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Technology Acceptance and Self-Directed Learning: Mediation Role of Positive Emotions, Learning Motivation and Technological Self-Efficacy

Boniface Aabeyir[1]*, Raymond Aabeyir[2], Samuel Amoako[3], Francis Ohene Boateng[4]

[1,4]Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development, Ghana.
[2]Simon Diedong Dombo University of Business and Integrated Development Studies, Ghana
[3]Akrokerri College of Education, Ghana

*Corresponding author: bybaabeyir@gmail.com

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Abstract

This study investigated the relationship between technology acceptance and self-directed learning among students in the colleges of education in the Ashanti region of Ghana, with a focus on the mediating roles of positive emotions, learning motivation, and technological self-efficacy. With a sample of 237 students and employing Smart Partial Least Squares Structural Equation Modelling, the study revealed that technology acceptance positively influenced technological self-efficacy, learning motivation and positive emotions. The study also indicated that technological self-efficacy and learning motivation insignificantly predicted students' self-directed learning, while positive emotions significantly predicted students' self-directed learning. The analysis identified learning motivation and technological self-efficacy as insignificant mediators in this relationship, but positive emotions positively and significantly mediated the relationship. It is recommended that the Colleges of Education in Ghana should focus on increasing student's confidence in their technological abilities through targeted training programmes and support resources.

Keywords: Learning motivation; Self-directed learning; Technology acceptance; Technological self-efficacy;

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1. Introduction

Technology now plays a crucial role in modern education, impacting students' engagement with the learning process. Smith and Anderson (2018) claim that the use of technology in the classroom has completely changed how kids learn by providing them with individualised and interactive learning opportunities. Furthermore, Johnson et al. (2020) discovered that more student interest and engagement are fostered by technology-enhanced instruction, which improves academic performance. Dynamic and interactive learning experiences are facilitated by the use of technology in the classroom. Tools such as multimedia presentations, educational apps, and virtual simulations enable educators to consider diverse learning styles and adapt their teaching methods accordingly (Jones, 2019). Furthermore, the use of Learning Management Systems (LMS) like Moodle and Canvas streamlines administrative tasks and provides a centralised platform for content delivery, communication, and assessment (Clark & Mayer, 2021). Technology-driven classrooms stimulate students' curiosity and encourage involvement. Interactive whiteboards, gamified learning modules, and virtual reality simulations offer immersive learning experiences that stimulate curiosity and creativity (Gupta & Sood, 2022). Moreover, online collaboration tools and discussion forums facilitate peer interaction and knowledge sharing, promoting collaborative learning and critical thinking skills development (Wang et al., 2023). Empirical evidence suggests that technology integration correlates positively with academic achievement. A meta-analysis conducted by Wang and Baker (2019) revealed a significant effect of technology-enhanced instruction on student learning outcomes across various subjects and grade levels. Moreover, instructors may monitor student progress, spot learning gaps, and offer prompt intervention tactics to encourage tailored learning with the help of adaptive learning platforms and data analytics technologies (Freeman et al., 2020).

Self-directed learning entails individuals taking charge of their learning journey and assuming responsibility for making various decisions pertaining to it (1975). One essential component of education that gives people the ability to take charge of their own learning outcomes and processes is self-directed learning. It is a vital skill for lifetime learning and has drawn a great deal of interest from scholars worldwide (Bolhuis, 2003). Self-directed learning is influenced by elements such as positive emotions and self-efficacy (Pekrun et al., 2002 & Sumuer, 2018). Feelings that fall under the category of positive emotions include joy, happiness, thankfulness, and satisfaction. They contribute to psychological well-being and are associated with improved cognitive functioning, social interactions, and overall life satisfaction (Fredrickson, 2001; Lyubomirsky et al., 2005). On the other side, self-efficacy is the conviction that one can carry out particular tasks and reach desired objectives. It is a fundamental idea in psychology that was put forth by Albert Bandura in his social cognitive theory. Beliefs in one's own abilities have an impact on one's thoughts, emotions, motivation, and behaviour. High self-efficacy people are more likely to set difficult objectives, keep going in the face of difficulties, and show more resilience in the face of failure (Bandura, 1977). The urge or desire for people to pursue their educational objectives and participate in learning activities is known as learning motivation. It includes elements that affect a person's motivation to devote time and energy to learning, including interest, curiosity, intrinsic rewards, and extrinsic incentives (Deci & Ryan, 2000).

The degree to which people actively engage in learning situations, persevere in the face of difficulties, and eventually meet learning objectives depends critically on their motivation. The propensity of people to adopt and use technology in educational settings is referred to as technology adoption (Davis, 1989). Technology integration in the classroom has the potential to improve self-directed learning by giving students access to a multitude of tools and resources. However, there is a complicated relationship between self-directed learning and technology acceptance that is influenced by a number of variables, such as positive emotions, learning motivation, and technological self-efficacy. Numerous elements that affect self-directed learning have been connected to the acceptance of technology in educational settings.

The literature on the relationship between technology acceptance and self-directed learning is becoming more and more abundant. However, it still lacks specific mechanisms that examine how positive emotions, learning motivation, and technological self-efficacy mediate this relationship. Many previous studies have investigated the direct relationship between technology acceptance and self-directed learning, failing to consider the mediating roles of positive emotions, learning motivation, and technology self-efficacy (Davis, 1989; Bandura, 1997; Zimmerman, 2002). For instance, Rashid & Asghar only investigated the interrelations of technology use, self-directed learning, student engagement and academic performance. Pan (2020) investigated the effect of technology acceptance and technological self-efficacy on students' attitudes toward technology-based self-directed learning, with learning motivation as the only mediator. An et al. (2022), while examining the connection between technology acceptance and self-directed learning, considered the mediating roles of only positive emotions and technological self-efficacy without considering the role of learning motivation. This oversight limits our understanding of how these factors interact and influence each other in educational contexts. For instance, while technology acceptance is crucial for engaging in self-directed learning, the influence of positive emotions and motivation, along with self-efficacy related to technology use, is often neglected (Venkatesh et al., 2003; Schunk & Zimmerman, 2012). Addressing this gap will enhance our comprehension of how to leverage technology effectively to support self-directed learning, particularly among students in Ashanti Region Colleges of Education.

