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**USER TO USER TOPIC RECOMMENDATION MODEL FOR
STUDENT SOCIAL INTERACTION**



AHMAD SUBHI BIN ZOLKAFLY

**DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
2025**

**USER TO USER TOPIC RECOMMENDATION MODEL FOR STUDENT SOCIAL
INTERACTION**



**BY
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UUM
Universiti Utara Malaysia

**Thesis Submitted to
School of Computing,
Universiti Utara Malaysia,
in Fulfilment of the Requirement for the Degree of Doctor of Philosophy**



Awang Had Salleh
Graduate School
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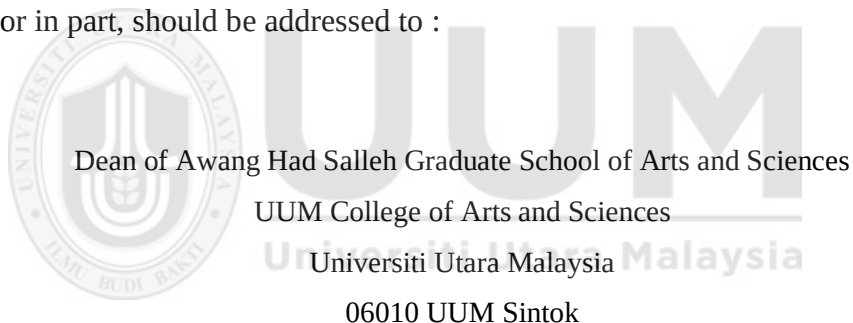
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Abstrak

Keterkaitan sosial adalah penting terutamanya didalam persekitaran akademik kerana ianya dapat membentuk perasaan kekitaan, meningkatkan sokongan emosi dan akademik yang dapat menyebabkan motivasi dan keputusan akademik menjadi lebih baik. Sistem pengesyor mempromosikan hubungan sosial dengan memupuk interaksi, berkongsi pengalaman dan semangat kekitaan antara rangkaian dan komuniti. Usaha dalam keterkaitan sosial pada masa kini sangat mengutamakan kepada interaksi digital, komuniti maya dan jangkauan secara global yang dikuasai oleh pacuan data peribadi. Sistem pengesyor sedia ada perlu mempertimbangkan kecenderungan manusia untuk bersama dengan orang yang mempunyai ciri-ciri yang sama atau seakan-akan sama berdasarkan kepada ciri-ciri psikografik dan personaliti yang perlu diperhalusi. Oleh itu, adalah penting untuk mempunyai sistem pengesyor yang dapat menyelesaikan isu ini dengan mencadangkan topik perbualan untuk menyokong interaksi sosial yang memfokuskan kepada hubungan antara pengguna dengan pengguna. Kajian ini menfokuskan kepada pembangunan model pengesyoran topik pengguna kepada pengguna untuk interaksi sosial pelajar (TReSIT). Model ini adalah bersandarkan kepada teori “homophily” iaitu teori yang menghuraikan kecenderungan individu untuk berinteraksi atau berhubungan dengan orang yang mempunyai ciri-ciri yang sama. Satu model ramalan TReSIT telah dibangunkan berdasarkan kepada faktor psikologi (“The Big 5”) dan psikografik (nilai dan cara hidup). Model ramalan analitik ini telah membandingkan antara ketepatan pengelas tunggal dan pengelas berbilang dalam meramalkan kepentingan topik terhadap individu. Kemudian, satu algoritma dibangunkan dipanggil sebagai algoritma cadangan sosial (SAR), telah memberi kedudukan dan mengesyorkan topik terbaik untuk interaksi sosial. Keputusan telah menunjukkan bahawa Fungsi Penilaian Kedudukan Asas Berparameter (PBREF) mempunyai nilai ketepatan yang tinggi (69.90%) berbanding Fungsi Penilaian Kedudukan Berbilang Berparameter (PMCREF) dengan nilai ketepatan sebanyak 64.58%. Satu kajian juga telah dijalankan untuk menilai tahap kepuasan terhadap topik yang dicadangkan. Sejumlah 16 kumpulan telah dibentuk berdasarkan kepada topik yang dicadangkan oleh SAR dan mereka telah berinteraksi bersama ahli kumpulan. Kemudian, mereka menilai kepuasan interaksi mereka. Keputusan menunjukkan nilai min tahap kepuasan sebanyak 3.873. Model ini boleh digunakan dalam persekitaran kerja untuk mencetuskan interaksi sosial berdasarkan kepada minat yang sama. Model ini juga boleh diimplimentasikan terhadap robot sosial yang boleh mencetuskan topik perbualan sesama individu dalam persekitaran yang dikongsi seperti tempat rehat. Perbualan ini kemudiannya dapat memupuk hubungan sosial, mengurangkan pengasingan diri dan mungkin dapat meningkatkan tahap kesihatan mental.

Kata kunci : Sistem pengesyor, Teori homopily, Model analitik ramalan, Algoritma cadangan sosial, Model TReSIT

Abstract

Social connectedness is important especially in academic setting because it can establish the sense of belonging, increase the emotional and academic support that result to higher motivation and better academic outcomes. Recommender systems can play a significant role in promoting social connectedness by fostering interactions, shared experiences, and a sense of belonging within communities or networks. Current social connectedness efforts heavily focus on digital interactions, online communities, and global reach that often powered by data-driven personalization. The current recommender systems also need to consider more homophily and homogeneity based on refined psychographic and personality traits. Hence, it is important to have a recommender system that suggested to solve these issues by recommending mutual topics for supporting social interactions and focusing on user-user relationship. This study focuses on developing a User to User Topic Recommendation Model for Student Social Interaction (TReSIT). This model is grounded on the theory of homophily, which describes individuals' tendency to interact with or be linked with others based on comparable characteristics or specific shared ideals. A predictive TReSIT model is developed based on psychological (the "big 5") and psychographics (values and lifestyles) factors. This predictive analytics model compared single and multi-classifier accuracy in predicting the importance of a topic for an individual. Then, a newly developed algorithm called the Social Recommendation (SAR) algorithm ranked and recommended the best topic for social interaction. The results show that the Parameterized Basic Ranking Evaluation Function (PBREF) has higher accuracy (69.90%) than Parameterized Multiple Classifier Ranking Evaluation Function (PMCREF) with 64.58%. An experiment also has been conducted to evaluate satisfaction towards the topic recommended. A total of 16 groups were formed based on the topic recommended by SAR and interacted with their team members. Later, they rated their interactions' satisfaction. The results show that the mean satisfaction level is 3.873. This model can be used in a working setting to trigger social interactions based on mutual interest. It can be implemented on a social robot that can trigger topics for conversations among individuals in a shared space like a resting area. The conversation later can foster social connectedness, reduce isolation, and possibly increase mental health.

Keywords : Recommender system, Homophily theory, Predictive analytics model, Social recommendation algorithms, TReSIT model

Acknowledgement

"By the pen and what they inscribe..." (68:1)

ALHAMDULILLAH, ALHAMDULILLAH, ALHAMDULILLAH... Praise be to Allah, the All-Powerful, the Most Merciful, and the Most Generous, for His blessings. Praise is then extended to our Prophet Muhammad (PBUH), his family, and his associates.

First and foremost, I would like to express my feeling to say that this thesis is a tribute to my late mother, Madam Halimah Ramli, who went to spend eternity with her Creator during my PhD journey. In memory of her, she raised me, helped me, and encouraged me on this journey, and as a remembrance, she was a devoted and wonderful mother. This thesis also serves as a present to my father, Mr. Zolkafly Hashim, who never stopped encouraging me by offering both financial and emotional support. To both of them, this is the prove that what you pray for, is granted!.

