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HOW SELF-EFFICACY EVOLUTION COMBINED WITH HELP SEEKING CHOICES IMPACTS ON LEARNING PERFORMANCE ON A MOBILE LEARNING APPLICATION

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ABSTRACT

This paper explores the concept of self-efficacy and its impact on help seeking and 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. Help-seeking while learning is an important part of the learning. This article will focus on the typology differentiating choosing instrumental help or executive help. As to investigate the relationship between self-efficacy, help-seeking type 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 learning. Second, we asked participants to learn to pilot a drone in a virtual environment providing instrumental and executive helps that they can choose. Our findings demonstrate that if self-efficacy increases, the individual learning performance will also increase. We also confirmed that the use of instrumental helps has a positive influence on the learning performance, and that the use of executive help has the opposite effect.

KEYWORDS

Self-Efficacy, Learning Performance, Help-Seeking, Instrumental/Executive Help, CBLE, Mobile Learning

1. INTRODUCTION

Self-efficacy (Bandura, 1986, 2012) can be likened to a tool, a confidence that guides an individual to be influenced by their actions and the resulting outcomes. Student's self-efficacy has an importance influence on their learning achievement (Yusuf, 2011).

According to research on self-regulated learning strategies that support students' learning, the right use of assistance can be helpful (Newman, 2000; Puustinen, 1998; Ryan and Pintrich, 1997; Ryan et al., 2001; Skaalvik and Skaalvik, 2005). Even so, a lot of students fail to effectively and appropriately employ help-seeking as a self-regulated learning technique. Lastly, among individuals who seek assistance, some become effective after doing so, while others do not. It has been seen that inadaptive help-seeking occurs in computer-based learning environments (CBLE) (Aleven et al., 2003; Clarebout and Elen, 2009).

Self-efficacy can be considered as a motivational factor not only for student's learning achievement but also for their help seeking strategy (Huet et al., 2016) which improves their Self-Regulating Learning (Zimmerman, 2002) which finally improves their learning performance.

While deploying their help seeking strategy, they have to choose one help between different types. The use of instrumental or executive helps (Nelson-Le Gall, 1985; Arbreton, 1998) is one of these types. (Karabenick and Knapp, 1991) has proved that using instrumental help provides better self-regulated learning, which, as a consequence, provides better learning performance.

This article explores the impact of both learners' self-efficacy evolution during a learning and the use of different king of helps: Instrumental or executive on the learner's performance.

Specifically, we aim to analyze the interaction of these variables in a computerized learning environment. 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, help-seeking choices and performance in a CBLE. We will describe how we checked our hypothesis implementing an experimental mobile drone learning application, and the results we got. 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 modelling, social pressure, and physiological and emotional states. For example, social modelling 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

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 all 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 hypotheses have been confirmed in most of the works as confirm meta-analysis like (Holden et al., 1990) or more recent studies like (Brown et al., 2012) confirming self-efficacy has a positive effect on problem solving.

2.1.4 Effects of Self-Efficacy in HLCEs or CBLEs

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 Kaput (1996), HLCEs encompass 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.

HLCE and Computer Based Learning Environment (CBLE) are very near concepts often exchangeable. We will consider them equivalent in this article.

Research has shown that the use of HLCEs and CBLEs can have many benefits, such as improving learning outcomes, engagement, and motivation (Van Leeuwen and Janssen, 2019). Additionally, CBLEs can offer more personalized learning experiences by adapting to individual needs and preferences (Martinez, 2013). With the growing demand for online and remote learning, CBLEs have become increasingly important tools in education and training.

Mobile learning environments are CBLEs integrated in mobile devices like smartphones or tablets. Lukuman (2022) has studied self-efficacy in a mobile learning 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 and Oluwadara (2016) have shown how important was the training to increase self-efficacy during CBLE mobile learning because they think that self-efficacy is important in order to achieve the learning goals.

Haeng-Nam et al. (2015) have found, in the context of CBLE 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 in a CBLE

We have found several experiments conducted on self-efficacy and performance on learning tasks provided by CBLEs.

Bicen and Kocakoyun (2018) studied the effect of self-efficacy on student engagement in a CBLE. 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 et 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.

Bandura has demonstrated that self-efficacy has effects on various variables, including learning and learning performances. Bicen and Kocakoyun (2018) and Wang et al. (2013) have shown that self-efficacy influences positively performance. Haeng-Nam et al. (2015) have shown that it is also true in a mobile CBLE for “expectancy”.

