAN	524	3.202	1.2745	0.075	0.380	1

As per Table 2, which highlights the R square values for our model, 48% of the variance in dependent variable is caused by the independent variables present in this model. R square and adjusted R square point to the percentage variance in dependent variable caused by independent variable(s). R square increases as the number of independent variables increase but adjusted R square may not as adjusted R square considers degrees of freedom. As adjusted R square in given model is close to R square, the model shows high reliability at an acceptable value of 0.485.

Table 2
Model Summary

Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**R Square Change**	**F Change**	**df1**	**df2**	**Sig. F Change**
1	0.699	0.488	0.485	0.30495	0.488	165.351	3	520	0

As per Table 3, which highlights the F values of the model, p at 0.000 is statistically significant at 95% confidence interval and thus we have a significant F. In regression F statistic highlights the significance of R square as it is an output of ANNOVA procedure or analysis of the variance. A large F value such as in Table 3 indicates that variation among construct means is not by chance.

Table 3
ANOVA Table

Model	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.(*p*)**
Regression	46.131	3	15.377	165.4	0.000
Residual	48.358	520	0.093		
Total	94.489	523			

In Table 4 below, the standardized beta coefficients of regression indicate the statistical relationship between each of the independent variables and the dependent variable. The p value at p = 0.000 shows a statistically significant relationship between academic self-efficacy (ASE) and dependent variable self-regulation (SR). This proves our hypothesis 1: (H1) holds true. That is, academic self-efficacy will be positively associated with self-regulation in an e-learning environment. As per standardized beta, 60.2% of the variance in dependent variable is caused by academic self-efficacy.

Similarly, the p value for p at 0.000 shows a significant relationship between internet self-efficacy (ISE) and dependent variable self-regulation (SR). This proves our hypothesis 2: (H2) holds true. That is, internet self-efficacy will be positively associated with self-regulation in an e-learning environment. As per standardized beta, 22.5% of the variance in dependent variable is caused by internet self-efficacy.

A standardized beta coefficient contrasts the strength of the association of each individual independent variable on the dependent variable. The absolute value of standardized Beta (ß) confirms that academic self-efficacy (ASE) has a greater impact than internet self-efficacy (ISE). There does exist a statistically significant relationship between ASE, ISE, and SR. We can say that people with higher self-efficacy positively associate with being self-regulated even in an e-learning environment and, per literature, such an association will enable superior outcomes in e-learning.

However, the p value for p at 0.959 indicates that experience in years is not associated with self-regulation. This disproves hypothesis 3, thus (H3) is not accepted. That is, as per the data in this study, experience in years is not positively associated with self-regulation in an e-learning environment.

Table 4 highlights the outcome of regression and the statistical significance of the standardized beta values. To reaffirm, ASE and ISE are positively and statistically associated with SR at a confidence interval of 95%. EXP does not have an association with SR in the context of e-learning.

Table 4
Coefficients: Significance Codes: *p < 0.1, **p < 0.05, ***p < 0.01

Model	Unstd. Beta	Std. Error	Std. Beta	t	Sig (p)	95% C. I. Lower	95% C. I. Upper
(Constant)	1.507	0.089		16.925	0.000	1.332	1.682
ASE_MEAN	0.443	0.024	.602***	18.46	0.000	0.396	0.49
ISE_MEAN	0.111	0.017	.225***	6.399	0.000	0.077	0.145
EXP_MEAN	0.001	0.011	0.002	0.052	0.959	-0.022	0.023

Table 5a and 5b highlight the level of multicollinearity. Multicollinearity measures the correlation between independent variables. A variance inflation factor (VIF) that is less than 10 and a tolerance which is greater than 0.20 is acceptable. From Table 5a, we observe values of VIF and tolerance are within bounds and thus we deduce that there is no overlap between the independent variables. This indicates correlation among independent variables is minimal and regression can be performed.

Table 5a
Collinearity Statistics

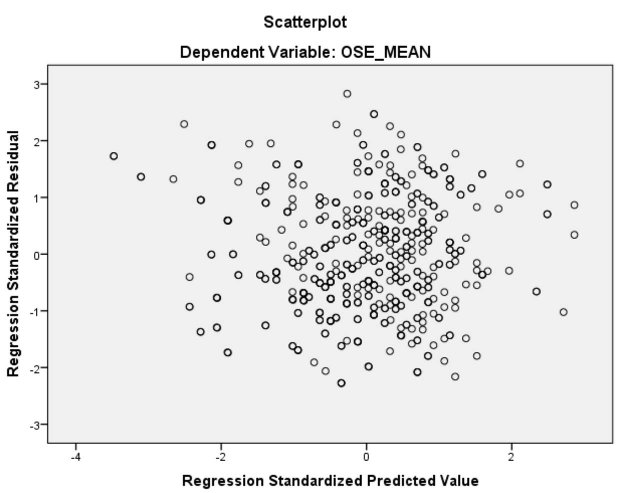
Model	Unstd. Beta	Std Error	Std. Beta	t	Sig (*p*)	Tolerance	VIF
(Constant)	1.507	0.089		16.925	0.000		
ASE_MEAN	0.443	0.024	0.602	18.46	0.000	0.924	1.082
ISE_MEAN	0.111	0.017	0.225	6.399	0.000	0.795	1.257
EXP_MEAN	0.001	0.011	0.002	0.052	0.959	0.855	1.17