My sincere gratitude is extended to both of my supervisors, Associate Professor Dr. Rahayu Ahmad and Associate Professor Dr. Azizi Ab. Aziz, for their advice, assistance, and support. Without them, I am unable to complete this wonderful journey on my own. I appreciate your continued confidence in my ability to complete this thesis.

A heartfelt thank you to my family members—Ahmad Shaffree, Ahmad Shahrezza, Nur Idzratul Nadia, Nur Izzatul Adila, Nur Nazihah, Ahmad Shaiful Arif, Nur Safarihan, Intan Jusina, Mohd Nasir, Muhd Ridhwan, and Mohd Azim—for always supporting me from the beginning to the end of this journey. I also want to express my gratitude to all my nieces and nephews—Iman, Rabiya, Iris, Dania, Raid, Uzra, Isya, Ruby, Dazreen, Rachel, Raisha, Ilmi, Raifaa, and the ones who will join in the future. May you all become the next doctorates in this legacy.

Last but not least, I would like to thank all of my teachers from Pasti ABIM Tasek Gelugor, Sekolah Kebangsaan Tasek Gelugor, Sekolah Rendah Agama At-Tahzibiyah Al-Islamiah Pokok Tampang, and Sekolah Menengah Kebangsaan Kampung Selamat (First Batch), as well as my lecturers from Universiti Teknologi MARA (Perak) and Universiti Utara Malaysia. Thank you for your dedication and support.

Lastly, My sincere thanks goes to all of my friends, Shahrane Khalid, Nur Izzati Liyana Azizan, Muhamad Zamri Anuar, Shahrin Saad, Wan Muhamad Yusof, Faizuddin, Muhd Sukor, Adly Ikhwan, Siti Farizah, Nurul Syafidah Jamil, Nurulhuda, Shakiroh, Bakr Salim, Ahmed, Athirah, Shahrul Izwan Md Hassan, Emy, my HCC lab members, my officemate, and all of my other friends and acquaintances, for their unwavering understanding, prayers, and support as I worked to finish this thesis. They made this voyage beautiful; without them, it would not have been. Much obliged!.

“Dare to have dreams to reach the stars in the sky, because Allah is always there to take care of you.”

(ASZ, 2023)

"In the name of Allah, the Most Gracious, the Most Merciful.

-Read in the name of your Lord Who created-

-He created man from a clot of blood-

-Read, and your Lord is Most Generous-

-Who taught by the pen-

-Taught man what he did not know-"

(96: 1-5)

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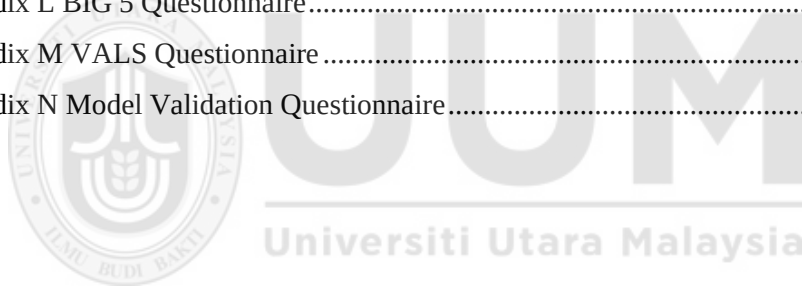
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Glossary of Terms

- GPV Group Preference Value (GPV) is a value that obtained by a group based on preferences
- LPE Lowest Pulling Effect (LPE) is a value obtained from the lowest value of predictive model in a function



List of Abbreviations

BREF	Basic Ranking Evaluation Function
CBF	Content Based Filtering
CF	Collaborative Filtering
DSRP	Design Science Research Process
DT	Decision Tree
FCBF	Fast Correlation Based Filter
GPV	Group Preference Value
IG	Information Gain
<i>k</i> -NN	<i>k</i> -Nearest Neighbor
LPE	Lowest Pulling Effect
LR	Logistic Regression
MCREF	Multiple Classifier Ranking Evaluation Function
MMHA	Malaysian Mental Health Association
NB	Naïve Bayes
NN	Neural Network
PBREF	Parameterized Basic Ranking Evaluation Function
PMCREF	Parameterized Basic Ranking Evaluation Function
RF	Random Forest
RST	Rough Set Theory
SAR	Social Recommendation
SVM	Support Vector Machine
TReSIT	Topic Recommendation for Social Interaction
UUM	Universiti Utara Malaysia
VALS	Values and Lifestyles
χ^2	Chi-square

CHAPTER ONE

INTRODUCTION

1.1 Background of The Study

The recommendation system (RS) is one of the intelligent systems applied in various areas such as e-health, e-commerce, and social networking (Moraes, Stiubiener, Braga, & Pimentel, 2020). These systems aid the user in decision-making and personalize results on several online sites based on the suggested topic and news (Moraes et al., 2020).

There are several types of recommender systems, such as sentiment-based recommender systems (Contratres, Alves-souza, Filgueiras, & DeSouza, 2018), predictive recommender systems (Kartoglu & Spratling, 2018), personalized recommender systems (Das, Sahoo, & Datta, 2017; Jain, Grover, Thakur, & Choudhary, 2015), user accepting recommendation services (F. Zhang et al., 2018), item based recommendation (H. Wu et al., 2018), traditional recommender system (user-item recommendation) (Lee, Noh, Oh, & Kim, 2018; Q. Zhang, Cao, Zhu, Li, & Sun, 2018; Zhou, Tang, Ding, & Yin, 2018), content based recommender system (Beutel et al., 2018; Chamoso, Rivas, Rodríguez, & Bajo, 2018; Ding, Li, Jiang, & Zhou, 2018), product recommendation system (Gilotte, Calauzènes, Nedelec, Abraham, & Dollé, 2018; Ramasamy & Razia Sulthana, 2018; Singh & Solanki, 2019), and user historical rating recommendation (Meng, Wang, Liu, & Zhang, 2018).

In addition, topic recommender systems (Cucchiarelli, Morbidoni, Stilo, & Velardi, 2019; Stilo, Velardi, Cucchiarelli, Marangoni, & Morbidoni, 2017; Zhao, Cheng,

