World Transactions on Engineering and Technology Education
Vol.20, No.3, 2022

The impact of motivation and cognitive ability on interface design skills

Rina Harimurti, Yeni Anistyasari, Meini Sondang S & Anita Qoiriah

State University of Surabaya
Surabaya, Indonesia

ABSTRACT: Human-computer interaction (HCI) is a design field, and supporting students' ability to create and implement interface designs with appropriate and systematic stages or processes is a key issue in design education. For students, the design process starts with determining the topic, preparing documentation in the form of worksheets, creating semantic nets, and finally implementing the design. This study aimed to examine the relationship between motivation and cognitive skills, and interface design skills. There were 40 students included as study participants. The obtained data were analysed using multiple linear regression. The analysis resulted in the equation $Y = 6.106 + 0.936\ X_1 - 0.17\ X_2$. This result showed that highly motivated students tend to competently design an interface without the suggested systematics or procedures. On the other hand, the regression coefficient of cognitive skills was negative, but the correlation was not significant. Hence, cognitive skills did not significantly affect interface design skills.

INTRODUCTION

The success of the teaching and learning process is strongly influenced by many factors, one of which is the students' skill mastery and learning attainment. To maximise the expected learning outcomes, all related factors must be considered so that the predetermined goals can be achieved. In the case outlined in this article, the goal is to achieve the expected level of interface design skills by students undertaking the Human and Computer Interaction course at an Indonesian university. Building on the basic concepts and knowledge, students need practice and experience to develop the required skills [1].

The development of students' interface design skills through suggested stages is the focus of this study. Students might be able to complete an interface design project, however, they mostly neglect the sequence in the process. The process encompasses determining the topic, making documentation in the form of worksheets, creating semantic nets, and finally implementing the design [2]. There are two independent variables estimated to affect students' interface design skills; namely, motivation and cognitive skills.

Motivation refers to the underlying reason for a particular behaviour and it involves the forces that make someone take or not take certain actions [3][4]. It is, moreover, an individual activity or a habit to achieve the desired goal even if the level of that habitual activity in a certain way depends on the intensity of the expected goal [5]. In the context of language learning, it has been described as the motor that stimulates action to achieve the predetermined learning goals [6].

Motivation also plays a role in helping students to concentrate on achieving the desired goal until it is reached. This is related to external factors that force a person to develop skills, so there is a willingness involved in that development and the greatest effort is undertaken to accomplish the desired goal [7]. As mentioned above, there must be a reason that underlies a person's involvement in certain activities or things that lead to the attainment of the expected goals. Also, motivation can be influenced by both internal and external factors, where the external factors may greatly affect one's skill development.

Cognitive skills are the second independent variable in this study, and relate to a rapidly developing research area of complex cognitive learning. In the current learning environment, students are often overwhelmed due to the many elements of information that need to be processed simultaneously before the core learning begins [8]. Design and technology topics in the curriculum require students to understand procedures and sequences which relate to cognitive aspects [9]. A person's cognitive skills are strongly influenced by their memory ability, often by their long-term memory (LTM) that is able to store information for a long period of time and has no limited capacity. Meanwhile, short-term memory or working memory (WM) is a temporary memory storage only with a limited capacity [10].

Basically, long-term memory is understood to be the main part of a person's cognitive skills. LTM contains a large amount of knowledge organised hierarchically, so that it allows the person to easily solve problems and choose appropriate solutions. One's cognitive level in LTM determines their level of performance.

In the present study, the focus is on the relationship between students' cognitive skills and the development of human-computer interface design skills considering human-computer interaction (HCI). Some studies indicate that to develop appropriate human-computer interfaces, developers must have good cognitive skills in the structure and representational dynamics of cognitive systems that interact with computers [11]. If one already has an understanding of representational mechanisms, then that person will have good cognitive skills and will be qualified to develop user interface design.

HCI is a combination of knowledge about computers and humans essential in designing interfaces that would have a user-friendly input and output of information, thus creating communicative and universal information technology and considering humans' action in human-computer interaction [12]. A user-friendly principle is one of the important characteristics that must be applied in developing an interface. Knowledge about HCI has grown rapidly and it involves also human-engaged computing (HEC). HEC is focused on developing HCI adaptable to a philosophical approach and aimed to build synergies between humans and computers [2]. Today's personal computers allow complex forms of user interaction in real-time and on a one-to-one basis, which is very different to older mainframe computers with batch processing functions. In modern computing, user interaction involves mixed initiatives (human and computer initiatives), logic, programming language and pointing gestures, and features reminiscent of interactions with humans [13].

