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A Genetic Algorithm-based Group Formation to Assign Student with Academic Advisor: A Study on User Acceptance Using UTAUT

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***Abstract*— Group formation to assign students with academic advisors based on student demography can be exhaustive as various possibilities and combinations can be formed. Hence, this paper proposed a genetic algorithm-based approach to automate group formation based on student demography to assign students to their academic advisors. The genetic algorithm (GA) will optimize the group formation of students with a balanced number of nationalities, races, and genders. Also, this paper examines the user acceptance of the proposed genetic algorithm-based application to automate group formation using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. The survey aims to study the impact of independent and moderating variables on dependent variables. The result proved that all the independent variables, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Condition (FC), have a positive impact on the dependent variable, Behavioral Intention (BI). In contrast, the moderating variable Experience (EX) and Voluntariness of Use (VU) have a negative impact on Behavioral Intention (BI). Thus, this paper concludes that the proposed application can increase the performance and efficiency of group formation and automatically assign students to academic advisors. However, respondents are reluctant and not ready to use the system. Thus, training and workshops can be conducted to introduce and train the users to utilize the system. Future works can be done where the application of the proposed genetic algorithm-based system can be further expanded to different academic purposes such as team formation for group assignment and team member selection for competition.**

***Keywords*— Genetic Algorithm; Group Formation; Academic Advising; UTAUT**

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I. INTRODUCTION

Tertiary education adapts the academic advising program for their students' entire study time at university. Program coordinators from each faculty are responsible for distributing each student to an academic advisor, while from the perspective of an academic advisor, a group of students will be assigned to a particular academic advisor. The academic advisor is assumed to be the academic staff from the faculty [1]. The student may meet with an academic advisor to discuss their academic-related problem. Academic advising plays an essential role in the student's study time. The main role of academic advisors is to ensure students fulfill their graduation requirements and help them in their future career exploration [1], [2].

The manual student group formation based on student demography may be exhaustive and complicated. Thus, a genetic algorithm can be implemented as it is one of the common approaches in group formation based on specific constraints such as student demography and courses. With the help of a genetic algorithm (GA) on group formation in the academic advising program, the program coordinator can easily assign a group of students to one academic advisor based on the desired constraint.

This paper aims to understand the acceptance of the GA-based approach to automate group formation to assign students to academic advisors in the academic advising program from a university in northern Malaysia. There are two objectives for this paper: 1) to propose a framework for an academic advisor assignment system using a GA, 2) to assess user acceptance using the Unified Theory of Acceptance and Use of Technology (UTAUT).

Genetic algorithms (GA) are widely used in group formation and team member selection. Various sectors, such as sports and education, are utilizing the use of GA for team member selection and team formation. AqilBurney et al. [3] discussed the team selection and formation of a cricket team. The algorithm takes the constraint of players' recent personal performance, team performance, and the different combinations of players for the most optimal team formation and selection. This paper showed that the proposed GA effectively adapts the constraints flexibly for team selection and formation.

Zhamri et al. [4] proposed the group formation method in a university group programming project. Systematic group formation using GA can ensure the student's group project is successful and delivered on time. The constraints applied to the proposed algorithm were the number of students with good, moderate, and poor programming skills. The algorithm ensured an equal amount of each constraint in the produced group. The result showed that the utilization of GA in group formation effectively produced groups of students with balance programming capability. This successfully improved the group's performance in completing their group project.

Revelo Sánchez et al. [5] proposed a GA to solve the group formation in collaborative learning. The constraints of the algorithm were the students' personality traits. Students would first undergo the Big Five personality model to determine their personality traits. Then, the result of the student was used in the algorithm as the constraint for the group formation. The formation of the group would be either homogenous (as similar as possible for the student's personal traits in one group), heterogenous (as different as possible for the student's personal characteristics in one group) or mixed (similar in some personal traits and differ is other personal traits) approach. The authors concluded that group formation using analytical or exhaustive search methods can be challenging in homogeneous, heterogeneous, and mixed approaches based on student personality traits. Thus, the implementation of GA in group formation can solve the problem.

GA was also used in a system in the classroom set-up to improve collaborative learning [6]. A team of students would be formed for one classroom. The algorithm generated and maintained heterogeneity in a classroom where students come from different backgrounds, knowledge, skills, ethnicity, and gender. The constraints of the algorithm were the student demography and their learning ability. The use of GA automated the heterogeneity group formation process based on the criteria set by the instructor rather than manually assigning students by looking into their grade performance.

