IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 9, 2019, accepted May 21, 2019, date of publication June 5, 2019, date of current version June 21, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2921219

Evaluation of the Likelihood of Friend Request Acceptance in Online Social Networks

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This work was supported by the Universiti Malaysia Pahang, Malaysia under Grant RDU182202-2.

ABSTRACT Recent years online social networks (OSNs) have become an essential digital platform in the daily life of billions of earth inhabitants. Despite the advantages of easy communication and information sharing, OSNs users often fell in trouble causing by security breaches and violations. A recurring example of the troubles arises due to a rash acceptance of the friendship request, which can lead to the disclosure of personal information and vulnerability to an attack. Support for making a secure friendship decision is limited in the modern OSNs, making their use hazardous especially for the groups of children and young people. To overcome this issue, the paper proposes a method for evaluating the likelihood to become a friend in support of promoting hazard-free cyber environments. The proposed approach allows a user to define a model of a friend-to-be, and incoming friend requests are evaluated with reference to this model. The model takes into account the attributes (like common interests) and the behavioral properties of a friend-to-be (like frequency of the posts). The method allows for filtering friend requests to the given users and triggering notification of anomalous behaviors in an OSN. An empirical study proves the validity of the proposed model and its favorable characteristics against existing methods in the current OSN platforms.

INDEX TERMS Online social network (OSN), friend request acceptance (FRA), decision making, recommender system, hazard-free cyber environment.

I. INTRODUCTION

Online Social Networks (OSNs) have improved the way people interact with each other in the context of their communal life. The OSN sites such as Facebook, YouTube, WhatsApp, WeChat, Instagram, Twitter, Skype, LinkedIn, etc. facilitate convenient access to extended social connectivity in which the users can easily catch up with each other by sharing contents like messages, photos, videos and exercising a number of online activities with associates. OSNs are not only used in a personal context but also provide a great instrument for business and professional networks. The sociable way of communication can easily attract users with the consequence that their engagement can unveil sensitive information and share it on the wall [1]. The popularity of OSN services can be seen by their current pervasive usage and massive penetration in the community. For example, Facebook, as an OSN platform, has around 2.23 billion active monthly users and an average of 1.45 billion daily active users as of October 2018 [2].

An OSN allows for creation of a public profile, which uses a representation model of a user to the outside world. In the process of interacting, OSN users disclose their personal information to others through the built-in OSN functionalities. Within this way of interaction, a user can potentially be exposed to dangerous online activities due to an unsecured OSN environment [3]. For instance, making a friendship with a stranger can bring a hazardous situation to an OSN user. More specifically, if this stranger is an unreliable or a fake individual, hazardous activities can be induced from expo-

The associate editor coordinating the review of this manuscript and approving it for publication was Claudio Ardagna.

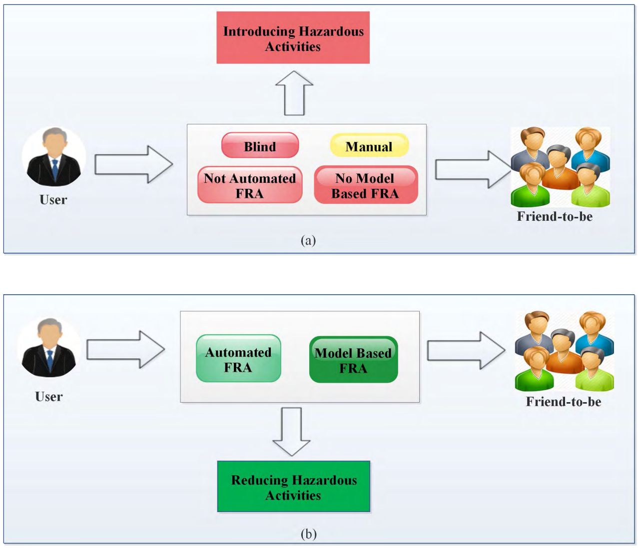

FIGURE 1. The motivation of the work: (a) Due to the lack of FRA mechanism, the traditional techniques are unable to recommend a friend, which increases hazards in OSN; (b) The automated technique can ensure the reliability of the FRA, which reduces hazards in OSN.

sure of sensitive personal information. In the current OSN platforms, existing functionalities do not feature any reliable procedure of making friendship. This vulnerability can be exploited by cyber adversaries to perform damaging online activities, including frauds, harassments, abuses, defamations, etc., with some of which translating into real-life offenses such as robbery, kidnapping and so on [4]–[8].

Most of the existing OSNs have a fragile mechanism to justify a friend-to-be (i.e., who sends a friend request) and convert it to friendship. There are two types of techniques endorsed to validate and decide on picking up a friend, namely blind and manual [9]. In the blind technique, a user confirms friendship without knowing any information about the friend-to-be, which makes a user account insecure. In the manual technique, the user allows to confirm a requesting friend only after seeing his/her profile, which is time-consuming, and at the same time not sufficiently reliable to rigorously evaluate the prospective friends' (friend-to-be) authenticity. As captured in Figure 1, an automated and reliable friend request acceptance (FRA) method is therefore crucial to mitigate vulnerabilities and incompetence of friendship filtering that inherently present in the existing (blind and manual) techniques. Along with this direction, an attempt has been initiated in our previous work [9] where a simplistic numerical metric based on the attributes and behavioral properties was calculated for FRA recommendation.