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Appendix A

Python Programming Code for TReSIT Model

```
import numpy as np
import pandas as pd

group = int(input('Enter Group Number:'))
mcperson = int(input('Enter Number of Individu :'))
classifier = int(input('Enter Number of Classifier :'))
a = float(input('Enter Alpha Value [0-1] :'))
eta= float(input('Enter Eta Value [0-1]:'))
trendHobby = float(input('Enter Hobby Trend Value :'))
trendSport = float(input('Enter Sport Trend Value :'))
trendFood = float(input('Enter Sport Trend Value :'))
trendMusic = float(input('Enter Music Trend Value :'))
trendFilm = float(input('Enter Film Trend Value :'))

meanHobby = float(input('Enter Hobby Mean Value :'))
meanSport = float(input('Enter Sport Mean Value :'))
meanFood = float(input('Enter Sport Mean Value :'))
meanMusic = float(input('Enter Music Mean Value :'))
meanFilm = float(input('Enter Film Mean Value :'))

mchobbylow = 0; mchobbymedium = 0; mchobbyhigh = 0; mcsportlow
=0; mcsportmedium = 0; mcsporthigh = 0; mcfoodlow =0;
mcfoodmedium =0; mcfoodhigh =0; mcmusiclow =0; mcmusicmedium =0;
mcmusichigh=0
mcfilmlow=0; mcfilmmedium =0; mcfilmhigh=0; mcworklow=0;
mcworkmedium=0; mcworkhigh=0 ; mctopiclow=0; mctopicmedium=0;
mctopichigh=0
mcwHL = 0; mcwHM=0; mcwHH=0 ; mctotalHobby =0; mcwSL = 0 ; mcwSM
=0; mcwSH =0; mctotalSport=0; mcwFDL = 0; mcwFDM =0; mcwFDH =0;
mctotalFood=0; mcwML = 0; mcwMM =0; mcwMH =0; mctotalMusic=0
mcwFLH = 0; mcwFLM =0; mcwFLH =0; mctotalFilm=0; high=0;
highparam=0;
looping=0; alpha, eta = 0, 0;

for x in range(mcperson):
    print('Individu :',x+1)
    for y in range(classifier):
        print('Classifier : ',y+1)
```

```

mchobby = int(input('Enter Hobby Prediction [1/2/3] :'))
mcsport = int(input('Enter Sport Prediction [1/2/3] :'))
mcfood = int(input('Enter Food Prediction [1/2/3] :'))
mcmusic = int(input('Enter Music Prediction [1/2/3] :'))
mcfilm = int(input('Enter Film Prediction [1/2/3] :'))

if mchobby ==1:
    mchobbylow +=1
if mchobby ==2:
    mchobbymedium += 1
if mchobby ==3:
    mchobbyhigh +=1
if mcsport ==1:
    mcsportlow +=1
if mcsport == 2:
    mcsportmedium +=1
if mcsport==3:
    mcsporthigh +=1
if mcfood==1:
    mcfoodlow +=1
if mcfood ==2:
    mcfoodmedium +=1
if mcfood ==3:
    mcfoodhigh+=1
if mcmusic==1:
    mcmusiclow +=1
if mcmusic ==2:
    mcmusicmedium +=1
if mcmusic ==3:
    mcmusichigh+=1
if mcfilm==1:
    mcfilmlow +=1
if mcfilm ==2:
    mcfilmmedium +=1
if mcfilm ==3:
    mcfilmhigh+=1

#Classifier without parameter
div = mcperson*classifier
mcwHL = mchobbylow / div
mcwHM = mchobbymedium / div
mcwHH = mchobbyhigh / div
mctotalHobby = (max(0, (mcwHH + mcwHM) -mcwHL))

mcwSL = mcsportlow / div
mcwSM = mcsportmedium / div

```

```

mcwSH = mcsporthigh / div
mctotalSport = (max(0, ((mcwSH + mcwSM)) - mcwSL))

mcwFDL = mcfoodlow / div
mcwFDM = mcfoodmedium / div
mcwFDH = mcfoodhigh / div
mctotalFood = (max(0, ((mcwFDH + mcwFDM)) - mcwFDL))

mcwML = mcmusiclow / div
mcwMM = mcmusicmedium / div
mcwMH = mcmusichigh / div
mctotalMusic = (max(0, ((mcwMH + mcwMM)) - mcwML))

mcwFLL = mcfilm_low / div
mcwFLM = mcfilmmedium / div
mcwFLH = mcfilmhigh / div
mctotalFilm = (max(0, ((mcwFLH + mcwFLM)) - mcwFLL))

#Checking redundant highest value

if mctotalHobby > max(mctotalSport, mctotalFood, mctotalMusic,
mctotalFilm):
    value = "Hobby"
elif mctotalSport > max(mctotalHobby, mctotalFood, mctotalMusic,
mctotalFilm):
    value = "Sport"
elif mctotalFood > max(mctotalHobby, mctotalSport, mctotalMusic,
mctotalFilm):
    value = "Food"
elif mctotalMusic > max(mctotalHobby, mctotalSport, mctotalFood,
mctotalFilm):
    value = "Music"
elif mctotalFilm > max(mctotalHobby, mctotalSport, mctotalFood,
mctotalMusic):
    value = "Film"
else:
    value = "None"

#if the highest value > 1, then the algorithm will multiply with
trend value
    if value == "None":
        looping = 1
        trend_Hobby = mctotalHobby * trendHobby
        trend_Sport = mctotalSport * trendSport
        trend_Food = mctotalFood * trendFood
        trend_Music = mctotalMusic * trendMusic

```

```

trend_Film = mctotalFilm * trendFilm

#Checking redundant highest value after multiply with trend value

    if trend_Hobby > max(trend_Sport, trend_Food, trend_Music,
trend_Film):
        value = "Hobby"
    elif trend_Sport > max(trend_Hobby, trend_Food, trend_Music,
trend_Film):
        value = "Sport"
    elif trend_Food > max(trend_Hobby, trend_Sport, trend_Music,
trend_Film):
        value = "Food"
    elif trend_Music > max(trend_Hobby, trend_Sport, trend_Food,
trend_Film):
        value = "Music"
    elif trend_Film > max(trend_Hobby, trend_Sport, trend_Food,
trend_Music):
        value = "Film"

else:
    value = "None"
    looping=2

#if there is multiple highest value after multiply with trend
value, then the new value will be multiply by mean value
    if value == "None":
        mean_Hobby = trend_Hobby * meanHobby
        mean_Sport = trend_Sport * meanSport
        mean_Food = trend_Food * meanFood
        mean_Music = trend_Music * meanMusic
        mean_Film = trend_Film * meanFilm

        if mean_Hobby > max(mean_Sport, mean_Food, mean_Music,
mean_Film):
            value = "Hobby"
        elif mean_Sport > max(mean_Hobby, mean_Food, mean_Music,
mean_Film):
            value = "Sport"
        elif mean_Food > max(mean_Hobby, mean_Sport, mean_Music,
mean_Film):
            value = "Food"
        elif mean_Music > max(mean_Hobby, mean_Sport, mean_Food,
mean_Film):
            value = "Music"

```

```

        elif mean_Film > max(mean_Hobby, mean_Sport, mean_Food,
mean_Music):
            value = "Film"
#classifier with parameter
div = mcperson*classifier
mcpwHL = float(mchobbylow / div)
mcpwHM = float(mchobbymedium / div)
mcpwHH = float(mchobbyhigh / div)
mcpwparam_totalHobby = (max(0.0, ((a*mcpwHH + ((1.0-a)*mcpwHM)) -
(eta*mcpwHL))))

mcpwSL = float(mcsportlow / div)
mcpwSM = float(mcsportmedium / div)
mcpwSH = float(mcsporthigh / div)
mcpwparam_totalSport = float(max(0.0, ((a*mcpwSH + ((1.0-
a)*mcpwSM)) - (eta*mcpwSL))))

mcpwFDL = float(mcfoodlow / div)
mcpwFDM = float(mcfoodmedium / div)
mcpwFDH = float(mcfoodhigh / div)
mcpwparam_totalFood = (max(0.0, ((a*mcpwFDH + ((1.0-a)*mcpwFDM)) -
(eta*mcpwFDL))))

mcpwML = float(mcmusiclow / div)
mcpwMM = float(mcmusicmedium / div)
mcpwMH = float(mcmusichigh / div)
mcpwparam_totalMusic = (max(0.0, ((a*mcpwMH + ((1.0-a)*mcpwMM)) -
(eta*mcpwML))))

mcpwFLL = float(mcfilmlow / div)
mcpwFLM = float(mcfilmmedium / div)
mcpwFLH = float(mcfilmhigh / div)
mcpwparam_totalFilm = (max(0.0, ((a*mcpwFLH + ((1.0-a)*mcpwFLM)) -
(eta*mcpwFLL))))

#Checking redundant highest value for parameter
if mcpwparam_totalHobby > max(mcpwparam_totalSport,
mcpwparam_totalFood, mcpwparam_totalMusic, mcpwparam_totalFilm):
    param_value = "Hobby"
elif mcpwparam_totalSport > max(mcpwparam_totalHobby,
mcpwparam_totalFood, mcpwparam_totalMusic, mcpwparam_totalFilm):
    param_value = "Sport"
elif mcpwparam_totalFood > max(mcpwparam_totalHobby,
mcpwparam_totalSport, mcpwparam_totalMusic, mcpwparam_totalFilm):