Teaching HCI is often a challenging experience as the skills required in HCI design are different from the cognitive and computational thinking skills that have been the focus of the curriculum. HCI teaching is often carried out as a series of lectures where students learn concepts, but do not improve their design skills. However, the introduction of an appropriate HCI teaching model can result in improved experience and better outcomes in the future [14].

It is very important to employ a systematic approach to improve usability. A systematic approach helps designers identify design problems, obtain user requirements, devise user-friendly concepts, use system architecture, assess the completed systems and prototypes, and evaluate them methodically [15]. Usability is very important in the development of user-friendly interfaces, but research on interface development based on usability principles is still insufficient. A study has been conducted to address this need by looking at the usability attributes and appropriate design elements from a learning perspective. The results show that the usability design elements identified through the use of the presented iterative design and evaluation model are essential for improving the usability of the user interface, and thereby facilitating user action and the learning process [16]. More specifically, the key attributes of interface design identified in that study included learnability, effectiveness, efficiency and satisfaction. From these attributes, design elements have been extracted, and then re-examined from a learner-based perspective [16]

Another study also pointed out that user acceptance is essential in interface design. A comprehensive analysis of usability evaluation and user acceptance shows that an interface based on a user-centric design can provide satisfaction to the user. This study provides in-depth additional information and improvements to the user interface with a user-centred design approach [17].

METHODOLOGY

The quantitative research approach of this current study involved: a) the process of collecting data using structured instruments, such as questionnaires, survey sheets; b) analysis of the results based on the samples generated at the population level that could be repeated to achieve a high level of reliability; and c) data in the form of numeric values (numbers) or other form of statistics [18].

The study was conducted with 40 students who were learning programming in the Human and Computer Interaction course. The data were collected from the results of the students' cognitive tests, motivation questionnaires in regard to programming in human and computer interaction, and performance tests for interface design (Table 1).

Table 1: Data collection in regard to the three variables.

No	Information	Value
1	N	40
2	Male	20
3	Female	20
4	Motivation value range	60 - 95
5	Cognitive ability score range	32 - 89
6	Interface design skill score range	60 - 95

The data were collected in regard to three variables of this study; namely, variable X_1 referred to students' motivation during course activities, variable X_2 to cognitive skills (students' understanding of the Human and Computer Interaction course material), and variable Y to students' skills demonstrated in the final design project of the Human and Computer Interaction course.

The data analysis method used in this study was multiple linear regression to determine the relationship between two or more variables [19]. Regression analysis was used to determine the type of relationship between the identified variables, especially to explore the patterns of that relationship not fully known, and to find out how variations of the independent variables affect the dependent variable in a complex setting. When the normally-distributed dependent variable was influenced by the independent variables, then multiple linear regression was used [20]. On the other hand, if there was only one independent and one dependent variable, then linear regression analysis was performed.

The multiple linear regression equation used is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots \ldots \quad (1)$$

In this equation, β_0 is the intercept, and β_1 is the slope of the regression line. The intercept was the value of the response variable when the value of each independent variable was 0. It represented the point where the regression line touched the y-axis when X_1 and X_2 were 0. The regression line was a smoothed average graph. The regression line was drawn in such a way that it minimised the error of the fitted value with respect to the actual value.

RESULTS AND DISCUSSION

Table 2 shows the values obtained from the data analysis undertaken using the SPSS program.

Table 2: Descriptive statistics.

	Mean	SD	N
Design skills	77.3750	8.69626	40
Motivation	77.1250	9.19082	40
Cognitive skills	51.2000	12.94604	40

From the output, the average value of interface design skills of the 40 students was 77.3750 with an SD score of 8.69626, while the average value for cognitive skills was 51.2 with an SD score of 12.946. The average value for motivation was 77.1250, while the standard deviation for motivation was 9.19082.

Table 2: Correlations.

