THE FEELING OF SELF-EFFICACY AND ITS IMPACT ON PERFORMANCE ON A MOBILE LEARNING APPLICATION

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ABSTRACT

This paper explores the concept of self-efficacy and its impact on individual performance on a mobile learning application. Self-efficacy refers to one's belief in their ability to achieve their goals and is a key factor in everyday life. To investigate the relationship between self-efficacy and performance, we conducted an experiment with 104 participants, which consisted of two parts. First, we evaluated their self-efficacy levels using a survey designed to assess their perceived self-efficacy levels before and after their tests. Second, we asked participants to pilot a drone in a virtual environment and complete a series of races as quickly as possible. Our findings demonstrate that self-efficacy does indeed affect the individual performance, as we observed a clear correlation between self-efficacy levels and task completion times.

KEYWORDS

Self-Efficacy, Learning Performance, HLCE, Mobile Learning

1. INTRODUCTION

Self-efficacy can be likened to a tool, a confidence that guides an individual to be influenced by their actions and the resulting outcomes. This article explores the impact of various forms of assistance on learners' self-efficacy with the uniqueness of this study lying in its experimental framework.

Specifically, we aim to analyze the effect of self-efficacy in a computerized learning environment (known as HLCE) on e-learning activities and tasks. In the first section, we will define the different concepts through a literature review. Then, we sought to see if there is a link between self-efficacy and performance in a computer-based environment. To do so, we measure three values, which are the self-efficacy before learning, the self-efficacy after learning, and the participant's performance at the end of the lesson. Finally, this will lead to a discussion on our experiment, analysis of the obtained results, and a conclusion.

2. LITERATURE REVIEW

2.1 State of The Art

2.1.1 Self-Efficacy Concept

Although there are numerous theories on self-efficacy, the theory most commonly used is Bandura's (1986, 2012) theory of self-efficacy. In this state of art, we will first define Bandura's theory before presenting other theories that challenge it. These alternative perspectives are relevant and necessary to provide a second point of view.

Bandura (1986) is among the most cited authors in his field, and his theories enjoy widespread acceptance among his peers. Although he engages in discussions on the concept of self-efficacy, it is an integral component of Social Cognitive Theory (SCT) (Bandura, 1986), which represents an interpretation of human actions and behaviors. According to this theory, behavior is shaped by intra-personal influences that intersect and form a part of the determining conditions governing the environment and life of each individual. In a sense, each person is considered the master of their destiny or, at the very least, of their influence on themselves, albeit unconsciously.

The sense of self-efficacy is one of the influences within these intra-personal factors. It is defined as a trait that both influences and is influenced by our goals and environment throughout our lifespan, and it is believed to impact our achievements. For instance, an individual who has developed a strong sense of self-efficacy in academic settings may be more inclined to undertake intellectual challenges and persevere in the face of obstacles. According to Bandura (2012), self-efficacy is an amalgamation of various elements, including mastery of personal experience, social modeling, social pressure, and physiological and emotional states. For example, social modeling could be illustrated by the observation that an individual, witnessing a role model succeed in a specific task despite challenges, may enhance their own belief in the capacity to overcome similar difficulties. These elements converge to shape an individual's sense of efficacy, which, in turn, influences our motivation and efforts.

2.1.2 How Does One Build Its Self-Efficacy

Albert Bandura (2004) identified four sources of self-efficacy: mastery experiences, vicarious experiences, verbal persuasion, and physiological and emotional states. Mastery experiences, the most significant source of self-efficacy, are heavily influenced by past successes and failures in a specific domain. Small successes can build up an individual's sense of self-efficacy over time.

Vicarious experiences, or observing the successes or failures of others, can also impact an individual's self-efficacy. However, comparing oneself to others can also lead to negative effects, so it's important to focus on progress and improvement.

Verbal persuasion, or receiving feedback from significant others, can be helpful in increasing self-efficacy if it's specific, respectful, non-attributive, and accompanied by recommendations for improvement.

Finally, physiological and emotional states can impact an individual's sense of self-efficacy, but techniques such as mood mapping or meditation can help regulate emotions and improve self-efficacy. Being aware of these sources can help individuals stay motivated and increase their chances of success in achieving their goals.

2.1.3 Consequences of Self-Efficacy on Other Variables

Bandura highlights the importance of social and self-evaluative consequences, where an individual judges their efficacy and the result they expect to obtain when thinking about performing an action.

Self-efficacy has multiple repercussions through one-self, its motivations and influences and finally the results obtained. In this schematic, two elements in particular play a crucial role: self-efficacy and result expectation.

