# A Study on the Factors Affecting Intention of Learning Python Programming: For Non-majors in University

Minjong Cheon, Ook Lee, Changbae Mun, and Hyodong Ha

***Abstract*—In an industry, society gets more interest in software. In accordance with this trend, in the process of composing the university's curriculum, it is increasingly emphasized that problem-based learning through computational thinking and programming ability based on logical thinking is weighted. This study conducted a study on how to identify students' educational characteristics and study intention. In particular, a methodology to explore the study intention for Python programming from the characteristics of each student was reviewed. For this analysis, the relationship between new technology from their point of view and factors is analyzed, factors are identified for methodologies, and statistical methodologies are used to verify them. The purpose of this study is to find improvements for software education operation and to provide help in educational policy decision-making of university members who conduct computer software education.**

***Index Terms*—Software education, Computer programming education, Software society, UTAUT2.**

## I. Introduction

The 4th Industrial Revolution, first mentioned by Klaus Schwab, affects whole fields of the industry through the convergence of various technologies such as big data and artificial intelligence and is expected to change the way organizations work and change the ecosystem of the industry. As the 4th Industrial Revolution brings about major changes in the labor market and workplace around the world, leaders should focus on preparing for labor and developing educational models in order to cooperate with intelligent machines [1]. For example, according to a research report by a government organization, about 3,000 out of 12,000 employees of 18 central government ministries in Korea can be replaced with the introduction of new technologies, such as artificial intelligence technologies [2]. Swimming with the tide, software (SW)-centered universities have been established since 2015 and have been operating in a number of universities [3].

SW-centered universities aim to cultivate SW professionals and strengthen their competitiveness and are based on the following five principles of operation [3].

1) Training SW professionals.
2) Expanding the base area of SW manpower training.
3) Effective industry-academic cooperation.
4) Establishment of a SW-specific educational environment.
5) Spreading SW value.

According to principle 2, SW basic education is also provided to non-majors other than those majoring in information technology (IT), and freshmen at the university must complete SW courses as electives. In addition, Non-majors could take advanced courses as they wish, via SW convergence curriculum specialized for each university. For instance, one of the universities in Korea conducts in-depth education on artificial intelligence and data science through cooperation with industries [4].

Students majoring in computer-related ones acquire, and internalize various programming languages to communicate with computers, and then engage in IT companies or related industries. On the other hand, the importance of programming is relatively low for non-majors. This situation is adaptable to the technology acceptance process, which has been studied a lot in the field of information systems, from the perspective that programming is new to them.

Therefore, our research conducts a survey on the intention of Python programming for non-majors using the extended unified theory of acceptance and use of technology (UTAUT2) model of Venkatesh, *et al*. (2012). As part of the university in Korea's compulsory and elective courses, a survey is conducted on students who took "creative computing" and "creative programming" classes. Finally, we analyzed the results of the collected responses statistically by structural equation modeling, derived meaningful factors, and verified how much influence they have on behavioral intention.

All organizations must learn how to utilize the knowledge and innovate systematically, and expand the scope of human capabilities through improving the tools which were used for working [5]. Even though they are not computer-related majors, learning programming as elective education paves the way for non-majors to grow into workers with programming knowledge. In this respect, our study is meaningful in conducting an empirical study to analyze the user's intention for Python programming by applying the UTAUT2 model. The purpose of this study is to derive improvements for lecture operation as basic data for fostering SW manpower and to provide help to make decisions for university faculty and stakeholders who conduct computer-related elective education.

## II. Background

Manuscript received October 31, 2001; revised December 27, 2021.

M. Cheon and O. Lee are with the Information Systems Department, Hanyang University, Seoul, Korea (e-mail: jmj2316@hanyang.ac.kr, ooklee@hanyang.ac.kr).

C. Mun is with the Electrical, Electronic & Communication Engineering Department, Hanyang Cyber University, Seoul, Korea (e-mail: changbae@hycu.ac.kr).

H. Ha is with Software Education Committee, Office of Academic Affairs, Hanyang University, Seoul, Korea (Corresponding author; e-mail: special007@hanyang.ac.kr) .

doi: 10.18178/ijiet.2022.12.5.1635

### *A. Computer Education for Liberal Arts in University*

Basic elective education is a universal education required for all students beyond various expertise in the academic field, including the cultivation of basic knowledge and autonomous academic ability required for overall university education [6]. Among the various areas of basic elective education, information literacy education that can decode data and information of digital civilization deals with the information distributed by information and communication technology as important. Furthermore, it requires novel transformable thinking [6].