```

```

    param_value = "Food"
elif mcparam_totalMusic > max(mcparam_totalHobby,
mcparam_totalSport, mcparam_totalFood, mcparam_totalFilm):
    param_value = "Music"
elif mcparam_totalFilm >
max(mcparam_totalHobby,mcparam_totalSport,mcparam_totalFood,
mcparam_totalMusic):
    param_value = "Film"
else:
    param_value = "None"

#If the highest value > 1 for parameter, then the algorithm will
multiply with trend value
    if param_value == "None":
        param_looping = 1
        mcparam_trend_Hobby = mcparam_totalHobby * trendHobby
        mcparam_trend_Sport = mcparam_totalSport * trendSport
        mcparam_trend_Food = mcparam_totalFood * trendFood
        mcparam_trend_Music = mcparam_totalMusic * trendMusic
        mcparam_trend_Film = mcparam_totalFilm * trendFilm

#Checking redundant highest value after multiply with trend value
for parameter
    if mcparam_trend_Hobby > max(mcparam_trend_Sport,
mcparam_trend_Food, mcparam_trend_Music, mcparam_trend_Film):
        param_value = "Hobby"
    elif mcparam_trend_Sport > max(mcparam_trend_Hobby,
mcparam_trend_Food, mcparam_trend_Music, mcparam_trend_Film):
        param_value = "Sport"
    elif mcparam_trend_Food > max(mcparam_trend_Hobby,
mcparam_trend_Sport, mcparam_trend_Music, mcparam_trend_Film):
        param_value = "Food"
    elif mcparam_trend_Music > max(mcparam_trend_Hobby,
mcparam_trend_Sport, mcparam_trend_Food, mcparam_trend_Film):
        param_value = "Music"
    elif mcparam_trend_Film > max(mcparam_trend_Hobby,
mcparam_trend_Sport, mcparam_trend_Food, mcparam_trend_Music):
        param_value = "Film"

    else:
        param_value = "None"
        param_looping=2

#If there is multiple highest value after multiply with trend
value for parameter, then the new value will be multiply by mean
value

```

```

if param_value == "None":
    mcparam_mean_Hobby = mcparam_trend_Hobby * meanHobby
    mcparam_mean_Sport = mcparam_trend_Sport * meanSport
    mcparam_mean_Food = mcparam_trend_Food * meanFood
    mcparam_mean_Music = mcparam_trend_Music * meanMusic
    mcparam_mean_Film = mcparam_trend_Film * meanFilm

#Checking redundant highest value for parameter
    if mcparam_mean_Hobby > max(mcparam_mean_Sport,
mcparam_mean_Food, mcparam_mean_Music, mcparam_mean_Film):
        param_value = "Hobby"
    elif mcparam_mean_Sport > max(mcparam_mean_Hobby,
mcparam_mean_Food, mcparam_mean_Music, mcparam_mean_Film):
        param_value = "Sport"
    elif mcparam_mean_Food > max(mcparam_mean_Hobby,
mcparam_mean_Sport, mcparam_mean_Music, mcparam_mean_Film):
        param_value = "Food"
    elif mcparam_mean_Music > max(mcparam_mean_Hobby,
mcparam_mean_Sport, mcparam_mean_Food, mcparam_mean_Film):
        param_value = "Music"
    elif mean_Film > max(mcparam_mean_Hobby,
mcparam_mean_Sport, mcparam_mean_Food, mcparam_mean_Music):
        param_value = "Film"

#PRINT RESULT

print('\n=====RECOMMENDATION=====')
print('The Topic Recommendation (Without Parameter) : ',value)
print('#loop : ',looping)
print('The Topic Recommendation (With Parameter) : ',param_value)
print('#loop_param : ',param_looping)

print('\n-----PREDICTIVE MODELING DATA-----')
print('Hobby',mchobbylow,mchobbymedium,mchobbyhigh)
print('Sport',mcsportlow,mcsportmedium,mcsporthigh)
print('Food', mcfoodlow,mcfoodmedium,mcfoodhigh)
print('Music',mcmusiclow,mcmusicmedium,mcmusichigh)
print('Film',mcfilmlow,mcfilmmedium,mcfilmhigh)

```

Appendix B

Sample Result of TReSIT Model

```
Enter Group Number:2
Enter Number of Individu :2
Enter Number of Classifier :1
Enter Alpha Value [0-1] :1
Enter Eta Value [0-1]:1
Enter Hobby Trend Value :2
Enter Sport Trend Value :1
Enter Sport Trend Value :2
Enter Music Trend Value :3
Enter Film Trend Value :4
Enter Hobby Mean Value :3
Enter Sport Mean Value :2
Enter Sport Mean Value :2
Enter Music Mean Value :3
Enter Film Mean Value :3
Individu : 1
Classifier : 1
Enter Hobby Prediction [1/2/3] :1
Enter Sport Prediction [1/2/3] :2
Enter Food Prediction [1/2/3] :3
Enter Music Prediction [1/2/3] :3
Enter Film Prediction [1/2/3] :2
Individu : 2
Classifier : 1
Enter Hobby Prediction [1/2/3] :1
Enter Sport Prediction [1/2/3] :1
Enter Food Prediction [1/2/3] :2
Enter Music Prediction [1/2/3] :2
Enter Film Prediction [1/2/3] :3
-----
```

RESULT

```
Group : 2
# Individu : 2
# Classifier: 1
```

```
-----
Total HOBBY 0
Total SPORT 0
Total FOOD 1.0
Total Music : 1.0
Total Film : 1.0
-----
```