People thus become their own active agents who shape their outcomes. It's no longer an external influence or even their personality traits (such as envy, shyness, etc.), but their own feelings that influence them: A group of persons is more likely to succeed in a task if it believes more in its ability compared to another group, despite both groups having similar abilities for this task (Bandura, 2012). This difference is the result of high self-efficacy, where individuals systematically identify their environment that will positively influence (in this case) their actions and therefore performances.

The effects of self-efficacy on other variables have been largely studied and Bandura’s hypothetis have been confirmed in most of the works as confirm meta-analysis like (Honden et al., 1990) or more recent studies like (Brown, 2012) confirming self-efficacy has a positive effect on problem solving.

2.1.4 Effects of Self-Efficacy in Hlces/Mobile Learning

A Human Learning Computer Environment (HLCE) is a set of systems designed to facilitate the learning of users (learners). They are often used to facilitate the acquisition of skills or knowledge, guided by the HLCE to varying degrees. According to Balacheff and al. (1996), HLCE encompasses education and training methods in all areas where knowledge transfer is desired. This implies that a computer-based learning environment encompasses various agents that interact in various ways, including human agents such as learners and teachers and artificial agents such as robots, accessing learning resources locally or via computer networks.

An HLCE can serve as a tool for information presentation and processing or as a means of communication between humans and machines or between humans through the machine. Koper (2001) describes an HLCE as a social system that facilitates interaction between human and artificial agents to form a cohesive unit with the primary goal of human learning. It includes all the objects, contexts, and behaviors of agents that play an important role in learning, matching computer-based learning environments to pedagogical environments.

Research has shown that the use of HLCEs can have many benefits, such as improving learning outcomes, engagement, and motivation (Bailey, 2014; Healy and al., 2017; Van Leeuwen & Janssen, 2019). Additionally, HLCEs can offer more personalized learning experiences by adapting to individual needs and preferences (Feng and al., 2018). With the growing demand for online and remote learning, HLCEs have become increasingly important tools in education and training.

Mobile learning is regarded as an instructional strategy that enables students to continue their learning activities outside of the traditional classroom by using digital devices like tablets and mobile phones (Crompton, 2013). Mobile learning can only exist thanks to an HLCE.

Lukuman (2023) has studied self-efficacy in this context explaining that mobile learning is essential to achieving continuous learning outside of the classroom. Their study has shown the importance of self-efficacy in order to achieve mobile learning.

Gloria (2016) has shown how important was the training to increase self-efficacy during mobile learning because they think that self-efficacy is important in order to achieve the learning goals. From our site, we aim to study this last part.

Haeng-Nam and al. (2015) have found, in the context of mobile learning, that higher level of self-efficacy results in higher levels of performance expectancy, social influence, and effort expectancy.

As we are more interested in effective performance, we will now review some studies about the link between self-efficacy and effective performance

2.1.5 Recent Experiments on The Link Between Self-Efficacy and Performance

We have found several experiments conducted on self-efficacy and performance on learning tasks provided by HLCEs but nearly nothing conducted with mobile learning.

* Bicen and Kocakoyun (2014) studied the effect of self-efficacy on student engagement in an online learning environment. The researchers recruited 132 university students enrolled in online courses, who completed questionnaires to assess their level of self-efficacy and engagement in learning.

The results showed that students with high self-efficacy were significantly more engaged in their learning than those with low self-efficacy. Furthermore, the researchers found that students with high self-efficacy had a greater sense of control over their learning and were more willing to take on challenging tasks. These findings suggest that self-efficacy may play an important role in promoting student engagement and success in online learning environments.

Moreover, the study highlights the importance of providing students with opportunities to develop and improve their self-efficacy. The researchers suggested that online instructors can foster self-efficacy by providing positive feedback and creating a supportive learning environment. By doing so, students may feel more confident in their abilities to learn and engage with course content, which can ultimately lead to better academic performance.

***** Wang and al. (2013) aimed to explore the impact of self-efficacy on student motivation in an online learning environment. The researchers recruited 320 university students who were taking online courses at a Chinese university. The participants completed questionnaires to assess their level of self-efficacy and motivation to learn.

The results showed that students with high self-efficacy were significantly more motivated than those with low self-efficacy. Additionally, students with high self-efficacy showed greater persistence in their online learning, meaning they were more likely to continue studying even in the face of difficulties. These findings suggest that self-efficacy may play an important role in student motivation and perseverance in online learning.

The study also highlights the importance of the learning environment for the development of self-efficacy. The researchers found that students who had access to high-quality educational resources and frequent online interactions with teachers were more likely to develop strong self-efficacy.