Building upon our previous result in [9], this paper proposes a new design of an automated recommender system that exploits a friend-to-be model in order to address the lack of proper FRA functionalities in the existing OSN platforms. A central point of the proposed technique lies in the modelling and derivation of a novel likelihood metric on the prospect of establishing friendship for a given friend request from a friend-to-be user. Based on this likelihood metric, an algorithm is presented to extract the requesting user attributes and subsequently evaluate the corresponding likelihood function of becoming a friend based on these attributes. An empirical study is then invoked to validate the effectiveness of the overall proposed system for FRA recommendation.

The empirical study demonstrated the responders' preferences in use of the proposed method versus the blind, the manual and the previous method [9]. The comparison of the proposed method against existing methods in terms of flexibility shows the magnitude at 2.98 of the users' preferences versus the blind, 1.47 versus the manual and 1.32 versus the previous method; security (2.98 versus the blind, 1.33 versus manual and 1.14 versus the previous method); effectiveness (2.16 versus the blind, 1.26 versus the manual and 1.14 versus the previous method) and satisfaction (2.09 versus the blind, 1.45 versus the manual and 1.20 versus the previous method).

The remainder of this paper is organized as follows. Section II critically analyses related works in the literature. Section III is dedicated for specific discussion on the previous method of [9], which serves as a benchmark. Section IV defines the model of a friend-to-be as well as the values, attributes, and weights. Moreover, the method and algorithm for evaluation of the likelihood of FRA are sub-categorized in this section. Evaluation of the proposed model and method is subsequently described in Section V. Finally, Section VI concludes the paper by summarizing the main contributions.

II. RELATED WORKS

A large body of works in the literature have attempted to address modelling users' behaviors in OSNs under varying aspects of security, trust, anomaly discovery and privacy preservation. Table 1 and Table 2 summarize the features and drawbacks of existing approaches by two parts.

In the context of our work, it is important to note that predicting the likelihood of friendship becomes a necessary service to be provided by OSN platforms.

Thus, friendship prediction becomes an important problem in OSN development and analysis. Application of the friend recommendation systems helps people finding new friends and expanding their networks. Friendship prediction in OSNs is also useful for various purposes, such as preserving privacy and marketing.

There are several [13], [16]–[18], [26] approaches to friendship modeling. The input is derived from the profiles of users' records such as existing relationships, social interactions, co-occurred places, etc. Friend recommendation systems may also take into account the topological structure of a social network.

Most of the existing approaches [20], [24], [26], [27] use machine learning (ML) algorithms to improve the prediction performance. Taking into account the significance of developed approaches, ML algorithms are complex and time-consuming. At the same time, their results are not always efficient because they can produce many superfluous and unordered friend suggestions.

TABLE 1. Features and drawbacks of existing approaches to modelling users' behaviors in OSNs [Part: 1].

Reference	Features	Drawbacks
Devineni et al. [10]	• An approach based on analyses of the common patterns of users' behaviors on Facebook. • Allows to identify the users' behavioral anomalies.	• Take into account only the wall activities of users'.
Fong et al. [11]	• A model incorporating generalization and formalization of Facebook's privacy preservation procedures. • Allows to express standards that have embedded social features.	• Covers only a privacy preservation mechanism. • Applicability is discussed for Facebook only.
Shao and Ross [12]	• Models the consumers' engagement in the communities of Facebook. • Based on gratification theory and mass media dependency theory.	• Only considers the branding and promoting activities in OSNs. • Does not take into account privacy and security aspects.
Abdel-Hafez and Xu [13]	• Explores different user modelling techniques in plan of the data used, application domain, representation method and construction methodology.	• Concerns the concepts of building users' profiles. • Does not take into account privacy and security aspects of an OSN.
Yin et al. [14]	• Models users' fundamental interests in the temporal context. • Allows to combine influences of fundamental interests a unified way. • Expanded to capture users' changing interests over time.	• Proposed temporal context-aware model accounts only for the user intentions and preferences. • It doesn't take into account the anomalies of OSN users' behavior.
Wu et al. [15]	• A model of switching user's behaviour of OSN users. • Based on the partial least square method.	• Only concerns the divergence of behavioral activities of OSNs users.
Dong [16]	• Models the inter-play between users' behaviour and subsequent emerging social phenomena. • Based on demographic inference, link recommendation and social impact prediction methods.	• Addressing the user modelling problems only in behavioral perspective. • Focused on the limited set of attributes of individual users.
Liu et. al [17]	• Formalization of user modelling techniques for recommendations of points of interest (POI).	• Application for friend recommendation is discussable. • Applicable for Location-based social networks.
Cho et al. [18]	• A model of the structural and mobility patterns in human movement correlated with social networks.	• Applicable only for the modelling patterns and effects of human mobility in an OSN.
AlFalahi et al. [19]	• Model metrics for measuring influencing probabilities in an OSN. • Allows for maximizing a social influence by selecting the most influential users in OSN.	• Limited to proposed metrics and measurement of the influence probabilities.
Chen and Fong [20]	• A quantitative model of the trust between friends in an OSN. • Based on the collaborative filtering technique.	• Allows for gathering tastes from the similar users. • Used a limited set of attributes.
Singer et al. [21]	• A model of the structuring of social networks in a fixed setting. • Allows to describe a self-organized community structures as a network of densely interconnected networks.	• Only models a structure of social network in the context of mutual interest. • Based only on the frequency of encounters and mutual interests.
Yang et al. [22]	• Models a target interest to match a user with services and for predicting friendship. • Based on the correlation between data retrieved from interest networks and friendship networks.	• Based only on the interest and friendship information, which is not enough to make for a reliable friend connection in OSN.
Xie [23]	• A friend recommendation framework by analyzing users' interests in two domains of context and content. • Combines a domain knowledge to enhance the quality of recommendation.	• An individual model of a friend-to-be is not used.
Chen and Liang [24]	• Method for friendship prediction on OSN by using links and content extraction from the interaction corpus. • Based on using a vector space machine.	• Algorithm can be complex for implementation in an OSN and time consuming in the case of multiple uses.
Parimi and Caragea [25]	• Approach for predicting a new friendship based on the interests and existing friendships. • Based on data mining technique and implicit interest ontology.	• Used a limited set of attributes.
Xu-Rui et al. [26]	• Friendship prediction techniques, incorporating social relationships, check-in distance and check-in type. • The prediction problem was considered as a classification problem with the use of a support vector machine.	• Applicable for LBSNs. • Based on the limited set of features.
Jianwei et al. [27]	• A friendship prediction algorithm based on topological and historical interaction information.	• Topological and historical interaction is not sufficient to give a reliable friendship recommendation

