

The Role of Socio-Cognitive Variables in Predicting Learning Satisfaction in Smart Schools

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Abstract

The present study aimed to investigate the role of Socio-Cognitive variables in predicting learning satisfaction in Smart Schools. The population was all the primary school students studying in smart schools in the city of Shiraz in the school year 2014-2015. The sample, randomly chosen through multi-stage cluster sampling, was 383 primary school students studying in smart schools in Shiraz. The instruments were the Computer Self-Efficiency Questionnaire developed by Torkzadeh (2003), Performance Expectation Questionnaire developed by Compeau and Higgins (1995), System Functionality and Content Feature Questionnaire developed by Pituch and Lee (2006), Interaction Questionnaire developed by Johnston, Killion and Oomen (2005), Learning Climate Questionnaire developed by Chou` and Liu (2005) and Learning Satisfaction Questionnaire developed by Chou and Liu (2005). In order to determine the possible relationship between variables and to predict the changes in the degree of satisfaction, we made use of correlational procedures and step-wise regression analysis. The results indicated that all the socio-cognitive variables have a positive and significant correlation with learning satisfaction. Out of the socio-cognitive variables in question, Computer Self-Efficiency, Performance Expectation and Learning Climate significantly explained 53% of the variance of learning satisfaction.

Keywords: Learning Satisfaction, Computer Self-Efficiency, Performance Expectation and Learning Climate, System Functionality.

Introduction

Incorporating technology into instruction, as one of the important aspects of information technology is considered a milestone in the social, vocational and educational life of human beings in the 21st Century and has opened up new avenues in educational institutions, especially in schools and universities (Rahimi & Yadollahi, 2011). Information and communication technology has the potentials to speed up, enrich and deepen acquisition of skills. It also helps with implementing fundamental changes in schools, promotes learning and creates opportunities to facilitate communication between schools and society (Davis, Tearle, 1999). In addition, information and communication technology

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could make schools more efficient and productive as it could provide a variety of means to promote and facilitate teachers' professional activities (Kirschner, Wopereis, 2003).

Smart schools represent a new approach to education. By combining information technology and curricula, such schools have brought about fundamental changes in the teaching-learning process (Umat, 2000). Technology, especially information and communication technology, has acted as a catalyst in transforming traditional schools to smart ones. In other words, information technology is inevitable if the transformation from traditional schools to smart schools is to take place (Hashim & Man, 1999).

Running and management of smart schools are based on computer technology and the Internet; the content is electronically delivered and parents are connected with the principal and the teachers online and keep abreast of the educational situation of their children (Sotani, 2012). In smart schools, the role of the teacher is one of guide, and not as a transmitter of knowledge and the role of the student is that of an active, creative and participating member of the class (Umat, 2000).

Traditional schools have been criticized for promoting passive learning, ignoring individual differences and needs of learners, ignoring problem-solving skills and critical thinking (Pelgrum, 2001). On the other hand, new developments in web-based technology have brought about challenges as well as opportunities in the virtual world so much so that nowadays, it is almost impossible to find higher education system in which the benefits of using technology have not been reaped (Ong & Ruthven, 2009; Ming et al., 2010). In these schools, the main idea is taken from electronic education technology, which has had substantial impacts on learning (Wu, Tennyson, Hsia & Liao, 2008) and learner satisfaction (Sung, Kwon, & Ryu, 2008).

While smart schools are said to have such advantages as richness of instruction, availability of knowledge content, provision of social interaction, and personal responsibility (Osguthorpe & Graham, 2003), nevertheless, dissatisfaction with learning could act as a threat to adopting smart schools (henceforth SS) (So & Brush, 2008). For example, research evidence suggests that in such schools, it is difficult for student to adjust to the smart system which may be due to technical failures, limited learner ability, inability to use state-of-the-art technology, and the like smart schools due attention should be paid to technological and human factors. These factors may be related to student attitudes and participation, and educational technologies (Wu et al., 2008; 2010). This calls for the scrutiny of learners in this system and the technologies used as these could contribute to learner satisfaction (Heba & Nouby, 2008).