2.2 Retained Hypothesis

Bandura has demonstrated that self-efficacy has effects on various variables, including learning and learning performances. Bican and Kocakoyun (2014) and Wang et al. (2013) have shown that self-efficacy influences positively performance. Haeng-Nam and al. (2015) have shown that it is also true in a mobile learning context for “expectancy”.

Therefore, we propose the following hypothesis: **A positive evolution of self-efficacy has a significant positive impact on performance in a mobile learning application.**

The hypothesis suggests that there may be a relationship between the changes in an individual's self-efficacy and their subsequent performance outcomes.

3. METHODOLOGY

During this experiment, we aim to verify whether a change in self-efficacy has an impact on actual performance.

To do so, we measure three values, which are the self-efficacy before learning, the self-efficacy after learning, and the participant's performance at the end of the lesson. Performance is evaluated by the time needed to complete their tasks, while we’re using surveys to evaluate their self-efficacy.

3.1 Participants

To conduct this experiment, we collected various data through two forms and a mobile drone piloting learning application. A total of 104 people signed up. The forms were collected with Qualtrics Europe which respects GDRP regulations.

The data obtained with the forms were collected between May 2022 and July 2022, and the drone piloting learning application was developed with Unity by the nonprofit AD2RV association.

All collected data is anonymous and has not been used for any purpose other than that of the experiment conducted within the scope of our hypothesis.

3.2 Experimentation Setup

The experiment consists of three parts. In the first part, the participant is asked to complete a survey to gather some information about themselves, such as their age and gender. After this, the participant receives a unique one-time-use code by email, which allows them to move on to the second stage of the experiment, which involves learning to pilot a drone.

In the second part of the experiment, the participant uses a smartphone android application on a personal smartphone (figure 1). The participant receives a brief explanatory video showing the final obstacle race they will have to complete. At the end of the video, the participant is asked to rate their degree of confidence in completing the race in less than 50 seconds on a scale of 1 to 100 (first measure of self-efficacy). After this question, the participant goes through seven different challenges of increasing difficulty to learn how to pilot the drone. The main goal of the participants is to learn piloting in order to complete the course in the shortest possible time. Before each of the 7 steps (lessons), the participant can decide to request assistance, which includes aids to facilitate their progress and a simple aid where an image shows how to direct the drone.

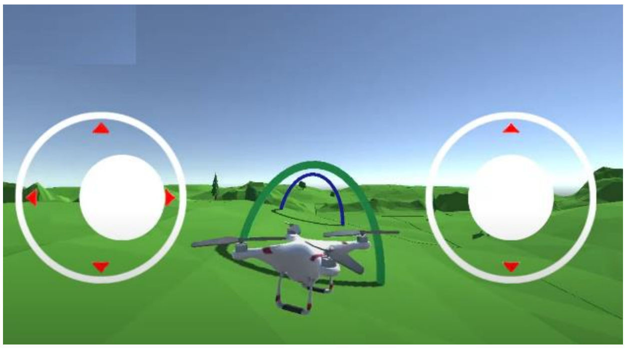

Figure 1. Illustration of the application.

At the end of the learning phase, the participant is asked to once again evaluate their ability to complete the final course within in less than 50 seconds (second measure of self-efficacy). Then the participant has to complete the final course with measurement of his performance. Finally, after completing the test, the participant is asked to fill out a final survey to gather information on difficulties they encountered.

4. RESULTS

4.1 Sample

Of the 104 participants approached, 44 people completed the experiment. 25 women and 19 men were remaining.

4.2 Descriptive Processing of Data

In the context of this experiment, 3 metrics were collected and used to create our measures of evolution and performance. The evolution of self-efficacy is represented by the difference between the self-efficacy after learning (metric 1) and the one before (metric 2). Therefore, the evolution will be positive if the participant feels more confident than at the beginning, and negative in the opposite case.

In addition, we use another value which is the time to complete the course in seconds (metrics 3). The lower this measure, the greater the participant's performance will be. Table 1 presents the descriptive statistics about our two main resulting variables.

Table 1. Descriptive statistics

	Self-Efficacy evolution	**Final Performance**
Minimum	-100	35.30
1st Quantile	-12	40.16
Median	0	49.91
Mean	-0.9512	79.88
3rd Quantile	11	83.01
Maximum	66	256.57

4.3 Inferential Statistics

To be able to evaluate and validate our hypothesis, we need to verify whether the evolution of our self-efficacy allows for an improvement in user performance. With two continuous variables at our disposal, it is therefore more appropriate to seek an answer through regression methods.