In order to improve this information literacy ability, Korean universities have provided curriculum education services according to social trends. Computer elective education in 1991 accounted for 32% of computerized introductory and 45.5% of programming languages, and only 5.3% of packages. However, in 1999, PC usage, Windows usage, word process, and Excel program were included in the required subjects [7]. In a study by Kim (2012), students took computer elective education with the aim of obtaining a MOS certificate provided by Microsoft [8]. Since the beginning of SW-centered university in 2015, how to effectively conduct classes for computer non-majors has been a huge question. Kim (2017) conducted a study on students' satisfaction and perception of the subject after Scratch and Python practice classes for science and engineering students [9]. Kim and Kim (2018) created a computational thinking ability evaluation framework to evaluate whether there is a competency improvement effect for elective class students [10]. Lee (2018) proposed a development-oriented educational model in which students produce new results on their own after conducting Python classes [11]. Park and Hyun (2020) suggested a method of measuring problem-solving ability by making students see visual outputs and write programs with Python [12]. Jeong (2021) conducted research on the teaching method of elective SW subjects in a situation where university classes are conducted non-face-to-face due to COVID-19 [13].

Depending on the times and social environment, basic computer elective education at universities has continuously changed and related studies have been conducted. However, there is no existing research conducted on the intention of computer programming of non-majors, therefore this research examines an empirical survey on students in elective SW subjects.

### *B. Extended Unified Theory of Acceptance and Use of Technology*

Technology acceptance theory is a theory that examines the factors affecting users' acceptance of new technologies and their behavioral intention. The information technology acceptance model presented by Davis (1989) proposed a research model on the main variables affected by users' acceptance of new technologies, based on rational behavioral theories [14]. This model was used for research purposes in various fields, but the explanatory power of the model remained at 40%. Legris, Ingham, and Collarette (2003) criticize problems of self-reported methods, which are not quite elaborate methods, compared to measuring actual system use and suggest that they need to be integrated into comprehensive models such as including organizational and social factors [15]. Among them, Venkatesh *et al*. (2003) presented a unified theory of acceptance and use of technology (UTAUT) that synthesizes eight existing theories from an integrated perspective [16]. In the model, independent variables such as performance expectancy, effort expectancy, and social influence affect the parameters of behavioral intention. In addition, parameters and facilitating conditions influence the dependent variable, user behavior. The definitions of independent variables on dual behavioral intention are as follows [16].

**Performance expectancy**: The degree to which it is believed that using the system can improve work performance.

**Effort expectancy**: the degree to which the system is easy to use.

**Social influence**: The degree to which important people around me believe that I should use a novel system.

Later, Venkatesh, Thong, and Xu (2012) proposed UTAUT2 for mobile Internet users [17]. From a consumer's point of view, this model affects behavioral intention in which hedonic motivation and price value are parameters along with existing factors. Unlike the existing model, the facilitating conditions in UTAUT2 affect behavioral intention. And it was found that it affects the dependent variable use along with the habit. Among them, the definitions of independent variables on behavioral intention are as follows [16], [17].

**Facilitating conditions**: the degree to which it is believed that organizational and technical infrastructure exists to help use the system.

**Hedonic motivation**: the degree of pleasure or satisfaction you feel while using technology.

**Price Value**: The degree of impact of the amount of price versus profit gained from using technology.

**Habit**: The degree to which users automatically do as they learn.

Python programming language is positively recognized as a tool for problem-solving by students in various majors, but it was found that the degree of interest in SW of individual students greatly affected the satisfaction of the subject [9]. Unlike IT students who have to continue programming, attitude toward new technologies is important to non-majors who are relatively less mandatory. Therefore, after students learn the Python programming language, it is necessary to investigate the behavioral intention to continuously perform according to their attitudes. Therefore, this paper attempts to analyze the Python programming intention of elective SW students using the UTAUT2 model.

## III. Model Development

### *A. Research Model Construct*

In order to analyze the intention of learning Python programming for non-majors, a research model is set up as shown in Fig. 1.

In order to improve students' academic achievement, universities need to closely grasp educational motivation from a long-term perspective and apply them to educational activities. It is vital to investigate technology acceptance and learning intentions in order for non-majors to absorb knowledge such as SW education suited to educational motivation and apply it to educational field practice. In this respect, the UTAUT2 model was introduced in this study. The UTAUT2 model was developed to satisfy the aspect of 'consumer practical use' to the UTAUT model, and variables such as hedonic motivation and habit were newly added to the UTAUT model. Above all, the UTAUT2 model comprises internal components of learning, such as pleasure motivation and habits, which are emotional variables in studies investigating positive acceptance of students' learning processes. Since this research applied intrinsic analysis elements, it is critical to highlight the influence link between the findings of this research and the emotional elements influencing students' adoption of technology. Therefore, in this paper, a model was constructed via the UTAUT2 model to examine the individual's attitude toward new technologies and behavioral intention to continuously perform them.