This study aims to explore the mediation role of positive emotions, learning motivation, and technological self-efficacy in the relationship between technology acceptance and self-directed learning. The specific objectives of the study are to: (i) determine the direct effects of technological self-efficacy, learning motivation and positive emotions on students' self-directed learning, (ii). determine the direct effect of technology acceptance on technological self-efficacy, learning motivation and positive emotions, and (iii) identify the mediating effect each of technological self-efficacy, learning motivation and positive emotions on the relationship between technology acceptance and self-directed learning.

1.1 Literature Review

The literature on technology acceptance and self-directed learning highlights the importance of understanding how individuals perceive and interact with technology in educational settings. Gibbons (2003) suggests that self-directed learning equips students to be proactive learners capable of adapting to the changes brought about by the Fourth Industrial Revolution. Mirzawati, Neviyarni & Rusdinal (2020) view self-directed learning as an independent study in which an individual puts in efforts aimed at achieving academic competency. According to Knowles, as referenced by Esham and Abdul (2010), self-directed learning involves learners taking charge of their own educational process. This includes identifying their learning needs, setting goals, selecting resources, employing appropriate strategies, and evaluating their learning results, either independently or with some assistance. Davis's Technology Acceptance Model (TAM) highlights that perceived ease of use and perceived usefulness are crucial factors influencing technology acceptance (Davis, 1989). Additionally, positive emotions like enjoyment and satisfaction have been shown to improve technology acceptance and increase participation in learning activities (Fredrickson, 2001). This is particularly relevant for self-directed learning among students, including those at Colleges of Education in the Ashanti Region.

1.2 Theoretical Framework

The theoretical framework for examining the relationship between technology acceptance, technological self-efficacy, learning motivation, and self-directed learning draws from several key theories in psychology and education. These theories provide a lens through which to understand how individuals interact with technology, perceive their abilities, and engage in learning activities.

According to Davis's Technology Acceptance Model (TAM), created in the 1980s, an individual's desire to use technology is mostly determined by how beneficial and easy they perceive it to be. TAM states that people are more likely to accept and adopt technology if they believe it to be helpful and simple to use. This paradigm has been extensively utilized to comprehend the acceptance of technology in diverse settings, such as supporting students in engaging in self-directed learning.

Social cognitive theory (SCT), put out by Bandura, places a strong emphasis on the part that self-efficacy plays in behavior. Self-efficacy is the conviction that one can carry out actions and accomplish objectives. Technological self-efficacy, as it relates to technology use, is a person's belief in their capacity to use technology efficiently. SCT also highlights the value of observational learning, in which people pick up knowledge by watching other people. According to SCT, people who have high levels of self-efficacy are more likely to take the initiative and stick with learning tasks through difficulties when it comes to self-directed learning. A student’s self-efficacy regarding technology use can significantly affect their acceptance of new educational tools. If students believe they can successfully use a particular technology, they are more likely to embrace it. Strong self-efficacy motivates students to take initiative and persevere through challenges, which improves autonomous learning. Students are more likely to participate in self-directed learning when they have confidence in their abilities to use technology tools efficiently.

Self-determination theory (SDT) emphasizes intrinsic and extrinsic motivations for behaviour. Individuals have three fundamental psychological demands, according to SDT: relatedness, competence, and autonomy. The desire for self-direction and control over one's behaviour is referred to as autonomy. Feeling effective in one's relationships with the environment is a prerequisite for competence. The need to feel a part of a social group and connected to others is known as relatedness. According to SDT, learning activities are more sustained and self-directed when intrinsic motivation, which results from the satisfying of these psychological requirements, is present. Overall, the research points to the possibility that positive emotions, learning motivation, and technological self-efficacy mediate the relationship between technology acceptance and self-directed learning. The goal of this research is to provide light on how technology acceptance affects self-directed learning outcomes in educational settings by looking at these mediating factors. When technology is embraced by students as a helpful tool, it can increase their intrinsic motivation if it fosters competence (by giving prompt feedback) and autonomy (by giving options for how to study). For example, if a learning platform allows students to choose their own projects, it aligns with their need for autonomy, boosting motivation. Higher levels of motivation, especially intrinsic motivation, can result in more successful autonomous learning. Independent use of technology is more common among students who feel capable and independent.

1.2.1 Relationship Between Learning Motivation and Self-Direct Learning

In the context of self-directed learning, motivation plays a crucial role in driving individuals to take initiative and control over their learning processes (Deci & Ryan, 2000). Learning motivation can be influenced by various factors, including intrinsic motivation, extrinsic rewards, and goal orientation (Pintrich & Schunk, 2002). One's sense of self-efficacy profoundly influences their approach to goals, tasks, and challenges (Luszczynska & Schwarzer, 2005). High self-efficacy can impact motivation positively or negatively. Individuals with high self-efficacy are more inclined to persist in learning endeavours (Hanaffin et al., 2003). They tend to proactively tackle obstacles and confront problems, whereas those with low self-efficacy may discontinue efforts when faced with challenges (Saeid & Eslaminejad, 2016). Learners with robust self-efficacy exhibit greater motivation and resilience, fostering perseverance in their learning journey (Saeid & Eslaminejad, 2016).