At first, we tried to use the raw data as it is to perform a linear regression. Unfortunately, the test of the normality of residuals was not conclusive. In turn, we attempted to apply transformations to our explanatory variables with the aim of discovering a new relationship or enhancing our results.

To try to reduce the range of our performance, we apply the following transformation:

$$y = \log10(performance - 35.2)$$

log10 function is used to reduce the range of our values, while the -35.2 centers performances around the minimum. Since the log10(x) function is not defined at 0, the minimum is slightly higher. As expected, the range of our data has been reduced (figure 2).

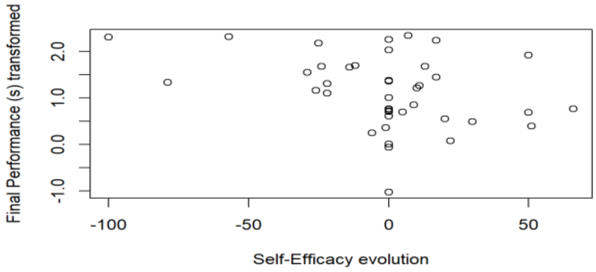

Figure 2. Graph of self-efficacy evolution by final performance transformed

Then, we calculate the coefficients of the regression line with our transformation:

$$\boldsymbol{y = -0.0085 * x + 1.1194.}$$

To validate these results, we must first show that the model coefficients are non-zero. By setting:

-H0: The coefficient is equal to 0.

-H1: The coefficient is different from 0.

Choosing alpha equal to 5%, we reject H0 (*p=0.0281*) and validate the non-nullity of the coefficients at the alpha threshold of 5%.

In the second step, we need to verify that the residuals of our model (figure 3) follow a normal distribution, meaning that the residuals are not correlated with each other.

With the help of the *Shapiro-Wilk* hypothesis test, with the following hypotheses:

-H0: the data follows a normal distribution with mean 0 and standard deviation 1.

-H1: the data does not follow a normal distribution.

The null hypothesis H0 is accepted at the 5% significance level (p=*0.348*). Our residuals (figure 3) do follow a centered and reduced normal distribution, and we can accept the previous results.

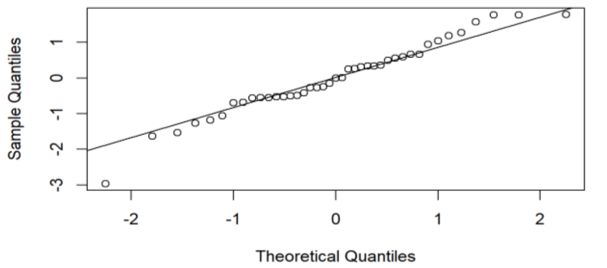

Figure 3. Representation of the residuals distribution with the performances transformed

Through the process of transformation, we can highlight a non-linear relationship between our variables.

By performing the inverse operation associated with our initial transformation on our regression line, we can visualize a new curve that corresponds to the same line in the original space, as seen below in the figure 4. The inverse transformation associated with y is: ***x = 10^y+35.2***

This function between self-efficacy evolution and final performance confirms that our main hypothesis is verified.

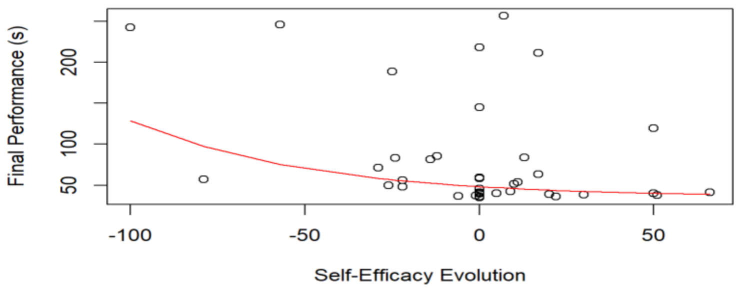

Figure 4. Final regression of self-efficacy over performance

5. DISCUSSION

The study aimed to analyze the relationship between learners' self-efficacy evolution and their performance in a learning task. The sample consisted of 44 participants, 25 females and 19 males, who completed the experiment. Four measures were collected: self-efficacy before and after learning, the time required to complete the task, and the final performance.

Firstly, the data was analyzed descriptively. The results showed that self-efficacy evolution was generally negative, although some participants showed significant improvement. Final performance was also highly variable, with completion times ranging from 35 to 256 seconds.

With these results, we tried to prove that the evolution of self-efficacy has a positive impact on performance. To do so, we conducted a linear regression with a transformation of the original variable, resulting in a verified non-linear relation between self-efficacy and performance. In addition, the original slope of the regression is lower than 0, showing a negative correlation: The higher the evolution of the self-efficacy is, the lower the performance (in our case, the unit for performance is the second).

