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Perceived usefulness of a machine learning-assisted recommendation system for generic competency development

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Abstract

Generic competency development activities (GCDAs) help students develop critical thinking, problem-solving, innovation, creativity, communication and social skills. This study evaluated students' acceptance of a machine learning-assisted recommendation system (MARS) developed to recommend GCDAs for students in a higher education institution. This study adopted a quantitative approach to evaluate the higher education students' perceived usefulness of MARS based on a new appropriate model derived from three widely used models related to technology adoption and leisure activities. In August 2023, the participants of orientation for freshmen were invited to complete an online questionnaire after they tried MARS. 351 valid responses were analyzed using multiple regression. The results revealed that the students positively perceive accepting MARS as a useful tool for choosing GCDAs and indicated the students' perceptions were affected more by their programs of study, career development and personal interests than by social influence and facilitating conditions on their selection of GCDAs. These findings based on the new model provide implications for the implementation of education technology for generic competency development.

Keywords: Generic competency development activities, Higher education, Leisure activities, Machine learning, Task-technology fit, Technology acceptance.

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Contents

Contribution of this paper to the literature

The contribution of this research is twofold. First, a new model has been developed to investigate the acceptance of the machine learning-assisted recommendation system for recommending generic competency development activities. Second, this research's findings using the new model can bring insights into the implementation of education technology for generic competency development.

1. Introduction

Generic competency development activities (GCDAs) are essential for higher education (Barrie, 2007; Tait & Godfrey, 1999; Wong, 2023). The College of Professional and Continuing Education at Hong Kong Polytechnic University, the case higher education institution for this study offers GCDAs that help students in higher education develop various skills, including critical thinking, problem-solving, innovation, creativity, communication and social skills. Critical thinking and problem-solving skills can help the students to have a better understanding of problems and develop their competencies in solving problems. Innovation and creativity skills can help the students gain insights into the development of new technology. Communication and social skills can help the students collaborate with their peers. These are the skills required for the students' adaption to the rapidly growing technological advancements and challenges in their future work and life.

Students may face difficulty in choosing GCDAs appropriate for their generic competency development. A machine learning-assisted recommendation system (MARS) was developed to recommend GCDAs for students inspired by the advice for students at higher education institutions to choose appropriate extracurricular activities for their generic competency development. MARS was based on the study by So et al. (2023) who pioneered the application of data analytics to generic competency development by performing machine learning and analytics on a dataset of 474 historical intake students' profiles from the year 2019 to 2020 including their academic performance results, self-rated Holland codes and levels of the achieved institutional intended learning outcomes. The major findings in this study by So et al. (2023) revealed that higher education students with better academic performance in their high or secondary school tend to have more involvement in GCDAs and these students' involvement in GCDAs has no negative effect on their academic performance in their higher education studies. Wong (2023) modified MARS by choosing a better-performing machine learning model from the collaborative filtering model and content-based recommendation models on the advisors' recommendations using these historical records as supervised training data. MARS manages to provide personalized recommendations to the students based on their individual learning and career aspirations as well as the gaps of their generic competency needs recognized by MARS by leveraging machine learning algorithms and the students' data (Wong, So, Tsang, & Wei, 2023a). MARS helps the students to improve their genetic competencies.

Studying these techniques is crucial since maintaining technology's resilience and ensuring its smooth operation are essential for its sustainability (Wong, Yeung, Lau, & So, 2021). This sustainability of the technology depends highly on whether users accept using the technology especially at the early stage of technological development and advancement. According to Wong, Yeung, Lau, and Kawasaki (2023b) if users do not accept using the technology at its infancy stage that technology cannot help the users effectively and therefore fails to sustain. Therefore, it is important to consider how a new technology can improve user performance. It is important to assess if MARS corresponds to higher education students' performance in choosing acceptable GCDAs well given that it was presented to them for the study's case study. The models related to technology acceptance cannot be fully applicable as MARS is mainly used for recommending extracurricular activities for leisure instead of study or job performance to evaluate the extent to which the students at the case higher education institution accept using MARS for recommending extracurricular activities for their generic competency development. In these regards, it is necessary to examine the factors influencing student's decision to participate in extracurricular activities and whether the extracurricular activities recommended by MARS's technology meet their demands. An appropriate model has not been explored in the literature to evaluate the usefulness of a tool that recommends GCDAs for students to participate.