Smart Schools are becoming more popular throughout the world. One of the reasons for their popularity is that these schools create learning atmosphere conducive to learning. Given that, it is necessary to gain insights into the factors which make smart schools popular with students and make these schools a success or failure, for that matter. This recognition could enhance learning satisfaction as well. For the purpose of evaluating the effectiveness of smart schools, it is necessary to determine the degree of learning satisfaction of learners with courses offered. Gaining insights into the factors determining learning satisfaction could help educational authorities to develop effective strategies as they relate to smart schools, that will, in turn, allow administrators and instructors in educational institutions to create new educational benefits and value for learners. Extensive studies have been carried out so far into the factors contributing to the learning satisfaction or dissatisfaction with learning in traditional schools. However, given the essential differences between traditional schools and smart schools, it is necessary to shed light on the cognitive, technological and social factors contributing to learning satisfaction with smart schools. More specifically, there is a dire need for more in-depth research to

gain insights into what determines student learning satisfaction in a Smart school environment and to investigate what determinants influence student perceptions of Smart school contexts and their correlations. This study, which is consistent with the Social Cognitive Theory (Bandura, 1986), is an attempt to investigate the primary determinants affecting student learning satisfaction in a Smart school environment.

The origins of smart schools date back to 1996. It was first initiated in Malaysia. One year later, efforts were underway to implement this system in schools. In order to accomplish this, they had to draw on the experiences of other countries. That is why they carried out a worldwide investigation to determine how the idea of smart schools had been put into use. Equipped with this knowledge, they produced the first plan for the smart schools in the same year (Zain, Atan, & Idrus, 2004). An attempt was made to draw upon latest technology and to bring the latest technology to schools (Chan, 2002; SSPT, 1997).

The objective of smart school concept was to help accomplish the ideals of education throughout the country, which could allow the country to regain lost ground and more important to meet new challenges. Doing this involved making major changes in the culture and educational practices. Thus, a totally new education system was sought for in which thinking, creativity and reflectivity were prized, rather than mechanical learning. Learners were to determine the pace with which they learned, to collaborate and to reflect on their own learning. In addition, teaching materials did not comprise just the printed books. Rather, electronic materials of various kinds were to support learning (Umat, 2000). This system could bring about fundamental changes in education. Among other things, the instructional methods were not fixed; students had the opportunity to make use of various educational technologies and interact with others in new ways. In addition, given the interactive learning environment available to them, the students had the opportunity to overcome the limitations of traditional schools (Pituch & Lee, 2006).

Social cognitive theory (Bandura, 1986) is the theoretical framework adopted in order to gain insight into what brings about learning satisfaction in Smart Schools. This theory is widely used in research endeavors which somehow attempt to investigate the predictability of human behavior, which can, in turn, allow us to see how human behavior could be changed. Essentially, this theory states that human beings progress in their behaviors through step-by-step interactions with the surrounding environment and that in order for such interaction to influence one's behavior, the surrounding environment must be exposed to the cognition. Moreover, this theory considers an interrelationship among cognitive, environmental factors and human behavior (Wood & Bandura, 1989). By cognition the reference is to individual cognition, affect and biological phenomena. In addition, social and physical environments comprise the environmental factors, which could have an impact on one's behavior. Cognitive mechanisms are the means by which environmental factors could influence behavior. It could be seen that according to social cognitive theorists, performance expectations and self-efficacy are two determining cognitive factors, with the latter being more important as it has a more important role in influencing one's behavior.

Self-efficacy is defined as the way an individual judges him/herself and how (s)he views his/her confidence and ability in accomplishing something. Needless to say, if an individual is not confident enough, there is no point in talking about his/her accomplishing something. Self-efficacy determines how successfully somebody can accomplish something, how much effort (s)he will put into it, how long the perseverance will last especially in the face of difficulties and how much the person is resistant. It could be seen that the relationship between self-efficacy and performance expectation is reciprocal, suggesting that self-efficacy could have a significant impact on performance expectations, which can, in turn, influence self-efficacy.

