

Modeling Diffusion of Blended Labs for Science Experiments Among Undergraduate Engineering Students

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Abstract. While there is large body of work examining efficacy of Virtual Labs in engineering education, studies to date have lacked modeling Blended Labs (BL) – mix of Virtual Labs (VL) and Physical Labs (PL) for science experimentation at the university engineering level. Using Rogers theory of perceived attributes, this paper provides a research framework that identifies the attributes for BL adoption in a social group comprising of (N=246) potential adopter undergraduate engineering students. Using Bass model the study also accounts for the interinfluence of related group of potential adopter faculties who are likely to exert positive influence on students. The results revealed that acceptance of BL as an innovation and its learning outcomes are strongly associated with innovation attributes like Relative Advantage, Compatibility, Ease of Use, Department and Faculty support. Learning outcomes are very positive under BL when compared to PL, though within BL, ordering of PL and VL was not significant. For certain innovation attributes gender differences were significant. Overall students expressed much more positive attitude to adopt BL model for learning than using only PL.

Keywords: Virtual labs · Blended learning · Innovation diffusion · Experiments · Engineering · Interinfluence

1 Introduction

With growing acceptance of educational technologies, significant emphasis is placed on the underlying pedagogical approach to attain desirable learning outcomes [1]. One of the recent emerging approaches to learning is known as blended learning. Blended learning involves a combination of online or virtual instruction in tandem with face-to-face sessions. According to [2] Blended Learning is an innovation if it is ‘perceived as new by an individual or other unit of adoption. If the idea seems new to the individual, it is an innovation’. An educational innovation like BL will not occur in isolation in an environment where two interrelated potential adopters namely faculties and students influence each other and both have to adopt for the innovation to be successful.

Physical experimentation in labs has been a critical component in science and engineering education. Specifically, imparting practical skills as well and obtaining

first-hand knowledge of challenges incurred in real environments can only be learnt in a physical lab. Research has shown that in spite of the important role physical experimentation has, the conceptual understanding of a phenomenon from practical lab experience alone is poor and ineffective in provoking student's innate creativity [3]. A combination of both learning environments did show enhancement in student understanding [4] and in some cases further improvements with virtual labs [5]. The level of visualization, flexibility, the repetitive practice that virtual labs allow, makes them far more effective learning tools. On the other hand, there are limitations to virtual labs in providing critical experiences of performing an experiment, the inability to grasp specific aspects of knowledge (for e.g. assumptions, measurement errors etc.) as in a physical lab [6]. These challenges can be surmounted by adopting a blended learning approach to lab education. The advantages of largely individualistic learning with virtual labs in combination with pragmatic skill development from physical labs are necessary to invoke motivation, enhance understanding and extend retention of complex phenomena. On the other hand, if all concepts were demonstrable in a laboratory our surmise is that it would in fact widen experiential learning and provide deeper understanding. This ideal scenario is nearly impractical for the exorbitant cost to host wide variety of instrumentation and difficulty in dovetailing them into the curricula under the constraint of limited allotted time and infrastructure for labs in most institutions. This paper provides directions to circumventing the challenges of current physical lab practices by introducing blended labs in mainstream under graduate engineering education. More importantly this paper provides the theoretical framework for the diffusion and the adoption patterns for blended labs using Rogers [2] theory of perceived attributes and takes into account the important intergroup influence of faculty on students.

2 Literature Survey

2.1 Diffusion of Educational Technologies

Roger [2] in his perceived theory of attributes writes that 'the perceived attributes of an innovation are one important explanation of the rate of adoption of an innovation'. The theory states that an innovation is perceived based on its relative advantage, compatibility, complexity, trialability, and observability. In order for an innovation to undergo a faster rate of diffusion the potential adopters must perceive that innovation (1) to have advantage relative to other innovations (2) to be compatible with existing practices and values (3) is not very complex (4) can be tried on a limited basis before adoption (5) offers observable results. According to Dayton [7] of these five attributes, relative advantage, compatibility and complexity influence the most when it comes to decision by potential adopters [8] focused on the importance of studying the adoption and diffusion of innovation in field of educational technology. The proportion of potential adopters who have adopted the innovation determines the success of any innovation. Over the years researchers have empirically confirmed that the rate of diffusion forms an S-shaped curve which represents a cumulative distribution of adopters. The shape of the curve rises slowly at first, because there are few adopters

initially and accelerates to a maximum value till the point of inflection is reached. Thereafter the curve's rate of increase slows down until the remaining individuals have adopted. The two-segment structure with asymmetric influence which assumes the existence of influentials and imitators was studied by [9] which is very relevant to high-technology, healthcare care products can also be seen in the context of educational innovation involving faculties and students.