In conclusion, this study shows that self-efficacy evolution has a positive effect on final performance in a learning task which also matches with (Haeng-Nam and al., 2015) results about performance expectancy.

In the specific context of CBLEs and mobile learning, the result is even more interesting because it is possible to automatize the intervention process such as with positive feedback (Peifer, 2020). We are currently doing a study to check if positive feedback could help to improve self-efficacy. Moreover, this study has broader implications for our understanding of human performance and achievement. The findings suggest that self-efficacy plays a crucial role in determining individual performance, and that self-belief is a key factor in achieving success. As such, it is critical to understand the role that self-efficacy plays in shaping individual outcomes and to develop strategies that help individuals cultivate a sense of self-efficacy to improve their performance.

As an opening question, it would be interesting to ask if the relationship between self-efficacy and performance is influenced by other factors, such as motivation, previous experience, or individual learning preferences. Future research could explore the effectiveness of self-efficacy interventions in different settings and with larger sample sizes.

6. CONCLUSION

In conclusion, this study, which has been conducted though a mobile learning application, provides insights into the relationship between self-efficacy and performance: A positive evolution of self-efficacy has a significant positive impact on performance in a mobile learning application. The main application of this result is that educators/CBLE/Mobile learning application designers should try to do their best in order to improve learner’s self-efficacy by digital means like positive feedback.

REFERENCES

Balacheff, N., Kaput, J.J. (1996). Computer-Based Learning Environments in Mathematics. In: Bishop, A.J., Clements, K., Keitel, C., Kilpatrick, J., Laborde, C. (eds) International Handbook of Mathematics Education. Kluwer International Handbooks of Education, vol 4. Springer, Dordrecht.

Bandura, A. (1986). Social foundation of thought and action: A social cognitive theory. Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (2004). Social Cognitive Theory for Personal and Social Change by Enabling Media. In A. Singhal, M. J. Cody, E. M. Rogers, & M. Sabido (Eds.).

Bandura, A. (2012). Social cognitive theory. In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.).

Peifer, C., Schönfeld, P., Wolters, G., Aust, F., Margraf, J. (2020). Well Done! Effects of Positive Feedback on Perceived Self-Efficacy, Flow and Performance in a Mental Arithmetic Task. Frontiers in Psychology. 11. 10.3389/fpsyg.2020.01008.

Bicen, H., & Kocakoyun, S. (2018). Perceptions of Students for Gamification Approach: Kahoot as a Case Study. International Journal of Emerging Technologies in Learning (iJET).

Brown, A.D., Dorfman, M.L., Marmar, C.R., Bryant, R.A.. The impact of perceived self-efficacy on mental time travel and social problem solving. Conscious Cogn. 2012 Mar;21(1):299-306. doi: 10.1016/j.concog.2011.09.023. Epub 2011 Oct 21. PMID: 22019214.

Crompton, H. (2013). A historical overview of mobile learning: Toward learner-centered education. In Z. L. Berge & L. Y. Muilenburg (Eds.), Handbook of mobile learning. Florence.

Haeng-Nam, S., Dae-Yul, J., Yeon-Su, J., Jae-Ik, S. (2015). The Relationship among Self-Efficacy, Social Influence, Performance Expectancy, Effort Expectancy, and Behavioral Intention in Mobile Learning Service. International Journal of u- and e- Service, Science and Technology. 8. 197-206.

Hashemi, M., Azizinezhad, M., Najafi, V., & Nesari, A. J. (2011). What is mobile learning? challenges and capabilities. Procedia-Social and Behavioural Sciences, 30, 2477-2481.

Holden G, Moncher MS, Schinke SP, Barker KM. Self-efficacy of children and adolescents: a meta-analysis. Psychol Rep. 1990 Jun;66(3 Pt 1):1044-6. doi: 10.2466/pr0.1990.66.3.1044. PMID: 2143028.

Koper, R. (2001). Modeling units of study from a pedagogical perspective. The pedagogical metamodel behind EML.

Lukuman, K. (2022). Examining students'readiness for mobile learning: Effects of mobile phone self-efficacy and internet self-efficacy. NOUN Journal of Education. Vol 8, 2022, pp. 96-110.

Wang, Chuang & Schwab, Götz & Fenn, Pete & Chang, Mei. (2013). Self-Efficacy and Self-Regulated Learning Strategies for English Language Learners: Comparison between Chinese and German College Students. Journal of Educational and Developmental Psychology.