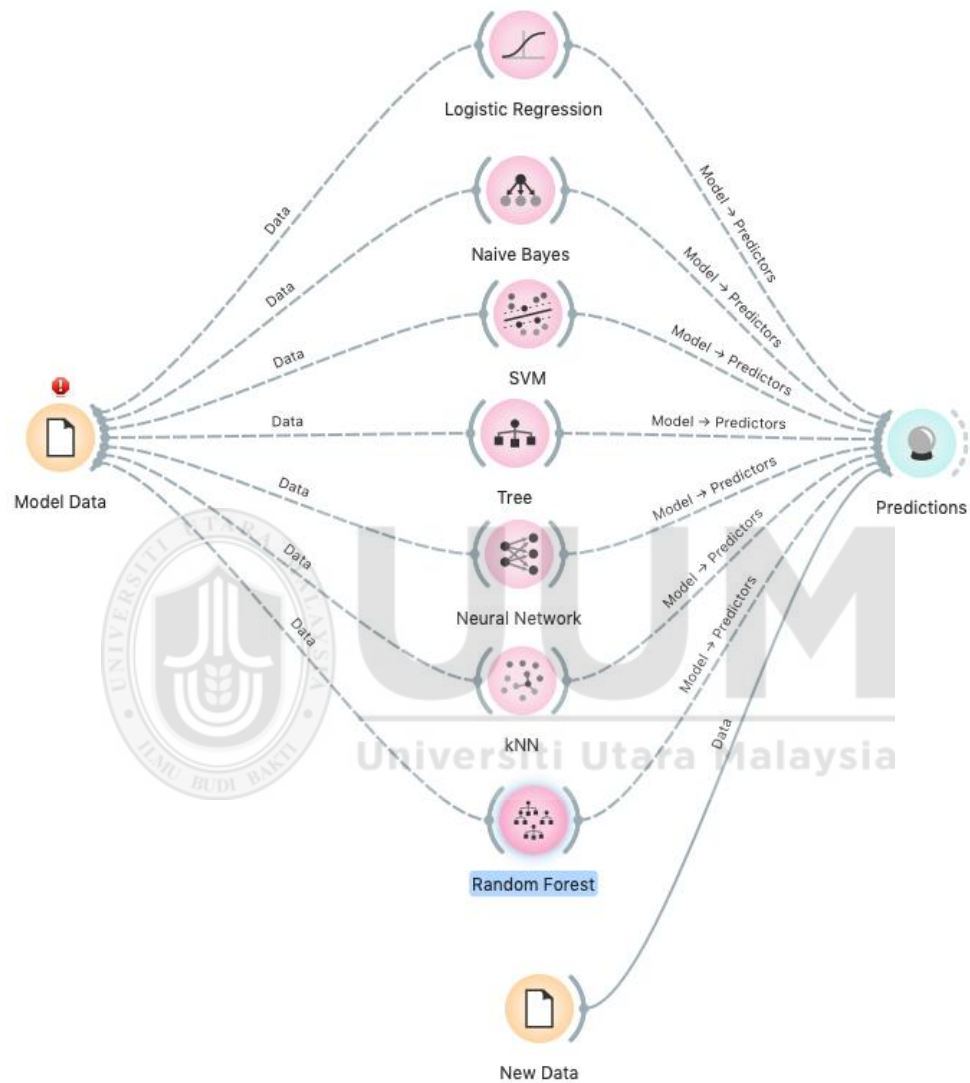
```
Total HOBBY WITH PARAMETER 0.0
Total SPORT WITH PARAMETER 0.0
Total FOOD WITH PARAMETER 0.5
Total Music WITH PARAMETER 0.5
Total Film WITH PARAMETER 0.5
```

```
=====RECOMMENDATION=====
The Topic Recommendation (Without Parameter) : Film
#loop : 1
The Topic Recommendation (With Parameter) : Film
#loop_param : 1
```

```
-----PREDICTIVE MODELLING DATA-----
Hobby 2 0 0
Sport 1 1 0
Food 0 1 1
Music 0 1 1
Film 0 1 1
```

Appendix C

Sample of Predictive Model Development using Orange



Appendix D

Result of The Training and Testing Data with 5,7,10 and 14 Features for Target Hobby, Sport, Food, Music and Film

Number of Features	Data	%	HOBBY	SPORT	FOOD	MUSIC	FILM
5	Training	90	0.70	0.74	0.68	0.78	0.59
	Testing	10	0.60	0.60	0.68	0.60	0.62
	Training	80	0.68	0.74	0.68	0.77	0.70
	Testing	20	0.57	0.54	0.67	0.53	0.56
	Training	70	0.54	0.56	0.68	0.60	0.53
	Testing	30	0.56	0.52	0.67	0.53	0.50
	Training	60	0.53	0.56	0.68	0.52	0.50
	Testing	40	0.57	0.53	0.67	0.53	0.50
	Training	50	0.54	0.55	0.68	0.51	0.50
	Testing	50	0.56	0.54	0.68	0.51	0.50
7	Training	90	0.76	0.65	0.68	0.63	0.59
	Testing	10	0.61	0.63	0.68	0.65	0.65
	Training	80	0.77	0.70	0.68	0.77	0.71
	Testing	20	0.57	0.54	0.67	0.53	0.46
	Training	70	0.54	0.56	0.68	0.53	0.49
	Testing	30	0.56	0.51	0.67	0.54	0.49
	Training	60	0.53	0.56	0.68	0.53	0.50
	Testing	40	0.57	0.53	0.67	0.53	0.49
	Training	50	0.54	0.55	0.68	0.52	0.50
	Testing	50	0.56	0.54	0.67	0.53	0.49
10	Training	90	0.66	0.64	0.68	0.56	0.70
	Testing	10	0.59	0.59	0.61	0.51	0.58
	Training	80	0.64	0.65	0.68	0.54	0.59
	Testing	20	0.57	0.53	0.60	0.53	0.59
	Training	70	0.54	0.56	0.68	0.53	0.49
	Testing	30	0.56	0.51	0.67	0.53	0.48
	Training	60	0.53	0.56	0.67	0.53	0.51
	Testing	40	0.57	0.53	0.67	0.53	0.47
	Training	50	0.54	0.56	0.68	0.52	0.50

	Testing	50	0.56	0.54	0.66	0.52	0.49
14	Training	90	0.66	0.56	0.68	0.64	0.62
	Testing	10	0.59	0.59	0.65	0.50	0.54
	Training	80	0.64	0.66	0.68	0.54	0.51
	Testing	20	0.57	0.55	0.65	0.52	0.59
	Training	70	0.54	0.58	0.68	0.54	0.51
	Testing	30	0.56	0.50	0.67	0.53	0.47
	Training	60	0.53	0.57	0.68	0.53	0.52
	Testing	40	0.57	0.51	0.66	0.53	0.47
	Training	50	0.54	0.58	0.68	0.52	0.53
	Testing	50	0.55	0.53	0.66	0.52	0.47



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Appendix E

Experiment result for algorithm verification

Number of Experiment	Number of Individuals	Number of Classifier	Predicted Result on target					Result
			Hobby	Sport	Food	Music	Film	
1	2	1	1	1	1	0	0	Correct
2	3	1	1	1	0.333	1	0.333	Correct
3	3	1	0.333	1	1	1	1	Correct
4	4	1	0.5	0	0.5	0.5	1	Correct
5	3	1	0.333	1	1	1	1	Correct
6	2	1	0	1	1	0	0	Correct
7	4	1	0.5	0.5	0.5	0.5	1	Correct
8	2	1	0	0	1	0	0	Correct
9	5	1	0.199	1	0	1	1	Correct
10	5	1	0.199	1	1	0	1	Correct
11	2	2	1	1	0.5	0.5	1	Correct
12	3	2	0	0.666	1	1	1	Correct
13	3	2	0.666	0.666	0	1	1	Correct
14	4	2	1	0.75	0.5	1	0.5	Correct
15	3	2	1	0.666	0	1	0	Correct
16	2	2	1	0.19	0.5	0.5	1	Correct
17	4	2	1	0.75	0.5	0	0	Correct
18	2	2	0	1	0.5	0.5	0	Correct
19	5	2	0.799	1	1	0.6000	0.799	Correct
20	5	2	0.799	0.799	0	0.6000	1.000	Correct
21	2	3	1	0.666	1	0.666	1	Correct
22	3	3	0.111	0.555	0.777	0.333	0.111	Correct
23	3	3	0.555	0.555	0	0.333	0.111	Correct
24	4	3	0.1666	0.333	0.333	0.3333	0.5	Correct
25	3	3	0	0.555	0	0.333	0.111	Correct
26	2	3	1	0.666	0.666	0.666	1	Correct
27	4	3	0.166	0	0.333	0	0.5	Correct
28	2	3	0	0.666	1	0	1	Correct
29	5	3	0.466	0.466	0.733	0.3333	0.333	Correct
30	5	3	0	1	0.733	0.3333	0.333	Correct