2.2 Blended Learning and Blended Labs

Web based networked technologies have provided the foundation for creation of new lab frameworks for science education in a blended learning context. There have been studies comparing the conceptual understanding in students when exposed to both physical and virtual labs. A framework for blending physical and virtual experiments was proposed by [5] based on specific learning outcomes such as cognitive, affective and psychomotor related objectives. The inference from this work was that blending physical and virtual labs did enhance student's conceptual understanding. Much of the literature talks about the importance of blended learning and hybridization of online and face-to-face instruction that could include a mixture of instructional modalities and methods [10]. The survey of the thesis's from a decade of research in blended learning portrayed insufficient emphasis on the impact of student motivation and engagement in blended learning environments [11]. Olympiou [12] in his work described the patterns of collaborative problem solving in an online experimental environment where groups of students conducted physical labs and online experiments collaboratively. The results indicated students performed better when the level of collaboration is high and when they were exposed to virtual labs prior to the physical labs. These results do not still indicate if individual learning has been progressive with this approach. When considering the use of VLS in a blended mode, one should anticipate its use by a growing scientific community of students that may be present at multiple locations. It becomes imperative to build scalable blended labs to accommodate a large number of students.

2.3 Virtual Labs for Engineering Education

One of the largest projects that have successfully built over 1500 virtual experiments as part of over 150 labs in nine disciplines of science and engineering to complement physical labs can be viewed at (www.vlab.co.in). The three fold objectives of VLS included: bridging digital divide and disparity in quality education across higher educational institutes, use of ICT in creating as nearly an experience of a lab to a remote learner and aligning content to complement the undergraduate and graduate curricula. These virtual labs cover different flavors of experiments from interactive animations, modeling and simulations with user interfaces mimicking reality to remote triggering equipment's made available over the web. As part of this mission, The Virtual Amrita Labs Universalizing Education project (VALUE) developed over 250 VL experiments in several areas including biotechnology, physics, chemistry,

mechanical engineering and computer science [13]. An in-depth study on the development of VL [14, 15] showed how diverse areas of biotechnology that may be either protocol intensive or computationally demanding could both be incorporated in VLs.

3 Case Study: Factors Affecting Diffusion of Blended Labs

3.1 Research Model and Hypothesis

In the diffusion model of blended lab technology for learning we chose student positive behavior intention as the dependent variable. The blended lab’s rate of adoption was investigated by assessing two groups of characteristics, which were the independent variables - innovation characteristics and environment characteristics (Fig. 1).

Employing Rogers [2] framework, Bass [16] proposed mathematical model as a nonlinear differential equation for diffusion of an innovation in a group of size M. In such a scenario [17] adoption of innovation is due to two influences viz. external influence (mass media) which is a linear mechanism and internal influence (word-of-mouth) which is a non-linear mechanism. The differential equation giving the diffusion is

$$\frac{dN(t)}{dt} = (p + qN(t))(M - N(t)) \tag{1}$$

where N(t) is the cumulative number of adopter-students who have already adopted by time t, M is total number of adopter-students who will eventually use the innovation, p is the coefficient of external influence and q is the coefficient of internal influence.

In terms of the fraction F(t) of potential adopter-students

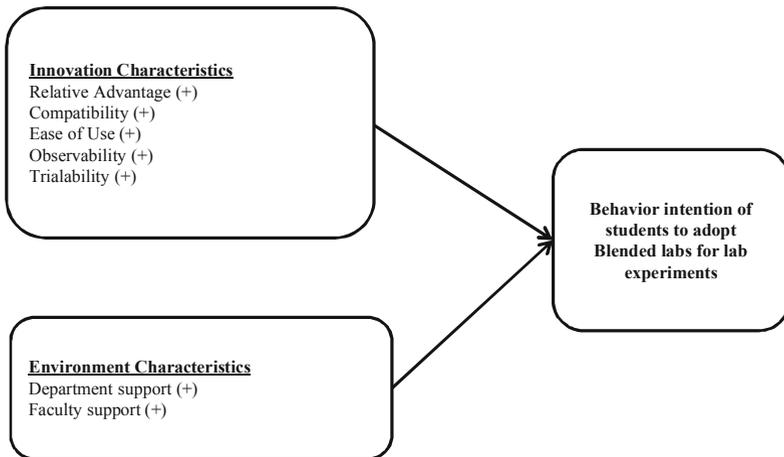


Fig. 1. Research model for diffusion of Blended Labs

$$F(t) = \frac{N(t)}{M} \tag{2}$$

the Bass model can be rewritten as

$$\frac{dN(t)}{dt} = (p + qMF(t))(1 - F(t)), F(t = 0) = F_0 \tag{3}$$

Equation (3) yields the S-shaped diffusion curve. It is assumed that the carrying capacity M of the adopter-students remains constant.