TABLE 2. Features and drawbacks of existing approaches to modelling users' behaviors in OSNs [Part: 2].

Reference	Features	Drawbacks
Luarn et al. [28]	• Analyzes strong interactions by the modelling the way of liking and messaging.	• Other types of interaction attributes are not taken into account.
Wu et al. [29]	• Analyses of FRA on the base of the OSN profile picture.	• Use of appealing profile picture for FRA is risky due to a fraudulent friend request or a fake account.
Li and Chen [30]	• A model built from correlations among users' friendship, mobility characteristics, social graph properties, and profiles in a commercial mobile social network.	• Model-driven friend suggestion is more effective in the case of proposing an open model of a friend-to-be.
Aiello et al. [31]	• A model is based on the definition of topical similarity among closely-related OSN users.	• This technique allows to recommend a fiend only having a certain level of relationships (for close to each other users). • Topical similarity only one rating is taken into account for prediction of social links.
Zhong et al. [32]	• A model based on the use the friendship data in other networks to predict the friendships in the current network.	• Applicable for users that are engaged in multiple networks • Can result in hazardous and unsecured FRA.
Luo et al. [33]	• Friendship prediction method for LBSNs by integrating geographical and topological features. • Prediction works by combining a choice of online/offline features.	• Only limited number of features are used - user social topology, location category, and check-in location. • Topology and geographical features are not enough to develop a hazard free FRA recommendation in OSN.
Cheng et al. [34]	• Prediction of FRA based on the users' mobility information (e.g. visiting similar places). • Visiting time interval is also taken into account.	• A number of co-occurrences and the visiting time interval not always can be indicator for users friendship.
Zhang and Pang [35]	• Friendship prediction based on a model exploiting location popularity and distance of a pair of users.	• Considering location and distance not always allow to give reliable recommendation for FRA, for the case of friends and strangers.
Lo and Lin [36]	• A recommendation algorithm based on the weighted minimum message ratio, which generates a customizable friend lists using the amount of interactions.	• Suggested method based only on the evaluation of amount of messaging among OSN members.
Gou et al. [37]	• An interactive visual system to facilitate exploration and finding of friends under a given context. • Exploit topological and semantic structures of activity data in an OSN.	• Allow to seek potential friends, but not to do evaluation and prediction.

There is also a problem on the correctness of the input information. A user may not always want to set up a friend connection with a person [28], [29] with whom he/she has similar attributes, social interactions or a number of co-occurred places. This why a friend recommendation system should give to a user a possibility to define a model of a friend-to-be. A useful concept is developed in [39], where authors proposed a framework that can mitigate the hazards by employing two phases of filtering (namely, pre- and post-techniques) in OSNs.

III. ANALYSIS OF THE PREVIOUS METHOD

To the best of our understanding, the most recently proposed method that addresses friend-to-be evaluation and friendship decision making is given by Rahman *et al.* [9]. The method exploited common attributes in the profiles of an OSN user and a friend-to-be for evaluation of the friendship prospect. These attributes are derived from the Facebook interest categories, including sport, music, movies, etc. More specifically, based on the input:

1. Profile of a user and the profiles of his/her friends.
2. Profile of a friend-to-be and the profiles of his/her friends.

The method outputs a value in the range of [0; 1], representing user' and friend-to-be' profiles matching ("the likelihood to become a friend"). While the method [9] offers a significant step toward the implementation of reliable friendship decision making in OSNs, it has several drawbacks as follows.

- Apart from the interest categories, other types of attributes were not taken into account (e.g., the date of birth, family relationships, social status, etc.).
- The preferences of a user in the evaluation of the attributes were not considered. E.g., a user may give a favor to the interests in the music versus the sport category.
- Only the common interests were taken into account. At the same time, a user may have a preference to set up a friendship with a person, with whom he/she has no common interests.
- There were no scales for the attributes evaluation. E.g., a user may have a preference to set up a friendship with a friend-to-be in the age group from 18 to 25 years, while disliking the friend-to-be requests received from the group from 12 to 17 years.
- Behavior aspects were not taken into account, i.e., common likes/dislikes, the frequency of posts, etc.