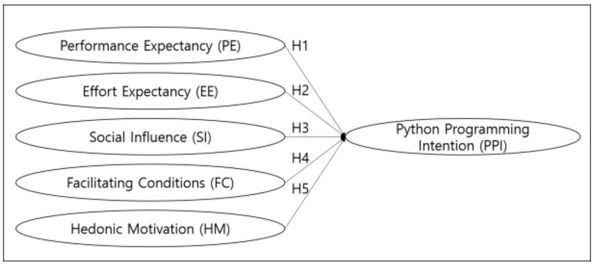

Fig 1. Research model.

Students' skills, that are learned through taking elective SW courses improve their productivity. Although students have learned a variety of software over time, Python is particularly powerful in executing complex algorithms in an efficient way [18].

Students can easily access Python language. In business administration, for example, coding now becomes an essential skill for the undergraduate student, even though it was mainly used by graduate students for research purposes [19]. Both Python and R are open sources, but compared to R, Python is easier to use, has a low learning curve, and is attractive to people who are new to the field of data analysis [19].

It is important for people around students to continue programming, especially those who could directly or indirectly influence students. How to incorporate computer technology in various academic fields is of great interest. Social science, for example, requires cooperation with computer programming, such as human-computer interaction and computer-supported cooperative work [20]. For this reason, various departments and IT-related departments are being fused, and programming education is emphasized for students.

Students can get help from various online and offline platforms and people while using Python. Python programming languages are highly utilized because there are many libraries available in various areas, and students can get appropriate help in that they can easily find solutions on sites such as stack overflow when they have questions. In addition, if we search Python in K-MOOC, an open online learning course that provides Korea's excellent higher education content, as of 2021, 29 courses such as big data and machine learning are provided [21].

It will be fun to use technology to derive creative ideas and apply them to students' major fields. According to Kyun and Jang's research, Python was studied for college students from the humanities, science, and engineering, and a social problem-solving-based start-up strategy was created [22]. As a result of the students' class satisfaction survey, it was found that students in the humanities and social sciences had the highest experience in dealing with programs and writing start-up plans. The departments of college students who earned the highest grade award as a result of performing the 2021 SW Value Spread Media Content Contest at the institution to which the writers belong are arts and sports [23].

Based on these factors, students will think positively about performing Python programming. The price value of the UTAUT2 model is excluded since Python is a non-profit open-source software managed by the Python Software Foundation. In addition, unlike the mobile Internet, where smartphones can be widely distributed, easily accessed and habituated, it is difficult to apply the concept of habituation of programming to non-majors. Therefore, in this study, habitual factors are excluded from hypotheses. Finally, the hypothesis established to analyze Python programming intention is as follows.

**H1**. The performance expectancy of non-majors will have a positive (+) effect on Python programming intention.

**H2**. The effort expectancy of non-majors will have a positive (+) effect on Python programming intention.

**H3**. The social influence of non-majors will have a positive (+) effect on Python programming intention.

**H4**. The facilitating conditions of non-majors will have a positive (+) effect on Python programming intention.

**H5**. The hedonic motivation of non-majors will have a positive (+) effect on Python programming intention.

### *B. Research Subject*

One of the universities in Korea has been selected as an SW-centered university since 2016 and has been conducting basic-in-depth convergence education for non-majors college students. As of 2020, 4,499 students took several courses, including creative computing, creative programming, artificial intelligence, and machine learning, as basic SW courses. This research targets non-majors college students who took "creative computing" and "creative programming" courses in the second semester of 2020. The 'Creative Computing' subject delivers an understanding of SW and procedural thinking methods using Python, while the 'Creative Programming' subject delivers programming techniques for data collection and processing. Creative computing consisted of three departments and creative programming was taken by students from various departments, including classes dedicated to humanities. In the second half of 2020, due to COVID-19, both subjects conducted non-face-to-face online recording classes, and feedback on practice was conducted through online communication channels such as email and SNS.

### *C. Evaluation Metrics of Variable*

The questionnaire was distributed to 277 students online at the end of the 15th week of the lecture, and finally, a total of 257 responses were analyzed. Students are in their early to mid-twenties. As a result of statistical verification analysis through the G*Power program, the minimum sample size was confirmed to be 77 [24]. The collected sample size sufficiently exceeds the minimum size, enabling a high level of statistical verification. Table I shows the demographic characteristics of the respondents used in the final analysis.