The significance of this research is to formulate a new model based on relevant constructs from existing models to evaluate the higher education students' acceptance of using MARS for recommending GCDAs for their generic competency development. It is important to investigate the students' acceptance of MARS for its sustainability, especially at this infancy stage of implementing MARS. In these regards, the following research questions were addressed from the perspectives of the students in higher education institutions:

1. Do students accept MARS for selecting appropriate GCDAs?
2. What are the factors that influence the students' acceptance of MARS?
3. What are the relative effects of the factors that influence the students' acceptance of MARS?

2. Literature Review

Researchers found three widely used models related to users' acceptance or adoption of technology, technology fit and factors affecting participation in leisure activities in literature through Internet search engines such as Google, ProQuest, Scopus and Web of Science (1) Goodhue and Thompson (1995) Task-Technology Fit (TTF) model, (2) Venkatesh, Morris, Davis, and Davis (2003) Unified Theory of Acceptance and Use of Technology (UTAUT) and (3) Crawford, Jackson, and Godbey (1991) and Hierarchical Model of Leisure Constraints (HMLC). The TTF model asserts the influence of a good fit of the technology on the tasks (e.g., recommendations of student activities) to be performed. In this theory, a construct called task characteristics includes the functions of a task. Another construct is called technology characteristics which refer to the functions and features of a technology. The degree of a match between task characteristics and technology characteristics is described by task-technology fit. The TTF model can be denoted by using an arrow to indicate determination or influence.

- Task characteristics and technology characteristics → task-technology fit.
- Task-technology fit → performance and utilization.

UTAUT was developed by reviewing and unifying eight models. These eight models are Fishbein and Ajzen's (1975) Theory of Reasoned Action, Davis's (1989) Technology Acceptance Model, the Motivational Model (Davis, Bagozzi, & Warshaw, 1992; Vallerand, 1997), Theory of Planned Behavior (Ajzen, 1985, 1991), Taylor and Todd's (1995) Combined Technology Acceptance Model and Theory of Planned Behavior, Thompson, Higgins, and Howell's (1991) Model of Personal Computer Utilization, Rogers's (1995) Innovation Diffusion Theory (or, Diffusion of Innovation), and Social Cognitive Theory (Bandura, 1986; Compeau & Higgins, 1995; Compeau, Higgins, & Huff, 1999). UTAUT contains moderating or indirect effects (i.e., gender, age, experience and voluntariness of use). These moderating effects were not examined in this study as this study is applied to any gender and any age. There was not much variance in the experience of using MARS and the voluntariness of use was not an issue as students were required to use MARS which had been adopted at their higher education institution. As theorized by UTAUT, the students' acceptance of MARS is indicated by their actual usage of MARS. In addition to actual usage, there are five other constructs (or, perceptions) in UTAUT such as (1) effort expectancy which is the degree of the users' perception of the digital literacy, self-efficacy and ease of use of MARS, (2) performance expectancy which is the degree of the users' belief that using MARS can enhance their task performance (e.g., their academic performance), (3) social influence which is the extent to which the users perceive that the people around them such as parents, teachers, peer students and friends expect that they should perform the technology usage behavior, (4) behavioral intention which is the students' perceived intention to use MARS and (5) facilitating conditions which refer to the conditions that facilitate the use of MARS such as availability of transportation and time to support the GCDAs. UTAUT can be denoted without the moderating effects.

- Effort expectancy, performance expectancy and social influence → behavioral intention.
- Behavioral intention and facilitating conditions → actual usage.

In HMLC, there are three constraints: (1) intrapersonal constraint, (2) interpersonal constraint, and (3) structural constraint. Intrapersonal constraint refers to someone's ability to have sensitivity in understanding himself or herself and appreciate his or her feelings, desires, skills, fears and motivations (Gardner, 1983). Intrapersonal constraint determines the student's leisure preferences (i.e., preferences for extracurricular activities). Crawford et al. (1991) used the word "constraint" to conceptualize barriers. For example, intrapersonal constraint can represent a person's stress, anxiety and physical inability which restrict that person's choice of physical activities.