This paper proposes a new method that gives a possibility for an OSN user to build a model of the friend-to-be. The model takes into account the user' preferences by setting weights to the attributes such as personal data, interests, relationships and also behavior properties. An important part of the model is the scales, allowing a user to evaluate the values of attributes of a friend-to-be. The use of scales allows for bringing into the model the negative factors to take into account users' dislikes.

The proposed approach allows an OSN user to express the preferences for evaluating the friendship likelihood of friend-to-be in a specific way, which in turn leads to the reliable decision making of friendship request. This model gives a possibility to evaluate a friend-to-be, which profile does not correspond literally to a user's profile. At the same time, if a user does not set up any of the choices of the friend-to-be model, the method may be used to build a default model based on the user' profile. This allows us to consider the method [9] as a partial case of this proposed method.

IV. MODEL AND EVALUATION

A. FRIEND-TO-BE MODEL

Let us illustrate a sample of the model of a friend-to-be by considering next attributes taken from the profile of a *friend-to-be*, which involve the categories as follows.

- **Personal data**
  - Gender
  - Age/date of birth
  - Education
- **Relationships**
  - The status of relationships of a friend-to-be
  - The number of common friends
  - Total number of friends of a friend-to-be
- **Interests and behavior**
  - Interests (sport, music, games, etc.)
  - The actual use of a social network
  - The frequency of posts of a friend-to-be
  - The number of the same and opposite likes and dislikes
- **Geographical attributes**
  - Country of living
  - Place of work or study
  - Visited places
- **Language**
  - English
  - German
  - Chinese

Remark that our model of a friend-to-be is not restricted to only the above attributes. Utilization of these items shall be interpreted for the purpose of illustrating by an example, which takes into account a subset of all attributes derived from the profile of a friend-to-be. Herein the key point of the approach lies on attributes weighting for evaluation of a likelihood to become a friend.

We next describe the possible values of the above attributes, giving an example from the personal data category. For the Gender attribute, the possible values are "Male" and "Female". For the Age attribute, the possible values can be: i) "Below 12"; ii) "From 12 to 17"; iii) "From 18 to 25"; iv) "From 26 to 35"; v) "From 36 to 54"; and vi) "Above 55". For the Education attribute, we may have the following categories: i) "School student"; ii) "University student"; "Bachelor"; "Master"; and "Doctorate".

In the proposed model, the weight of an attribute can be evaluated using a five-level Likert scale, reflecting a user preference as Very High (4), High (3), Moderate (2), Low (1), Very Low (0). Thus, the five-level natural number assigns a weight to a given model attribute. The zero (0) weight literally means non-importance of the attribute, while the number 4 gives a maximum weight.

Table 3 shows a sample distribution of the weights for a user defined model. It aims at the attribute of Age, Gender and Education. Here, the scaling of preference (weight) is stretched between (0 to 4). For this sample, the user defines the highest (4) weight for the "female" and the Moderate (2) for the male at the Gender attribute. For the Age attribute, this user wants to neglect friend requests from the groups: "Below 12", "From 36 to 54" and "Above 55", giving them the Very Low (0) weights, except the age group of "18 to 25" that weighs the highest (4) and mostly prefer "University Student" for the attribute of education.

To illustrate the approach of existing friend recommendation systems, let us consider a weights assignment that might be automatically derived from a user OSN profile. Suppose, we have a 20-year old female user who is a university student. Her age falls within the group "From 18 to 25", and thus the maximum weight (4) will be automatically assigned to this value. Other weights of the attributes are assigned by some built-in OSN algorithm (in our example, we have the group: "From 12 to 17" assigned by weight "3" and the group "Below 12" assigned by weight "2").

From Table 3, we can observe that a user's model of a friend-to-be based on his/her preferences may have a significant contrast to the weighting values that are automatically derived from the user profile (which serve as an input in existing recommendation systems) since the user may have a preference to communicate with people having different interests or belonging to different social groups.

B. EVALUATING THE LIKELIHOOD OF FRA

Following section describes the proposed method to evaluate the likelihood of establishing friendship given an incoming

TABLE 3. A Sample of the model of a friend-to-be.

Attribute	Scale	Weight assigned by user	Weight, automatically derived from a user profile
Gender	Male	2	3
	Female	**4**	**4**
Age	Below 12	0	2
	From 12 to 17	1	3
	From 18 to 25	**3**	**4**
	From 26 to 35	4	3
	From 36 to 54	0	2
	Above 55	0	1
Education	School student	1	3
	University student	**4**	**4**
	Bachelor	4	3
	Master	4	2
	Doctorate	0	1

TABLE 4. Sample of evaluation.

Sample	A friend-to-be (sample one)		A friend-to-be (sample two)		A friend-to-be (sample three)	
	Attribute value	Weight	Attribute value	Weight	Attribute value	Weight
Gender	Male	2	Female	4	Male	2
Age	From 26 to 35	4	From 12 to 17	1	Above 55	0
Education	Master	4	School student	1	Doctorate	0

friend request. By construction, the input and output of the method are given by

- **Input:** Defined by a user model of friend-to-be;
- **Output:** The value [0; 1] of matching the model of friend-to-be and actual friend-to-be profile.