Now we extend the Bass model to account for the interinfluence of faculty on students. We define the following terms.

- p_1 external influence for the adopter-faculties
- q_1 internal influence for the adopter-faculties
- F total number of adopter-faculties who will eventually adopt the innovation
- f cumulative number of adopter-faculties who have already adopted by time t
- p_2 external influence for the adopter-students
- q internal influence for the adopter-students
- S total number of adopter-students who will eventually adopt the innovation
- s cumulative number of adopter-students who have already adopted by time t
- m total number of adopters who will eventually adopt the innovation
- μ relative importance students give to faculties for their support ($0 \leq \mu \leq 1$)
- α proportion of faculties in the total population of potential adopters ($0 \leq \alpha \leq 1$).

The differential equation giving the diffusion for faculties (f) is

$$\frac{df}{dt} = f(t) = (p_1 + q_1f)(F - f). \tag{4}$$

The differential equation giving the diffusion for students (s) is

$$\frac{ds}{dt} = s(t) = (p_2 + q_2s + \mu f)(S - s). \tag{5}$$

The Eq. (5) takes into account the influence of faculty on students.

The differential equation giving the diffusion for the combined population of potential adopters (m) (students and faculties) is

$$\frac{dm}{dt} = m(t) = \alpha f(t) + (1 - \alpha)s(t). \tag{6}$$

3.2 Innovation Characteristics

Relative Advantage: Rogers [2] theory of perceived attributes takes into account the notion of relative advantage, which he defines as – ‘the degree to which an innovation is perceived as being better than the idea that it supersedes’. The most obvious advantage of BL is in the mixing of both PL and VL to offer best of both worlds.

Our hypothesis is Relative advantage of BL positively affects student's intention to adopt it (H1).

Compatibility: [2] defines compatibility as 'the degree to which an innovation is perceived as consistent with existing values, past experiences, and needs of potential adopters'. In terms of compatibility, BL learning approach is compatible in its functionality with the learning approach of PL. Our hypothesis is Compatibility of BL positively affects student's intention to adopt it (H2).

Complexity: Any innovation quickly gains a reputation as to its ease or difficulty of use [2]. In this context an important question is to what extent BL is perceived by users as complicated to use. In specific, the idea of complexity, as described by [2] was formulated from an "Ease of use" perspective in this study whereas the notion of adoption was substituted with the notion of attitude towards use. Our hypothesis is Ease of Use of BL positively affects student's intention to adopt it (H3).

Trialability: Trialability is "the degree to which an innovation may be experimented with on a limited basis" [2]. Innovations that potential adopter can experiment with on a trial basis are more easily adopted because an innovation that can be tried presents less risk to the potential adopter. Our hypothesis is Trialability of BL positively affects student's intention to adopt it (H4).

Observability: Another aspect of [2] is related to – the degree to which the results of an innovation are visible to others. Sometimes, observability refers to the ease with which the innovation is communicated to potential adopters. Our hypothesis is Observability of BL positively affects student's intention to adopt it (H5).

Department Support: More often teachers and students are motivated to consider technology decisions that are sanctioned and supported by the management since those will have adequate support resources. Department head who is the final decision maker for technology decision can play a pivotal role in encouraging students to use BL for learning. Our hypothesis is Department Support for BL positively affects student's intention to adopt it (H6).

Faculty Support: Since faculties play a pivotal role in implementing educational innovations, their perception of the innovation will strongly influence their students thinking. In other words, for the innovation to be successful, the personal willingness of faculty to adopt and integrate innovation into their classroom practice is crucial. The faculty has a positive interinfluence effect on the students. Our hypothesis is Faculty Support for BL positively affects student's intention to adopt it (H7).

4 Research Methodology

4.1 Participants

In this study, 246 students participated (54 % male, 46 % female). All students were either typical undergraduate engineering students who were enrolled in the engineering curriculum of Computer Science, Mechanical Engineering or integrated Master of Science majors in Physics and Chemistry. They were all in the first year of their study and had physical labs as part of their curriculum. None of the students had any exposure to these experiments prior to this study.