Interpersonal constraint is like social influence in UTAUT in the sense that interpersonal constraint and social influence both refer to the influence received by the student from others such as their friends, peer students, teachers and parents. This is what someone thinks of in the process of connecting or relating himself or herself with others through social interaction or communication. Similarly, this is regarded as one's capacity to "discern and respond appropriately to the moods, temperaments, motivations and desires of other people" (Gardner & Hatch, 1989). Interpersonal constraint affects one's interpersonal compatibility and coordination unlike UTAUT's social influence which affects one's attention to use technology.

In HMLC, both interpersonal constraints and leisure preferences determine the student's interpersonal compatibility and coordination. A structural constraint is similar to facilitating conditions in UTAUT in the sense that structural constraint and facilitating conditions both refer to the infrastructure (e.g., wireless fidelity (Wi-Fi), Internet, and organizations), conditions (e.g., workability, security, climate, quality environment), resources (e.g., time, cost, and energy), availability (e.g., accessibility and shareability) of the equipment (e.g., room, space, computer etc.) for specific activities. Structural constraint affects leisure activities while facilitating conditions affect technology usage activities. Structural constraint and interpersonal compatibility and coordination determine participation or non-participation) in extracurricular activities. HMLC can be denoted by:

- Intrapersonal constraint → leisure preferences.
- Intrapersonal constraint and leisure preferences → interpersonal compatibility and coordination.
- Interpersonal compatibility, coordination and structural constraint → participation.

The construct of task-technology fit in the TTF model can be extended to the fit between MARS' recommended GCDAs and the students' selected preferred GCDAs. The fit is neither a complete match nor a mostly match. For this study, the fit refers to the students' perceived usefulness of MARS. That is the situation in which the students regard MARS as a useful tool that can give proper recommended GCDAs for them to develop their generic competency.

As MARS is used by the students without much effort and technical skills to obtain recommendations for extracurricular activities for leisure instead of job or study performance, UTAUT which involves job or study performance expectancy and technology usage effort expectancy does not fully fit this study. However, the students' perceived usefulness of MARS is like performance expectancy in UTAUT such that MARS can help the students to perform selection of appropriate GCDAs to participate. Consequently, for this study, a new more appropriate unified model from HLMC, TTF and UTAUT is needed.

3. Formulation of the Theoretical Model

The following four constructs derived from HLMC, TTF and UTAUT were used for this study: (1) students' background, (2) social influence for selecting GCDAs, (2) facilitating conditions for conducting GCDAs and (4) the student's perceived usefulness of MARS. The student's background in this study was derived from intrapersonal constraints in HMLC in the sense that the students have considered their constraints when choosing extracurricular activities to join. Social influence in this study was derived from interpersonal constraint in HMLC as social influence and interpersonal constraint both refer to the influence of the students' social network on their selection of GCDAs. The construct of facilitating conditions in this study was derived from structural constraint in HMLC as facilitating conditions and structural constraints both mean the facilities that help and support the students' involvement in GCDAs. These four constructs formulate the following model as indicated in Figure 1:

- Students' background, social influence and facilitating conditions → perceived usefulness.

The students should consider their background when choosing the extracurricular activities to join. Therefore, the students' background influences their perceived usefulness of MARS. In actual situations, the students may not be able to participate in the extracurricular activities recommended by MARS because of the clashes with social influence and facilitating conditions. For example, the students may not be able to join an extracurricular activity recommended by MARS as their friends do not want to join that activity or there is a time conflict with their class schedule. Therefore, social influence and facilitating conditions affect the students' perceived usefulness of MARS. An arrow indicates an influence in Figure 1.