Table 5b
Coefficient Correlations

Model		EXP_MEAN	ASE_MEAN	ISE_MEAN
Correlations	EXP_MEAN	1.000	.032	-.375
	ASE_MEAN	.032	1.000	-.266
	ISE_MEAN	-.375	-.266	1.000

Further, the presence of any multicollinearity can be graphically checked through heteroscedasticity of the error terms in the regression equation (U = y – ŷ). In Figure 3 the graph of the data confirms the absence of multicollinearity and heteroscedasticity. This also helps to verify the outcome of this multiple regression model.

Figure 3
Homoscedasticity of Residuals



Discussion & Implications

The findings in this study can prove meaningful for individuals undertaking e-learning programs, learning & development leaders, corporate trainers, academics, organizations, and research institutes (Naz et al., 2020; Teo et al., 2020; KPMG Report, 2021). The study findings add to the extant literature as we find that hypothesis 1 (H1) and hypothesis 2 (H2) hold true. H1 confirms a statistically significant relationship between academic self-efficacy and self-regulation in the context of e-learning (Honicke & Broadbent, 2016) and H2 confirms a statistically significant relationship between internet self-efficacy and self-regulation in the context of e-learning **(**Paraskeva et al*.,* 2009). Thus, the findings from H1 & H2 clearly indicate that self-regulation is dependent on domain specific constraints; that is academic self-efficacy and internet self-efficacy. H3 indicates that self-regulation however does not co-relate with work experience in years. Implications for academics and practitioners are discussed below.

Theoretical Implications

The findings in this paper build on the extant literature. The conceptual model examined in this study highlights the significant effect that academic self-efficacy and internet self-efficacy can have on self-regulation even in an e-learning environment (Hull, 2017). The findings extend the boundary conditions of social cognition theory as the delineated variables hold strong even in an e-learning environment (Bradley et al., 2017; Duchatelet & Donche, 2019). Thus, from the examination of domain-specific self-efficacy (Bamel et al*.,* 2017) on self-regulation we can derive that the tenets of self-efficacy, personal mastery, vicarious learning, verbal persuasion, and emotional arousal hold strong even in an e-learning environment.

Also, the findings from hypothesis 3 can be explained by the fact that the sample represents a student population from business school. Students need greater interventions in the form of program design and peer support mechanisms to enhance self-regulation behaviors in an e-learning environment (Huie et al., 2014; Dignath-van Ewijk et al., 2015). Research confirms there is an immediate need for increased interventions to enhance self-regulation behaviors (Lai & Hwang, 2021).

Practice Implications

The findings in this paper *c*an be used by practitioners and academics as criteria for formulating interventions that equip individual learners to develop essential traits to enhance self-efficacy and self-regulation (Makarius & Larson, 2017). Individuals can develop the requisite behaviors when facilitated through pedagogy, customized course content, formative feedback, and other approaches (Blau et al., 2020; Lai & Hwang, 2021). Such interventions form the core of strategic HRM (human resources management) best practices as they focus on organizational talent development goals that lead to skill augmentation.

The findings in this study also support the case for deployment of organization-wide LMS (learning management systems) that are customized to the learning styles of different stakeholders (An & Carr, 2017; Shishakly et al., 2021). Such customized learning management systems increase learner involvement and reduce the chances of drop-out (Noesgaard, 2016). Learning Management systems equip learners with all the benefits provided by an e-learning environment such as anytime, anywhere learning. Amazon is known to spend up to $1 million on employee trainings, supported by e-learning LMS platforms. As per ATD, organizations have 218% higher income and 24% higher profit margins when offering comprehensive learning programs (ATD Report, 2019), which can be deployed across diverse stakeholders because they are customizable.

Conclusion

The objective of this study was to examine the statistical relationship between self-efficacy, experience in years, and self-regulation in an e-learning environment. This study builds on the literature in this field, as very few prior studies have focused on examining the discussed relationships in the context of e-learning. The study has important implications for individuals in both academic and professional environments. This research is pertinent and relevant due to the exponential growth of e-learning in recent years; the global e-learning market was about $107 billion in 2015. It is predicted that by 2025, the global e-learning market will be valued at $325 billion as enrolment in e-learning programs by individuals pursuing higher education is increasing at a CAGR of 25% globally (ATD Report, 2019).

This study has a few drawbacks that can be addressed in future research. First, the findings of this research should be verified through other non-business school student populations. Second, the findings should be further supplemented through a mixed-method study. A mixed-method study will include qualitative interviews that will help highlight the other key approaches individuals adopt to ensure efficacious outcomes in e-learning environment. Third, such a study can be further expanded by including mediating and moderating variables such as parental support and socio-economic background (John et al., 2018).

Declarations

The authors confirm there are no conflicts of interest.
The authors declare no funding for this research.
The authors confirm they have adhered to the ethical guidelines such as informed consent and confidentiality while collecting and utilizing the data, but do not state approval from a specific ethics board.

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