# WHEN TECHNOLOGY-BASED LEARNING IS THE ONLY OPTION: EVALUATING PERCEIVED USEFULNESS OF SOCIAL MEDIA

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## ABSTRACT

During unusual times involving discontinued face to face sessions in formal education settings, mobile learning (m-learning) involving social networking sites has become a popular alternative since students are always in possession of handheld electronic devices. When connection through technology was the only option due to social distancing in current pandemic, students who were already active extensive users of social networks found online learning as a new way of getting formal education. The objective of this study was to explore how the state of student's behavioral intention for social media based online learning is driven by external factors like subjective norm and self-efficacy. To fulfill this aim, this study uses a quantitative approach to study the factors that mediate the decision behavior of students towards social media employed as a learning platform and use of m-learning involving social networks. A sample of management science students (n= 255) from four universities participated in the research. Analysis of data suggested that subjective norm and self-efficacy were significant predictors for student participation in e-learning initiatives involving social media and networks. The proposed serial mediation model revealed that self-efficacy and perceived usefulness in that order were playing a positive significant role in student use of social networking for learning. No significant differences were observed between either gender when self-efficacy, perceived usefulness, and use of social media in education were considered.

**Keywords:** E-learning, m-learning, social media, serial mediation, technology based learning.

## INTRODUCTION

The use of electronic and digital communication technologies has revolutionized student learning and has helped in playing a vital role in changing perceptions towards e-learning. Learning evolved from behaviorism through cognitivism, moving on to social constructivism thereby taking a path from knowledge that was communicated to one that was negotiated and then became collected knowledge (Kundi & Nawaz, 2010). Considering the positive aspects of e-learning specifically in the context of being asynchronous and location independent, it easily accounts for different learning styles due to its ability to distribute personalized content in a more comfortable and adjusted learning environment (Zaric et al, 2018). A noteworthy increase in learning and academic effectiveness is possible by employing e-learning when it is put into practice by giving importance to requirements of the learners (Bennet, 2008; Hakak et al, 2019). Self-regulated learning and material that supports it clearly are key aspects of online learning. Face to face learning is preferred when shared understanding is needed when communicating or when interpersonal relations are vital (Paechter & Maier, 2010). Self-regulated learning skills among students are essential for successful adoption of e-learning programs because students will not be subject to teacher-dependent instructional methods (McConnell, 2017). Popularity of multimedia based e-learning systems cannot be ignored. According to Dongson & Zhou (2003), e-learning delivery with interactive multimedia helps learners develop better understanding and they perform in a manner comparable to classroom learning. Rapid changes in educational world are causing rapid changes to the learning and teaching strategies of higher education institutions (Almaiah et al, 2020; Vershitskaya et al, 2020). Many have started to provide virtual learning opportunities and others are employing the Internet to deliver online educational content in addition to traditional methods of education (Erich & Vargolici, 2008). However, it was also suggested that use of ICT based education alone was insufficient to improve educational outcomes (Kirkwood 2009). Expectations of students with regards to learning and assessment were equally important. Similarly, the practices and beliefs of the faculty regarding teaching and assessment were important due to their impact on the learning process experienced by the students. Bowers and Kumar (2017) studied teacher and social presence in online learning environment and found that it was stronger in such an environment as compared to traditional classroom.