Therefore, we propose the first following hypothesis: **Ha) A positive evolution of self-efficacy has a significant positive impact on performance in a CBLE.**

2.2 Help-Seeking During Learning

Researchers have suggested that there exist various types of help seeking, which vary in their capacity to foster learning and mastery (Nelson-Le Gall, 1985). These types of behaviors include instrumental help seeking, executive help seeking, and avoidance of help-seeking (Butler and Neuman, 1995; Arbreton, 1998). When students go for ready-made solutions rather than attempting to solve an issue on their own, this is known as executive help seeking. Because it depends on surface-level cognitive processing, this help-seeking strategy is not seen to be adaptive for learning (Arbreton, 1998; Nolen and Haladyna, 1990). Researchers have contended that instrumental help is the one form of support that can enhance learning. The term "instrumental help seeking" describes a circumstance in which students look for the bare minimum of knowledge/help required to complete the activity autonomously.

For instance, students seek hints but figure out the answer on their own (Karabenick and Knapp, 1991). Because the students actively participate in problem solving and the assistance only acts as additional input for deep processing, this help-seeking behavior is adaptive for learning (Nolen and Haladyna, 1990). Finally, pupils who know they need help but choose not to ask for it are said to be engaging in help-seeking avoidance. They are unable to improve their learning because of this kind of behavior (Karabenick and Knapp, 1991; Newman, 1990).

These forms of help-seeking are:

(a) either assessed as help-seeking intentions and they are typically measured using self-reports (Maillard et al., 2013),

(b) or actually measured by effective computerized tracing of actual help use (Huet et al., 2016; Mulet et al., 2017).

With the first approach, some doubt persists regarding its external validity because there is often a gap between intentions and real behaviors (e.g., Gollwitzer et al., 2009; Sheeran, 2002). The results of these two approaches are rather different: Results based on intentions have shown that instrumental help-seeking and favorably correlated with grade (Kitsantas and Chow, 2007). For the results based on effective use of help, some studies have shown no correlation between higher use of help and gains in performance (Clarebout and Elen, 2009), others have discovered a positive association between assistance use and performance (Elen and Clarebout, 2006). Sakdavong et al. (2011) have found that effective instrumental use of help did not improved performance even if it is a good adaptative way of learning.

Karabenick and Knapp (1991) have connected the choice of using instrumental helps (vs executive) to a better SRL which ensures better performances. To our knowledge, there is no consensus between researchers studying these variables (Huet et al., 2013).

As there are much less studies about effective help-seeking behavior than help-seeking intentions ones, we propose this second hypothesis keeping the idea of Nelson-Le Gall. (1985): **Hb) The effective use of instrumental helps has a bigger impact on performance than the use of executive helps.**

As a consequence, to our two previous hypotheses, we also propose this last hypothesis: **Hc) The learning performance is a positive function of the effective use of instrumental helps and evolution of self-efficacy, and a negative function of the effective use of executive helps.**

3. METHODOLOGY

To check our three hypotheses, we have to study three variables: the evolution of self-efficacy during learning, the use of instrumental help, the use of executive help and the learning performance.

To do so, we measure have to measure the following indicators: the self-efficacy before learning, the self-efficacy after learning, the amount of instrumental help used, the amount of executive help used and the participant's performance at the end of the learning.

To conduct this experiment, we designed a mobile drone piloting learning application which allows to compute the necessary indicators by having two self-efficacy polls (before and after), evaluating the performance by the time needed to complete the piloting task. To allow to count the use of executive and instrumental help, the application proposes to use helps before every of the learning steps except the first and the last one (5 times).

The drone piloting learning application was developed with Unity by the non-profit AD2RV association

3.1 Participants

We collected various data through two survey 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 and the traces were held in a secure OVH server in France.

The data obtained with the forms were collected between May 2022 and July 2022. All collected data is anonymous.

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).