4.2 Implementation Methodology

The students were randomly divided into three groups. All measurements targeted individuals and not the groups.

- PL: Physical Labs Only. This group of students performed experiments only under the Physical lab (PL) condition.
- BLEND1: Blended Labs. The second group performed experiments under Blended Lab condition (PL followed by VL).
- BLEND2: Blended Labs. The third group performed experiments under Blended lab condition (VL followed by PL).

In BL students were given a complete orientation on how to perform experiments under VL. The orientation included showing pages that listed the objectives of the experiment followed by the procedural sequence to performing the experiment and concluding with the assignment. Pointers to the critical features such as viewing the video that had an overview of the experiment followed by interactive animation, if available and use of online help were presented. All of the students had fair amount of experience using computers on a day-to-day basis. Similarly in the case of PL, students were given written description of the experiment, objectives and its background. The procedure was then described. Each student had an opportunity to perform one or two iterations of the experiment to collect the necessary data. The number of iterations students did in PL and VL were held constant. The post lab assessment questions were almost identical in most cases. In cases where physical measurements were taken (for e.g. of the bar magnet) in PL, this data was given for VL students. More flexibility and additional variable factors were available in VL, so students got deeper understanding of the physical concepts and the impact of variables. The feedback was collected from students from both the BLEND1, BLEND2 groups. The Likert scaled feedback questions were modified based on a pre-survey study of five students (2 males and 3 females). A total of 33 questions were given to them and discussions with them were held to ensure that the questions were unambiguous and more importantly pertinent to their experiences with the blended lab approach. The total count of questions was reduced to 26 after this initial pre-survey study.

4.3 Measures

The post lab questions administered to the students tested their scientific grasp of the experiments. Both in PL and VL, students tabulated data in identical formats. Mathematical manipulations were required after data collection to arrive at the stipulated results. No auto-calculation facility was provided in VL and derivations needed to be done on paper as in PL. The results from both PL and VL were graded.

4.4 Research Procedure

Experiments that pertained to characterization techniques in three distinct areas related to magnetism, mechanics and optics were chosen in this study.

Deflection & Vibration Magnetometers: This experiments involved understanding the magnetic dipole moment of bar magnets and the horizontal intensity of earth's magnetic field. This required several trial data to be collected for the period of oscillation of the bar magnet as a function of its size using the vibration magnetometer and then on the deflection magnetometer, where the directions of the magnets were varied between tanA, tanB and tanC directions to calculate the ratio of the dipole moment to the earth's horizontal intensity. In the VL scenario, a complete animation sequence showing the entire experiment is provided. The animation allows students to get a full feel of the experiment after reading the theory (Fig. 2). Using the simulation engine of the VL experiment, students were allowed to vary a set of factors as in the physical lab like the size of the magnet, stop watch, rotation of the graduated scale that seats the compass box and the orientation of the magnet. To note the compass readings a tabular spreadsheet allows the students to immediately the values they see on the stop watch, the compass and the scale. Other than feeling the weight of the magnet and other components, every other aspect of the experiment was successfully replicated on the VL experiment.

At the end of both PL and VL experiments, the students calculated the moment of inertia of the magnet, the dipole of the magnet, and horizontal intensity of the magnetic field. On the VL experiments, additional questions were asked to observe variations from using magnets of different sizes.

Determining Young's Modulus of a Material: The learning objectives of this experiment included deciphering the young's modulus of a material using uniform bending technique and the factors that influence it (Fig. 3). The material of the beam could be wood, aluminum, copper or steel. The beam is supported on two knife edges. The parameters that can be varied include: (1) the distance between the knife edges (2) the addition of weights to the two hangers suspended symmetrically from the beam (3) the distance between the suspended weights. By focusing a microscope on the small