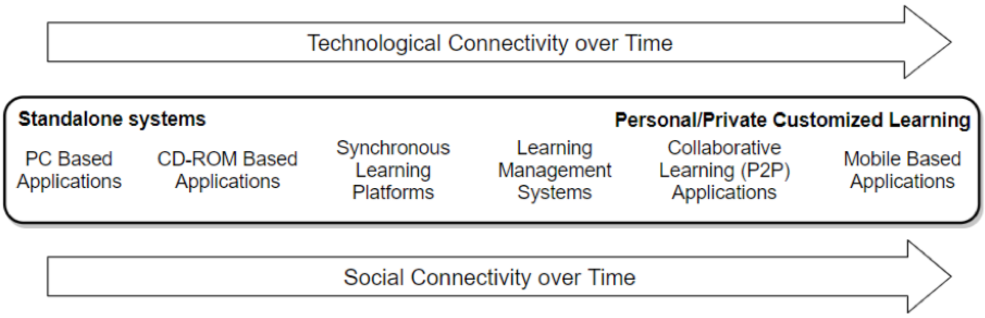


**Figure 1.** Evolution of Learning Systems over Time

Technological advancements in Internet and then mobile technologies have revolutionized learning systems by increasing both technological and social connectivity over the years as seen in Fig 1. The present era of the Internet has transformed social interactions to new levels. Immediate access to information is available through mobile devices having great potential to change the way students are learning and educating themselves beyond the classroom. Social media is extremely popular among young college students. Websites and corresponding mobile applications like Facebook, WhatsApp, Instagram, Twitter, Snapchat and YouTube are among the most common ones these days (Al-Abdullatif & Aladsani, 2021). Among college students, sharing of ideas and information through social networks is emerging in the educational context as well. While students of engineering and computer sciences are expected to learn new technologies in their academic curriculum, students of management sciences are not left behind when uses of mobile technologies for learning are considered and explored. These students readily understand the benefits of social media assisted technology-based learning (Vate-U-Lan, 2020). Identifying the role of factors affecting technology adoption for learning is the central idea of this research.

This research study is based upon the theoretical framework of the Technology Acceptance Model (Davis, Bagozzi & Warshaw 1989) and explores how the state of student's behavioral intention for social media based online learning is driven by external factors like subjective norm and self-efficacy. These factors associate with and influence perceived usefulness of technology and thereby motivate subsequent use of technology for learning purposes. The next section begins with an account of the past researches conducted in this area and identifies the proposed hypotheses to be tested. The methodology, description of the data, and results of the analyses are presented. Finally, the discussion on results is provided and the paper concludes with mentioning implications and limitations of the research.

## REVIEW OF PRIOR RESEARCH

It is important to understand how learning theories have evolved over time as technology developed over the years. Three main learning theories, behaviorism, cognitivism, and constructivism were widely known before the impact of technology on learning changed everything (Schunk, 1996). The traditional approach of teaching and learning is an approach where the teacher is in control and a source of information. This approach is still practiced in higher education institutions but the development of technologies has made the student responsible for his activities and learning. Fig 2 shows the key features of learning theories.

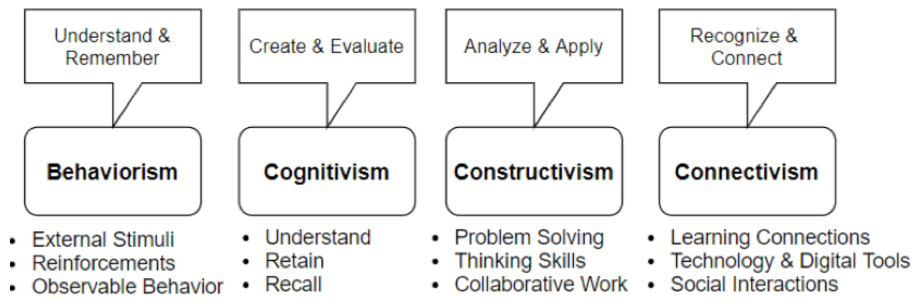


**Figure 2.** Learning Theories

A key reason is the limitations of the three mentioned learning theories, that they do not address learning which takes place through usage of technology. Moreover, these theories are not focused on the value of what is being learned. Learning or actionable knowledge can be present within an organization or a database (outside an individual) and is targeted on making and connecting specialized information sets which enable our learning (Siemens, 2004). Connectivism was proposed by Siemens (2004) characterizing it as the theory of the digital age which considers the presence of computer networks and contemplates the knowledge and abilities as a consequence of reciprocated interconnection of information and individuals. Technology has brought students closer than before to multiple knowledge sources previously unreachable and they can interact with other teachers and connect to students located anywhere. It is due to technology that a large number of people have been connected to continuing education and lifelong learning opportunities. It was previously unthinkable that anyone could be allowed to enroll in a course for learning. However, technology-based education made this possible. Massive open online courses (MOOCs) are based extensively on mutual interconnections between learners as a way of imparting modern education making connectivism very relevant as it influences those taking these courses and trying to apply it in teaching and learning (Bell, 2011; O'Connor, 2014).