In addition, according to research evidence, environmental factors could have a significant impact on the performance and behavior of individuals. Earlier, it was the case learning environment was seen as a function of physical and social factors. Learning environment was later expanded by Piccoli et al. (2001). They recognized a number of environmental factors which could distinguish e-learning environment from classroom environment and include technology, content, interaction, learning model, and learner control. It is possible to classify these factors into two rather distinct categories which are directly relevant to smart schools. The first category has to do with technological environment and the second with social environment.

The discussion so far has delineated the social cognitive theory which forms the theoretical underpinnings applicable to smart schools. As discussed above, learning satisfaction with smart schools could be discussed in terms of learners' cognitive factors, technological factors and social factors.

Cognitive factors are related to learners' cognitive beliefs and have an impact on learners' behaviors in the use of smart schools. It is believed that two cognitive variables, namely computer self-efficacy and performance expectations are the factors determining human behavior in using an information system (IS), (Compeau & Higgins, 1995; Compeau, Higgins, & Huff, 1999; Venkatesh, Morris, Davis, & Davis, 2003). According to the theorists of the social cognitive theory, performance expectations are defined as the perceived consequences of a behavior. They also hold that these expectations determine individuals' actions. Individual judgements made about the outcomes of behaviors determine performance expectations. It is more likely that individuals will be involved in behaviors that they have every reason to believe that they will result in positive benefits. Thus, it is less likely that they will perform behaviors which they believe will not produce favorable consequences. Performance expectations have been defined as the degree to which learners believe that electronic learning system could help them to accomplish the performance goals they have in mind. The definition is consistent with the related concept of perceived usefulness, which is, in turn, taken from Davis's (1989) Technology Acceptance Model (Venkatesh et al., 2003). It is necessary to point out that there is some research evidence suggesting the influence of performance expectations on individual behavior when it comes to using computer systems (Compeau & Higgins, 1995, Compeau et al., 1999, & Venkatesh et al., 2003). Specifically, it has already been shown that performance expectations positively correlate with students' learning performance (Bolt, Killough & Koh, 2001; Kazu, Demirkol, 2014) and learning satisfaction (Martins & Kellermanns, 2004; Martirosyan, Saxon & Wanjohi, 2014; Shih, 2006).

Personal beliefs lead to individual attitudes. For example, behavioral beliefs are directly related to a person's intention to perform a certain behavior (Ajzen & Fishbein, 1980). Consistent with the Theory of Reasoned Action (Taylor & Todd, 1995), positive attitudes of users toward the information system could be measured by the degree of user acceptance, which could be used for the purpose of predicting the behaviours of the users while using the system. Learning satisfaction is taken to be a good measure for user acceptance and that is why in computer-mediated learning studies, it is frequently used to gauge learners' attitudes (Chou & Liu, 2005; Piccoli et al., 2001). Thus, it is possible to conceptualize learners' attitudes toward Smart Schools as the learning satisfaction with Smart Schools. This satisfaction is defined as the totality of beliefs and attitudes of learners resulting from putting together all the benefits that learners receive from Smart Schools.

Another related cognitive factor relevant to the current study is self-efficacy, which has been defined as the beliefs which individuals hold about their capabilities to successfully carry out certain behaviors (Bandura, 1986). Social cognitive theorists opine that

perceptions of self-efficacy toward a task are formed based on the cue received from several information sources: (1) past experience and familiarity with similar activities, (2) vicarious learning, (3) social support and encouragement, and (4) attitudes toward the task. According to Bandura (1986), self-efficacy is specific to certain tasks and when it comes to measuring it, it is necessary to pay due attention to the context in which it occurs. Consistent with the characterization given of self-efficacy, several studies have been carried out in which self-efficacy beliefs towards tasks such as computers and IS-related behaviors have been investigated (Compeau & Higgins, 1995; Compeau et al., 1999). In line with this general definition given for self-efficacy, computer self-efficacy has been defined as the ability of individuals in using information technology to successfully carry out computer-related tasks or jobs (Marakas, Yi, & Johnson, 1998). In the context of smart schools, self-efficacy could be defined as individuals' confidence in using their ability to perform particular learning tasks. Research findings have indicated that increased computer self-efficacy could help improve students' initiative and persistence, which could, in turn, result in improved performance or outcome expectations (Johnston, Killion, & Oomen, 2005; Kuo, Walker, Schroder & Belland, 2014; Piccoli et al., 2001; Wu et al., 2010), including attitude and behavioral intention (Venkatesh & Davis, 2000). As far as computer-mediated learning is concerned, research evidence suggests that improved computer self-efficacy could help promote students' confidence in their computer-related abilities, which could in turn result in perceived positive performance expectations to the learning courses (Bolt et al., 2001; Jawahar & Elango, 2001; Santhanam, Sasidharan & Webster, 2008; Shen, Cho, Tsai & Marra, 2013; Shih, 2006; Wu et al., 2010).