31	2	4	1	0.666	1	0.666	1	Correct
32	3	4	0.111	0.555	0.777	0.333	0.111	Correct
33	3	4	0.555	0	0	1	0.111	Correct
34	4	4	0.166	0.333	0.333	0.3333	0.5	Correct
35	3	4	0	0.555	0	0.555	0.111	Correct
36	2	4	1	0.666	0.666	0.666	1	Correct
37	4	4	0.166	0	0.333	0	0.5	Correct
38	2	4	0	0.700	1	0	1	Correct
39	5	4	0.466	0.466	0	0.333	0	Correct
40	5	4	0	1	0.733	0	0.333	Correct
41	2	5	0	0.666	1	0.666	1	Correct
42	3	5	0.111	0.5	0.777	0.333	0.111	Correct
43	3	5	0.555	0.6	0	0.333	0.111	Correct
44	4	5	0.166	0.333	0.333	0.3333	0.5	Correct
45	3	5	0	0.46	0	0.333	0.111	Correct
46	2	5	1	0.666	0.444	0.666	1	Correct
47	4	5	0.166	0	0.333	0	0.5	Correct
48	2	5	1	0.666	0	0	1	Correct
49	5	5	0.466	0.466	0.4	0.3333	0.333	Correct
50	5	5	0	1	0.733	0.4	0.333	Correct

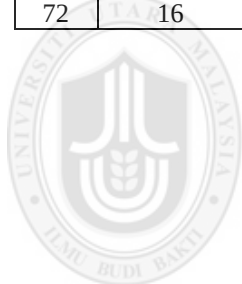
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Appendix F

User Target's Ranking

ID	GROUP	HOBBY	SPORT	FOOD	FILM	MUSIC
1	1	2	1	5	4	3
2	1	5	1	2	4	3
3	1	3	1	2	4	5
4	1	4	2	1	3	5
5	2	2	1	5	4	3
6	2	3	1	4	5	2
7	2	5	2	4	3	1
8	2	2	1	4	3	5
9	2	3	1	2	5	4
10	3	5	4	3	1	2
11	3	4	1	3	2	5
12	3	5	4	3	2	1
13	3	2	1	3	4	5
14	3	2	1	3	4	5
15	4	2	1	5	3	4
16	4	5	4	2	1	3
17	4	4	5	3	2	1
18	4	4	3	5	2	1
19	4	1	3	5	4	2
20	5	1	2	5	4	3
21	5	1	2	3	4	5
22	5	2	5	1	3	4
23	6	2	3	1	4	5
24	6	5	3	4	2	1
25	6	2	3	1	4	5
26	6	2	1	3	4	5
27	7	5	1	2	4	3
28	7	4	1	5	3	2
29	7	4	2	5	3	1
30	7	1	5	2	3	4
31	8	1	2	5	4	3
32	8	3	5	2	4	1
33	8	4	3	2	1	5
34	8	1	2	5	4	3
35	9	4	3	2	1	5
36	9	5	4	1	3	2
37	9	2	1	3	4	5
38	9	1	2	3	4	5
39	9	2	5	4	3	1
40	10	3	5	1	4	2
41	10	3	5	4	2	1
42	10	1	5	2	3	4
43	10	5	3	2	4	1
44	10	5	3	2	4	1
45	11	3	4	5	2	1
46	11	1	2	5	4	3
47	11	1	2	3	4	5
48	11	1	2	3	4	5

49	11	1	2	5	4	3
50	12	2	5	1	3	4
51	12	3	5	2	4	1
52	12	5	2	1	3	4
53	12	1	2	5	4	3
54	12	5	2	1	3	4
55	12	1	2	5	4	3
56	13	1	5	2	4	3
57	13	1	3	5	2	4
58	13	1	3	2	5	4
59	13	4	5	1	2	3
60	13	1	3	2	5	4
61	14	2	1	4	5	3
62	14	4	1	2	3	5
63	14	2	1	4	5	3
64	14	1	4	2	3	5
65	15	3	1	5	4	2
66	15	2	3	4	1	5
67	15	3	1	5	4	2
68	15	2	3	4	1	5
69	16	2	3	1	4	5
70	16	1	2	5	3	4
71	16	4	2	3	5	1
72	16	2	1	5	4	3



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Appendix G

Result Experiment of BREF

BREF							
Group	System Predicted	User Ranking	Sim	>80% Sim	Accuracy	>60% Sim	Accuracy
G1	Food	5	20%	3/4	75%	3/4	75%
		2	80%				
		2	80%				
		1	100%				
G2	Sport	1	100%	5/5	100%	5/5	100%
		1	100%				
		2	80%				
		1	100%				
		1	100%				
G3	Sport	4	40%	3/5	60%	3/5	60%
		1	100%				
		4	40%				
		1	100%				
		1	100%				
G4	Food	5	20%	1/5	20%	2/5	40%
		2	80%				
		3	60%				
		5	20%				
		5	20%				
G5	Sports	2	80%	2/3	67%	2/3	67%
		2	80%				
		5	20%				
G6	Food	1	100%	2/4	50%	3/4	75%
		4	40%				
		1	100%				
		3	60%				
G7	Hobby	5	20%	1/4	25%	1/4	25%
		4	40%				
		4	40%				
		1	100%				

G8	Sport	2	80%	2/4	50%	3/4	75%
		5	20%				
		3	60%				
		2	80%				
G9	Sport	3	60%	2/5	40%	3/5	60%
		4	40%				
		1	100%				
		2	80%				
		5	20%				
G10	Food	1	100%	4/5	80%	4/5	80%
		4	40%				
		2	80%				
		2	80%				
		2	80%				
G11	Food	5	20%	0/5	0%	2/5	40%
		5	20%				
		3	60%				
		3	60%				
		5	20%				
G12	Hobby	2	80%	3/6	50%	4/6	67%
		3	60%				
		5	20%				
		1	100%				
		5	20%				
		1	100%				
G13	Food	2	80%	4/5	80%	4/5	80%
		5	20%				
		2	80%				
		1	100%				
		2	80%				
G14	Sport	1	100%	3/4	75%	3/4	75%
		1	100%				
		1	100%				
		4	40%				
G15	Hobby	3	60%	2/4	50%	4/4	100%
		2	80%				
		3	60%				

		2	80%				
G16	Food	1	100%	1/4	25%	2/4	50%
		5	20%				
		3	60%				
		5	20%				
AVERAGE					52.94%		66.81%



Appendix H

Summary Result Experiment of PBREF

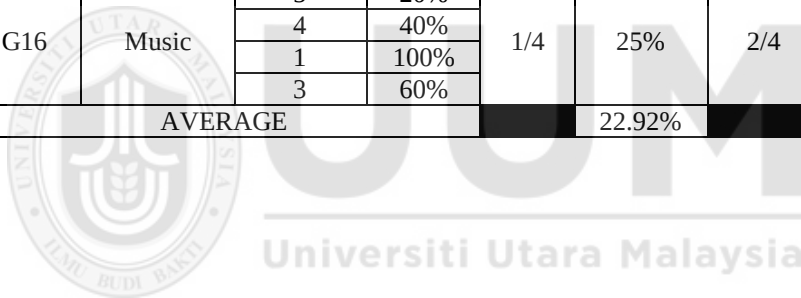
Parameter (α, η)	Average accuracy >80%	Average accuracy >60%
0, 0.25	25.73%	45.21%
0, 0.5	35.00%	59.17%
0, 0.75	22.60%	42.08%
0.5, 0.25	35.00%	59.17%
0.5, 0.5	35.00%	59.17%
0.5, 0.75	35.00%	59.17%
1, 0.25	52.40%	69.90%
1, 0.5	44.17%	62.71%
1, 0.75	54.19%	65.23%