Several models can be used to study user acceptance of technology. The UTAUT model is an established theory commonly applied to study technology acceptance, including computer-related systems [7]. Another popular model - the Technology Acceptance Model (TAM) [8], has been reported to have strength in its two most prominent variables: perceived usefulness and perceived use [9]. However, Alam et al. [10] affirmed in their studies, that UTAUT has a clearer objective in understanding the users' acceptance of the technology studied. It was mentioned that UTAUT model is very valuable because of the fact that to study the technology acceptance, it utilizes social and organizational variables [11]. The UTAUT was also found to have the appropriate reliability and construct factorial validity [12]. In a review of UTAUT, the model was reported to be the most comprehensive model, compared to other acceptance models such as TAM, Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB) and others[13] Alsyouf and Ishak [14] applied the UTAUT model to study the factors that affect the users' intention to use an electronic health record system. Some researchers choose to extend the UTAUT model to fit their research's requirements. For example, the UTAUT model was extended by Howard et al. [15] to understand the insights of building information modeling (BIM). To achieve this, the moderators that the researchers used are experience and voluntariness. In their finding, it was reported that the policies needed to be reassessed to improve the acceptance towards BIM.

A collaborative team formation was developed using the Fuzzy and GA approach, and the acceptance study of the system was carried out using UTAUT [16]. The moderator voluntariness was utilized, and the results showed that the respondents were not prepared to be formed into a collaborative team voluntarily. However, they would use the system if required, and acceptance was reported to be positive.

The UTAUT model was used to study students' acceptance of a university's artificial intelligence-based early warning system [17]. The study is divided into two stages: pre- and post-usage toward the system. The model is used to design the pre-usage and post-usage student acceptance surveys. In contrast, Structural Equation Modelling analyses the relationship or changes in the user's acceptance between the pre-usage and post-usage of the proposed system. The result shows that the student's acceptance changed in a negative relationship over time. In the pre-usage stage, the student started with a high level of expectancy, but the post-usage stage shows lower user acceptance as the student disagrees with the proposed construct: usefulness, facilitating condition, level of trust, and expected effort. The students might not be ready to use the system without appropriate training.

The UTAUT model has also been used to study the factors affecting students' behavior toward using university e-learning systems 18]. This study found that performance expectancy, effort expectancy, facilitating condition, and behavioral intention affect the student's choice to make use of the e-learning application. However, social influence does not influence the student's behavior using the system. This may be because the current generation of students does not rely on the influence of instructors or peers as they are born in a digital environment that heavily relies on internet sources.

Another research was conducted to study the factor that affects the intention of people to use the e-banking services using UTAUT model [19]. This study found that performance expectancy, effort expectancy, facilitation condition, and behavior intention significantly affect the acceptance of people using e-banking services. However, social influence did not influence the people using e-banking services. The paper studies the social influence factor in 2 perspectives: (1) subjective norm, which whether people's behaviors will be influenced by social pressure. (2) image, where the use of technology can enhance their social status. The result found that social pressure and personal social image do not influence the user's behavior to use e-banking services.

A study was carried out to understand the acceptance of using mobile phones in academic library services among Iranian students using the UTAUT model [20]. Experience, gender, and age were included in the study as moderating variables. The results show that the experience notably moderates the user behavior in using mobile phones to use library services. Also, the result indicates that the construct variable, price value, does not influence user behavior. The studies show an overall positive acceptance of the staff and students toward using mobile phones in library services.

This paper discusses the related works about group formation using a Genetic Algorithm (GA) in section II. Next, Section III explains the proposed GA-based application for group formation based on different student demography. Section IV presents the survey for the proposed GA-based application on group formation to assign students to academic advisors. Then, Section V discusses the survey result on study acceptance towards the GA-based system. Section VI concludes the findings of this paper.

II. MATERIALS AND METHOD

A. Proposed Work Using Genetic Algorithm

The proposed solution uses GA to optimize group formation to assign students to academic advisors based on student demography. The assigned students are undergraduate students at a public university in Malaysia that consists of a mixture of races, gender, and local and international students. Table I shows the modified genetic algorithm implemented in this project. Four parameters were obtained from input: the array of the student to be assigned, the number of students to be assigned, the number of academic advisors, and the constraint to run the algorithm.

B. Initial Population

The algorithm starts by building the initial population. The number of individuals in a chromosome can be defined by dividing the students' number and academic advisors. The individual's number in a chromosome will represent the number of students assigned to an academic advisor. The number of chromosomes in the initial population is based on the number of advisors assigned. The individual will then be randomly and uniquely assigned to a chromosome.

C. Initial Fitness Value Calculation

Few calculations need to be done to calculate the fitness value of each chromosome. Fig. 1 shows the equation for calculating the fitness value. MinGroup in the equation indicates the lowest number of students in each criterion that must be preserved in one chromosome. MinSTU indicates whether the chromosome meets the MinGroup for each criterion.