As an initial step, the method evaluates the sum of the weights given by

$$W = \sum_{n=1}^{N} W_n^f \tag{1}$$

where W_n^f is defined by the user's weighting preference of the value of friend-to-be attribute n, N is the total number of attributes used for evaluation and $n \in \{1, \ldots, N\}$. The maximum possible sum of the weights of all attributes is given by

$$W_{max} = \sum_{n=1}^{N} W_n^M \tag{2}$$

where W_n^M is a maximum value of the attribute n, which in our sample it is given by $W_n^M = 4$ for all $n = 1, \ldots, N$. Note, that in general, the weights of different attributes might be measured in different scales. Finally, the ratio $R \in [0, 1]$ that defines the prospect to become a friend is given by

$$R = \frac{W}{W_{max}}. \tag{3}$$

Table 4 demonstrates an example of applying the proposed method to evaluate the likelihood of becoming a friend. Remark that the maximum weights of all the attributes are taken from Table 3, which are given by 4.

Based on equations (1)–(3), we can compute the ratio R that defines the prospect to become a friend for the above three samples as follows.

- For a friend-to-be (sample one), we have $N = 3$, $W = 2 + 4 + 4 = 10$, $W_{max} = 12$ and $R = 10/12 \approx 0.83$. This ratio means 83% prospect (likelihood) to become a friend.
- For a friend-to-be (sample two), we obtain $N = 3$, $W = 4 + 1 + 1 = 6$, $W_{max} = 12$ and $R = 6/12 = 0.50$. This ratio means 50% prospect (likelihood) to become a friend.
- For a friend-to-be (sample three), we have N, $W = 2 + 0 + 0 = 2$, $W_{max} = 12$, $R = 2/12 \approx 0.17$. This ratio means 17% prospect (likelihood) to become a friend.

Algorithm 1 Evaluation of Prospect to become a friend

```
integer n = 0
floating point W = 0, W_max = 0, R = 0
for all weighted by a user attributes in the model of a friend-to-be do
    search a corresponding attribute in the profile of a friend-to-be
    if the attribute found then
        add the weight of the attribute into the sum W
        increment n
    end if
end for
compute the maximum weight W_max of all values of n found attributes
compute the likelihood to become a friend as the ratio R = W / W_max
return R
```

The way we compute the ratios R in the above examples can be generalized into Algorithm 1 for any weighting configuration and the maximum values. This algorithm has the following properties.

- It is well applicable to incomplete models (when a user does not weight all values of all attributes).
- The weight is taken into account if only the match is found in the profile of a friend-to-be.
- Attributes, which are not defined in the model of friend-to-be, are not taken into account.
- The total number and weights of the attributes are calculated dynamically during the algorithm execution.

V. VALIDATION AND DISCUSSION

For the assessment of the proposed method in evaluating the likelihood of becoming a friend, a survey has been developed (see Appendix A). The survey consists of 3 parts, i.e.,

1) **Personal data:** This section includes Gender, Age, Education, Status of relationship, Actual use of a social network, Current number of OSN friends, Interests, The average frequency of the posts per day and the Language attributes. For example, for the Interests attribute the possible values are Music, Books, Study, Sport, Computer Games (multiple choices). See Appendix A for the details.
2) **Model of a preferred friend-to-be:** This section contains the same attributes as the Personal data part. It allows a responder to build the model of a preferred friend-to-be by weighting the values of the attributes.
3) **Randomly generated profiles of the OSN users:** This section contains ten randomly generated profiles of OSN users, which correspond to the model of a preferred friend-to-be.

   Responders of the survey were asked to evaluate the likelihood to accept a friend request by assessing randomly generated profiles. A responder should give the number in the range of [0; 100], where 0 means zero probability of accepting a friend request, while 100 means a maximum probability of accepting a friend request.

An example of these randomly generated profiles is given by Profile 1, who is a male, below 12, a school student, single, with a very high actual use of social networks and having 500+ OSN friends. His interests are movies and computer games. He has 0-3 common friends with a responder and makes average 20+ posts per day. He can speak Malay and Chinese and lives in Malaysia. See Appendix A for the details.

A. PILOT STUDY

The pilot test is an essential phase of the empirical study that provides initial indications and ensures the validity of the instrument. To that end, this work implemented a pilot test in order to assess the content and validity of the instrument as a prior step before conducting the final stage. Hunt *et al.* [38] pointed out that a minimum sample for conducting the pilot test is at least 30 respondents. Accordingly, we selected 30 respondents to participate in the pilot test from lecturers, postgraduate students and technical staff of the Faculty of Computer Systems and Software Engineering at the University Malaysia Pahang.

B. MAIN STAGE OF THE EMPIRICAL STUDY

The main stage of data collection was conducted identically to the pilot study. In May 2018, where 83 participants were selected from lecturers, students and staff of the Faculty of Computer Systems and Software Engineering at the University Malaysia Pahang. Participants were asked to evaluate the proposed method by the survey, described in Appendix A. After the initial data screening process, it was noticed that 7 respondents fail to answer one or more question(s) of the survey, not weighing all the values of the attributes. Since the proposed algorithm is applicable even for the incomplete models of a friend-to-be, the incomplete responses were also taken into account.