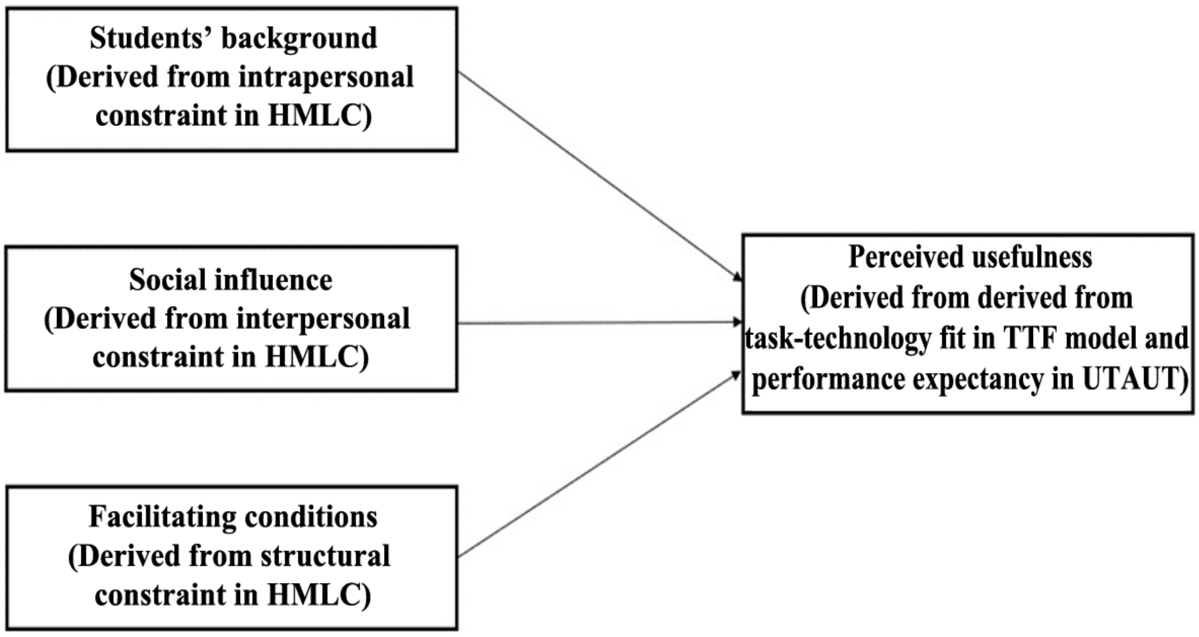

Figure 1. The model for this study.

4. Methodology

The participants in this study were new students who joined orientation programs in higher education institutions (i.e., the College of Professional and Continuing Education, the Hong Kong Polytechnic University). The orientation programs were organized for the new students to get familiar with the new environment of study in higher education institutions, get information about the facilities (e.g., online education systems, email, students' portal, computer facilities, teaching venues, administrative support etc.) and opportunities (e.g., program information, articulation and career opportunities, financial aids etc.) and meet their teachers and peer students. These participants experienced using MARS after the orientation programs and obtained recommendations of GCDAs from MARS. Convenience sampling was adopted to select the participants to join a survey. The data collected from the survey were analyzed by multiple regression to provide findings about the effectiveness of MARS.

4.1. Research Design

Convenience sampling was used as it was time-effective and cost-effective to invite a group of new students who joined the orientation programs in higher education institutions in August 2023 to participate in an experimental study. A major drawback of convenience sampling is the difficulty of generalizing. However, in this study, the population was the students in higher education institutions. Therefore, generalizability problems were not exhibited even though convenience sampling was used. After the orientation programs, the students were invited to experience the experimental study in which the students were informed of the research purpose, scope, procedure and their rights to withdraw from this study at any time then asked to fill in their backgrounds, choose extracurricular activities and view the extracurricular activities recommended by MARS.

4.2. Research Participants and Instrument

After the experimental study, the students were asked to join an online anonymous survey that was designed to evaluate the students' acceptance of MARS. For this evaluation, the four constructs (i.e., students' background, social influence, facilitating conditions and perceived usefulness) used were derived from HLMC, TTF, and UTAUT. Then, the measuring items with a 5-point Likert scale with the option "strongly agree" scoring 5, "agree" scoring 4, "neutral" scoring 3, "disagree" scoring 2 and "strongly disagree" scoring 1) on an online questionnaire for the survey were formulated. These measuring items are the questions on the online questionnaire as shown in Table 1.