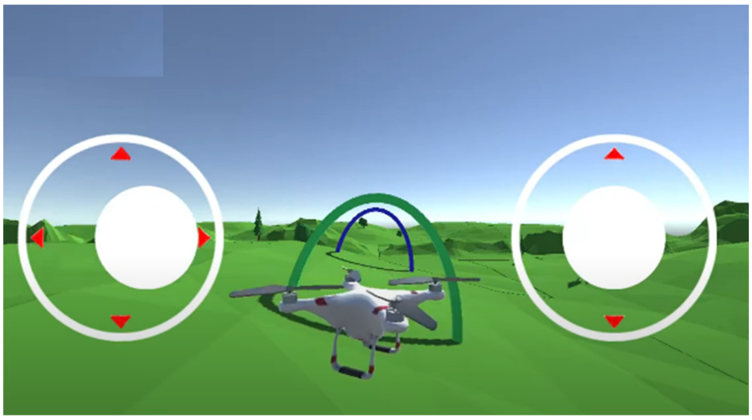

Figure 1. Illustration of the application

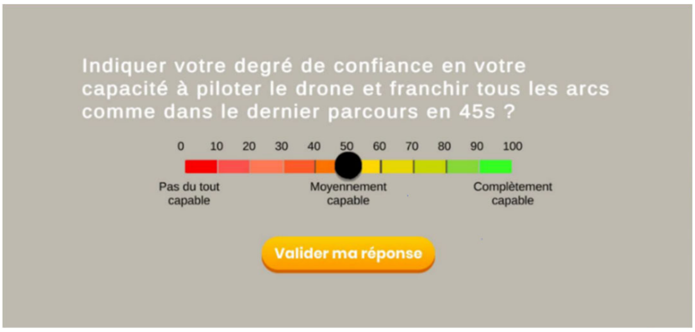

Figure 2. Self-efficacy questionnaire used before and after the learning

The participant receives a brief explanatory video showing the final obstacle race they will have to complete. While learning how to pilot and doing a course during evening learning steps, participants will have to go through arcs (as show in figure 1).

At the end of the video, we measure the participant's self-efficacy with the questionnaire show in Figure 2. 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).

Translation of figure 2: "Indicate your level of confidence in your ability to pilot the drone and cross all the arches as in the last course in 45 second" "Not at all capable" – "Moderately capable" – "Completely capable". 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 5 steps (7 lessons but only 5 with helps available), the participant can decide to use one or many helps (figure 3). Two instrument helps and two executive helps were available respecting the definition of Butler and Neuman (1995) and Arbreton (1998). The executive ones are automatic orientation of the drone (left/right) or/and automatic elevation of the drone (up/down) during the whole track. The instrumental ones are a projection of the ideal trajectory in real time and/or enlargement of the arcs in order to facilitate to learn piloting.

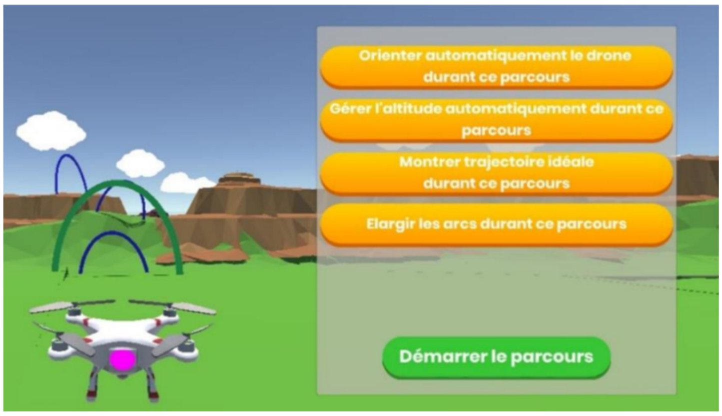

Figure 3. Available helps before each lesson

Translation of figure 3: “Orientate automatically the drone during this course, Level automatically the drone during this course, Show the ideal trajectory during this course, Enlarge the arcs during this course”

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) as already done in figure 2. Then the participant has to complete the final course with measurement of his performance (time to finish the final course). During this final course, the helps are not available.

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

We removed 3 outliners who have spent more the 257 seconds in order to finish the final course (performance measurement). These outliners were identified with the Jamovi software.

Table 1. Descriptive statistics

	Self-Efficacy Evolution	Performance (Smaller=Better)	Executive Helps	Instrumental Helps
N	41	41	41	41
Missing	0	0	0	0
Mean	-0.951	79.9	1.63	2.20
Median	0	49.9	0	0
Standard deviation	31.0	66.5	2.57	5.73
Minimum	-100	35.3	0	0
Maximum	66	257	10	35

If the self-efficacy evolution is positive, it means the participant have a greater self-efficacy assessment than at the beginning of the learning, and negative in the opposite case.

The time to complete the course in seconds represents what we call the performance variable. The lower this measure is, the greater the participant's performance will be. Table 1 presents the descriptive statistics about our two main resulting variables.

The table 1 shows us that the descriptive statistics of these variable. We can remark that helps were not used much.