The collected data were used for assessing the effectiveness of the proposed formula (3). The evaluation was based on the comparison of results taken from the survey (observed values of the likelihood of a friend request acceptance) and values calculated by the formula (3). Every responder evaluates 10 randomly generated profiles of a friend-to-be (see Appendix A).

Table 5 shows an example of the observed and predicted values of the likelihood of FRA. Pearson correlation between observed and predicted values was calculated. Since the correlation depends on the model of a friend-to-be, given by a survey responder, 83 evaluations were done. In all considered cases, the test shows a strong positive correlation ranging between 0.58 and 0.99 with the mean of 0.84. For the case presented in Table 5 the Pearson correlation coefficient is 0.98.

However, Pearson correlation cannot prove accuracy of the proposed formula with some statistical significance.

TABLE 5. Observed predicted values of the likelihood of a friend request acceptance.

Friend-to-be profile No.	Observed values	Value, calculated by the formula (3)
1	25%	33%
2	30%	40%
3	90%	83%
4	85%	75%
5	70%	63%
6	35%	42%
7	30%	45%
8	20%	35%
9	10%	15%
10	10%	22%

TABLE 6. Likelihood intervals to compare the observed (empirical) with the expected (theoretical) distribution.

Likelihood intervals, %	Empirical	Predicted
0-4	7	5
5-9	12	10
10-14	18	17
15-19	22	17
20-24	32	34
25-29	38	44
30-34	47	49
35-39	44	51
40-44	54	58
45-49	58	57
50-54	62	59
55-59	65	59
60-64	64	65
65-69	74	70
70-74	66	74
75-79	58	49
80-84	36	33
85-89	28	31
90-94	26	28
95-100	19	21
Total Observation	830	830

In considered case, the mean of the likelihood of a friend request acceptance will strive to 50% both for the observed and predicted values. This means that for a big sample of diverse profiles, the evaluation will result in the average $\frac{1}{2}$ likelihood of accepting and $\frac{1}{2}$ of not accepting friend requests.

Chi-Square goodness of fit test [40] was then employed to analyze how the observed values taken from the survey differ from the expected values, calculated by the formula (3). This test is non-parametric, which does not explicitly require a normal distribution of the data. For implementation, the data samples were segmented into likelihood ranges to compare empirical distribution coming from the samples with the anticipated probability distribution. Table 6 shows the numbers of observed and expected values that fall into the likelihood intervals.

Three important aspects of Chi-Square goodness of fit test include

- **Null hypothesis:** There is no significant difference between the observed and theoretical values.
- **Alternative hypothesis:** There is a significant difference between the observed and theoretical values.

TABLE 7. Hypothesis Testing.

If	Then
p value $< a, a = 0.05$	Reject the null hypothesis
p value $> a, a = 0.05$	Cannot reject the null hypothesis

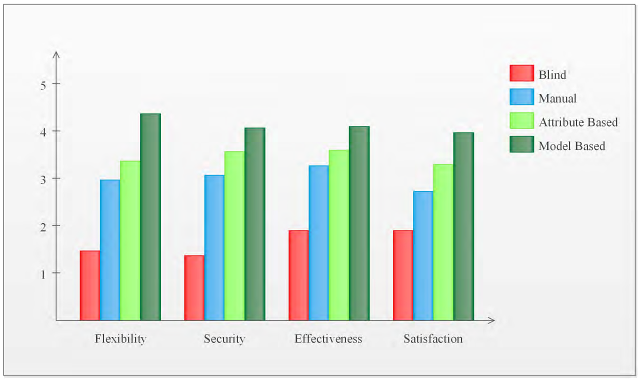

FIGURE 2. Users' evaluation of 'flexibility', 'security', 'effectiveness' and 'satisfaction'.

- **Hypothesis testing:** It involves calculation of the probability (the p-value) of significant difference between the observed and the expected frequency of values. The details can be seen in Table 7.

C. FEASIBILITY TEST

Figure 2 reflects the mean values among the four different methods of accepting friend request subject to specified criteria in OSNs, namely *flexibility, security, effectiveness* and *satisfaction*. The findings are discussed as follows:

1) PERCEPTIVENESS TOWARDS FLEXIBILITY

In terms of flexibility, it is perceived that the majority of the users give preference to the proposed method by measuring the mean at 4.37, whereas the other approaches such as the blind, manual and previous method in [9] yields the mean values of $m = 1.47$, $m = 2.97$ and $m = 3.30$, respectively. The observed values show that the users have a higher preference in setting up their own friend-to-be models for establishing friendship in a flexible manner.

2) PERCEPTIVENESS TOWARDS SECURITY

It can be observed that the mainstream of the users have favorable inclination towards the proposed method with the mean value of $m = 4.07$ in terms of security compared to the other approaches, i.e., the blind method ($m = 1.37$), manual method ($m = 3.07$) and the previous method [9] ($m = 3.57$). The motivation behind this is given by the fact that a large proportion of the users believed that a secured type of the model to evaluate a person who desires to befriend them is critical in OSN platforms.

3) PERCEPTIVENESS TOWARDS EFFECTIVENESS

Figure 2 demonstrates a varying level of users perception towards effectiveness in approving friend requests as provided by different methods. The proposed method shows a higher mean value of ($m = 4.10$) on the effectiveness metric in comparison to the other procedures, namely the blind method ($m = 1.90$), manual method ($m = 3.27$) and previous method in [9] ($m = 3.60$).