Effective learning in Smart Schools could be attributed to such factors as the quality and dependability of an e-learning system, easy access to effective educational technologies, material content, and course-related information (Piccoli et al., 2001). Thus, it could be seen that the functionality of this system along with content features can be considered as important technological environment factors related to Smart Schools. These features are very influential in learners' acceptance and use of Smart Schools. Previous research findings have invariably shown that system functionality could significantly impact user beliefs in different computer-related contexts (Igbaria, Gamers, & Davis, 1995; Venkatesh & Davis, 2000). For example, research evidence was clearly indicative of the fact that specific system functionality is a determinant, influencing the use of e-learning system (Hong, Thong, Wong, & Tam, 2002; Pituch & Lee, 2006; Wu et al., 2010). System functionality has been defined as an individual's perception of ability of an e-learning system in facilitating flexible access to instructional and related media (Pituch & Lee, 2006). In the context of the current study, system functionality could be defined as the perceived ability of Smart Schools in providing flexible access to instructional and the related media. These media allow students to have access to course materials and content, submit their homework assignments, to complete tests given and take quizzes online. Content is utilized to recognize different formats and types of information (Wu et al., 2010; Zhang, Keeling, & Pavur, 2000). In the current study, content is defined as the technology-based materials and the information related to various courses which could be used by students in the context of Smart Schools. In Smart Schools, educational goals are accomplished through sharing and delivering course content, using different media such as tutorials, or web-based courses. Given the variety of delivery methods, a major concern is to decided how to design and present content. In addition, the formats and types need to correspond to delivery or access in Smart Schools (So & Brush, 2008). When it comes to designing Smart Schools, appropriate content features, and the effective design are essential considerations in such design (Piccoli et al., 2001). Drawing on the previous research (Zhang et al., 2000), in the current study, content features are defined as the

characteristics and presentation of content of courses and information in Smart Schools. Some examples of content features in the environment of Smart Schools are: text, hypertext, graphics, audio and video, computer animations and simulations, embedded tests, and multimedia information.

Given the discussion so far, it could be seen that system functionality and content feature could directly impact perceived usefulness of IS (Hong et al., 2002; Pituch & Lee, 2006). In a number of empirical studies, it has been found that both content features (Tajuddin, Baharudin & Hoon, 2013; Wu et al., 2010; Zhang et al., 2000) and system functionality (Pituch & Lee, 2006; Shen et al., 2013; Wu et al., 2010) directly affect the effectiveness of computer-mediated learning.

In designing Smart Schools in which instruction is mediated through computers, designers increasingly pay close attention to facilitating interaction between humans and computers. This could be accomplished in the form of online collaboration, creation of virtual communities, and allowing instant messaging in the context of Smart Schools (Graham, 2006). As far as group interaction is concerned, social environment factors, such as collaborative learning (Francescato et al., 2006), learning climate (Chou & Liu, 2005; Wu et al., 2010) and social interaction (Johnston et al., 2005) are important determinants of beliefs students hold about using an e-learning system. In the same vein, it has been found that social interaction has a direct impact on the utilization of an e-learning system (Kuo et al., 2014; Pituch & Lee, 2006; Tajuddin et al., 2013). Likewise, from a learning perspective, the interactions among students themselves, between teachers and students and learning collaboration are the keys to the effectiveness of a learning process.