TABLE I: DEMOGRAPHIC CHARACTERISTICS

| Characteristics | | N | % of total sample |
|---|---|---|---|
| Gender | Male | 102 | 40 |
| | Female | 155 | 60 |
| Grade | Freshman | 163 | 63.42 |
| | Sophomore | 52 | 20.23 |
| | Junior | 26 | 10.12 |
| | Senior | 16 | 6.23 |
| Subject | Creative computing | 129 | 50.2 |
| | Creative programming | 128 | 49.8 |
| Creative computing (dept) | A | 37 | 28.68 |
| | B | 54 | 41.86 |
| | C | 38 | 29.46 |
| Creative programming (college) | Humanities | 60 | 47 |
| | Business and Economics | 17 | 13 |
| | Natural Sciences | 10 | 7.8 |
| | Human Ecology | 4 | 3.1 |
| | Economics and Finance | 13 | 10 |
| | Social Sciences | 11 | 8.6 |
| | Policy Science | 2 | 1.6 |
| | Music | 6 | 4.7 |
| | Industrial Information Studies | 1 | 0.8 |
| | Education | 1 | 0.8 |
| | Sports and Arts | 3 | 2.3 |

In this study, a research model was established based on UTAUT2's performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and behavioral intention. The questionnaire was based on a model developed by Venkatesh, Thong, and Xu (2012), and the questionnaire items in each area were revised and reorganized suitable to the purpose of this study so that non-majors could identify Python programming intention. In addition, all measurement questions used a Likert 7-point scale.

## IV. MODEL VERIFICATION

### A. Variable Reliability and Validity Analysis

Structural equation modeling is an analysis method for viewing both the part and the whole, where a significant path between factors can be found. The verification of the study model is performed with partial least squares (PLS)-based structural equation modeling, using SmartPLS 3. PLS structural equation modeling is a nonparametric method of estimating coefficients by repeatedly performing exploratory factor analysis to minimize residuals and prediction errors, and aims to maximize predictive power by estimating coefficients maximizing R2.

First of all, as a result of confirming kurtosis and extrapolation to examine data normality as shown in Table II, it exists within the allowable range of -1 to +1, which is judged that there exists no problem with irregularity.

In order to evaluate the outer model, internal consistency reliability, concentrated validity, and discriminant validity were considered. First, Cronbach alpha, Dijkstra-Henseller's rho_A, and composite reliability (CR) criteria were used to evaluate internal consistency reliability. As shown in Table III, all Cronbach alpha values showed high reliability of 0.8 or higher, rho_A showed desirable reliability of 0.7 or higher, and all CRs with dispersion between 0 and 1 showed 0.8 or higher. Exogenous latent variables such as effort expectation, hedonic motivation, social impact, and endogenous latent variables, including Python programming intention, are both measured above 0.95 which implies that they are both measured by the same item, and can be evaluated as undesirable. However, since the questionnaires used in this study have been verified in a number of studies, it can be concluded that there is no problem.

In the following concentrated validity, outer loading level (OLR), indicator reliability (IR), and average variance extracted (AVE) criteria were used. As shown in Table IV, the ORL was confirmed to be 0.7 or higher to maintain the measurement variable, and in IR, the square of outer loading was measured to be 0.5 or higher, except FC4, which is the measurement variable of the facilitating conditions. However, FC4 was included as it was close to 0.5. In addition, in AVE, which explains how much the latent variables are the variance of the measurement variables, all of them were 0.5 or higher, and it could be judged that the concentrated validity was secured.

Finally, in the discriminant validity, the heterotrat-monotrat ratio (HTML) criterion was used. HTML is calculated as the percentage of correlation between the measurement variables constituting the latent variables, the correlation and the correlation measured by different methods, and the correlation measured by different methods. As shown in Fig. 2, it is determined that the discriminant validity is secured as all HTMT values are less than the threshold of 0.9.

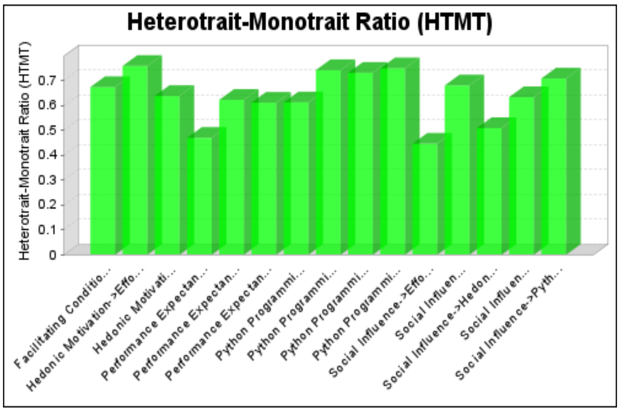

Fig. 2. HTMT result.