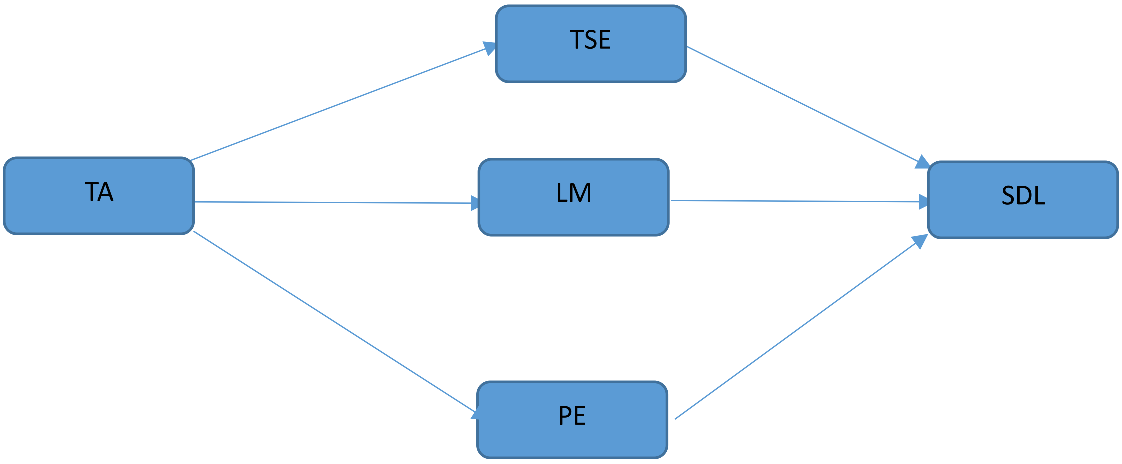
1.2.2 Relationship Between Technological Self-Efficacy and Self-Direct Learning

Another important predictor of technology acceptance and adoption has been found to be technological self-efficacy, or people's perceptions about their capacity to use technology (Compeau & Higgins, 1995). Self-directed learning and technical self-efficacy may have a mutually beneficial relationship in which each influences and supports the other. People who have a high level of technological self-efficacy are more likely to use technology to explore a variety of learning opportunities and resources through self-directed learning practices (Teo, 2011). Conversely, as learners embrace self-directed learning, they become more adept at utilizing technology to facilitate their learning goals, thereby enhancing their technological self-efficacy (Ally, 2008). In advanced EFL students, Basereh & Pishkar (2016) found a significant and positive relationship between self-efficacy and self-directed learning. Likewise, Lema & Agrusa (2008) verified that the degree of self-efficacy exhibited by students in the hospitality industry was consistent with the theory that self-efficacy plays a major role in predicting students' self-directed learning. In a study conducted by Mirzawati, Neviyarni & Rusdinal (2020) on the topic "The Relationship between Self-efficacy and Learning Environment with Students' Self-directed Learning" using correlational research design, the findings demonstrate a notable and positive correlation between self-efficacy and self-directed learning.

Understanding the dynamic interplay between technological self-efficacy and self-directed learning holds significant implications for educational institutions, instructional designers, and practitioners. Educators can leverage technology-enhanced learning environments to cultivate both technological self-efficacy and self-directed learning skills among students (Hwang & Liaw, 2011). By integrating scaffolded learning experiences and fostering a culture of experimentation and reflection, educators can empower learners to become self-directed, technologically savvy individuals equipped for the demands of the digital era.

1.2.3 *The Nexus Between Positive Emotions and Self-Direct Learning*

Positive emotions act as triggers for the expansion of cognition and behaviour, according to Fredrickson's broaden-and-build theory (Fredrickson, 1998, 2001). Positive emotions increase a person's propensity for creative thinking, experimental behaviour, and cognitive flexibility. Positive emotions also facilitate the retrieval and integration of information, enhancing learning and problem-solving abilities (Isen, 2000). Positive emotions play a crucial role in fostering the mindset and behaviours conducive to self-directed learning. When individuals experience positive affect, they are more inclined to approach learning tasks with enthusiasm and curiosity, leading to greater exploration and discovery of new knowledge (Fredrickson, 2001). Moreover, positive emotions can bolster individuals' resilience and motivation, enabling them to overcome obstacles and persist in their learning endeavours (Froh et al., 2009).



Key

TA=Technology Acceptance
LM=Learning Motivation
SDL=Students Self-Directed Learning
TSE= Technological Self-Efficacy
PE=Positive Emotions

Figure 1 Conceptual Framework

Figure 1 shows the conceptual framework of the study. Technological self-efficacy, learning motivation, and self-directed learning are mediating the relationships between technology acceptance and self-directed learning. Technology acceptance predicts technology self-efficacy, learning motivation and positive emotions, whilst technology self-efficacy, learning motivation, and positive emotions also predict self-directed learning.

2. Methods

2.1. Research Paradigm

The research paradigm used in this study is positivism. Since positivism emphasizes quantification and objective measurement, it is a good fit for examining causal linkages in the context of education and technological acceptance. Through the use of organized approaches such as questionnaires, researchers can get quantitative data regarding aspects including motivation, self-efficacy, and adoption of technology. This makes it possible to use statistical methods like structural equation modelling to find trends and deduce causes. This method assists in identifying particular elements that impact technology adoption in the educational setting, empowering teachers to make informed decisions based on evidence. In the end, positivism offers a strict framework for comprehending the interactions between these factors, which supports efficient instructional techniques and the use of technology.

2.2. Research Design and Method

The research design used for investigating the relationship between technology acceptance, technological self-efficacy, learning motivation, positive emotions, and self-directed learning was quantitative method. Survey was used to quantitatively assess individuals' perceptions, attitudes, and behaviours related to technology acceptance, technological self-efficacy, learning motivation, positive emotions, and self-directed learning using a five-point Likert Scale.