Advances in information and communication technologies have reached new heights consistently. Mobile phone penetration in the masses is increasing in every country. Linking this development with technology-based learning, mobile technologies and the widespread use of smartphones among students has made mobile learning (m-learning) a significant educational technology element in higher education. Since students are connected to each other through social networks, m-learning makes it promising for students to learn, cooperate, and share ideas and educational material with each other using this technology. Use of social networks in education has been widely researched and it has been proven that teaching and learning undertakings in educational segments can be enhanced by using social networks and e-learning tools (Balakrishnan, 2014; Rennie & Morrison 2013; Al-Emran et al, 2016).

Since social media has integrated itself into everyday lives, scholars have argued for its integration as an educational tool in order to mediate and enhance instruction delivery and promote active learning in students (Tess, 2013). However, some pedagogical issues or institutional constraints are likely to limit and restrict social media use in classrooms and instructors may not be inclined to integrate them in their teaching practices (Manca, S., & Ranieri, 2016). Although perceived basically for non-academic use, students were positive using Facebook instructionally as compared to the faculty. However, time brings rapid changes towards technological attitudes as evident by progress made in the last few years, and it can be stated that social media will have a greater role to play in education (Roblyer et al, 2010; Klimova & Poulova, 2015).

Advantages gained by using mobile devices in student learning are primarily quick access to information and offering ways of communication and collaboration in different ways to fulfill student needs. Mobile devices coupled with social media and networks have shaped prospects for interaction and collaboration. Other uses include social media for content creation and sharing besides communication and working with web-based tools having continuous connectivity (Ortiz & Green, 2019; Gikas, J., & Grant, 2013). Use of social media for cooperative learning was studied and significant relationships were found between perceived usefulness and collaborative learning with intent to use social media for learning (Al-Rahimi & Othman, 2013). Hence, use of social networking sites (SNS) and social media with related technologies for learning is identified as a variable of primary interest in this research.

The issue of technology based learning to be accepted as a way of imparting education in universities then becomes a matter of technology acceptance with a requirement to explore factors that cause users to accept and utilize newer technologies for learning. The Technology Acceptance Model (TAM) suggests a number of factors influencing the decision about how and when users will use the new proposed technology (Davis et al, 1989; Shao, 2020). However, in case of technology based learning systems, as already mentioned, some additional factors need to be considered. Technology based systems require a study of variables from cognitive and social domains with knowledge of learner's personal characteristics in their design and employment (Siadaty & Taghiyareh, 2008). Therefore, it follows that technology acceptance depends upon a number of factors that need to be researched. TAM proposes two primary concepts (Davis, 1989). First, perceived usefulness (PU) is the extent to which a learner believes using technology will increase his or her learning. Secondly, perceived ease of use (PEOU) implies that using technology for learning will be free of mental and intellectual effort. TAM has been widely explored in the educational field to evaluate the effect of PU and PEOU on student learning through acceptance and use of e-learning initiatives (Park, 2009; Park, Nam & Cha, 2012).

The present study uses a theoretical framework based upon TAM to explore the approach of technology acceptance as behavioral aspect of technology adoption. The same has been studied in different researches in the past in different contexts. Factors affecting attitude toward utilizing social media through factors like PEOU and PU were identified (Woojin Lee et al, 2013). For example, in an Australian study, the findings indicated that perceived usefulness and management support were significant in explaining technology adoption (Talukder, 2012). As far as personal factors were concerned, student self-efficacy was found to be an important variable to understand user's acceptance of e-learning and the attitude towards its adoption (Park, 2009). Social factors have been reported to influence technology acceptance (Niehaves et al, 2012). Rupak (2014) studied technology adoption behavior of social network sites and support the technology acceptance model for their evaluation process. In the cooperative learning environment, the ability to share information impacts intent and attitude toward technology acceptance and adoption (Chung and Veugel, 2013). Another study related to use of mobile learning confirms the validity of the technology acceptance model and highlights student attitude as the most important construct to use technology (Coelho Junior et al, 2019; Park et al, 2012).