Appendix I

Result Experiment of MCREF

MCREF							
Group	System Predicted	User Ranking	Sim	>80% Sim	Accuracy	>60% Sim	Accuracy
G1	Film	4	40%	0/4	0%	1/4	25%
		4	40%				
		4	40%				
		3	60%				
G2	Film	4	40%	0/5	0%	2/5	40%
		5	20%				
		3	60%				
		3	60%				
		5	20%				
G3	Music	2	80%	2/5	40%	2/5	40%
		5	20%				
		1	100%				
		5	20%				
		5	20%				
G4	Food	5	20%	1/5	20%	2/5	40%
		2	80%				
		3	60%				
		5	20%				
		5	20%				
G5	Music	3	60%	0/3	0%	1/3	33.33%
		5	20%				
		4	40%				
G6	Food	1	100%	2/4	50%	3/4	75%
		4	40%				
		1	100%				
		3	60%				
G7	Music	3	60%	2/4	50%	3/4	75%
		2	80%				
		1	100%				
		4	40%				
G8	Music	3	60%	1/4	25%	2/4	50%
		1	100%				
		5	20%				
		3	30%				
G9	Film	1	100%	1/5	20%	3/5	60%
		3	60%				
		4	40%				
		4	40%				
		3	60%				
G10	Music	2	80%	4/5	80%	4/5	80%
		1	100%				
		4	40%				
		1	100%				
		1	100%				
G11	Food	5	20%	0/5	0%	2/5	40%
		5	20%				

		3	60%				
		3	60%				
		5	20%				
G12	Music	4	40%	1/6	16.67%	3/6	50%
		1	100%				
		4	40%				
		3	60%				
		4	40%				
		3	60%				
G13	Film	4	40%	2/5	40%	2/5	40%
		2	80%				
		5	20%				
		2	80%				
		5	20%				
G14	Music	3	60%	0/4	0%	2/4	50%
		5	20%				
		3	60%				
		5	20%				
G15	Food	5	20%	0/4	0%	0/4	0%
		4	40%				
		5	20%				
		4	40%				
G16	Music	5	20%	1/4	25%	2/4	50%
		4	40%				
		1	100%				
		3	60%				
AVERAGE					22.92%		46.77%



Appendix J

Summary Result Experiment of PMCREF

Parameter (α, η)	Average accuracy >80%	Average accuracy >60%
0, 0.25	24.48%	46.46%
0, 0.5	22.92%	46.77%
0, 0.75	25.73%	45.21%
0.5, 0.25	25.42%	49.27%
0.5, 0.5	22.92%	46.77%
0.5, 0.75	25.00%	48.85%
1, 0.25	48.65%	64.58%
1, 0.5	48.65%	64.58%
1, 0.75	48.65%	64.58%

Appendix K

Demographic Questionnaire

21/08/2023, 21:53

A TOPIC RECOMMENDER FOR SOCIAL INTERACTION MODEL

A TOPIC RECOMMENDER FOR SOCIAL INTERACTION MODEL

Responden yang dihormati,

Soal selidik ini dijalankan untuk membentuk model "A TOPIC RECOMMENDER FOR SOCIAL INTERACTION MODEL" di UUM / Malaysia. Soal selidik ini dijalankan untuk mengenal pasti faktor-faktor yang boleh menghubungkan orang-orang di sekeliling kita. Kajian ini akan memenuhi sebahagian daripada keperluan untuk memperoleh ijazah kedoktoran di Universiti Utara Malaysia (UUM). Semua jawapan Individu akan DIRAHSIAKAN supaya anda boleh berasa bebas untuk menjawab dengan jujur dalam jawapan anda. Kami memberi jaminan bahawa semua jawapan hanya akan digunakan untuk kajian ini dan hanya diketahui oleh penyelidik sahaja.

TERIMA KASIH DIATAS KESUDIAN ANDA MENGAMBIL BAHAGIAN DALAM SOAL SELIDIK INI.

Pusat Pengajian Pengkomputeran
Universiti Utara Malaysia

Researcher : Ahmad Subhi Zolkafly (subhizolkafly@icloud.com)
Supervisors : PM Dr. Rahayu Ahmad (rahayu@uum.edu.my)
PM Dr. Azizi Ab. Aziz (aziziaziz@uum.edu.my)

* Indicates required question

BAHAGIAN A : INFORMASI DEMOGRAFI

1. Sila Masukkan EMAIL anda *

2. JANTINA *

Mark only one oval.

- ☐ Lelaki
☐ Perempuan

3. TARIKH LAHIR (DD/MM/YYYY) *

4. KEWARGANEGARAAN *

Mark only one oval.☐ Malaysia☐ Other:

5. BANGSA *

Mark only one oval.☐ Melayu☐ Cina☐ India☐ Bumiputera Sabah☐ Bumiputera Sarawak☐ Other:

6. PENDIDIKAN TERTINGGI *

Mark only one oval.☐ Sijil☐ Diploma☐ Sarjana Muda (Degree)☐ Sarjana (Master)☐ PhD☐ Other:



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7. BIDANG PEKERJAAN *

Mark only one oval.

- ☐ Pertanian Skip to question 8
- ☐ Perhutanan Skip to question 8
- ☐ Perikanan Skip to question 8
- ☐ Perlombongan Skip to question 8
- ☐ Pembinaan Skip to question 8
- ☐ Pembuatan (Kilang, Dll) Skip to question 8
- ☐ Industri elektrik / gas / bekalan haba / air Skip to question 8
- ☐ Teknologi maklumat dan komunikasi Skip to question 8
- ☐ Pengangkutan Skip to question 8
- ☐ Pemborongan / Peruncitan Skip to question 8
- ☐ Kewangan / Insuran Skip to question 8
- ☐ Hartanah Skip to question 8
- ☐ Restoren / Penginapan Skip to question 8
- ☐ Perubatan / Kebajikan Skip to question 8
- ☐ Pendidikan / Bantuan pembelajaran Skip to question 8
- ☐ Industri perkhidmatan Skip to question 8
- ☐ Perkhidmatan awam (selain daripada di atas) Skip to question 9
- ☐ Entrepreneur / Kerja Sendiri Skip to question 9
- ☐ Tidak Bekerja / Suri Rumah Skip to question 11
- ☐ Pelajar Skip to question 10
- ☐ Other: _____

SEKTOR

8. SEKTOR *

Mark only one oval.

- ☐ AWAM Skip to question 9
- ☐ SWASTA Skip to question 9

Skip to question 9

JAWATAN

9. JAWATAN *

Mark only one oval.

- ☐ Pekerja Am
- ☐ Kerani / Pembantu Tadbir
- ☐ Setiausaha
- ☐ Penolong Pegawai
- ☐ Pegawai / Eksekutif
- ☐ Pengarah / Pengarah Urusan / Ketua Jabatan
- ☐ Ketua Pegawai Eksekutif
- ☐ Pensyarah / Pensyarah Kanan
- ☐ Other: _____

*Skip to question 11***PELAJAR**

10. PELAJAR *

Mark only one oval.

- ☐ Sekolah
- ☐ Sijil / Institut / Kolej
- ☐ Universiti (Undergraduate)
- ☐ Universiti (Postgraduate)

*Skip to question 11***TARAF PERKAHWINAN**

11. TARAF PERKAHWINAN *

Mark only one oval.