2.3. Participants, Instruments of Data Collection

The study was carried out in the six Colleges of Education in the Ashanti Region of Ghana. Convenience sampling is useful when researchers need to gather data quickly and easily. In your case, the researchers selected three out of six colleges and then used convenience sampling and a simple random sampling technique was used to select 237 participants who were students pursuing Mathematics and ICT as well as Mathematics and Science programmes. The study sought to involve all students pursuing these two programmes. Validated scales were used to measure technology acceptance, learning motivation, technological self-efficacy and self-directed learning. For measuring technology acceptance, ten of the measurement items were adapted from Austerman & Mertins (2014) who also adapted them from different sources (Chang, 2004; Cowen, 2009; Lu et al., 2005). To collect data on students' technological self-efficacy (TSE), ten of the items adapted by Liwanag & Galicia (2023) from Majadas (2022) based on the International Society for Technology in Education – National Educational Technology Standard for Students were adopted. For learning motivation (LM), the questionnaire used to measure it was the Motivation to Learn Online Questionnaire (MLOQ) by Fowler (2018) adapted by Liwanag & Galicia (2023). Eight of the items with four each from the subscale intrinsic and extrinsic motivation and also two from control of learning beliefs were adapted. Ten measurement items from Liwanag & Galicia (2023) were adapted and used to measure self-directed learning. To also collect data on positive emotions, ten measurement items from Achievement Emotions Questionnaire (AEQ) for studying developed by Pekrun et al. (2002) were also adapted. The designed closed ended questionnaires consisted of the general information of the respondents and questions on technology acceptance, positive emotions, learning motivation, technological self-efficacy and self-directed learning each on a five-point Likert scale with strongly disagree=1, disagreed=2, neutral=3, agree=4 and strongly agree=5. The questionnaires were administered by the researchers with the help of the various heads of department.

The statistical tool used in the analysis is Partial Least Squares Structural Equation Modelling. Partial Least Squares Structural Equation Modelling (PLS-SEM) was chosen as the analysis method for this research due to several key reasons that align well with the complexity of the study's framework, which involves multiple variables and mediating relationships. PLS-SEM is ideal for examining complex causal pathways in the social sciences since it enables the simultaneous assessment of various associations among variables (Hair et al., 2019). This study offers a complex framework that PLS-SEM may evaluate because of the interactions between technological acceptance, technological self-efficacy, positive emotions, learning motivation, and self-directed learning. The steps in the analysis involved data preparation, moel specification, estimation and evaluation. Data preparation entails screening for missing values and outliers and adherence to the assumptions required for PLS-SEM, ensuring data quality and integrity. Model specification involves specifying the model to articulate how observed variables relate to their respective latent constructs. This involves identifying indicators for each variable based on theoretical frameworks. A structural model is developed to illustrate hypothesised relationships among the constructs, including both direct effects and mediating paths. The Partial Least Squares (PLS) algorithm is utilized to estimate path coefficients, which reflect the strength and direction of relationships among variables (Ringle et al., 2015). The reliability of constructs is evaluated using metrics like Cronbach's alpha and composite reliability. Validity is assessed through convergent and discriminant validity tests (Hair et al., 2019). The structural model was assessed by effect sizes (f^2) to understand the impact of predictors. The software used was SmartPLS 4.0.

The data gathered were entered into SPSS 20 to obtain descriptive statistics on the participants' demography. The data was then imported into SmartPLS 4 for further analysis.

3. Results and Discussion

3.1. Results

3.1.1. Demographic Information of Participants

The general information of participants included gender, age, name of college and programme of study. Table 1 shows the demographic information of the participants.

Table 1 - General Information of Participants

Variable	Frequency	Percentage (%)
Gender		
Male	133	56.1
Female	104	43.9
Age (in years)		
16-18	27	11.4
19-21	153	64.6
22-24	28	11.8
25-27	18	7.6
Above 27	11	4.6
Name of College		
Mampong College of Education	70	29.5
Offinso College of Education	96	40.5
Wesley College of Education	71	30.0
Programme of Study		
Mathematics & Science	129	54.4
Mathematics & ICT	108	45.6

From Table 1, out of the 237 participants, 133 representing 56.1% where males while 104 representing 43.9% were females. On the distribution of age, 11, representing 4.6%, were above 27 years, while most of the participant's ages were in the range of 19-21, as illustrated in Table 1. Seventy (70), representing 29.5%, were selected from Mampong College of Education, 96 from Offinso College of Education and 71, representing 30.0%, were from Wesley College of Education. The programmes of study of participants were the Mathematics and Science programme and Mathematics and

ICT, with 129 of them studying Mathematics and Science and the rest offering the Mathematics and ICT programme. The descriptive statistics of the measurement items are presented in Table 2.

Table 2 - Descriptive Statistics of the Measurement of Items of the Constructs

Measurement Item	Mean	Std Dev.
Technology Acceptance		
TA1: Technology enables me to accomplish tasks more quickly when searching for innovations.	4.051	1.018
TA3: Technology makes it easier to innovate.	3.890	1.025
TA7: Overall, technology is easy to use.	3.899	1.105
TA8: Learning to operate with technology was easy for me.	4.118	0.982
TA10: Using technology enables me to have more accurate information.	3.958	1.005
Technological Self-efficacy		
TSE4: If there is something I want to learn, I can figure out a way to learn it.	3.835	0.965
TSE6: It takes me a while to get started on new projects.	3.852	1.075
TSE9: I work very well on my own	3.869	1.093
TSE11: If I discover a need for information that I don't have, I know where to go to get it.	3.924	1.049
Learning Motivation		
LM1: Getting a good grade is the most satisfying thing for me.	3.996	0.992
LM4: I want to do well in my classes because it's important to show my ability to my family, friends, employer, or others.	3.941	1.034
LM5: I prefer material that really challenges me, so I can learn new things.	3.882	1.012
LM10: If I try hard enough, then I'll understand the material presented.	3.819	1.017
Self-Directed Learning		
SDL2: I know what I want to learn.	3.675	1.176
SDL5: I love to learn.	3.536	1.077
SDL7: In a classroom, I expect the teacher to tell all class members exactly what to do at all times.	3.688	1.189
SDL9: I work very well on my own.	3.688	1.142
Positive Emotions		
PE2: I enjoy the challenge of learning Mathematics material.	3.506	1.124
PE4: I am so happy about the progress I made that I am motivated to continue studying.	3.527	1.069
PE5: I have an optimistic view toward studying Mathematics.	3.561	1.064
PE6: I feel confident when studying Mathematics.	3.595	1.196
PE7: I study mathematics more than required because I enjoy it very much.	3.637	1.174
PE8: I enjoy dealing with the course material.	3.633	1.271

Table 2 shows the measurement items retained in the modelling with their corresponding means and standard deviations. Table 3 illustrates the interpretation of the means of a five-point Likert scale with 1=strongly disagreed, 2=disagreed, 3=neutral, 4= agree, and 5=strongly agreed designed by Aynalem (2020).