G = Number of groups
LM = Number of local Malay students
LC = Number of local Chinese students
LI = Number of local Indian students
LO = Number of local other races students
IN = Number of international students
Female = Number of female students
Male = Number of male students
MinGroup = Minimum number of LM|LC|LI|LO|IN|Female|Male in a group
G = Number of academic advisors
MinGroup = (LM|LC|LI|LO|IN|Female|Male) / G
Fitness of grade in a group, MinSTU= 10000 if equal or greater than MinGroup; Or
Fitness of grade in a group, MinSTU= 0 if less than MinGroup
Total fitness of chromosome = $MinSTU_{LM} + MinSTU_{LC} + MinSTU_{LI} + MinSTU_{LO} + MinSTU_{IN} + MinSTU_{Female} + MinSTU_{Male}$

Fig. 1 Equation of fitness value calculation

The equation in Fig. 1 determines the minimum number (MinGroup) of local Malay, local Chinese, local Indian, and other races students, female, male, and international students in a group. Then, the MinGroup will be compared to the chromosome's number of local and international students and gender to produce MinSTU. Finally, fitness value can be obtained by adding all the MinSTU.

For example, there is 35 student and five academic advisors to be assigned. Among the 35 students:

- The number of local Malay students (LM) is 14 students, with eight female and six male Malay students.
- Local Chinese student (LC) is ten students, with five female and five male Chinese students.
- Local Indian student (LI) is six students, with three female and three male students.
- Local other races student (LO) is two students with one female and one male student.
- International student (IN) is three students with two female and one male student.

D. Calculation of MinGroup for each criterion

Based on the equation shown in Fig. 1, the MinGroup of each criterion can be calculated by getting the number of students from the respective criteria and dividing the number of groups. The total number of groups will depend on the number of academic advisors selected. Below shows the number of groups and MinGroup for each criterion:

- The number of group (G) = 5
- $MinGroup_{LM} = 2$
- $MinGroup_{LC} = 2$
- $MinGroup_{LI} = 1$
- $MinGroup_{LO} = 0$
- $MinGroup_{IN} = 0$
- $MinGroup_{Female} = 3$
- $MinGroup_{Male} = 3$

E. Calculation of MinSTU for Each Criterion in One Chromosome

Consider this example, if there is one local female Malay student, two female international students, one male local Indian student, and two female and one male local Chinese and none of other races student in a chromosome. Then:

- The $MinSTU_{LM}$ will be 0 as it is less than $MinGroup_{LM}$.
- The $MinSTU_{LC}$ will be 10000 as it is equal than $MinGroup_{LC}$.
- The $MinSTU_{LI}$ will be 10000 as it is equal than $MinGroup_{LI}$.

- The $MinSTU^{LO}$ will be 10000, equal to $MinGroup^{LO}$.
- The $MinSTU^{IN}$ will be 10000 as it is greater than $MinGroup^{IN}$.
- The $MinSTU^{Female}$ will be 10000 as it is greater than $MinGroup^{Female}$.
- The $MinSTU^{Male}$ will be 0 as it is less than $MinGroup^{Male}$.

TABLE I
GA PSEUDOCODE FOR GROUP FORMATION

Input	**List of students and academic advisors to be assigned, the number of students, the number of academic advisors, and selected constraint**
Output	List of students and their assigned academic advisor
Start	
	//Initialize the population
	Identify the number of chromosomes in population
	Calculate the number of genes in a chromosome
	Assign students to their respective chromosome
	//Calculate MinGroup of each criterion
	Get the number of local Malay students, local Chinese students, local Indian students, local other race students, international students, female students, and male students from list of selected students
	Calculate MinGroup for each of the criteria
	// Calculate the initial fitness value of each chromosome
	Get the number of local Malay students, local Chinese students, local Indian students, local other race students, international students, female students, and male students in chromosome
	Determine MinSTU for each of the criteria on each chromosome
	Calculate chromosome fitness value by totaling up MinSTU of each of the criteria of the chromosome
	Repeat
	Random select two chromosomes
	Random choosing crossing over point
	//Crossing over
	If the crossing-over rate is more than 0.95
	Crossover
	// Mutation
	If the mutation rate is less than 0.1
	Mutation
	//Calculate the offspring's fitness value
	Get the number of local Malay students, local Chinese students, local Indian students, local other race students, international students, and female and male students in each offspring
	Determine the MinSTU for each of the criteria of each offspring
	Calculate offspring fitness value by totaling up the MinSTU of each criterion for each offspring
	//Replacement
	Compare both offspring's fitness values with their parent
	If the fitness value of the offspring shows improvement
	replace both parents with their offspring
	Check the fitness value of each chromosome in the population and determine if the chromosome already meets stopping criteria or not
	Until each of the chromosomes meet the targeted fitness value
	Assign chromosome to selected academic advisor

F. Calculation of Fitness Value of one Chromosome

The fitness value of this chromosome will be $MinSTU^{LM} + MinSTU^{LC} + MinSTU^{LI} + MinSTU^{LO} + MinSTU^{IN} + MinSTU^{Female} + MinSTU^{Male} = 50000$.