TABLE II: DATA DISTRIBUTION

| | Mean | Standard Deviation | Excess Kurtosis | Skewness | | Mean | Standard Deviation | Excess Kurtosis | Skewness |
|---|---|---|---|---|---|---|---|---|---|
| PE1 | 5.37 | 1.41 | 0.25 | -0.89 | FC1 | 4.80 | 1.38 | 0.17 | -0.61 |
| PE2 | 5.44 | 1.32 | 0.77 | -0.97 | FC2 | 4.60 | 1.34 | -0.05 | -0.51 |
| PE3 | 4.91 | 1.49 | -0.41 | -0.46 | FC3 | 4.01 | 1.64 | -0.77 | -0.07 |
| PE4 | 5.28 | 1.44 | 0.24 | -0.81 | FC4 | 4.98 | 1.55 | -0.37 | -0.67 |
| EE1 | 3.89 | 1.56 | -0.73 | 0.00 | HM1 | 5.14 | 1.45 | -0.04 | -0.69 |
| EE2 | 4.44 | 1.50 | -0.52 | -0.35 | HM2 | 4.98 | 1.49 | -0.29 | -0.51 |
| EE3 | 4.27 | 1.62 | -0.70 | -0.25 | HM3 | 4.58 | 1.62 | -0.61 | -0.23 |
| EE4 | 4.08 | 1.50 | -0.72 | 0.01 | PPI1 | 4.73 | 1.58 | -0.40 | -0.40 |
| SI1 | 4.23 | 1.65 | -0.68 | -0.18 | PPI2 | 4.88 | 1.53 | -0.37 | -0.47 |
| SI2 | 4.18 | 1.63 | -0.65 | -0.13 | PPI3 | 4.33 | 1.67 | -0.81 | -0.18 |
| SI3 | 4.39 | 1.64 | -0.51 | -0.31 | | | | | |

TABLE III: THE EVALUATION OF INTERNAL CONSISTENCY RELIABILITY

| | Cronbach Alpha | $rho\_A$ | Composite Reliability | | Cronbach Alpha | $rho\_A$ | Composite Reliability |
|---|---|---|---|---|---|---|---|
| PE | 0.913 | 0.918 | 0.938 | FC | 0.83 | 0.854 | 0.887 |
| EE | 0.934 | 0.939 | 0.953 | HM | 0.958 | 0.959 | 0.973 |
| SI | 0.942 | 0.943 | 0.963 | PPI | 0.952 | 0.953 | 0.969 |

TABLE IV: THE EVALUATION OF CONVERGENT VALIDITY

| | Outer loading relevance | Indicator reliability | Average variance extracted | | Outer loading relevance | Indicator reliability | Average variance extracted |
|---|---|---|---|---|---|---|---|
| PE1 | 0.911 | 0.830 | 0.792 | FC1 | 0.837 | 0.701 | 0.663 |
| PE2 | 0.885 | 0.783 | | FC2 | 0.873 | 0.762 | |
| PE3 | 0.867 | 0.752 | | FC3 | 0.837 | 0.701 | |
| PE4 | 0.897 | 0.805 | | FC4 | 0.701 | 0.491 | |
| EE1 | 0.930 | 0.865 | 0.836 | HM1 | 0.954 | 0.910 | 0.923 |
| EE2 | 0.912 | 0.832 | | HM2 | 0.980 | 0.960 | |
| EE3 | 0.928 | 0.861 | | HM3 | 0.949 | 0.901 | |
| EE4 | 0.886 | 0.785 | | PPI1 | 0.959 | 0.920 | 0.912 |
| SI1 | 0.955 | 0.912 | 0.897 | PPI2 | 0.951 | 0.904 | |
| SI2 | 0.963 | 0.927 | | PPI3 | 0.955 | 0.912 | |
| SI3 | 0.923 | 0.852 | | | | | |

### B. The Evaluation of Structural Model

The evaluation of the structural model is conducted to confirm suitability from the perspective of how well the exogenous latent variable of the next structural model predicts the endogenous latent variable. Evaluation criteria include multicollinearity, coefficient of determination, effect size, predictive suitability, and significance and suitability of path coefficients.