Table 3 - Interpretation of Mean Scores

Range of mean score	Interpretation
1.0-1.80	Strongly disagree
1.81-2.60	Disagree
2.61-3.40	true to some extent
3.41-4.20	Agree
4.21-5.00	Strongly agree

From Table 2, participants agreed with the statements that technology enables me to accomplish tasks more quickly when searching for innovations, technology makes it easier to innovate, technology is easy to use, learning to operate with technology was easy for me and using technology enables me to have more accurate information. Similarly, Table 2 shows that participants also agreed with the measurement items of technological self-efficacy, learning motivation, positive emotions and self-directed learning.

3.1.2. Assessing the Outer Model

The partial least square was used to test the connection between technology acceptance, technological self-efficacy, learning motivation, and positive emotions, as well as self-directed learning and their indicators. In analysing the outer model, the foremost step was the determination of the suitability of the theoretically defined constructs. Four things are considered in ensuring that the designed questionnaires determine the variables that were supposed to measure while at the same time making sure that the instruments are reliable. These four things are the factor loadings, Cronbach alpha, composite reliability and the average variance extracted. Hair et al. (2011) recommended the minimum factor loadings for each construct to be 0.5; other researchers, such as Chin et al. (1997), recommended the minimum threshold to be 0.6. The details of the factor loadings are indicated in Figure 2. The Cronbach alpha and composite reliability measure the extent to which an indicator or measurement item consistently measures its construct. The minimum threshold for the Cronbach alpha and composite reliability, according to Hair et al. (2011), is 0.7. The minimum threshold recommended AVE in literature is 0.5.

Table 4 -Construct Reliability and Validity

Construct	Cronbach Alpha	Composite Reliability	Average Variance Extracted (AVE)
Technological Acceptance (TA)	0.814	0.871	0.574
Technological Self-Efficacy (TSE)	0.791	0.864	0.614
Positive Emotions (PE)	0.758	0.831	0.451
Learning Motivation (LM)	0.845	0.895	0.681
Self-Directed Learning (SDL)	0.854	0.901	0.695

From Figure 2, the T values of the indicators for each construct were well above 1.96, indicating that each construct significantly accounts for the variation in the indicators as required in the literature. Table 4 indicates each construct with its Cronbach alpha, composite reliability and average variance extracted. Both the Cronbach alpha and composite reliability exceeded the minimum threshold, meaning that construct validity had been attained. The values of Cronbach alpha and composite reliability implied that the measurement items (indicators) for each construct were closely related as a group. The AVE values in the table were also above the least recommended value except for the construct positive emotions (PE). Those AVE values greater than 0.5 indicated that their respective constructs accounted for more than 50% of the variations in their measurement items. Although the AVE value for positive emotions was 0.451, indicating that positive emotions accounted for less than 50% of the variation in its indicators, raising concerns that the indicators might not adequately represent the construct and therefore, the construct must be dropped, its retention takes consolation in other scholarly works which emphasize that "composite reliability alone is adequate to conclude convergent validity" (Malholtra, 2010, p. 702; Fornell & Larcker, 1981).

Table 5 - Discriminant Validity- Fornell-Larcker Criterion

	TA	TSE	PE	LM	SDL
TA	**0.825**				
TSE	0.439	**0.672**			
PE	0.288	0.378	**0.833**		
LM	0.400	0.305	0.096	**0.757**	
SDL	0.319	0.187	0.178	0.325	**0.784**

To check the discriminant validity which is the extent to which the constructs were uncorrelated, the Fornell-Larcker criterion was use. The extent to which the constructs were uncorrelated had been shown in Figure 2. Table 3 shows the correlations between the constructs and the square roots the AVE which had been bolded. According to literatures, to established discriminant validity the correlations between the constructs should be less than the square root of the average variance extracted. Apparently, the square root of the values of AVE were higher than the correlations between the constructs so discriminant validity had been achieved.

Table 6 - Collinearity Statistics (VIF)

Construct	LM	PE	SDL	TA	TSE
LM			1.335		
PE			1.243		
SDL					
TA	1	1			1
TSE			1.116		

The next step to assess the validity of the model is to check the model for multicollinearity issues by examining the variance inflation factor (VIF) values of all set of predictor constructs. Hair et al. (2016) recommended that VIF<5. Table 6 shows the values of VIF in the model. Multicollinearity is when independent variables in the model are excessively correlated. From Table 6, values of VIF were below 5 as recommended by Hair et al. (2016) indicating the absence of multicollinearity issues.