As the criteria for determining the minimum number of students in a group is a constant variable, thus, the maximum number of fitness values can be obtained, which is 70000. This is the most optimum solution for the grouping task when each chromosome in a population reaches its fitness value at 70000. This will also be the general stopping criteria for genetic algorithms.

In summary, calculating a chromosome's fitness value will first calculate the minimum number (MinGroup) of local Malay, Chinese, Indian, other races, international, female, and male students. Next, the fitness value of each chromosome was calculated by totaling up the MinSTU value of the chromosome. A chromosome obeying the MinGroup value of each local, international, and gender student criteria will get a higher fitness value. The higher fitness value indicates the chromosome is fitter in a population.

G. Crossover and Mutation

After calculating the initial fitness value of the chromosome, the algorithm randomly selects two chromosomes for crossover and mutation. Single point crossover is chosen to implement in this algorithm. So, there will be only one crossing-over point randomly generated. Then, starting from the crossing-over point, the crossing-over is done by exchanging the individual from one parent to another. Then, the mutation is carried out by randomly choosing a mutation point. The mutation point will be one of the indexes in the chromosome array. Both offspring will exchange the element in the mutation point (index).

The crossover rate is the probability of crossover occurring in two parents to produce offspring. The mutation rate is the probability of a mutation occurring in the offspring. The population size is estimated to range between 20 to 40 chromosomes. Hassanat et al. [21] suggested that this range of population size is suitable for using high crossover rates (0.95 rates) and low mutation rates (0.01 rates). Therefore, a 95% crossover rate and 1% mutation rate are implemented in the algorithm.

Before crossover takes place, the algorithm will check for the crossover rate. A crossover rate pool will be generated with 5% of chances not to cross over and 95 % of chances to crossover. Then a random number will be generated. If the random number falls on 95% of the crossover section, the crossing over will occur; otherwise, no crossover will happen. Similar to crossing over, a 1% mutation rate mutation pool is generated. The mutation occurs if the random number falls in the 1% mutation section.

The offspring's fitness was calculated by adding the MinSTU of each criterion of the chromosome. Next, for replacement, both offspring's fitness values are compared with their parent's. If the fitness value of both the offspring shows improvement and is greater than both of their parents, replace both parents with their offspring. This is to ensure there will not be any individual loss or individual repeated in crossing over and replacement. Then, the fitness value of all chromosomes will be checked to determine whether the overall fitness value reaches the stopping criteria.

The selection, crossover, mutation, and replacement processes were repeated until the stopping criteria were met.

H. Stopping Criteria

Before the genetic algorithm runs, the system prompts the user to choose the constraint. The constraint will be the dynamic input determined by the user to run the algorithm based on their needs. The design and purpose of the genetic algorithm are to produce a mixture of local races and international students in a group. Therefore, the default stopping criteria will be 5000 (based on the value of $MinSTU_{LM} + MinSTU_{LC} + MinSTU_{LI} + MinSTU_{LO} + MinSTU_{IN}$). Users can select the add-on constraint to filter gender. This constraint intended to produce a group of students with an equal number of female and male students. The fitness value of this constraint will be added on top of the default fitness value to become 7000 (based on the value of $MinSTU_{LM} + MinSTU_{LC} + MinSTU_{LI} + MinSTU_{LO} + MinSTU_{IN} + MinSTU_{Female} + MinSTU_{Male}$). Therefore, the stopping criteria will be 7000 fitness values.

Fig. 2 to 5 show the system's user interface for the group formation to assign students to academic advisors. Fig. 2 and 3 show the coordinator's interface to select the available academic advisor and unassigned student. Then the coordinator selected the constraints to run the algorithm in Fig. 4.

There are two constraints for the selection of users. First is nationality and race, where the algorithm will form a group of students with a mixture of different races of Malaysian and non-Malaysia students. The second constraint is gender, where the algorithm will create a group of students with a balanced number of genders. Fig. 5 shows the result of the algorithm. Each group (chromosome) formed will be assigned to each selected academic advisor.

1. Select Academic Advisor

Show 10 entries

Name	Staff No
AZLEENA MOHD KASSIM	1231/11
KIM SOO	1234/44
LEE CINDY	1235/55
SENTHURAN A/L KURMA	1233/33
TAN BOON KEONG	1232/22

Fig. 2 Select the available academic advisor.