Table 1. Online questionnaire.

Cluster	Questions	Measuring items	Source of derivation
Students' background	Q1	I have considered the objectives (i.e., intended learning outcomes) of my program of study when choosing extracurricular activities to join.	Interpersonal constraint in Crawford et al.'s (1991) HMLC.
	Q2	I have considered my career development when choosing extracurricular activities to join.	
	Q3	I have considered my interest when choosing extracurricular activities to join.	
Social influence	Q4	I have considered building up social relationships when choosing extracurricular activities to join.	Intrapersonal constraint in HMLC
	Q5	The advice from the people around me (e.g., teachers, parents, friends, peer students and friends) is important for my decision to join an extracurricular	

Cluster	Questions	Measuring items	Source of derivation
		activity.	
Facilitating conditions	Q6	My previous participation in an extracurricular activity depends on the extracurricular activity time schedule.	Structural constraint in HMLC
	Q7	My participation in an extracurricular activity depends on my study load and workload.	
	Q8	My participation in an extracurricular activity depends on whether there is transportation to the location of the activity.	
	Q9	My participation in an extracurricular activity depends on whether there is appropriate equipment for the activity.	
Perceived usefulness	Q10	MARS' recommendations have encouraged me to think of appropriate extracurricular activities for whole-person development.	Task technology fit in Goodhue and Thompson's (1995) TTF model and performance expectancy in Venkatesh et al.'s (2003) UTAUT
	Q11	MARS' recommendations can help me to have a better understanding of my strengths and determine appropriate extracurricular activities for whole-person development.	
	Q12	MARS' recommendations can help me identify appropriate extracurricular activities for improving my weaknesses.	
	Q13	MARS' recommendations can help me to make better decisions for joining appropriate extracurricular activities for whole-person development.	

These questions on the online questionnaire can be clustered as follows:

- Students' background: The first three questions (Q1 to Q3) of the questionnaire measure the degree to which the students agree that they have considered their background (i.e., Q1 for considering the intended learning outcomes of the student's program of study, Q2 for considering the student's career development, and Q3 for considering the student's interest when choosing extracurricular activities to join).
- Social influence: Q4 to Q5 measure the degree to which the students agree that they have concerns about social gatherings and advice from their social groups when considering extracurricular activities to join.
- Facilitating conditions: Q6 to Q9 measure the degree to which the students agree that the facilitating conditions (i.e., schedule in Q6, study load or workload in Q7, transportation to the location of the activity in Q8 and appropriate equipment for the activity in Q9) influence their choice of extracurricular activities.
- Perceived usefulness: Q10 to Q13 measure the extent to which the students agree that MARS helps them to decide on extracurricular activities to join.

Implied consent (Lune & Berg, 2017) was applied to indicate the sampled students' agreement to participate in the survey when they completed the online questionnaire. The participating students aged under 18 had to explicitly inform the researchers who would then follow up with their parent's consent. A total of 433 students joined the orientation programs and the experimental study and 351 of them completed the online questionnaire, reaching a rather good response rate of 81%.

4.3. Validity and Reliability Tests

For the validity test, the measuring items for the four constructs (i.e., students' background, social influence, facilitating conditions and perceived usefulness) in the online questionnaire were derived from the constructs validated by Goodhue and Thompson (1995), Venkatesh et al. (2003) and Crawford et al. (1991).

For the reliability test, the statistical analysis application software, namely, Statistical Product and Service Solutions (SPSS) version 28 was adopted. Table 2 shows the reliability generated by SPSS. According to Pallant (2020) internal consistency reliability can be used to assess the degree to which the measuring items (e.g., Q1 to Q3) that make up the scale can all measure the same construct (e.g., background) and can be measured by the widely adopted Cronbach's (1951) alpha (α).

Table 2. Reliabilities and statistics.