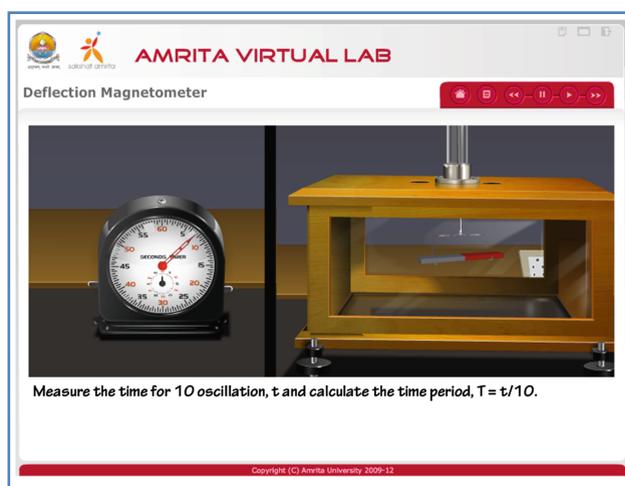


Fig. 2. Virtual Lab for Deflection Magnetometer



Fig. 3. Virtual Lab for Young's Modulus

deflections from bending and measuring it, the Young's modulus is calculated. In VL experiments, as in the PL, the microscope knobs can be adjusted to focus the crosswire on the pin mounted on the beam. The zoom feature allows accurate measurement of the beam deflection. There are two key distinctions between the PL and VL experiments in this case. They are (1) the beam width and thickness can be varied in VL and (2) the environment of the experiment with varying gravities can be easily changed in the VL. In PL, the beams are not varied and the experimental environment is a constant.

Measure Refractive Index using Prism Spectrometer: The learning objectives included understanding the methodology to determine the refractive index of a glass prism by measuring the angles of refraction of various spectral lines using a spectrometer (Fig. 4). The variables in the experiment are limited in that the prism is placed on the vernier table and the telescope is rotated to focus on the transmitted light. The most time consuming element in PL was training the students in the process sequence for accurate calculation of the angles. In VL with repeated attempts of changing the incident light and looking for the spectral lines of the transmitted light students were able to identify this minimum angle effortlessly and plug them into the Snell's law.

5 Results Analysis

SPSS and R were used to analyze the data. Some innovation attributes emerged as dominant and more relevant to the behavior intention under study. In this section we do a systematic testing of the various hypotheses starting with reliability, discriminant and convergent validity analysis. According to [18] for internal consistency, reliability Cronbach Alpha values of 0.70 and above is acceptable. In our study reliability of the seven factors had values ranging from 0.89 to 0.94. For discriminant validity analysis



Fig. 4. Virtual Lab for Prism Spectrometer

we confirmed that Average Variance Extracted (AVE) between the attributes were larger than off-diagonal elements and AVE’s were well above the recommended 0.50 level. Regression analysis was performed using all the 7 independent variables. Results are summarized in the Table 1. There is strong support for Hypothesis H1 (Relative Advantage), H2 (Compatibility), H3 (Ease of Use), H6 (Department Support) and H7 (Teacher support). The regression model was statistically significant ($p < 0.0001$) and accounting for 81 % of the variation in intention to adopt ($R^2 = 0.81$).

Further analysis of the two BL conditions (BLEND1, BLEND2) against the PL yielded interesting results (Table 2). Regardless of the order sequence of PL and VL within the BL, student learning outcomes under BL condition were better.

According to the independent t-test results to determine gender differences (Table 3), Male students were found more positive about adopting BL than Female students. The gender difference was significant for innovation attributes like Ease of Use, Relative Advantage and Trialability.

Table 1. Summary of Hypothesis results

Attributes		Beta	t-values	Result
Relative Advantage*	H1	0.41	3.56	Accepted
Compatibility*	H2	0.34	3.29	Accepted
Ease of Use*	H3	0.29	2.89	Accepted
Trialability	H4	-0.25	-2.14	Rejected
Observability	H5	-0.42	-2.45	Rejected
Department support*	H6	0.54	3.41	Accepted
Faculty support*	H7	0.49	2.94	Accepted
R^2	0.81			
Adjusted R^2	0.76			

* $p < 0.0001$

Table 2. Summary of Hypothesis results

Experiment		BLEND1 (PL, VL)	BLEND2 (VL, PL)
Deflection magnetometer	PL	t = -1.823 df = 97 p-value = 0.03859	t = -1.674 df = 97 p-value = 0.03525
Spectrometer	PL	t = -1.712 df = 97 p-value = 0.03261	t = -1.701 df = 97 p-value = 0.03471
Young's Modulus	PL	t = -1.852 df = 97 p-value = 0.03452	t = -1.734 df = 97 p-value = 0.03347

Table 3. Gender Differences in Attitudes towards Blended Labs

Attribute	Gender	Mean	SD	t value	p-value
RA Relative Advantage	Female	21	4	2.4446	0.007
	Male	22	4		
COM Compatibility	Female	10	2	1.027	0.15
	Male	10	2		
EOU Ease of Use	Female	13	2	3.2853	0.0005
	Male	14	2		
OBS Observability	Female	13	2	1.31	0.14
	Male	14	3		
TRI Triability	Female	13	2	2.7099	0.003
	Male	14	2		
DS Department Support	Female	11	2	0.5743	0.283
	Male	11	2		
FS Faculty Support	Female	13	2	2.2287	0.14
	Male	14	3		