2. Select Student

Show 10 entries

Name	Matric No	Year
ABDUL HALIM BIN HASIB	140019	201
ABDUL KARIM BIN HASIB	140020	201
ALEX DAVID	140028	211
ALEX LEONG CHI KIN	140004	181
ASHLEY WANG SZE MEI	140002	181
Atina Belcher	140018	201
BAHAUDDIN BIN BADRUN	140021	211
CHONG HUI XIN	140003	181
IRMAYUSI HOMBING	140027	211
KALPEN A/L JAIDEN	140026	211

Fig. 3 Select unassigned student.

3. Select constraint for automatically pairing

Select	Contraint	Details
☑	Nationality & Race	Assign student to advisor with mixture of different races
☐	Gender	Assign student to advisor with mixture of different stude

Fig. 4 Select constraint.

Profesor AZLEENA MOHD KASSIM

Name	Matric No.	Race
BAHAUDDIN BIN BADRUN	140021	MALAY
SIDDH A/L ZAYN	140025	INDIAN
SITI AATHI BINTI SAFUH	140012	MALAY
SITI NABILA BINTI NASAFI	140016	MALAY
PEE LING HONG	140001	CHINESE
ALEX DAVID	140028	OTHER
CHONG HUI XIN	140003	CHINESE

Fig. 5 The algorithm results.

This section evaluates the user's acceptance of the GA-based application for group formation to assign students to academic advisors. A survey was carried out, and the Unified Theory of Acceptance and Use of Technology (UTAUT) model was used to collect and evaluate the opinion and acceptance of the user toward the proposed system. The proposed UTAUT framework and the hypothesis is discussed.

I. UTAUT Framework Proposed

User acceptance is tested using the UTAUT method proposed by Venkatesh et al. [22]. Fig. 6 shows the illustration of the UTAUT Model defined by Venkatesh et al. [22]. The model has four key constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Age, Gender, Experience, and Voluntariness of Use moderate them.

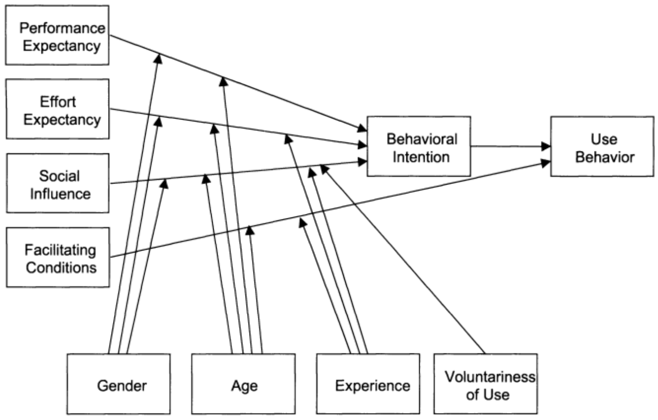

Fig. 6 UTAUT Model [22]

In this paper, a UTAUT framework is proposed to analyze the user acceptance of the GA-based group formation by the student and lecturer. The constructs included are Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). The moderator included are the Experience (EX) and Voluntariness of Use (VU). The two moderators and four constructs will be validated through the questionnaire approach. Fig. 7 shows the proposed UTAUT model for the system.

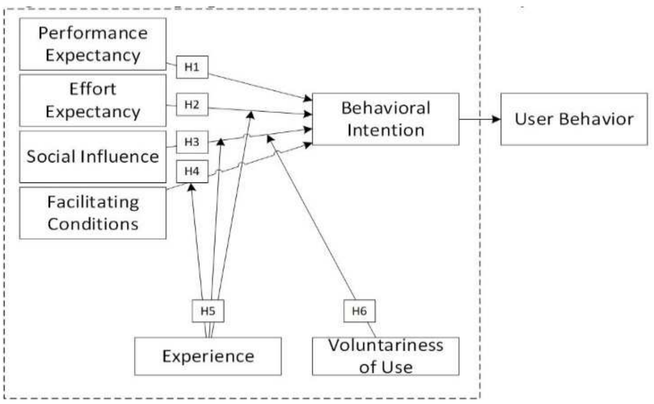

Fig. 7 Proposed UTAUT Model

1) Independent Variable and Hypothesis: This paper predicts that the four independent variables: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) will influence the Behavioral Intention (BI) of the respondent. Behavioral Intention (BI) will be the dependent variable that refers to one's intention to use the technology. Following is the hypothesis established:

- Hypothesis 1 (H1): Performance Expectancy positively affects individual's Behavioral Intention to use the GA-based group formation application.
- Hypothesis 2 (H2): Effort Expectancy positively affects individual's Behavioral Intention to use the GA-based group formation application.
- Hypothesis 3 (H3): Social Influence will positively influence an individual's Behavioral Intention to use GA-based group formation application.
- Hypothesis 4 (H4): Facilitating conditions have a positive correlation with individual's Behavioral Intention to use the GA-based group formation application.