Method

The research design adopted was descriptive and predictive in nature. In the present study, satisfaction was considered as the criterion variable and computer self-efficiency, expected performance, cognitive variables, system efficiency and content characteristics (Technological environment), interaction and learning environment (social environment) were considered as predictive variables of satisfaction. The population was all the male and female students studying in smart schools in Shiraz in the school year 2014-2015. The sample was 400 students of Primary Schools, chosen through random multistage cluster sampling as follows. First out of the education districts in Shiraz, District 2 and 3 were chosen randomly. Out of District 2, 2 schools for males and females, and in each school, four classes were randomly chosen. The questionnaires were administered to all of them. The questionnaires were checked to make sure they were completed correctly and contained the essential information. Given that 17 questionnaires were found to be incomplete, they were left out. Thus, 383 questionnaires remained for further analysis. Seven questionnaires were used to collect the data. Except the Computer Self-Efficiency Questionnaire, which was in Persian, all the other questionnaires were originally constructed in English. The scales were translated from English to Persian and then from Persian back to English by two university professors majoring in TEFL. The translated versions were piloted on 100 students similar to the target group, which resulted in some modification of the form. In addition some items were deleted and some more were added. In addition, the scales were examined by four university professors majoring in Psychology and Educational Sciences for content validity. The construct validity was established through correlating the score of each item with the total score. The following questionnaires were used in the study.

Computer Self-Efficiency Questionnaire

This questionnaire was developed by Torkzadeh, Koufteros and Pflughoeft (2003). The original form of the questionnaire consists of 37 items, measuring the ability or inability of

the respondents in using computers on a 5-point scale, ranging from 5 (completely agree) to 1 (completely disagree). Zamanpour, Khani and Moradiani Deizehrud (2013) established the reliability to be 0.80 and validity as satisfactory. In the current study, Cronbach Alpha was used to establish the reliability of the instrument, which was 0.92.

Performance Expectancy Questionnaire

Compiu and Higgings' Questionnaire (1995) was used to investigate the performance expectancy. This questionnaire consists of 4 items, measuring the success or failure of the respondents in performance expectancy. Chiu, Hsu, Sun, Lin, & Sun (2005) reported the reliability index of the measure as 0.90 and validity as satisfactory. In the present study, the reliability of the scales, established through Cronbach Alpha was 0.73.

System Capability Questionnaire

Pitich and Lee's Capability Questionnaire (2006) was used to measure system capability. This questionnaire has 6 items and measures the respondent's ability in performance expectancy. Pitich and Lee (2006) reported the reliability of the questionnaire as 0.83 and validity as satisfactory. In the present study, Cronbach Alpha was used to establish the reliability of the scale, which was established to be 0.82.

Content Specifications Questionnaire

Pitich and Lee's Content Specifications Questionnaire (2006) was used for this purpose. This questionnaire consists of 8 items. Wu et al. (2010) established the reliability of the questionnaire as 0.89 and the validity as satisfactory. In the present study, the reliability, established through Cronbach Alpha, was 0.92.

Interaction Questionnaire

Johnson et al.'s Interaction Questionnaire (2005) was used for this purpose. It has four items and measures interaction on a scale of 5. The reliability of the questionnaire was established by Pitich and Lee (2006), which was 0.90. They also reported the validity as satisfactory. In the current study, the reliability of the questionnaire established through Cronbach Alpha was 0.62.

Learning Climate Questionnaire

Chou and Liu's Learning Climate Questionnaire (2005) was used for this purpose. It has 11 items and measures learning climate on a scale of 5. The reliability of the questionnaire was established by Wu et al. (2010), which was 0.92. They also reported the validity as satisfactory. In the current study, the reliability of the questionnaire established through Cronbach Alpha was 0.83.

Learning Satisfaction Questionnaire

Chou and Liu's Learning Satisfaction Questionnaire (2005) was used for this purpose. It has 10 items and measures satisfaction with learning on a scale of 5. The reliability of the questionnaire was established by Chou and Liu (2005), which was 0.86. They also reported the validity as satisfactory. In the current study, the reliability of the questionnaire established through Cronbach Alpha was 0.85.