First, the inner VIF values of the structural model are used to evaluate the multicollinearity between latent variables. The high correlation between independent variables results in overlapping usage of similar independent variables, so even if there exists no multicollinearity, it should be very small. As shown in Table V, since all of them are less than 5, it is judged that multicollinearity does not exist between latent variables.

Secondly, the coefficient of determination (R2) is the variance ratio of endogenous latent variables described by exogenous latent variables, which means the predictive power of the model. R2 showed moderate explanatory power at 0.703 between 0.5 and 0.75.

Thirdly, the effect size (f2) is the relative influence of the exogenous latent variable on the endogenous latent variable, that is, the degree to which exogenous latent variables contribute to the R2 of the endogenous latent variable. The performance expectancy is 0.135, close to 0.15, which has a moderate effect size, and social influence, and facilitating conditions, and hedonic motivation are evaluated to have a small effect size. It is considered that the effort expectancy has little effect size as it yields 0.002.

Moreover, Stone-Geisser Q2 is a measure that can determine how predictive suitability is for endogenous latent variables, and it showed 0.63. Since it is larger than 0, it is determined that it possesses predictive suitability.

TABLE V: THE EVALUATION OF STRUCTURAL MODEL

| | **Inner VIF values** | **coefficient of determination** | **f square** | **$Q^2$** |
|---|---|---|---|---|
| PE | 1.892 | $R^2$= 0.703 | 0.135 | 0.631 |
| EE | 2.32 | $R^2$adjusted = 0.697 | 0.002 | |
| SI | 1.89 | | 0.101 | |
| FC | 2.171 | | 0.052 | |
| HM | 2.54 | | 0.112 | |

The last ones are the significance and suitability of the path coefficient. The path coefficient is a standardized regression coefficient with a value of -1 to +1, and if it is close to 0, the relationship between latent variables is statistically significant and weak. Table VI shows the significance verification results for the path coefficient. As a result of hypothesis verification, hypothesis 2 is rejected and adopted the rest of all. The factor that have the greatest influence on Python programming intention was hedonic motivation, followed by performance expectancy, social influence, and facilitating conditions. The path coefficient of effort expectancy was 0.04, close to 0, which did not have a statistically significant effect. Python languages are relatively easy to use compared to other languages such as C and Java, but it is difficult for non-major students who are new to computer engineering. Fig. 3 is the model test result of this study, based on the analysis results.

TABLE VI: HYPOTHESIS VERIFICATION

| Hypothetical path | Path coefficients | T value | P-value | Result (p<0.05) |
|---|---|---|---|---|
| PE - PPI | 0.276 | 5.496 | 0 | Accepted |
| EE - PPI | 0.04 | 0.774 | 0.439 | Rejected |
| SI - PPI | 0.239 | 4.517 | 0 | Accepted |
| FC - PPI | 0.183 | 2.982 | 0.003 | Accepted |
| HM - PPI | 0.29 | 4.42 | 0 | Accepted |

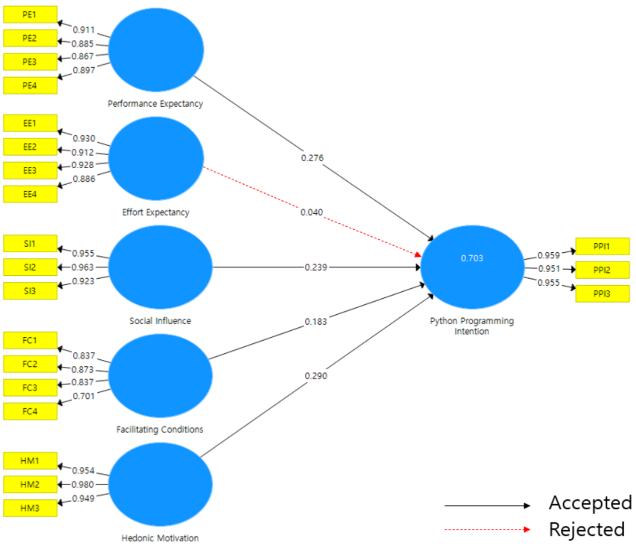

Fig 3. The result of research model verification.

## C. Analysis of Practical Use

Based on the previous analysis results, two utilization methods are examined to help make decisions about class management.

First, the relative contribution is confirmed through the strategy matrix through the combination of influence and index.