2) Moderating Variable and Hypothesis: The moderating variables are the Experience (EX) and the Voluntariness to Use (VU). Higher experience in using the booking system, e-learning portal, academic advising management-related system, and higher experience in meeting with an academic advisor/ advisee will have a higher Behavioral Intention (BI) to use the GA-based group formation application. This is because they will have better knowledge of using the proposed system to manage student assignments with academic advisors. Voluntariness to Use (VU) was hypothesized to moderate the effects of the constructs on Behavioral Intention (BI). Higher voluntariness will positively influence the Behavioral Intention (BI) to use the system.

Thus, the hypothesis is summarized as follows:

- Hypothesis 5 (H5): People with higher experience in using the booking system, e-learning portal, academic advising management-related system, and meeting with academic advisors/advisees have a higher tendency on Behavioral Intention to use GA-based group formation applications.
- Hypothesis 6 (H6): People with higher voluntariness to use the system have a higher tendency on Behavioral Intention to use the GA-based group formation application.

A. *Data Collection*

Likert scale questions usually been used in the UTAUT questionnaire to collect feedback from the respondents. The questionnaire is distributed among undergraduate students and lecturers from a university in northern Malaysia to investigate their acceptance of the proposed GA-based application for group formation to assign students with academic advisors. The questionnaire Google form with a proposed system demonstration video, system user guild, and proposed system website is distributed among undergraduate students through WhatsApp and Facebook Messenger. Respondents may review the demonstration video and user guild before they proceed with the system testing. There are a total of 35 respondents in this survey. The questionnaire design is based on the proposed UTAUT framework in Fig. 7, and Table II shows the constructed questions. The first column (Item) is coded based on the variables construct, where each numbering for each code shows the number of question items under the same variables. The second column lists the questions with citations of the work from which the questions were adapted.

III. Results and Discussion

The result of the data collected is discussed in this section. The system demonstration link and system website were sent to the respondents to test the proposed system, and the questionnaire was distributed through social media such as WhatsApp and Facebook Messenger. Using the proposed UTAUT framework to analyze the proposed GA-based application's user acceptance, the collected result represents the respondents' intention to use the proposed GA-based group formation system.

A. Descriptive Analysis

The data collected from the questionnaires is used to analyze the hypotheses mentioned in Sections IV. The questionnaires using the five-point Likert scale range from 1 to 5, representing the Strongly disagree, Disagree, Neutral, Agree, and Strongly Agree, respectively. The result will then be analyzed using statistical software, SPSS.

The UTAUT constructs and moderators' descriptive statistics are shown in Table III. The mean for the PE, EE, SI, FC, and BI are between 4 and 5, which implies that most respondents agree or strongly agree with the constructs question. The mean values for the moderator EX and VU mostly fall from 3 to 5, suggesting that most of the respondents are neutral, agree, or strongly agree with the moderator question.

TABLE II
QUESTION ITEM

Item	Question Item
PE1	I would find the GA-based group formation helpful to manage academic advisory-related task [16]
PE2	Using the GA-based group formation application will increase my productivity in managing my academic advisory-related task [23]
PE3	Using the GA-based group formation application will enable me to accomplish the academic advisory-related task more quickly [16]
PE4	Using the GA-based group formation application will improve my performance in managing the academic advisory-related task [16]
EE1	I can quickly get familiar with the GA-based group formation application to complete my task [13]
EE2	It is easy for me to learn to use the GA-based group formation application [16]
EE3	I understand how to use the GA-based group formation application [16]
EE4	I can easily explain the benefit of using GA-based group formation application [16]
SI1	People who impact my behavior may think I should use the GA-based group formation application [16]
SI2	If people around me use the GA-based group formation application, I will also try to use it [16]
SI3	People who are important to me (e.g., students or academic advisors) think I should use the GA-based group formation application [16], [24]
SI4	I would recommend the GA-based group formation application to others [25]
FC1	I would have the resources necessary to use the GA-based group formation application [16]
FC2	I would have the knowledge necessary to use the GA-based group formation application [16]
FC3	Assistance or help is available if there are difficulties in using the GA-based group formation application [26]
FC4	I think using the GA-based group formation application fits well with how I like to manage the academic advisory-related task [27]
BI1	I plan to use the GA-based group formation application if it is made available [16]
BI2	I expect that I will use the GA-based group formation application in the future [16]
BI3	I choose to utilize this GA-based group formation application to manage the academic advisory-related task [16]
BI4	I plan to make use of this GA-based group formation application in the future [16]
EX1	Do you have experience in using campus online? If yes, please select your experience in years [28]
EX2	Do you have experience in using eLearning? If yes, please select your experience in years [29]
EX3	Do you have experience using Padlet? If yes, please select your experience in years [29]
EX4	Do you have experience booking appointments to meet your academic advisor/ advisee? If yes, please select your experience in years [28]
VU1	My study or job does not require me to use the GA-based group formation application [16]
VU2	The choice of using GA-based group formation application is optional for my study/ job, although it might be helpful [16]
VU3	My preference to use the GA-based group formation application is voluntary [16]