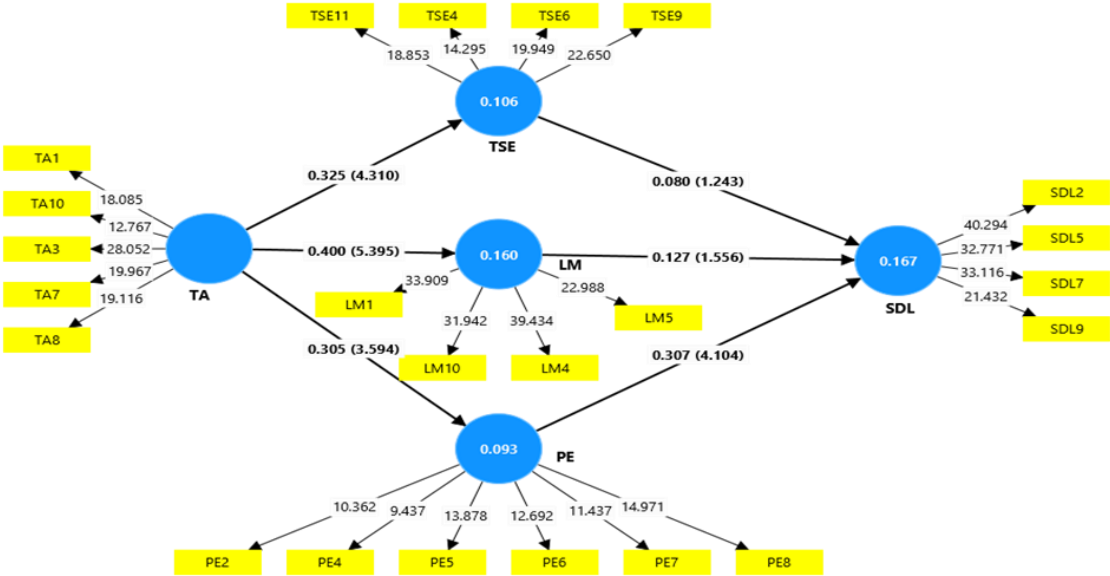


Figure 2 Outer and Inner Model

Figure 2 shows the embedded outer and inner model with each construct with its indicators, the test statistic values (T values) of each indicator, and the path coefficients, with their test statistic values in brackets. From the model, out of the ten indicators of technology acceptance (TA), five were retained in the model, while the other five whose factor loadings were below the minimum threshold were deleted. Technological self-efficacy, learning motivation and self-directed learning each retained four of the ten indicators. For positive emotions, six of the ten indicators were retained.

From the model, the direct effects of technology acceptance on technological self-efficacy, learning motivation and positive emotions were 0.325, 0.400 and 0.305, respectively, and their corresponding T values were 4.310, 5.395 and 3.594. These values were clearly greater than 1.96 (The value from the normal distribution table for two tail tests at a 5% level of significance), indicating that these effects were significantly different from zero. The direct effect of technological self-efficacy on self-directed learning was 0.080, and its T value was 1.243. the T value was not greater than 1.96, indicating that the impact of learning motivation on self-directed learning was not significant. From the figure, the effect of positive emotions on self-directed learning was 0.307, and its T value was above 1.96, indicating a significant influence of positive emotions on self-directed learning.

Table 7 - Direct Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T statistics (|O/STDEV|)	P-values
LM -> SDL	0.127	0.127	0.082	1.556	0.120
PE -> SDL	0.307	0.316	0.075	4.104	0.000
TA -> LM	0.400	0.407	0.074	5.395	0.000
TA -> PE	0.305	0.313	0.085	3.594	0.000
TA -> TSE	0.325	0.337	0.075	4.310	0.000
TSE -> SDL	0.080	0.081	0.064	1.243	0.214

The tabular representation of the relationship between the constructs with path coefficients (original sample), sample mean, standard deviation, T statistics and the p values were indicated in Table 7. As illustrated in the model in Figure 2, all the direct path coefficients were significantly different from zero except the effect of learning motivation and technological self-efficacy on self-directed learning and that had been confirmed in Table 7 as their p values were greater than 0.05 level of significance.

Table 8 - Mediating Analysis

Indirect Effect	Origina Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T statistics (|O/STDEV|)	P-value
TA -> TSE -> SDL	0.026	0.027	0.023	1.138	0.255
TA -> PE -> SDL	0.094	0.098	0.033	2.862	0.004
TA -> LM -> SDL	0.051	0.050	0.033	1.540	0.124

Table 8 shows the results of the mediating analysis. The indirect effect of technological self-efficacy on self-directed learning through technology acceptance was 0. 026 with a standard deviation of 0.023, a test statistics value of 1.138, and a p-value of 0.255. Clearly, the p-value indicated that the indirect effect of technological self-efficacy on self-directed learning through technology acceptance was not significant. Similarly, the indirect effect of learning motivation on self-directed learning through technology acceptance was insignificant since the p-value was greater than 0.05 level of significance. The indirect effect of positive emotions on self-directed learning was found to be significant at a 5% level of significance since the p-value was 0.004.

Table 6 - Effect Size (F-Square)

	LM	PE	SDL	TA	TSE
LM			0.015		
PE			0.091		
SDL					
TA	0.190	0.103			0.118
TSE			0.007		

Table 6 shows the effect size of dropping each relationship from the model. From the table, the effect size of dropping learning motivation on self-directed learning was calculated to be 0.015, while the effect sizes of technology acceptance on learning motivation, positive emotions and technological self-directed learning were 0.190, 0.103 and 0.118, respectively. The effect size of dropping the relationship between positive emotions and self-directed learning was 0.091, while that of technological self-efficacy and self-directed learning was 0.007. According to Cohen (1988), if $F2 \geq 0.02$ it is deemed small if $F2 \geq 0.15$, it is considered medium, and if $F2 \geq 0.35$ is considered to be large. The effect sizes of learning motivation on self-directed learning, positive emotions on self-directed learning, and technological self-efficacy on self-directed learning were considered negligible. However, the effect sizes of technology acceptance of positive emotions and technological self-efficacy were small. The effect size of technology acceptance on learning motivation was large.

3.2. Discussion

The study's findings revealed that more males were involved as participants than females, and the commonest age group of the participants or respondents was 19 to 21 years. The majority of the respondents were pursuing Mathematics and Science programmes rather than Mathematics and ICT.