Construct	Measuring item (N=351)	Mean scores	Standard deviation	Number of measuring items	Cronbach's α	Mean inter-item correlation
Students' background	Q1	3.42 (Min)	0.747	3	0.647	0.379
	Q2	3.72	0.763			
	Q3	3.92 (Max)	0.773			
Social influence	Q4	3.67	0.720	2	0.573	0.402
	Q5	3.55	0.750			
Facilitating conditions	Q6	3.58	0.724	4	0.792	0.488
	Q7	3.75	0.723			
	Q8	3.51	0.799			
	Q9	3.55	0.731			
Perceived usefulness	Q10	3.50	0.705	4	0.877	0.643
	Q11	3.52	0.675			
	Q12	3.56	0.682			
	Q13	3.52	0.671			

The Cronbach's alpha for Q1 to Q3 for measuring the students' background is 0.647 and for Q4 to Q5 for measuring social influence, it is 0.573 which is below 0.7, the minimum value for internal consistency reliability (DeVellis, 2022; Nunnally, 1978). However, when the number of measuring items in a scale is less than 10 (that is, the number of measuring items is all below 10 in Table 2), Cronbach's alpha tends to be small. For the case with the number of measuring items on a scale less than 10, like the case in this study, the mean inter-item correlation for the items is used instead (Pallant, 2020). Briggs and Cheek (1986) recommended the range for the optimal mean inter-item correlation to be 0.2 to 0.4. All the mean inter-item correlations are within or above this range indicating acceptable internal consistency reliability for all these constructs in Table 2. The Cronbach's alpha for Q6 to Q9 for measuring facilitating conditions is 0.792 and for Q10 to Q13 for measuring the students' perceived usefulness of MARS is 0.877 which is above 0.7, the minimum value for internal consistency reliability (DeVellis, 2022; Nunnally, 1978) indicating these scales contain a rather good internal consistency reliability. All the mean scores for these questions Q1 to Q13 are around the range of 3.42 to 3.92 with standard deviations less than 1 as shown in Table 2.

5. Quantitative Analysis

To analyze the collected quantitative data from the survey, the following model is used:

- Students' background, social influence and facilitating conditions → perceived usefulness.

For this study, there can be a regression model for multiple regression analysis by SPSS. In this model, the student's background, social influence and facilitating conditions are independent variables that influence or predict the dependent variable perceived usefulness.

Before conducting multiple regression analysis, first the assumptions for multiple regression must be ensured. These conditions include appropriate sample size, no multicollinearity among the independent variables, no outliers affecting the multiple regression analysis, normality of residuals, linearity of residuals and homoscedasticity of residuals.

For sample size, Tabachnick and Fidell (2019) recommended the following for calculating the sample size requirement for multiple regression analysis:

- Sample size > 50 + 8 × the number of independent variables.

The regression model contains 3 independent variables; the threshold is 50 + 8 × 3 = 74. In this study, the sample size 351 is much larger than the threshold 74 meeting the sample size requirement for multiple regression.

Multicollinearity exists when highly correlated independent variables exist in a regression model making multiple regression analysis difficult in separating the unique contribution of each independent variable to the regression model and therefore affecting multiple regression analysis. The tolerance value in Table 3 indicates multicollinearity among the independent variables. If the tolerance is less than 0.1, multicollinearity exists (Pallant, 2020). All tolerance values are above 0.1 in Table 3 indicating that no multicollinearity exists in the regression model for this study.

Table 3. Regression results explaining perceived usefulness.

Independent variables	Students (N = 351, R^2 = 0.490)	Tolerance
	β	
Students' background	0.373 ***	0.608
Social influence	0.202 ***	0.667
Facilitating conditions	0.258 ***	0.583

Note: *** $\rho < 0.001$.
β standardized regression coefficient.

The conditions of no outliers affecting the multiple regression analysis, normality of residuals, linearity of residuals and homoscedasticity of residuals are indicated in Figures 2 and 3.