Since student’s perception of faculty support emerged as a significant factor for adoption of Blended Labs, we looked at the shape of the resulting diffusion curve using intergroup influence adoption diffusion equations. It is intuitive to assume that the proportion of teachers is much less than that of the students. To illustrate different types of diffusion patterns we plot the $m(t)$ (Eq. 6) along with its two parts $\alpha f(t)$ and $(1 - \alpha)s(t)$ for different set of parameter values of p ’s, q ’s, α and μ (Table 4).

In Fig. 5, Case (1) deals with the situation of high faculty support for students and results in a bell shaped diffusion curve. Case (2) deals with the situation of very low faculty support which results in delayed start of adoption by students but still results in a bell shaped diffusion curve. Case (3) where there is low faculty support results in a bimodal diffusion curve as faculties have reached their peak adoption levels before the students start adopting. It is easy to observe that low values of faculty support results in delay of diffusion among students.

Table 4. Set of parameters for different diffusion patterns with varying levels of faculty support

Case	Faculty parameters	Student parameters	Level of faculty support (μ)	Proportion of faculty (α)
1	$p_1 = 0.02$ $q_1 = 0.4$	$p_2 = 0.005$ $q_2 = 0.2$	0.3 (high)	0.2
2	$p_1 = 0.02$ $q_1 = 0.4$	$p_2 = 0.005$ $q_2 = 0.2$	0.005 (very low)	0.2
3	$p_1 = 0.02$ $q_1 = 0.4$	$p_2 = 0.005$ $q_2 = 0.2$	0.05 (low)	0.2

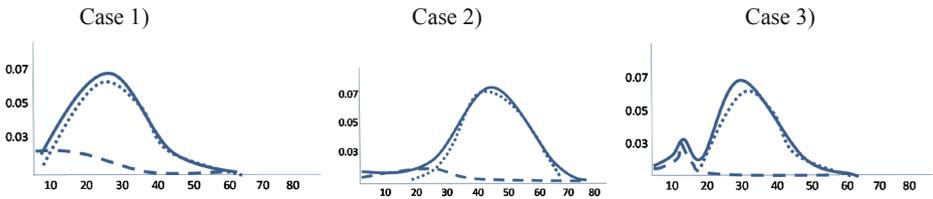


Fig. 5. Diffusion patterns based on students perception of varying levels of faculty support

6 Conclusions

Diffusion of Innovations framework when applied to blended learning in the context of lab education from this study showed its perception as a novelty and therefore an innovation by potential-adopter students. They ranked innovation attributes like Relative Advantage, Ease of Use, Compatibility, Department support and Faculty support as dominant factors. The Blended Labs innovation was better than the previous approach of using only Physical Labs or Virtual Labs (Relative Advantage); it was compatible with previously adopted idea of Virtual Labs (Compatibility); the concept was relatively easy to understand and use (Ease of Use); Students were able to try it out on a limited basis (Trialability), and finally the students could observe the results on the new Blended labs approach (observability). An interesting finding from our work is the emergence of Faculty support as a dominant factor for adoption of Blended Labs which confirms that for an educational innovation to diffuse both faculty and student adopters have to be targetted. Low levels of faculty support generally results in delayed diffusion among students. Our study results also indicate strong positive learning outcomes under BL when compared to PL though within BL, order sequence of PL and VL was not significant. For certain innovation attributes like Relative Advantage, Ease of Use and Trialability gender differences were significant. Unlike the difficulties faced with blended courses due to lack of teacher adoption [19] the data in this paper shows acceptance of blended approach to lab experiments by students. [20] noted ‘Blended learning should be viewed as a pedagogical approach that combines the effectiveness and socialization opportunities of the classroom with the technologically enhanced active learning possibilities of the online environment’. The blended labs combine the best elements of physical labs and virtual labs.

An activity like lab experiment, whether done through Virtual Labs or Physical Labs is reasonably equally effective if the students performing them are cognitively active by constructing the experiments. Such a constructivist learning is supported by Blended Labs. The value of enhancing students skills by integrating virtual labs with physical labs not only provides improved conceptual learning but provides an ideal strategy to scale laboratory infrastructure easily.

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