3.2.1. Direct Effect of Technological Self-Efficacy on Self-Directed Learning

The findings of the study, which indicated that technological self-efficacy did not significantly predict students' self-directed learning, confirm the conclusions drawn by Kim & Kwon (2014), Cheng & Ho (2017), Sönmez & Eşit (2018), Liaw & Huang (2014), and Lee & Tsai (2016). All these studies collectively suggest that while technological self-efficacy is recognised as an important factor in the learning process, it does not directly lead to enhanced self-directed learning outcomes. The study reinforces the existing body of research by indicating that technological self-efficacy, while important, does not serve as a significant predictor of self-directed learning. This consistency across multiple studies suggests a robust trend in the literature, indicating that other elements such as intrinsic motivation, metacognitive skills, and contextual factors are likely more influential in determining self-directed learning outcomes. The finding prompts a re-evaluation of existing theories surrounding self-efficacy, learning, and technology integration. Traditional self-efficacy models, particularly those based on Bandura's framework, suggest that confidence in one's abilities is a crucial determinant of behaviour and outcomes. The finding challenges the assumption that higher technological self-efficacy automatically translates into better learning outcomes. This calls for a refinement of these models to incorporate a more complex interplay of factors that contribute to learning, suggesting that self-efficacy is necessary but not sufficient for fostering self-directed learning.

The findings of the recent study suggest that technological self-efficacy does not significantly predict students' self-directed learning. This contrasts sharply with the work of Papanastasiou and Zembylas (2008), who found a positive correlation between technological self-efficacy and self-directed learning, indicating that students with higher confidence in their technological skills are more likely to engage in self-directed learning behaviours. Similarly, research by Chen and Jang (2010), Hsu and Lin (2015), and Liu, Tsai, and Wu (2017) supports this notion, collectively concluding that enhanced technological self-efficacy contributes to increased self-directed learning engagement. The discrepancy in findings raises important questions about the factors influencing self-directed learning and the role of technology within that context. One possible explanation for the differing results could be variations in sample populations or contexts. For instance, the previous studies often focused on specific educational settings or age groups, which may have different levels of exposure to technology or varying cultural attitudes toward self-directed learning. Moreover, it is essential to consider the methods employed in these studies. Differences in measurement tools and definitions of self-directed learning could also account for the variations in findings.

These findings contribute significantly to the field by highlighting the complexity of the relationship between technological self-efficacy and self-directed learning. They suggest that while confidence in technology is beneficial, it may not be the sole predictor of self-directed learning capabilities. This insight encourages educators and researchers to explore additional factors such as motivation, learning environment, and instructional strategies that may mediate this relationship. Future studies could benefit from a more nuanced approach that considers these variables, potentially leading to more comprehensive frameworks for understanding how students can effectively harness technology to foster self-directed learning.

3.2.2. Direct Effect of Learning Motivation on Self-Directed Learning

The study revealed that learning motivation had no significant impact on self-directed learning. If a student is demotivated to learn, he might see no need to engage in self-directed learning. According to a publication by Cortes (2024), one of the five challenges of self-directed learning is that people might be proficient but lack the drive to learn continuously. Pintrich and De Groot (1990) revealed in their studies that while motivation is an important factor, it did not always significantly predict self-directed learning outcomes. Their study emphasised that other cognitive and behavioural factors may play a more crucial role. Elliot and McGregor (2001) investigated the impact of various types of motivation on self-directed learning and found that learning motivation did not consistently predict self-directed learning.

The outcome of this study indicating that learning motivation is not a significant predictor of self-directed learning is at variance with the result of a study conducted by Dunlap & & Lowenthal (2011) in which they revealed that intrinsic motivation encourages learners to take a more self-directed approach to their own learning activities. Also, the finding was not in agreement with that of Dabbagh & Kitsantas (2012) and Wolters (2011) who asserted that motivational factors, such as engaging with interesting and enjoyable learning resources, support learners in retaining their learning activities, sustaining their motivation, and overcoming periods of decreased motivation. Similarly, Liwanag & Galicia (2023) revealed in their study that there was a significantly high relationship between the respondents' level of learning motivation and level of self-directed learning.

3.2.3. Direct Effect of Positive Emotions on Self-Directed Learning

The study also revealed that positive emotions are a significant predictor of self-directed learning. Positive emotions enhance students' learning behaviours, which can be observed in their control strategies, willpower, and ability to elaborate on the material (Artelt, Baumert, Julius-McElvany & Peschar, 2003). The result was in consonant with a study conducted by An et al. (2022) on the topic "Relationship between Technology Acceptance and Self-Directed Learning: Mediation Role of Positive Emotions and Technological Self-Efficacy" the result revealed that positive emotions significantly predicted self-directed learning. Pekrun et al. (2002) found that positive emotions, such as enjoyment and hope, significantly contribute to self-directed learning. Their study emphasised that positive emotions enhance students' engagement and motivation, which are critical for effective self-directed learning. Also, the finding of this study resonates with that of Schutz & Pekrun (2007), who investigated how different types of emotions affect learning outcomes and self-regulation. Their findings indicated that positive emotions, including joy and interest, were significant predictors of self-directed learning, as they enhance students' engagement and persistence in learning tasks.

However, some studies discount that positive emotions significantly predict self-directed learning. Linnenbrink-Garcia et al. (2011) examined the relationship between emotions and academic outcomes, including self-directed learning. Their research found that while positive emotions are beneficial for general learning, they do not consistently predict self-directed learning outcomes. Pekrun et al. (2014), on the role of academic emotions in self-regulated learning, revealed that while positive emotions can enhance engagement, they do not always significantly predict self-directed learning. In the same vein, Núñez et al. (2015) found that positive emotions did not consistently predict self-directed learning behaviours. Cox & Macrae (2013) and Sutton & Harper (2017) also established that positive emotions can improve engagement. Still, they do not consistently lead to increased self-directed learning without the presence of other supportive factors.