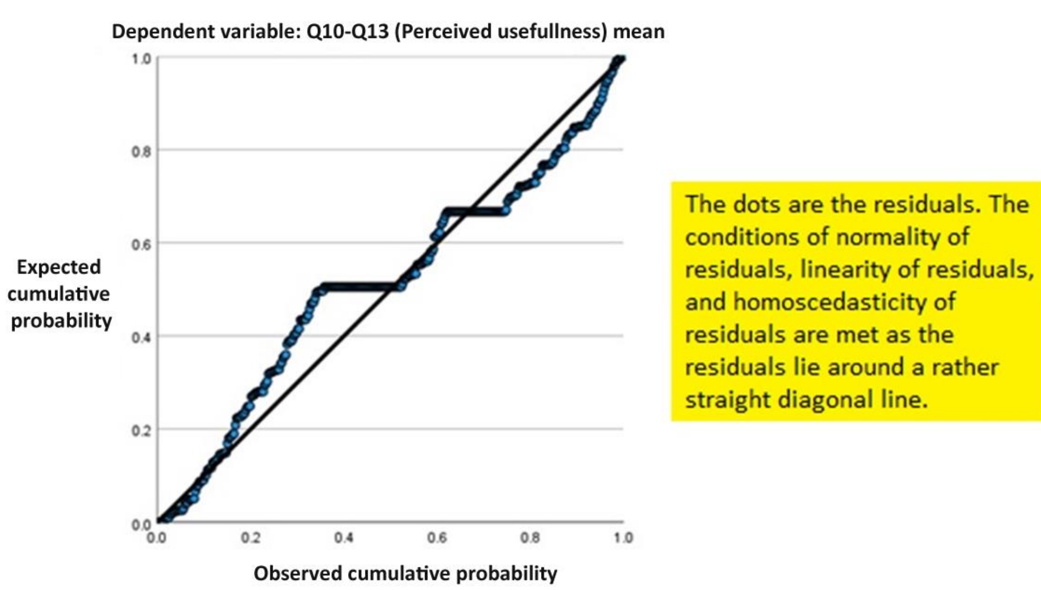

Figure 2. Normal probability plot of the regression standardized residuals.

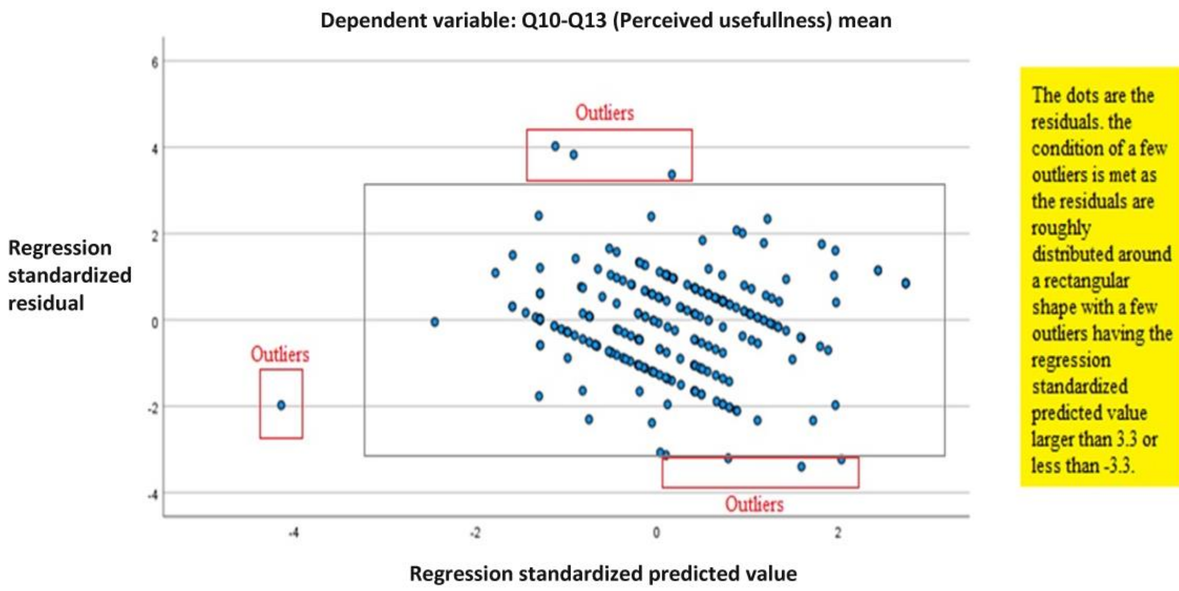

Figure 3. Standardized predicted value versus standardized residuals.