External factors have been studied and found to be important determinants of technology adoption. This research focuses on the relationship of self-efficacy and subjective norm towards technology adoption. Self-efficacy (SE) has been identified as a commonly occurring external factor of TAM in literature. Computer Self-Efficacy (CSE) is what an individual believes is their ability to undertake a certain task using the computer (Kher, Downey, & Monk, 2013; Vekiri & Chronaki, 2008). There is a commonality between computer literacy and anxiety as the constructs having an influence in terms of positive or negative self-efficacy because those who perceive computers as too complex and think they are not able to use computers will avoid those (Lee & Huang, 2014). On the contrary, users of computers in early life have much lower computer anxiety and hence a greater technological self-efficacy (Shank and Cottec, 2014). This advocates that learners having higher technological self-efficacy are more certain to adopt e-learning and computer supported education (Celik & Yesilyurt, 2013; Chang et al, 2014; Pellas, 2014).

Subjective Norm (SN) relates to the influence a person has on his or her perception or thinking caused by people close to him or her about performing a certain behavior (Venkatesh et al., 2003). In case of e-learning in an educational context, it is about the influence of family and friends on a student's inclination to use e-learning. Subjective norm could also be considered like an environmental or peer pressure which a student feels or considers to practice e-learning (Agudo-Peregrina et al. 2013). It is commonly observed in real life that a person gets influenced by people who are valued. Similarly, if a student is influenced by closer ones into adopting e-learning in addition to regular classroom education, he or she is very likely to give due importance to these suggestions and will consider using e-learning initiatives. Here, an intrinsic motivator in form of subjective norm influences student behavior by making a positive attitude towards use of e-learning (Park et al, 2012). To generalize this argument, it could be concluded that affirmative beliefs about use of technology-based learning and its applications in real life could be brought about by people who are close, respected and valued. Decisions regarding technology adoption among males and females have been linked to subjective norm, attitude towards technology and usage behavior.

Although the relationship between SE and PU has been studied in the past and an average medium effect size has been reported by Abdullah & Ward (2016), this research explores the serial mediating effect of SE and PU (in this order) on use of social media for learning. To the best of the author's knowledge, this serial mediation model and corresponding relationships have not been explored in previous studies and therefore considered a significant contribution of this research. Previous researches have reported findings highlighting both significant differences and no differences among males and females as far as technology adoption and use was concerned (Ramirez-Correa et al, 2015). Relevant hypotheses have been developed and are presented in the next section.

## RESEARCH HYPOTHESIS

Given the theory and evidence from the literature above, it is hypothesized that SN is related to use of social media for learning through SE first and then PU. Integrating the two models with mediation through SE and with mediation through PU suggests a three-path serial mediation model, depicted in Figure 1 (Hayes, 2013). It was tested whether self-efficacy and perceived usefulness sequentially mediate the relationship between subjective norm and social media use for learning. Moreover, the hypotheses that PU, SE and SN scale scores are significantly different across gender and program groups is also presented. The following hypotheses are being proposed according to the previously stated objectives:

- H1: The relationship between subjective norm (SN) and use of Social Media (USM) for learning is mediated by self-efficacy (SE).
- H2: Perceived Usefulness (PU) mediates the relationship between subjective norm (SN) and use of Social Media (USM) for learning.
- H3: The relationship between subjective norm (SN) and use of Social Media (USM) for learning is sequentially mediated by self-efficacy (SE) and perceived usefulness (PU).

## METHOD

In order to achieve the research objectives, quantitative research method was applied to collect data for further processing and analysis. This study utilizes cross sectional survey research design involving data collection from university students through a group administered questionnaire. The data for analysis was collected from students who were using social media and the internet for learning in addition to routine classroom education. The questionnaire used in this research was adapted from Park, Nam & Cha (2012) and Park (2009).

### Participants

To undertake data collection, an online questionnaire was used and 301 usable responses with no missing data were received. A stratified sampling approach was used to select management science students from four universities in the Islamabad and Rawalpindi region. This data was considered statistically adequate for analysis purposes. Considering the requirements of sample size, the acceptable sample size limit would require a 10:1 ratio between responses and variables to be analyzed (Hair & Anderson et al, 2010). Hence, the original sample size of 301 for this research was considered appropriate as it was more than the minimum requirement of 220 cases for this research. For closed ended questions, five point Likert-scale was used. The reliability statistic (Cronbach alpha) was 0.91 indicating high internal consistency. Amongst the respondents, 68 percent were males and 32 percent were females. The institution and program-wise distribution of participating students after data screening is given in Table 1.