B. Person's Correlation

Pearson correlation is used to explain the strength of the relationship between 2 variables, whether strong, moderate, or weak. Table IV shows Pearson's correlation coefficient strength [30]. By studying the impact of independent variables, presented as: PE, EE, SI, FC, towards the dependent variable, BI, from the proposed UTAUT framework, the user's acceptance of the proposed GA-based group formation system can be evaluated. Also, the moderating variable, EX, and VU, toward BI were assessed. The result of Pearson's correlation analysis between independent and moderating variables toward BI (M-BI) is presented in Table V. The mean for each of the variables is encoded as M-PE, M-EE, M-SI, M-FC respectively for the independent variables, whereas M-EX and M-VU respectively for the moderating variables.

TABLE III
DESCRIPTIVE STATISTICS

Code	Min	Max	Std. Deviation
PE: Performance Expectancy			
PE 1	3	5	4.69
PE 2	3	5	4.66
PE 3	2	5	4.57
PE 4	3	5	4.54
EE: Effort Expectancy			
EE 1	3	5	4.43
EE 2	4	5	4.60
EE 3	2	5	4.29
EE 4	2	5	4.17
SI: Social Influence			
SI 1	3	5	4.31
SI 2	3	5	4.54
SI 3	2	5	4.26
SI 4	2	5	4.46
FC: Facilitating Conditions			
FC 1	2	5	4.31
FC 2	2	5	4.29
FC 3	3	5	4.14
FC 4	3	5	4.46
BI : Behavioral Intention			
BI 1	3	5	4.57
BI 2	3	5	4.40
BI 3	3	5	4.43
BI 4	1	5	4.40
EX: Experience			
EX 1	3	5	4.17
EX 2	3	5	4.20
EX 3	1	5	3.37

Code	Min	Max	Std. Deviation
EX 4	1	5	2.34
VU: Voluntariness of Use			
VU 1	1	5	3.83
VU 2	1	5	3.77
VU 3	1	5	4.23

TABLE IV
PEARSON'S CORRELATION COEFFICIENT STRENGTH [30]

Range Value	Strength of Relationship
0.00-0.19	Very weak relationship
0.20-0.39	Weak relationship
0.40-0.59	Moderate relationship
0.60-0.79	Strong relationship
0.80-1.00	Very strong relationship

TABLE V
PEARSON'S CORRELATION ANALYSIS RESULT FOR INDEPENDENT AND MODERATING VARIABLES TOWARD BI

	M_BI
M-PE	.764**
M-EE	.810**
M-SI	.881**
M-FC	.640**
M-BI	1
M-EX	.249
M-VU	.008

**. Correlation is significant at the 0.01 level (2-tailed).

C. Hypothesis Evaluation

The six hypotheses proposed in Section IV are evaluated by referring the correlation values in Table V to the Pearson's correlation coefficient strength in Table IV:

- H1: Pearson correlation for M-PE and M-BI = 0.764. PE has a strong positive effect on BI. Therefore, this hypothesis is **supported.**
- H2: Pearson correlation M-EE and M-BI = 0.810. EE has very strong positive effect on BI. Therefore, this hypothesis is **supported.**
- H3: Pearson correlation for M-SI and M-BI = 0.881. SI has a very strong positive effect on BI. Therefore, this hypothesis is **supported.**
- H4: Pearson correlation for M-FCM-BI = 0.640. FC has a strong positive effect on BI. Therefore, this hypothesis is **supported.**
- H5: Pearson correlation M-EX and M-BI = 0.249. EX has a weak positive effect on BI. Therefore, this hypothesis is **not supported.**
- Hypothesis 6: Pearson correlation for M-VU and M-BI = 0.008. Voluntariness has a very weak positive effect on BI. Therefore, this hypothesis is **not supported.**

D. Discussion

As described above, the correlation result of independent and moderating variables toward BI can be determined by referring the correlation value in Table V to the Pearson's correlation coefficient strength range in Table IV. First, the connection of the independent variable, Performance Expectancy (PE), toward the Behavioral Intention (BI) can be referred to as the correlation value of mean PE (M-PE) to mean BI (M-BI), which is 0.764. Similarly, the mean EE (M-EE) to mean BI (M-BI) can be used to represent the relationship between the Effort Expectancy (EE) and BI, which has a correlation value of 0.810. Then, the connection of Social Influence (SI) toward BI has a correlation value of 0.881 by referring to mean SI (M-SI) to mean BI (M-BI). Then, the correlation value of Facilitating Condition (FC) toward BI is 0.640. These four hypotheses (H1 to H4) represented by PE, EE, I and FC all have a positive correlation with the BI, which can be found in similar works that reported positive and significant correlation of the same variable towards intention of use [16], [31], [32] .