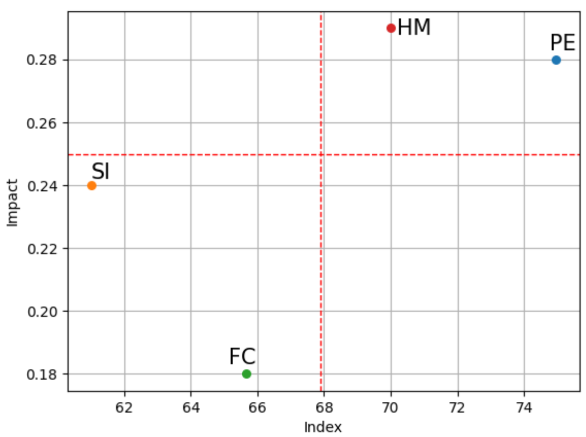

Fig. 4. The matrix of Python programming intention.

Fig. 4 is a matrix including the influence on Python programming intention and the index for each factor. The index is a value obtained by converting the average of measurement variables to a total score of 100. The current score of Python programming intention is 66.37, and in order to increase this value, it can be considered to prioritize performance expectations and hedonic motivation which lie in the area above the average line.

Second, it investigated if there exists a difference in Python programming intention between students of creative computing and students of creative programming. After separating the variables into subjects, the independent sample T-test, which is a hypothesis test for the mean of the two populations, was performed.

After freshmen students completed creative computing classes, which are basic essential subjects, the average of Python programming intention rose slightly after taking creative programming classes as elective courses. However, as a result of the equivalent variance test of Levene in table VII, it could be concluded that homogeneity was not hypothesized because the significance probability was less than 0.05, and the absolute value of the test statistic t was 0.435, which was greater than the significance level 0.05, so which made it not statistically significant.

TABLE VII: GROUP STATISTICS AND INDEPENDENT SAMPLE TEST

| | Mean | Std. Deviation | Levene's Test for Equality of Variances | | t-test for Equality of Means | | |
|---|---|---|---|---|---|---|---|
| | | | F | Sig. | t | df | Sig. (2-tailed) |
| CC | 4.60 | 1.31 | 10.12 | 0.002 | -0.435 | 237.78 | 0.664 |
| CP | 4.69 | 1.71 | | | | | |

*CC: Creative computing; **CP: Creative programming.

## V. CONCLUSIONS

In this study, an empirical study was conducted on how to identify students' educational characteristics and study their intention. In order to analyze factors, a UTAUT2 theory was introduced to explore the intention for new technology from the characteristics of individual students. For this analysis, the relationship between Python programming intention and 5 factors was analyzed, and the statistical method, structural equation modeling, was verified. As a result of the experiment, the factor of hedonic motivation in programming intention became the highest one, and the factor with the second-highest influence was performance expectancy. In relation to the purpose and results of this study, it is necessary to target students with a high interest in programming. In the process of finding improvement points for SW education operation and developing educational programs that can help these students in their career paths, students can expect high educational outcomes.

On the other hand, there is a restriction in that it could not be observed for a long period by reflecting the SW education features described in this study and the disparities in the particular characteristics and surroundings of students' majors in the study. As a result, while the classification of students' desire to adopt technology was offered, further studies based on long-term study are conceivable in the future. Furthermore, it will be required to investigate the differences in student perception and the process of SW adoption in relation to the variety of used SW technologies. Furthermore, given that students in their 20s now have a favorable response to the usage of SW and are actively engaged in SW learning, there may be major variances in technology adoption based on students' age or learning time distribution. In the case of this study, the difference in the age group within the sample was not reflected due to the limitations of the student sample. If the follow-up study is designed by groups of various factors, it is thought that it will be a study that differentiates itself from the results of this study and overcomes the limitations of this study.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

M. Cheon, O. Lee, and C. Mun developed the idea of research. H. Ha prepared the theoretical base of research and conducted a survey and statistical analysis of data.