		Design skills	Motivation	Cognitive skills
Pearson correlation	Design skills	1.000	0.986	0.078
	Motivation	0.986	1.000	0.104
	Cognitive skills	0.078	0.104	1.000
Sig. (1-tailed)	Design skills	.	0.000	0.317
	Motivation	0.000	.	0.261
	Cognitive skills	0.317	0.261	.
N	Design skills/ motivation/cognitive skills	40	40	40

Table 3 shows that the relationship value between the variables of interface design skills and motivation was 0.986 and the significance F was 0.000 ($F < 0.050$), indicating a significant positive relationship, so the higher the student's motivation, the higher their interface design skills. However, the relationship value between cognitive skills and interface design skills was 0.078 and the significance F was 0.317 ($F > 0.050$), which means the correlation was nonsignificant.

Finally, the motivation and the cognitive relationship was 0.104 and the significance $F = 0.261$ ($F > 0.050$), which indicates that the correlation is not significant.

Table 3: Model summary.

Model	R	R square	Adjusted R square	Std. error of the estimate
1	0.986[a]	0.973	0.971	1.47762

Table 4 shows that the value of the R square was 0.973, which was the result of the square of the correlation coefficient (0.986). The standard error of the estimate was 1.47762 and the standard deviation of interface design skills was 8.69, which was larger than the standard error. As the SE of the estimate was smaller than the SD of interface design skills, regression analysis was necessary to be conducted.

Table 4: ANOVA.

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	2,868.591	2	1434.295	656.921	0.000[b]
	Residual	80.784	37	2.183		
	Total	2,949.375	39			

Regarding Table 5, the following hypotheses were formulated: H_0: $\beta_1 = \beta_2 = 0$ and Ha: $\beta_i \neq$ zero. If F count $\leq$ F table or probability ≥ 0.05, then H_0 is accepted. If F count > F table or probability < 0.05, then H_0 is rejected.

From the table above, the F count was 656.921, while the F table could be obtained using the F score with degrees of freedom (df) residual (remaining) of 37 as df denominator and df regression (treatment) of 2 as df numerator with a level significance of 0.05, so that the F table was 3.25. Because F count > F table, then H_0 was rejected. Based on the significance value, the probability of 0.000 was less than 0.05, so H_0 was rejected.

The conclusion from the hypothesis was that there were non-zero coefficients or significant coefficients, so the regression model can predict the interface design skills.

Table 6: Coefficients.

Model		Unstandardised coefficients		Standardised coefficients	*t*	Sig.
		B	Std. error	Beta		
1	(Constant)	6.106	2.129		2.867	0.007
	Motivation	0.935	0.026	0.989	36.134	0.000
	Cognitive skills	-0.017	0.018	-0.025	-0.922	0.362

Based on Table 6, the hypothesis: H_0: $\beta_i = 0$ and Ha: $\beta_i \neq$ zero, i = 1 or 2. If T count $\leq$ T table or probability ≥ 0.05, then H_0 is accepted. If T count > T table or probability < 0.05, then H_0 is rejected. From the table above, the T count for constant was 2.867 and the T table with 37 db, and a significance level of 0.05 was 1.68. Since T count > T table, then H_0 was rejected. While the significant value in the table β was 0.007, which meant the probability was 0.007. As the probability was less than 0.05, then it was rejected. This was meaningful and predictable not through the point (0,0). Furthermore, in coping with the motivation variable, the T count for motivation was 36.134.

The T table with 37 db and a significance level of 0.05 was 1.68. As T count > T table, then H_0 was rejected. While the significant value in the table β was 0.000, which meant that the probability was 0.000. Consequently, if the probability was less than 0.05, then it was rejected. Then, it could be concluded that β had a meaning.

Regarding the next variable; namely, cognitive skills, the T count for cognitive skills was -0.922. The T table with 37 db and 0.05 significance level obtained 1.68. As T count < T table, then H_0 is accepted. While the significant value in the table β was 0.362, which meant the probability was 0.362. Because the probability was more than 0.05, then H_0 was accepted. Then, it was concluded that β was not meaningful. Based on the analysis, the following predictive regression model could be generated: $Y = 6.106 + 0.936 X_1 - 0.17 X_2$.