Given that the impact of intelligent schools is more pronounced in some courses, the students were asked to consider the course of Physical Sciences in answering the questions. In addition to descriptive statistics of frequency, mean and standard deviation, use was made of Pearson Correlation Coefficient and Stepwise Regression.

Results

The first research question posed in the current study was “What are the most important predictive psychosocial variables of satisfaction with learning in smart schools?”

Table 1. Zero -order correlation matrix between the variables

Variable	MD	SD	1	2	3	4	5	6	7
Computer self-efficacy	73.32	13.51	1						
Performance expectations	14.86	3.48	0.38**	1					
System functionality	22.10	6.08	0.29**	0.55**	1				
Content feature	29.57	7.29	0.26**	0.63**	0.84**	1			
Learning climate	7.62	1.90	0.27**	0.56**	0.64**	0.64**	1		
Interaction	42.47	7.65	0.26**	0.54**	0.56**	0.55**	0.73**	1	
Learning satisfaction	40.30	7.12	0.60**	0.56**	0.42**	0.45**	0.50**	0.44**	1

Note: ** $p < 0.01$.

Table 1 depicts the results concerning the relationship between predictive and criterion variables. According to this table, cognitive factors (i.e., computer self-efficacy and performance expectancy), technological environment (i.e., system capability and content specifications) and social environment (i.e., interaction and learning atmosphere) have significant and positive relationship with learning satisfaction. The correlation between learning satisfaction and the variables in the study ranges from 0.41 to 0.59. The significant correlations are marked with an asterisk.

Given that cognitive factors(i.e., computer self-efficacy and performance expectancy), technological environment (i.e., system capability and content specifications) and social environment (i.e., interaction and learning atmosphere) have significant correlation with learning satisfaction, in further analysis, use was made of step-wise regression analysis, which required entering cognitive factors, followed by social factors (technological environment and social environment) into the analysis.

The results in Table 2 indicate that out of predictive variables, computer self-efficacy, performance expectancy and learning atmosphere could predict learning satisfaction. The other factors were left out as they could not predict learning satisfaction. It could be seen that the F value is significant for the variable of computer self-efficacy ($p < 0.01$). This variable alone can account for 36% of the variance of learning satisfaction. Adding performance expectancy to the regression analysis, a major portion of variance could be accounted for (i.e., 49%). It could thus be seen that almost 13% of the variance of learning satisfaction could be accounted for by performance expectancy, which is significant ($p < 0.01$). Finally, adding learning atmosphere, which belongs to social environment, the variance amounts to 53%, 4% of which belongs to the social environment.

Table 2. Results of Stepwise regression to predict satisfaction with learning

Step	Variable	R	R^2	Sd	F	p	B	β	t	p
1	Computer self-efficacy	0.60	0.36	5.72	211.38	0.001	17.20	0.60	10.66	0.001
2	Performance expectations	0.70	0.49	5.11	180.99	0.001	11.01	0.45	11.37	0.001
3	Learning climate	0.73	0.53	4.93	139.64	0.001	6.18	0.43	11.34	0.001

Discussion and Conclusion

The findings of the present study demonstrated that learning satisfaction in smart schools is the result of an interplay between various cognitive, technological and social factors. While technology is a pre-requisite for learning, it is in no way adequate and cannot bring about learning satisfaction. This finding is in line with the theorizing in social cognitive theory, which, essentially, is about the reciprocal relationship between cognitive, environmental and behavioural factors (Bandura, 1986).

The findings of the study suggest that computer self-efficacy, performance expectancy and learning environment, respectively, are the best predictors of learning satisfaction with smart schools. Students with higher self-efficacy expose themselves more to the computer and the Internet. They utilize their skills to achieve more in less time. In the current study, one of the findings was that computer self-efficacy, as an important cognitive variable, is significantly and positively correlated with learning satisfaction. This finding is in line with a number of studies (Chou & Liu, 2005; Jin & Lin, 2012; Kuo et al., 2014; Shen et al., 2013; Wu et al., 2010). This finding is indicative of the fact that self-efficacy could be accounted for based on Bandura's anthropological concepts. This could be attributed to the fact that in the socio-cognitive approach, the emphasis is laid upon motivational processes, perception and feeling of individual about his or her merits.