## REFERENCES


[1] K. Schwab, "The fourth industrial revolution," *Currency*, 2017.
[2] M, Moon *et al*, "Government manpower management plan according to the introduction of future new technology," The Ministry of Public Administration and Security of the Republic of Korea.
[3] Software-centered University, What is Software-centered University? [Online]. Available: https://www.swuniv.kr/33
[4] D. Oh, "KT-Hanyang University cooperation to strengthen artificial intelligence practical training," NEWSIS.
[5] P. F. Drucker, *The Essential Drucker*, Routledge. 2020.
[6] Korean National Institute for General Education. The standard model of university liberal arts basic education. [Online]. Available: http://www.konige.kr/english/sub02_05_view.php?bbs_cd=2017080900003&stx=%EB%8C%80%ED%95%99%20%EA%B5%90%EC%96%91%EA%B8%B0%EC%B4%88%EA%B5%90%EC%9C%A1%EC%9D%98%20%ED%91%9C%EC%A4%80%20%EB%AA%A8&bsearch=b.c_title&cdiv=&pageno=1
[7] H. Rieh, "The current status and development direction of school-wide mandatory computer education in Korean Universities," *Korean Society for Educational Technology*, vol. 15, issue 3, pp. 299-313, Jan 1999.
[8] W. Kim, "A study on factors of education's outcome in liberal computer education using regression and data mining analysis," *Korean Journal of General Education*, vol. 6, no. 3, pp. 743-767, Sep 2012.
[9] W. Kim, "A study on the recognition of freshman on computational thinking as essential course," *The Korea Society of Culture and Convergence*, vol. 39, no. 6, pp. 141-170, Dec 2017.
[10] M. Kim and H. Kim, "Effectiveness analysis based on computational thinking of a computing course for non-computer majors," *Journal of Korean Association of Computer Education*, vol. 21, no. 1, pp. 11-21, Jan 2018.
[11] Y. Lee, "Python-based software education model for non-computer majors," *Journal of the Korea Convergence Society*, vol. 9, no. 3, pp. 73-78, March 2018.
[12] C. Park and J. Hyun, "Analysis of the effects of learners' visual literacy and thinking patterns on program understanding and writing in basic coding education for computer non-majors," *The Korean Association of Computer Education*, vol. 23, no. 2, pp. 1-11, Mar 2020.
[13] H. Jeong, "An empirical study for the change of software lecture in general education by COVID-19," *The Journal of Korean Institute of Information Technology*, vol. 19, no. 4, pp. 119-124, Apr 2021.
[14] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp.319-340, Feb 2012.
[15] P. Legris, J. Ingham, and P. Collerette, "Why do people use information technology? A critical review of the technology acceptance model," *Information & Management*, vol. 40, no. 3, pp. 191-204, Jan 2003.
[16] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quarterly*, vol. 27, no. 3, pp. 425-478, Sep. 2003.
[17] V. Venkatesh, J. Y. Thong, and X. Xu, "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology," *MIS Quarterly*, vol. 36, no. 1, pp.157-178, Feb. 2012.
[18] J. C. Chaves *et al*., "Octave and python: High-level scripting languages productivity and performance evaluation," in *Proc. 2006 HPCMP Users Group Conference (HPCMP-UGC'06)*, pp. 429-434, June 2006.
[19] R. Vallat, "Pingouin: Statistics in Python," *Journal of Open Source Software*, vol. 3, no. 31, p. 1026, 2018.
[20] P. Brooker, *Programming with Python for Social Scientists*, SAGE Publications, 2020.
[21] Departmental courses: K-MOOC. [Online]. Available: http://www.kmooc.kr/courses?search_query=%ED%8C%8C%EC%9D%B4%EC%8D%AC
[22] S. Kyun and J. Jang, "A case study on the intensive semester operation of online-based project learning using python: Focusing on S women's university," *Journal of Engineering Education Research*, vol. 24, no. 5, pp. 3-14, Sep 2021.
[23] Software-Centered University, Announcement. [Online]. Available: http://hysoft.hanyang.ac.kr/modules/board/bd_view.html?id=wt_notice&no=102
[24] F. Faul, E. Erdfelder, L. Albert-Georg, and A. Buchner, "G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences," *Behavior Research Methods*, vol. 39, pp. 175-191, May 2007.




**MinJong Cheon** earned his BS degree from Hanyang University, Seoul, Korea in 2020. Now he is a PhD student and works as a researcher of information systems lab at Hanyang University in Seoul, Korea. His major of interest and expertise are information systems, deep learning, and machine learning.

**Ook Lee** earned his PhD degree from Claremont Graduate University, USA in 1997. Now he serves as a professor of information systems at Hanyang University in Seoul, Korea. His major of interest and expertise are information systems, deep learning, and machine learning.

**Changbae Mun** earned his PhD degree from Hanyang University, Seoul, Korea in 2018. Now he serves as a professor of information system and communication engineering in Hanyang Cyber University in Seoul, Korea. His major of interest and expertise are intelligent platform, information systems, and data analytics.

**Hyodong Ha** earned his PhD degree from Hanyang University, Seoul, Korea in 2020. Now he serves as a collaboration professor of software education committee, office of academic affairs in Hanyang University in Seoul, Korea. His major of interest and expertise are big data, information systems, and software education.