**Table 1**. Demographic Features of Respondents

| Variables | | f | % |
|---|---|---|---|
| Institution | Public Sector | 117 | 45.9 |
| | Private Sector | 138 | 54.1 |
| Program | Undergrad Year 1 & 2 | 48 | 18.8 |
| | Undergrad Year 3 & 4 | 70 | 27.5 |
| | Graduate (Masters) | 137 | 53.7 |
| Gender | Male | 175 | 68.6 |
| | Female | 80 | 31.4 |

The autonomy of individual respondents for this research was given due consideration by the researchers and all participation in the survey was voluntary. Confidentiality of participants and informed consent were specifically ensured. All participants were informed that their identity and individual responses were to be treated as anonymous and utilized only for the purpose of this research.

## Data Preprocessing and Screening

From the 301 collected responses, 43 cases (28 males and 15 females) were removed owing to unengaged responses to the Likert scales (stdev < 0.50) leaving a sample size of 258. Multivariate outliers in the data were checked using Mahalanobis distance and three cases were identified and removed as outliers (Tabachnick & Fiddell, 2013) leaving the total number of cases to 255 as the final sample size for further analysis. All data analysis was done using SPSS® software and mediation analysis was done using the PROCESS computational tool (Hayes, 2012).

## FINDINGS

The mean, standard deviation, correlations, and reliability (Cronbach alpha) values for the study variables are given in Table 2. The Pearson's correlation coefficient values between the constructs under study represent all moderate to strong positive and statistically significant associations. There is no negative correlation as expected in this study. Since these are self-reported measures, common method bias was considered and evaluated through Harman's single-factor test approach (Podsakoff et al, 2003). Since the items did not significantly load onto a single factor, it was ascertained that there was no common method bias in the collected data.

**Table 2.** Correlation Matrix for the Variables

| Variables | (1) | (2) | (3) | (4) | M | SD | (α) |
|---|---|---|---|---|---|---|---|
| (1) USM | 1 | .584** | .642** | .396** | 3.61 | .032 | 0.84 |
| (2) PU | -- | 1 | .553** | .429** | 3.60 | .055 | 0.77 |
| (3) SE | -- | -- | 1 | .437** | 3.72 | .071 | 0.85 |
| (4) SN | -- | -- | -- | 1 | 3.59 | .055 | 0.84 |

Note: ** Correlation is significant at 0.01 level (2-tailed), N=255, p=.000

USM: Use of Social media, PU: Perceived Usefulness, SE: Self-efficacy, SN: Subjective Norm

The mediation hypotheses testing approach directly tests the indirect effect between predictor and the response variable through the two mediators in series using a bootstrapping procedure (Hayes, 2013). The tests were undertaken by following serial mediation model 6 using the PROCESS software for SPSS (Hayes, 2012). To test the mediation hypotheses, it was established whether the relationship between subjective norm and social media use were mediated by self-efficacy and perceived usefulness in the same order. Fig 3 shows these mentioned paths with path coefficients. Initially, the total direct (c) for subjective norm was significant (0.492, 95% CI= [0.351, 0.653], t= 6.861, p= .000). After the mediating variables were incorporated in the order given, the direct effect (c') was reduced to non-significant level (coefficient=0.09, t=1.374, p=0.171). It was observed that the effect of subjective norm on social media use was fully mediated by the two mediators. Hypothesis H1 and H2 were supported as evident from statistically significant path coefficients in Fig 3. Further explanation is offered in subsequent paragraph. The total indirect effect (coefficient=0.40) and the significance of this indirect effect were tested using bootstrapping procedures. Unstandardized indirect effects were calculated for 5000 bootstrapped samples, SE=.063 and the 95% CI = [0.29, 0.54]. Thus, the indirect effect was statistically significant. These results supported the mediation hypothesis H3. The specific indirect paths are explained subsequently.