4) PERCEPTIVENESS TOWARDS SATISFACTION

The flexibility in OSNs emphasizes users' satisfaction and timesaving issues. It can be seen from Figure 2 that the most favorable result of users' consents goes to the proposed method with the mean value of ($m = 3.97$). On the other hand, alternative methods appear worse than the proposed method, i.e. with the blind, manual and previous method in [9] having the mean values of $m = 1.90$, $m = 2.73$ and $m = 3.30$, respectively. In fact, satisfaction in OSNs is shared by a particular user through his/her contacts.

5) T-TEST ANALYSIS

An independent T-test analysis is carried out to check the feasibility of the proposed automated model-based FRA technique as shown in Table 8. The proposed method expressively outclasses the existing (blind and manual) approaches and the previous technique in [9]. It can be observed from the table 8, the statistical differences in evaluation of the proposed method towards other methods are quite significant (i.e., $p < 0.05$) in terms of *flexibility, security, effectiveness* and *satisfaction*.

TABLE 8. T-test Analysis.

Method	$Mean$	SD	df	t	p	Features
Blind &	1.47	0.37	29	14.11	0.0000	Flexibility
Proposed	4.36	0.86				
Manual &	2.97	1.61	29	4.64	0.0000	
Proposed	4.36	0.86				
Attribute Based &	3.30	1.60	29	3.88	0.0005	
Proposed	4.36	0.86				
Blind &	1.37	0.57	29	14.01	0.0000	Security
Proposed	4.07	0.82				
Manual &	3.07	1.17	29	4.26	0.0003	
Proposed	4.07	0.82				
Attribute Based &	3.57	1.29	29	2.13	0.0004	
Proposed	4.07	0.82				
Blind &	1.90	1.61	29	8.06	0.0000	Effectiveness
Proposed	4.10	0.71				
Manual &	3.27	0.82	29	4.21	0.0002	
Proposed	4.10	0.71				
Attribute Based &	3.60	0.80	29	2.06	0.0037	
Proposed	4.10	0.71				
Blind &	1.90	1.68	29	5.92	0.0000	Satisfaction
Proposed	3.97	0.98				
Manual &	2.73	0.48	29	5.95	0.0000	
Proposed	3.97	0.98				
Attribute Based &	3.30	0.96	29	2.52	0.0017	
Proposed	3.97	0.98				

D. CONSIDERING THE TRUST MODEL

The proposed approach is general and used to evaluate friend requests based on some predefined set of attributes. To illustrate the generality of our approach, given case study considers the most common attributes as Interests (sport, music, games etc.). At the same time, with allocation of a proper subset of attributes the method can be applied for evaluation of fraudulent and suspicious friend requests. Examples of such attributes are the frequency and content of the posts of a friend-to-be, very high or very low actual use of a social network, absence of common friends, etc. Allocation of such subset leads us to the definition of the trust model of friend request acceptance in OSNs.

Together with emphasis on security aspects of FRA in OSN, elaboration of the trust model needs change of weights of attributes and also the method output.

The initial proposal was to consider the value [0; 1] of matching the model of friend-to-be' and actual friend-to-be' profile as the output of the method. In the proposed trust model, the general output [0; 1] will be dived into the ranges:

$$[0.0; 0.2) - Suspicious$$
$$[0.2; 0.4) - Questionable$$
$$[0.4; 0.6) - Neutral$$
$$[0.6; 0.8) - Recommended$$
$$[0.8; 1.0] - HighlyRecommended\ (Reliable)$$

E. LIMITATIONS OF THE STUDY AND FUTURE WORK

For the sake of completeness, we outline the limitations of our empirical study as follows.

- Survey participants were only university students & staffs. To increase the validity of the study, an involvement of different social groups is needed.
- The study was conducted only in one country (Malaysia).
- Only a limited set of attributes in the model of a friend-to-be was taken into account for evaluation of the proposed method.

In order to improve the method presented in this work, future directions will include learning an influence of the personal attributes as well as increasing the validity of the corresponding empirical study. One of our future work directions will be allocation of the metrics for evaluation of anonymous behavior of a user.

VI. CONCLUSION

The paper has proposed a new method that gives an opportunity for an OSN user to figure out a model of the friend-to-be. The proposed model weights up the user' preferences by setting values to the attributes such as personal data, interests, relationships and behavior properties. These weighted attributes provide an outline of the friend-to-be and consequently give authentic information to establish a friendship. The most important part of the model is the scaling opportunities, allowing a user to evaluate the weights assignment of the attributes of a friend-to-be. The use of scales allows us to factor in the negative factors into the model, i.e., by taking into account users' dislikes. The proposed method thus allows an OSN user to express the preferences for evaluating a friend-to-be model in a specific way, which in turn leads to the reliable decision making of FRA. Unlike existing recommender systems, the proposed method gives a possibility to evaluate a friend-to-be whose profile does not correspond to a user's profile. It also allows for filtering the friend requests, which exhibit an anomalous behavior in an OSN.Through an empirical study by Pearson correlation and Chi-Square goodness of fit tests, the validity of the proposed method has been proved in terms of *flexibility, security, effectiveness* and *satisfaction* criteria.