4.3 Inferential Statistics

Hypothesis Ha: A positive evolution of self-efficacy has a significant positive impact on performance in a mobile learning application.

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:

$$y = \log10(\text{performance} - 35.2)$$

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 4 and table 2).

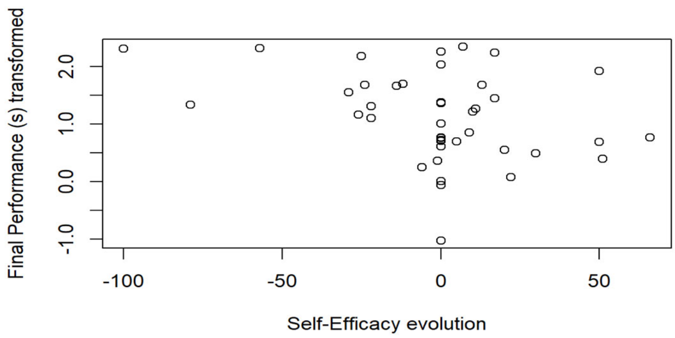

Figure 4. Graph of self-efficacy evolution by final performance transformed

Table 2. Descriptive statistics with transformed performance

	Self-Efficacy Evolution	Transformed Performance (Smaller=Better)	Executive Helps	Instrumental Helps
N	41	41	41	41
Missing	0	0	0	0
Mean	-0.951	1.13	1.63	2.20
Median	0	1.17	0	0
Standard deviation	31.0	0.769	2.57	5.73
Minimum	-100	-1.02	0	0
Maximum	66	2.35	10	35

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

Transformed performance = -0.0085 * Self-efficacy evolution + 1.1194.

The p-value for the Intercept 1.1195 is (*p<.01*) and for Self-Efficacity evolution is (*p=.0281*).

We also need to verify that the residuals of our model (figure 5) follow a normal distribution, meaning that the residuals are not correlated with each other.

With the help of the *Shapiro-Wilk* hypothesis test, we found (*p=.348*) which confirms a normal distribution. Our residuals (figure 3) do follow a centered and reduced normal distribution, and we can accept the linear regression between the transformed self-efficacy evolution and the learning performance.

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

Performance = 10 ^ (-0.0085 * Self efficacy evolution + 1.1194) + 35.2

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 6. The inverse transformation associated with y is: ***x = 10^y+35.2***

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

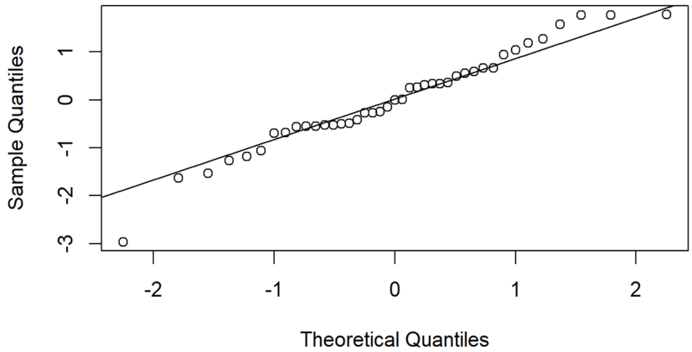

Figure 5. Representation of residuals distribution with the transformed performance

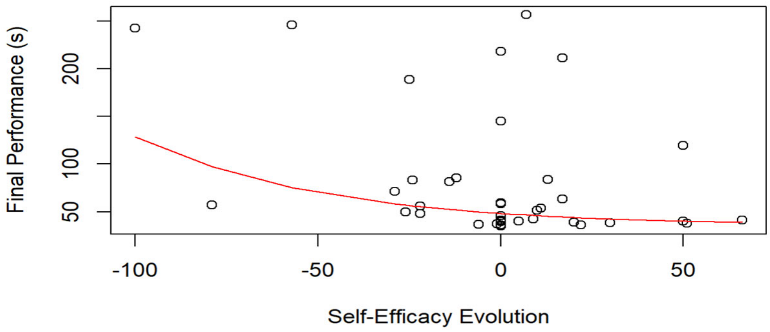

Figure 6. Final regression of self-efficacy over performance

Hypothesis Hb: The effective use of instrumental helps has a bigger impact on performance than the use of executive helps.

To be able to evaluate and validate our hypothesis Hb, we have three continuous variables at our disposal, it is therefore more appropriate to seek an answer through regression methods.