The moderator variable Experience (EX) and Voluntariness of Use (VU) are also included to study their relationship with the dependent variable BI. The relationship of EX to BI can be referred to as the mean EX (M-EX) to the mean BI (M-BI) correlation value, where the value was 0.249. Khechine and Augier [28] carried out their study with the use of EX as one of the moderating variables but however they found that the variable was not able to be used as moderating variable in their study as the variance showed almost null value. In our work, there is a correlation value of 0.249, however the value shows a weak correlation between EX to the BI. Tusyanah et al. [29]studied the EX as moderating variable, where it was correlated using EE, SI and FC. They reported a positive correlation with EE, but EX had negative correlation in both SI and FC in their work.

The correlation value of VU toward BI is 0.008. From Table V, the correlation value of both independent variable PE and FC toward dependent variable BI fall within the range of 0.6-0.79, while the correlation value of the other two independent variables, EE and SI, fall within the range of 0.8-1.0. This shows that the independent variable has a strong to a very strong relationship with the dependent variable, BI. Thus, this study indicates that the respondent positively accepted the proposed GA-based group formation application to assign students to academic advisors. The intention of users to use the proposed system is high.

A strong relationship exists between the independent variable PE and FC toward the dependent variable BI. This can be further interpreted to where the respondent found that if the proposed system is implemented in managing the assignment of students with academic advisors, the task can be easier to manage increasing productivity, efficiency, and performance. The correlation value of FC toward BI is lesser than the correlation value of PE toward BI, but it still falls in the strong relationship range. This means that the student and lecturer will get sufficient help or assistance while using the proposed system for group formation to assign students to academic advisors.

There is a very strong relationship between the independent variable SI and EE toward the BI. SI's correlation value with BI was the highest among the independent variables. This shows that the colleague can influence the respondent to use the proposed system for managing the group formation task to assign students with academic advisors. This is an important finding where the acceptance of new technology can be influenced among colleagues. The independent variable EE has a very strong relationship with BI. This can be further interpreted that the user or respondent will have no issue making an effort in using the proposed system to form a group of students and assign them to academic advisors.

Although all the independent variables positively affect the respondent's intention to use the proposed group formation system to assign students with academic advisors, the moderating variables are not. The correlation value of moderating variable EX falls under the weak relationship range, while the VU is in the range of a very weak relationship.

The weak relationship for EX and VU can be interpreted as although the respondent has the knowledge to use the proposed system and have similar experience in managing the group formation task in assigning student to academic advisor, however, the respondent is not keen on using the proposed system voluntarily. They may not be ready to transform the assigned task into using the proposed system to automate the process unless the organization makes it compulsory. As found in the previous study by Howard et al. [15] and Kassim et al. [16], the same finding related to the voluntariness moderator was reported. It may be commonly associated to the unfamiliarity towards a new system and thus the voluntary acceptance may be improved over time when the users are more familiar to the system.

IV. Conclusion

A genetic approach for group formation to assign students to academic advisors has been developed using the genetic algorithm. This application will automate the group formation process and assign each group formed to a selected academic advisor. The student demography will act as the algorithm's input constraint. There is a total of two constraints, first will be nationality and race, where the algorithm will output a group of students with a mixture of different races of Malaysian and non-Malaysia students. The second constraint is gender, where the algorithm will form a group of students with a balanced number of genders.

This paper also studies the user acceptance of a GA-based group formation to assign students to academic advisors using the proposed UTAUT framework. The result shows a positive user acceptance of the proposed GA-based application for group formation to assign students to academic advisors. This result is supported by the positive impact of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) toward Behavioral Intention (BI). Thus, this proposed GA-based application is believed to increase the performance and efficiency of the task of group formation and assigning students to academic advisors.

However, the respondent is not ready to voluntarily use the system to automate the group formation task to assign students to academic advisors. Also, there is no relationship between the user's experience and their intention to use the system. The respondent has experience using a system similar to the proposed system, but it does not mean they will use it to automate the group formation task. This is supported by the weak relationship of Experience (EX) and Voluntariness of Use (VU) toward Behavioral Intention (BI). Hence, effort must be taken to increase the user's voluntarism to use the proposed system to automate the group formation process for assigning students with academic advisors. Further encouragement or user engagement can be made by introducing some workshops highlighting the benefits of the academic advisory system to the potential users to increase volunteerism to use the system.

The future work can be applied where the GA-based application can further expand in different academic purposes such as team formation for group assignment and team member selection for the competition. Extra constraints to the algorithm can also be added, not just restricted to student demography.

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