APPENDIX

Survey for the evaluation of the proposed method to become a friend with an OSN user is sumarized in Table 9.

TABLE 9. Summary of the survey.

Description: This survey consists of 4 parts: • Model of the responder of the survey (personal data section at Table 10) • Model of the preferred friends-to-be • Evaluation of the prospect to become a friend with randomly . generated profiles of OSN users • Evaluation of feasibility of the proposed method	
Conducted by: S M Nazmus Sadat	Date: May 2018

TABLE 10. Personal data.

Gender		
☐ Male	☐ Female	
Age (single choice)		
☐ Below 12	☐ 12 to 17	☐ 18 to 25
☐ 26 to 35	☐ 36 to 54	☐ Above 54
Education (single choice)		
☐ School Student	☐ University/ college Student	☐ Bachelor
☐ Masters	☐ Doctorate	
Relationship Status (single choice)		
☐ Single	☐ Married	
☐ Divorced	☐ Widow / Widower	
Actual use of a social network (single choice)		
☐ School Student	☐ Low	☐ Moderate
☐ High	☐ Very High	
Number of OSN Friends (single choice)		
☐ (0-10)	☐ (11-50)	☐ (51-200)
☐ (201-500)	☐ (501-1000)	☐ 1000+
Interests (multiple choice)		
☐ Movies	☐ Music	☐ Books
☐ Study	☐ Sport	☐ Computer Games
Average frequency of posts (single choice)		
☐ (0-2) per day	☐ (3-8) per day	☐ (9-20) per day
☐ (20+) per day		
Language (multiple choice)		
☐ Malay	☐ English	☐ Chinese
☐ Tamil	☐ Arabic	☐ Japanese
Number of common friends (single choice)		
☐ (0-3)	☐ (4-10)	☐ (11-25)
☐ (26-50)	☐ (50+)	

Table 11 allows a responder to build a model of a preferred friend-to-be, where given attributes to be evaluated by the scale from 0 to 4. The method supposes that not all attributes may be weighted. The zero (0) weight means a non-importance of the attribute, while the number 4 means its maximum importance for a responder. Table 12 gives an

TABLE 11. Model of the preferred friend-to-be.

Gender		
Male: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Female: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	
Age		
Below 12: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	12 to 17: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	18 to 25: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
26 to 35: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	36 to 54: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Above 55: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
Education		
School Student: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	University/ College: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Bachelor: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
Masters: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Doctorate: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	
Relationship Status		
Single: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Married: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	
Divorced: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Widow/ Widower: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	
Actual use of Online Social Network		
☐ Very Low	☐ Low	☐ Moderate
☐ High	☐ Very High	
Number of OSN Friend		
(0-10): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	(11-50): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	(51-200): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
(201-500): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	(501-1000): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	(1000+): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
Interest		
Movies: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Music: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Books: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
Study: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Sports: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Computer Games: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
Average frequency of posts		
(0-2) per day: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	(3-8) per day: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	(9-20) per day: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
(20+) per day: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4		
Language		
Malay: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	English: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Chinese: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
Tamil: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Arabic: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	Japanese: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
Number of Common/ Mutual Friends		
(0-3): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	(4-10): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	(11-25): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
(26-50): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	(50+): ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	
Preferred Country of living		
Malaysia: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	India: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	China: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4
A country of Europe: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	An Arabic Country: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4	USA: ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4

TABLE 12. Evaluation of the likelihood to accept a friend request by assessment randomly generated profiles of OSN users.

Attribute	Profile 01	Profile 02	Profile 03	Profile 04	Profile 05	Profile 06	Profile 07	Profile 08	Profile 09	Profile 10
Gender	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Age	Below 12	12 to 17	18 to 25	18 to 25	26 to 35	26 to 35	36 to 54	36 to 54	Above 55	Above 55
Education	School student	School student	University/ college student	University/ college student	Bachelor	Master	Master	Doctorate	Bachelor	Doctorate
Relationship	Single	Single	Single	Single	Single	Married	Married	Married	Divorced	Widow
Actual use of a social network	Very High	High	High	Moderate	Moderate	Moderate	Low	Low	Very Low	Very Low
Number of OSN Friends	500+	201-500	201-500	201-500	51-100	51-200	51-200	51-200	11-50	0-10
Interests	Movies; Computer Games	Music; Study	Study; Sport	Study; Sport	Music; Books	Movies	Music; Computer Games	Books	Sport	Movies; Books
Average frequency of posts per day	20+	9-20	9-20	9-20	3-8	3-8	0-2	0-2	0-2	0-2
Language	Malay; Chinese	English; Malay	Malay; Tamil	English; Japanese	Malay; Chinese	English; Arabic	Malay; Tamil	English; Arabic	Malay	English; Japanese
Number of common friends	0-3	4-10	11-25	0-3	4-10	11-25	0-3	4-10	26-50	0-3
Country of living	Malaysia	India	Malaysia	China	A country of Europe	Malaysia	An Arabic country	A country of Europe	Malaysia	USA
Evaluation										

example of the randomly generated profiles of OSN users. A responder needs to evaluate the likelihood of the FRA, by giving value in the range [0;100] (where 0 means the zero probability of accepting a friend request, while 100 implies a maximum probability of the FRA).

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