As for Ha, we do not get a normal distribution, therefore we try the same transformation which again brings a normal distribution (*p=.632*). Then we calculate the coefficients of the regression lines with our transformation:

Transformed performance = -0.0492 * Instrumental helps used + 0.2281 * Executive helps used + 0.8628

The p-value for the Intercept 0.8628 is (*p<.01*), for the Instrumental helps -0.0492 is (*p=.045*) and for the Executive helps 0.2281 is (*p<.01*).

With the help of the *Shapiro-Wilk* hypothesis test, we found (*p=.632*) which confirms a normal distribution. We can conclude that there is a multiple regression between the Transformed performance, which allows us to confirm again a non-linear relationship between our variables:

Performance = 10^(-7. 0492 * Instrumental helps used + 0.2281 * Executive helps used + 0.8628) + 35.2

This allows us to confirm that Hb is verified as 1) the decimal power is an increasing function, 2) the more instrumental helps are used, the lower the variable performance will be (as smaller it, is better it is) and 3) the more executive helps are used, the greater the variable performance will be.

<u>Hypothesis Hc:</u> The learning performance is a positive function of the effective use of instrumental helps and evolution of self-efficacy, and a negative function of the effective use of executive helps.

To be able to evaluate and validate our hypothesis Hb, we have four continuous variables at our disposal, it is again therefore more appropriate to seek an answer through regression methods.

As for Ha and Hb, we do not get a normal distribution, therefore we try the same transformation which again brings a normal distribution (*p=.230*) for the regression. Then we calculate the coefficients of the regression lines with our transformation:

Transformed performance = Self-efficacy evolution * 0.00707 - 0.0402 * Instrumental helps used
+ 0.21146 * Executive helps used + 0.86351

The p-value for the Intercept 0.86351 is (*p<.01*) and for Self-Efficacity evolution is (*p=.031*), for the Instrumental helps -0.0402 is (*p=.087*) and for the Executive helps 0.21146 is (*p=<.01*).

With the help of the *Shapiro-Wilk* hypothesis test, we found (*p=.230*) which confirms a normal distribution.

We can conclude that Hc is only partially confirmed as all coefficients are confirming the hypothesis but the Instrumental helps one (*p=.087*).

5. DISCUSSION

The study aimed to analyze the relationship between learners' self-efficacy evolution, type of help used and their performance in a learning task. The final sample consisted of 41 participants, 23 females and 18 males, who completed the experiment. Six measures were collected: self-efficacy before and after learning, the amount of instrumental help used, of executive help used, 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 proved that the evolution of self-efficacy has a positive impact on performance (Ha). 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 variable which has to be small to be good (in our case, the unit for performance is the second).

This study shows that self-efficacy evolution has a positive effect on final performance in a learning task which also matches with (Haeng-Nam et 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 et al., 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.

We have also successfully demonstrated the Hb hypothesis, which asserts that the increased use of instrumental aids corresponds to a decrease in variable performance (with a smaller value indicating better performance). Conversely, the more executive aids are used, the more the variable performance increases (which means the results are worse).

Studies on help-seeking behaviors show the significance of distinguishing between different types of assistance, with instrumental help-seeking enhancing learning outcomes. Therefore, we confirmed (Karabenick and Knapp, 1991) results even if there is no consensus between other researchers studying these variables (Huet et al., 2013).

As a consequence, either CBLEs' designers should not propose executive help, or promote the use of instrumental helps to learners.

We partially confirmed hypothesis Hc (the learning performance is a positive function of the effective use of instrumental helps and evolution of self-efficacy, and a negative function of the effective use of executive helps) as only instruments helps and self-efficacy coefficients got a significant p-value. We are currently trying to find a better modeling of the performance variable.

The size of the sample is a limitation to this work even if the inferential statistics were significative, future work should have bigger sample. Our findings should also be confirmed with other subjects than drone piloting and with longer learnings.

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.

6. CONCLUSION

This study, conducted via a mobile learning application, reveals a significant positive impact of improved self-efficacy on performance. This suggests that educators, CBLE (Computer-Based Learning Environment) designers, and mobile learning application creators should strive to enhance learners' self-efficacy through digital means, such as positive feedback.

We also find that the more instrumental helps are used, the better is the learning, and the executive helps have the opposite effect. As a consequence, either CBLEs' designers should not propose executive help, or promote the use of instrumental helps to learners.

Future research should explore the effectiveness of self-efficacy/help seeking interventions in different settings, with larger sample sizes, and longitudinal studies could offer a more comprehensive understanding of the dynamics of self-efficacy and help-seeking behaviors over time.

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