3.2.4. Direct Effect Technology Acceptance on Technological Self-Efficacy, Learning Motivation and Positive Emotions

From the results, technology acceptance was a significant predictor of technological self-efficacy, learning motivation and positive emotions. Venkatesh and Bala (2008) study supported that technology acceptance, particularly perceived ease of use and perceived usefulness, significantly predicted technological self-efficacy among users. Their study emphasised that positive perceptions of technology contribute to increased confidence in using technology effectively. The finding was in line with that of Chen and Hung (2016), who discovered that higher levels of technology acceptance were associated with increased technological self-efficacy but contradicted that of Li et al. (2015), who indicated that technological self-efficacy was more strongly influenced by factors such as hands-on experience and training rather than acceptance alone. The view of Li et al. (2015) was supported by Hsu & Ching (2013) and Sykes et al. (2014) who also revealed that though technology acceptance is important for technology use, it did not significantly predict technological self-efficacy.

The study also revealed that technology acceptance significantly predicted learning motivation. This was confirmed by Liaw et al. (2007) found that technology acceptance is a significant predictor of learning motivation, with users who have positive attitudes towards technology being more motivated to engage in learning activities that involve technology. Hwang et al. (2013) investigated the impact of technology acceptance on learning motivation within mobile learning environments. Their study demonstrated that higher technology acceptance, characterised by positive perceptions of ease of use and usefulness, significantly predicts increased learning motivation. Hsu and Ching (2013), however, revealed that technology acceptance did not significantly predict learning motivation.

The study further revealed that technology acceptance significantly predicted positive emotions, and this is supported by a study conducted by An et al. (2022) in which they showed that technology acceptance significantly influences positive emotions. Venkatesh et al. (2003) corroborated this when they discovered in their study that higher technology acceptance, characterised by perceived ease of use and perceived usefulness, leads to more positive emotions towards the technology, such as satisfaction and enjoyment. Lee & Rho (2014), in their research, showed that positive technology acceptance experiences are linked to increased positive emotions, such as satisfaction and pleasure, enhancing the overall user experience.

3.2.5. Mediating Roles of Technological Self-Efficacy Between Technology Acceptance and Self-Direct Learning

From the results, technological self-efficacy did not significantly mediate the relationship between technology acceptance and self-directed learning. The finding is at variance with that of An et al. (2022), who, in their study, discovered that technological self-efficacy mediates the relationship between technology acceptance and self-directed learning. Also, a study by DeLisi et al. (2020) found that technological self-efficacy fully mediated the relationship between technology acceptance and self-directed learning in a higher education context. This suggests that technology acceptance enhances self-efficacy, which in turn facilitates more effective self-directed learning. However, high levels of technological self-efficacy might lead to overconfidence, which can negatively impact self-directed learning. Johnson and Levine (2017) highlighted that overconfidence in one's technological abilities could lead to reduced effort in seeking help or exploring alternative learning strategies, thereby undermining the effectiveness of self-directed learning. Cultural and demographic differences might also influence the effectiveness of technological self-efficacy as a mediator. A study by Liu et al. (2018) indicated that cultural factors and demographic variables such as age and educational background could affect the relationship between technology acceptance, self-efficacy, and self-directed learning, leading to varying outcomes across different populations.

3.2.6. Mediating Role of Learning Motivation

From the findings of the study, learning motivation positively but insignificantly influences students' self-directed learning. While motivation plays a key role in encouraging students to take initiative and manage their own learning, its impact, in this context, is not overwhelmingly strong. This indicates that while motivating factors are important, they are just one of many elements that contribute to effective self-directed learning. Smith & Johnson (2023) and Lee et al. (2022) confirmed this in their studies when they established that Learning motivation has been found to influence students' self-directed learning positively. However, the effect size is relatively small. This suggests that while motivation plays a supportive role, its impact is not overwhelmingly significant compared to other factors influencing self-directed learning.

3.2.7. Mediating Role of Positive Emotions

The study revealed that positive emotions significantly mediated the relationship between technology acceptance and self-directed learning. The more open students are to using technology, the more probable it is that they will experience positive emotions while engaging with technology for learning purposes. Pekrun's (2006) control-value theory says that experiencing positive emotions will enhance students' confidence and influence their attitudes and readiness to utilise technology. A study by Lee et al. (2017) found that positive emotions significantly mediated the relationship between technology acceptance and self-directed learning. Their study showed that when students experienced positive emotions towards technology, they were more likely to engage in self-directed learning, suggesting that positive emotions enhance the effectiveness of technology acceptance in learning contexts. A study by Chang and Lin (2021) reported that positive emotions significantly mediate the relationship between technology acceptance and self-directed learning engagement. Their findings suggest that learners who experience positive emotions towards technology are more likely to be engaged in self-directed learning, leading to improved educational outcomes. These studies collectively support the mediating role of positive emotions in the relationship between technology acceptance and self-directed learning. They highlight how positive emotions can enhance learners' engagement, motivation, and overall effectiveness in self-directed learning by improving their attitudes towards technology.

4. Conclusions

The study established that technological self-efficacy and learning motivation did not significantly impact students' self-directed learning, but the impact of positive emotions was significant. The study also revealed that technology acceptance significantly influenced technological self-efficacy, learning motivation and positive emotions. The study further established that technological self-efficacy and learning motivation did not significantly mediate the relationship between technology acceptance and self-directed learning but positive emotions significantly mediated the relationship between technology acceptance and self-directed learning.

It is recommended that the Colleges of Education, especially in the Ashanti Region of Ghana, should focus on increasing student's confidence in their technological abilities through targeted training programmes and the provision of technological resources. This can help students feel more competent in using technology for learning purposes, thereby enhancing self-directed learning. Also, technology-related educational strategies that promote positive emotional experiences should be developed. For instance, incorporating user-friendly educational technologies can help students develop a positive attitude toward learning and technology. Programmes that arouse students' intrinsic motivation for learning should be encouraged. This might include offering incentives, creating conducive learning environments, and providing relevant and interesting content to maintain high levels of motivation.

Conflict of Interest

The authors declare no conflicts of interest.

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