The findings of the study also showed that in addition to computer self-efficacy, performance expectancy is one of the strongest predictors of learning satisfaction (Compeau & Higgins, 1995; Shen et al., 2013; Wu et al., 2010). It is highly likely that individuals get involved in activities which, they believe, bring about their satisfaction. By developing their expectancy of the possible results of their actions, students are enabled to see the outcomes of their actions before actually doing them. They can also predict the possible rewards and punishments. Students with higher efficacy have higher expectations to overcome the possible problems they are likely to encounter, and thus, demonstrate more learning satisfaction. This essentially means that the higher the self-efficacy, the more confident the student is that what he is doing is important and useful. This confidence could, in turn, bring about behaviors which lead to further progress and success.

In the present study, Learning Climate was the third most important predictor of learning satisfaction. In some studies carried out in the same vein, it has been found that learning atmosphere does indeed lead to learning satisfaction (Kuo et al., 2014; Wu, Wu, & Tasi, 2014; Wu et al., 2010). In the classroom situation, teachers are primarily responsible for establishing law and order, optimum use of resources and instructional materials, use of learning/teaching strategies and the evaluation of learning achievement. Accomplishing all of these requires proper classroom management which is possible through proper planning and organization, leadership, supervision, control and evaluation. The result of the interaction among all these variables is learning environment which is conducive to learning. The learning atmosphere is a tangible feature which could be felt upon entrance to a classroom. The proper management finally determines achievement and final output in the classroom.

It is necessary to point out that to make the most out of smart schools, learners should have the required computer competence. Otherwise, they could fail in exercising control over their learning activities. Given the indispensable role that computer competency plays in this regard, it is highly necessary for the authorities in smart schools to provide the necessary encouragement for learners to attend the relevant courses and acquire the necessary computer self-efficacy for effective academic functioning. Needless to say, the specific needs of language learners in different settings should also be taken into account.

Active participation of learners in smart school environment could create a learning atmosphere conducive to easy and natural learning. If smart schools manage to create such a positive social environment, the odds are they could bring about interaction among the students themselves and with their teachers. This way, it is highly likely that they will interact more with their peers and their teachers, which can, in turn, improve the learning climate. Learners in such a situation will perceive better performance on the part of smart schools and this can enhance learning satisfaction.

In spite of the fact that the present study provides important insights into the factors contributing to learning satisfaction in smart schools, given the limitations of the study, the findings should be interpreted with caution. First, the research instrument was validated using participants in smart schools in the Iranian context. Given that, the findings could not be generalized to other contexts. It is, thus, necessary to use samples from other contexts to see whether the same findings will be replicated. Second, measuring computer self-efficacy and performance expectancy required the use of self-report instruments. Given the shortcomings associated with such measures, the findings should be interpreted with caution. Third, while the study sheds lights on some of the factors contributing to learning satisfaction in smart schools, it is in no way exhaustive in addressing all the possible contributing factors. Future research might unravel other determinants of learning satisfaction in smart schools.

Opportunities for further research, mean that the findings of the study should be interpreted with caution. First, the research was validated using sample data gathered from the Smart Schools in the Iranian context. Given that the participants were chosen from a single country, the generalization of the findings should be done with utmost care. Other samples from different nations, cultures, and contexts could be gathered in future research endeavors to confirm or refine the findings of the present study. Second, as is the case with all self-report measures, in the current study, use was made of self-report instruments to measure computer self-efficacy and performance expectations. This needs to be taken into account when it comes to interpreting the findings. Third, even if the current study sets a timely stage for future research in understanding the determinants of learning satisfaction in a Smart Schools environment, it is advisable to adopt a longitudinal design and to examine the relationships among the identified research variables. This could be a useful extension of the current study. Finally, the list given of the determinants of learning satisfaction in Smart Schools is no way exhaustive. Future studies could unravel additional determinants of student learning satisfaction with Smart Schools.



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