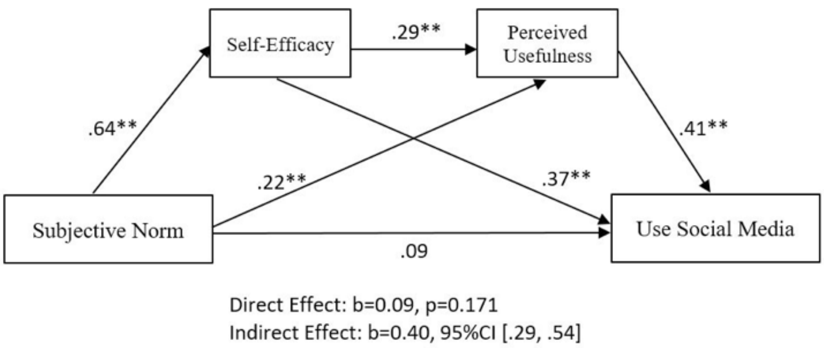


**Figure 3.** Three Path Mediation Model with Regression Coefficients

The estimates of indirect effects and the 95% bias corrected bootstrapped confidence intervals for path estimates are provided in Table 3. Hypothesis H1 stated that the relationship between SN and USM for learning is mediated by SE. This hypothesis is supported. Hypothesis H2 stated that PU mediates the relationship between SN and USM for learning and this hypothesis is also supported. As per hypothesis H3, the relationship between SN and USM for learning is sequentially mediated by SE and PU. This hypothesis was also supported.

The analyses conducted shows that self-efficacy mediated the relationship between subjective norm and perceived usefulness, and that perceived usefulness mediated the relationship between subjective norm and social media use. Formal testing of hypothesis H3 concluded that subjective norm was positively associated with self-efficacy and perceived ease of use, which related to use of social media for learning.

**Table 3** Path Coefficients and Indirect Effects for Mediation Models

| | Path Coefficients | | | Indirect Effects | |
|---|---|---|---|---|---|
| | Use SM | SE | PU | Estimate | Bootstrap 95% CI |
| SN | 0.09 (0.06) | 0.64 (0.08) | 0.22 (0.05) | | |
| SE | 0.37 (0.05) | | 0.29 (0.04) | | |
| PU | 0.41 (0.07) | | | | |
| Total | | | | 0.40 (.06) | 0.29, 0.54 |
| Ind1 | | | | 0.24 (0.05) | 0.15, 0.35 |
| Ind2 | | | | 0.08 (0.02) | 0.04, 0.13 |
| Ind3 | | | | 0.09 (0.04) | 0.03, 0.17 |

*Note: N = 255. Bootstrap confidence intervals were constructed using 5000 samples. Standard error in parentheses. SN: Subjective norm; SE: Self-efficacy; PU: Perceived usefulness*

*Total effect (Sub Norm → UseSocMed ) = 0.49 (.07)*

*Ind1: Sub Norm → SelfEffi → UseSocMed*

*Ind2: Sub Norm → SelfEffi → PercUsef → UseSocMed*

*Ind3: Sub Norm → PercUsef → UseSocMed*

## DISCUSSIONS AND CONCLUSION

Widespread availability of mobile technology and corresponding increase in social media use has provided ubiquitous tools for social connectivity in everyday lives. The frequent use of smartphones by the young generation have provided for an emerging mode of learning, where social media is used in the mobile learning mode. Since over 80 percent of students' own smartphones, the omnipresence of social media and its usage is evident at institutes of higher education. The primary objective of this study were to ascertain the relationship between subjective norm (beliefs of students towards usefulness and suitability of e-learning) and the actual use of social media in education. This research found a significant relationship between the two, meaning that students find e-learning useful and are thus willing to incorporate the social networking into formal learning by using relevant tools in practice. These results are consistent with the findings of Morbey, Sabeti & Frank (2014) who observed that majority of students in their study were willing to incorporate social media into higher education and faculty members were also capitalizing upon existing social media strengths of students to improve formal academic practices (Stathopoulou et al, 2019). Using technology in education that is relevant (as it fully supports the connectivism theory) and familiar to students is a positive sign since it does not require any complex training to develop expertise for its use. In another study, it was found that students participating in Facebook study groups were learning and performing better in university studies (Cuesta, Eklund, Rydin & Witt, 2016), however, the integration of social networking in education is a choice that each instructor could make at their own level (Tess, 2013).