A residual is the difference between an obtained dependent variable score and a predicted dependent variable score. In Figure 2, the conditions of normality of residuals, linearity of residuals and homoscedasticity of residuals are met as the residuals lie around a rather straight diagonal line. In Figure 3, the condition of a few outliers is met as the residuals are roughly distributed around a rectangular shape with a few outliers having the regression standardized predicted value larger than 3.3 or less than -3.3. The situation of a few outliers is acceptable in a large sample (Pallant, 2020).

Table 3 shows the multiple regression results. The R^2 value means the following model explained 49% of the variance in perceived usefulness:

- Students' background, social influence and facilitating conditions → perceived usefulness.

According to Table 3, all results are significant with $\rho < 0.01$. The students' background has the largest standardized regression coefficient (β) 0.373 among the three independent variables (i.e., students' background, social influence and facilitating conditions). Social influence has the smallest β value of 0.202 while the construct of facilitating conditions has the medium β value of 0.258.

6. Results and Discussions

The analytical results as shown in Table 2 indicate that all the mean scores for the questions Q1 to Q13 on the online questionnaire are within the range of 3.42 to 3.92 on the 5-point Likert scale. These results leaning on the score 5 which means "strongly agree" indicate that the students tend to agree that

- The students have considered their background.
- Social influence affects the students' choice of extracurricular activities.
- Facilitating conditions also influence the students' choice of extracurricular activities.
- Students think MARS is useful.

Table 3 shows how well the collected quantitative data (i.e., the students' background, social influence, facilitating conditions and perceived usefulness) fit the regression model and indicates the relative effects of the students' background, social influence and facilitating conditions on perceived usefulness. The R^2 value is 49%, which means that the regression model explained 49% of the variance in perceived usefulness and indicated a rather large, combined effect of the students' background, social influence and facilitating conditions on perceived usefulness. The R^2 value between 10% and 50% is acceptable in a research study related to social science when some or most of the independent variables are statistically significant (Ozili, 2023). The significant results indicated by $\rho < 0.01$ show that the student's background was a stronger determinant with a larger β of 0.373 by comparison with social influence and facilitating conditions. These results indicate a larger effect of the students' background while a smaller effect of social influence and facilitating conditions on perceived usefulness.

The quantitative results revealed the major findings that the students perceive MARS as an effective tool for recommending GCDAs as MARS considers the students' background when recommending GCDAs and the students regard their background as exhibiting a larger effect on their selection of GCDAs while social influence and facilitating conditions which are not considered by MARs exhibit a smaller effect on their selection of GCDAs.

7. Conclusion and Future Work

MARS was developed to recommend appropriate GCDAs for generic competency development based on the student's background as the students at the higher education institutions faced difficulty in choosing appropriate GCDAs for their generic competency development. Higher education institutions may optimize resource allocation and streamline operational procedures. This study formulated appropriate measuring items to investigate the degree to which the students at the higher education institution accept using MARS to evaluate the effectiveness of MARS. Multiple regression was adopted to analyze the collected data. The quantitative analysis of the data from 351 participating students revealed that the students regard their background has a larger effect on their selection of GCDAs and MARS can effectively make recommended GCDAs for their generic competency development as MARS also considers their background when making recommendations. However, facilitating conditions and social influence that are not considered by MARS when making recommendations have a smaller effect on their selection of GCDAs.

MARS learns from the students' backgrounds to make recommendations for GCDAs. In addition, higher education students regard facilitating conditions and social influence as determinants of their choice of GCDAs. A system that considers the students' social influence and facilitating conditions is proposed to be built on top of MARS to enhance the students' involvement in GCDAs. Similarly, as a follow-up to obtain further views on how social influence and facilitating conditions can be handled by a new system, a further study using in-depth interviews is proposed. Moreover, the evaluation of the effectiveness of MARS in this study depends on the student's subjective views. The effectiveness of MARS can also be evaluated objectively by examining whether there are improvements in the generic competencies of the existing students who take the recommendations of MARS. This proposed objective evaluation is also a future direction.

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