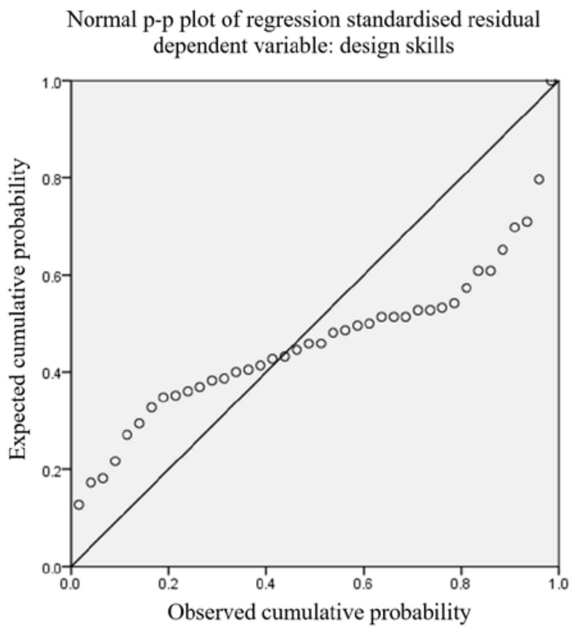

Figure 1: Multiple linear regression equation - graphical representation.

If the residuals came from a normal distribution, then the values of the data distribution would lie around a straight line. It could be seen that almost all data in the above image is distributed not on the normal axis, so it could be said that the statement of normality could not be fulfilled.

From the results of the analysis using the SPSS program, the regression equation was obtained: $Y = 6.106 + 0.936\ X_1 - 0.17\ X_2$. The equation meant that the constant value of 6.106 was a positive constant that showed a positive influence on the independent variable (e.g. motivation and cognitive skills). If the independent variable increased, it would have an effect in one unit, then the dependent variable, namely, interface design skills would increase too. Furthermore, the regression coefficient value of the motivation variable (X_1) was 0.936 for the interface design skill variable (Y), which meant that if the motivation (X_1) had increased by one unit, the interface design skill variable (Y) would have increased by 0.936. The positive coefficient meant that the variables X_1 and Y had a positive relationship [21]. This showed that an increase in motivation would result in an increase in interface design skills.

The next independent variable was cognitive skills (X^2), which had a coefficient value of -0.17. Meaning that, if the other independent variables had a fixed value and the X^2 variable increased by one unit, the Y variable would decrease by 0.17. However, according to Table 3, the correlation was not significant. In other words, cognitive skills did not significantly affect interface design skills. This was possible even though basically the regression equation was feasible to use [22].

Students are expected to be skilled in interface design and that proficiency is influenced by several variables. Teaching effective self-learning and enabling the use of technology to enhance cognitive abilities and design task skills are essential to successful outcomes [23]. To achieve this goal, students must develop knowledge about the structure and representational dynamics of cognitive systems in relation to computers [11]. So, in interface design, the most important aspects must be considered; namely, cognitive understanding, experience and skills [8].

The overall objective is to improve the quality of education, so that students acquire knowledge and skills that become a habit in their future work as designers. Also important is the prevention of student stress levels, encouragement to think creatively and motivating students to adapt to the challenging era of computer technology [24].

CONCLUSIONS

The study presented in this article focused on the relationships between students' design skills, their motivation and cognitive skills. It was found that F count > F table and the sig. value was 0.000 ($p < 0.05$). Hence, the two independent variables, motivation and cognitive skills, simultaneously affect the dependent variable, design skills. The generated regression model: $Y = 6.106 + 0.936\ X_1 - 0.17\ X_2$ can be used to predict the interface design skills of students. The motivation variable has a positive relationship, while the cognitive skills have a negative relationship.

Students tend to have a high motivation to be able to design an effective interface not based on systematic procedures. Some of them experience difficulties in mastering the concepts and theories that they must understand and subsequently use in interface designs. Several procedural steps that must be carried out until the interface is ready for use are not well accomplished. This is reflected in the coefficient value of the cognitive skills (X_2) of -0.17, which is negative. This indicated that the relationship between the cognitive skills and interface design skills is negative. This study was limited to two variables that could impact on interface design skills, however, it is possible that other variables not analysed here significantly influence these skills.

ACKNOWLEDGEMENTS

The authors would like to thank the students in the Human and Computer Interaction course at the State University of Surabaya (Universitas Negeri Surabaya) who participated in this study.

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