Secondly, this research explored the mediating roles of self-efficacy (SE) and perceived usefulness (PU) towards social media use in education and a positive relationship was observed between them in this research. SE and PU have been separately studied in many researches and positive significant associations have been observed between them and intention to use and actual use of technology for learning. However, this research makes an additional contribution to the literature by finding significant mediating effects of these constructs. A positive relationship between SE and PU with an average medium effect size has been reported by Abdullah & Ward (2016) after reviewing the relevant literature and the present research is in agreement with the finding with the additional serial mediating effect of SE and PU (in this order) on use of social media for learning.

The effect of SN on e-learning acceptance has been established in this research and significant positive relationship has been found which is in agreement with previous studies done on the two constructs (Abdullah & Ward, 2016; Park, 2009; Choi & Chung, 2013; Hanif, Qaisar & Imran, 2018). While SN is like an extrinsic motivational factors, it is found to strongly influence student intention to use social media for learning and with the significant mediating effects through self-efficacy and perceived usefulness on social media adoption, the implications of these findings are vital. Students who are already users of the technology primarily for social interactions need to be encouraged by the faculty to use it for learning purposes and accept the change caused by the ubiquitous interconnected environment that supports education and learning across any boundaries. The positive influence of subjective norm can then come from the faculty and administration who must make it easier for students to adopt mobile based social media assisted e-learning as such experiences will be valuable for their forthcoming professional lives.

Considering the role of gender on self-efficacy, this research did not find any significant differences between males and females and found them equally self-sufficient to use technology. Although technology is traditionally thought of as male dominated, this is changing rapidly as far as technological advancements in ICT are concerned. The respondents of this study were undergraduate and graduate students and the results are in agreement with studies which concluded that higher levels of technological proficiency and self-efficacy existed in students of age group 18 to 25 years (McCoy, C. 2010). Moreover, male learners did not have added self-efficacy and affirmative attitude than females concerning the use of technology (Yau and Leung, 2016; Al Qaysi et al, 2019). That explains why there were no significant differences between undergraduate and master's students as far as self-efficacy and perceived usefulness were concerned. Young students are more technology savvy and gender differences drop intensely among the younger group and a unisex pattern of equality emerges as far as technological self-efficacy is concerned (Morris, Venkatesh, & Ackerman, 2005).

The technology acceptance model has been studied extensively in previous researchers, however, very few researches have attempted to explore and understand the mediating effects of external factors of technology adoption for social media based learning. This study explores TAM in current learning environments where majority of the students have access to mobile technology for learning. Hence, the significance of this research is to identify underlying factors that mediate and influence students' intents to use innovative learning technologies that involve social networking applications. Collaborative technology and its adoption for learning is largely influenced by near ones as seen by the positive relationship discovered in this study. The perceived usefulness of these technologies is important and regardless of gender or level of education, subjective norm and self-efficacy of the students are positively associated with technology-based learning.

Practical implications for this research can be seen in times like the COVID-19 pandemic when the only way left for continuation of formal education was through the use of technology. Adding to problem was a situation where face to face meetings became impossible and student collaboration through social networks took over as a new norm. Since students are deeply involved in use of mobile technologies for social use, there is a need to use research on effective learning strategies that help students connect with technology by engaging them to promote collaborative learning. Course material and assignments preparation efforts by the faculty with the additional use of personal mobile devices can help expand student engagement by leveraging blended learning opportunities.

## Limitations and Future Research

One limitation of this research study is sampling of students from four universities only and may limit the boundaries of generalizing the drawn conclusions from the analyzed data. Other variations could be explored in the research model by adding more dimensions to explain student participation in e-learning initiatives. For example, attitude towards learning technologies and personal characteristics of learners are dimensions that can be explored to explain student participation in future research. Additional research can link more external factors with the studied outcome variables along with their mediating and moderating effects on the behavioral intention of technology adoption to make users acceptance of e-learning programs a success.

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