- ☐ BUJANG
- ☐ BERKAHWIN
- ☐ BERCERAI / JANDA / DUDA

12. JUMLAH ANAK (Min = 0) *

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Appendix L

BIG 5 Questionnaire

BIG 5 Personality Traits

5 = Sangat Setuju, 4 = Setuju, 3 = Neutral, 2 = Tidak Setuju, 1 = Sangat Tidak Setuju

subhizolkafly1@gmail.com [Switch account](#)



Not shared

* Indicates required question

BIG5 *

	5	4	3	2	1
Saya melihat diri sebagai orang yang banyak bercakap	☐	☐	☐	☐	☐
Saya melihat diri saya sebagai seseorang yang cenderung mencari salah orang lain	☐	☐	☐	☐	☐
Saya melihat diri saya sebagai orang yang melakukan kerja yang teliti	☐	☐	☐	☐	☐

Saya melihat diri
saya sebagai
seseorang yang
tertekan dan
bersedih

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
menjadi diri
sendiri, datang
dengan idea-idea
baru

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
pemalu atau
orang yang
sederhana yang
tidak dengan
mudah
menyatakan
perasaan

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
membantu dan
tidak
mementingkan
diri sendiri

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
boleh menjadi
agak cuai

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
santai, dapat
mengendalikan
tekanan dengan
baik

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang ingin
tahu tentang
banyak perkara
yang berbeza

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
bertenaga

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
memulakan
pertengkaran
dengan orang
lain

☐☐☐☐☐

Saya melihat diri
saya sebagai
seorang pekerja
yang boleh
dipercayai

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
boleh menjadi
tertekan

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang bijak,
berfikir secara
mendalam

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
mencetuskan
semangat

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
mempunyai sifat
pemaaf

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
cenderung tidak
teratur

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
sering bimbang

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
mempunyai
imaginasi yang
aktif

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
cenderung untuk
menjadi pendiam

☐☐☐☐☐

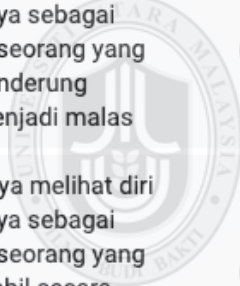
Saya melihat diri
saya sebagai
orang yang
umumnya
mempunyai sifat
mempercayai

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
cenderung
menjadi malas

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
stabil secara
emosi, tidak
mudah kecewa

☐☐☐☐☐

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Saya melihat diri
saya sebagai
seseorang yang
menggalakkan
seseorang
melakukan
sesuatu

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
mempunyai
keperibadian
tegas

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang tidak
ramah dan
menyendiri

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang tekun
sehingga tugas
selesai

☐☐☐☐☐

Saya melihat diri
saya sebagai
seorang yang
boleh menjadi
murung

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
menghargai
pengalaman seni
dan estetik

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
malu dan
tersekat

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
bertimbang rasa
dan baik kepada
hampir semua
orang

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
melakukan
perkara dengan
cekap

☐☐☐☐☐

Saya melihat diri
saya sebagai
seseorang yang
kekal tenang
dalam keadaan
tegang

☐☐☐☐☐

Saya melihat diri saya sebagai orang yang suka kerja yang rutin	☐	☐	☐	☐	☐
Saya melihat diri saya sebagai orang yang mesra dan ramah	☐	☐	☐	☐	☐
Saya melihat diri saya sebagai orang yang kadang-kadang tidak sopan kepada orang lain	☐	☐	☐	☐	☐
Saya melihat diri saya sebagai orang yang membuat perancangan dan mengikutinya	☐	☐	☐	☐	☐
Saya melihat diri saya sebagai seseorang yang mudah gelisah	☐	☐	☐	☐	☐
Saya melihat diri saya sebagai orang yang suka berfikir secara mendalam, bermain dengan idea-idea	☐	☐	☐	☐	☒

Saya melihat diri
saya sebagai
seseorang yang
mempunyai
sedikit minat
terhadap
kesenian

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang suka
bekerjasama
dengan orang
lain

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
mudah
terganggu

☐☐☐☐☐

Saya melihat diri
saya sebagai
orang yang
berpengetahuan
dalam seni,
muzik atau
kesusasteraan

☐☐☐☐☐

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Appendix M

VALS Questionnaire

Values and Lifestyle (VALS)

4 = Sangat Setuju, 3 = Setuju, 2 = Tidak Setuju, 1 = Sangat Tidak Setuju

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Not shared

* Indicates required question

VALS *

	4	3	2	1
Saya sering berminat dengan teori	☐	☐	☐	☐
Saya suka orang dan perkara yang luar biasa	☐	☐	☐	☐
Saya suka kepelbagaian dalam hidup saya	☐	☐	☐	☐
Saya suka membuat benda yang boleh saya gunakan setiap hari	☐	☐	☐	☐
Saya mengikuti trend dan fesyen/gadget terkini	☐	☐	☐	☐

Saya percaya pada satu kuasa tertinggi yang mengawal segalanya	☐	☐	☐	☐
Saya suka mengetuai kumpulan	☐	☐	☐	☐
Saya suka mempelajari budaya, seni, dan sejarah	☐	☐	☐	☐
Saya sering mengidamkan keseronokan	☐	☐	☐	☐
Saya hanya berminat dalam beberapa perkara	☐	☐	☐	☐
Saya lebih suka membuat sesuatu daripada membelinya	☐	☐	☐	☐
Saya berpakaian lebih bergaya daripada kebanyakan orang	☐	☐	☐	☐
Kerajaan persekutuan/organisasi harus menyediakan tempat untuk sembahyang	☐	☐	☐	☐
Saya mempunyai keupayaan lebih daripada kebanyakan orang	☐	☐	☐	☐

Saya menganggap diri saya sebagai intelektual	☐	☐	☐	☐
Saya harus mengakui bahawa saya suka menunjuk-nunjuk	☐	☐	☐	☐
Saya suka mencuba benda baru	☐	☐	☐	☐
Saya berminat dengan perkara mekanikal, seperti bagaimana enjin bekerja	☐	☐	☐	☐
Saya suka berpakaian mengikut fesyen terkini	☐	☐	☐	☐
Terdapat terlalu banyak adegan yang tidak sesuai di televisyen hari ini	☐	☐	☐	☐
Saya suka memimpin orang lain	☐	☐	☐	☐
Saya suka menghabiskan masa setahun atau lebih di negara asing	☐	☐	☐	☐
Saya sukakan keseronokan yang banyak dalam hidup saya	☐	☐	☐	☐

Saya harus mengakui bahawa minat saya agak sempit dan terhad	☐	☐	☐	☐
Saya suka membuat benda-benda daripada kayu, logam atau lain-lain daripada bahan tersebut	☐	☐	☐	☐
Saya mahu dianggap bergaya (berfesyen)	☐	☐	☐	☐
Kehidupan seseorang dapat dipenuhi jika dia dapat memberikan rumahtangga yang bahagia untuk keluarganya	☐	☐	☐	☐
Saya suka cabaran dalam melakukan sesuatu yang tidak pernah saya lakukan sebelum ini	☐	☐	☐	☐
Saya suka mempelajari banyak perkara walaupun ianya tidak akan digunakan oleh saya	☐	☐	☐	☐
Saya suka membuat perkara dengan tangan saya sendiri	☐	☐	☐	☐

Saya suka membuat perkara dengan tangan saya sendiri	☐	☐	☐	☐
Saya sentiasa mencari sesuatu yang mengujakan	☐	☐	☐	☐
Saya suka melakukan perkara yang baru dan berbeza	☐	☐	☐	☐
Saya suka melihat perkakasan atau kedai automotif	☐	☐	☐	☐
Saya ingin memahami lebih lanjut mengenai bagaimana alam semesta berfungsi	☐	☐	☐	☐
Saya suka hidup saya menjadi hampir sama dari minggu ke minggu	☐	☐	☐	☐

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Appendix N

Model Validation Questionnaire

VALIDATION OF TOPIC RECOMMENDER FOR SOCIAL INTERACTION (TReSIT) MODEL

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* Indicates required question

SKALA LIKERT (1- Sangat Tidak Setuju, 2-Tidak Setuju, 3- Neutral, 4-Setuju, 5- Sangat Setuju)

SOALAN : *

	1	2	3	4	5
Saya merasa puas berkomunikasi dengan rakan saya mengenai topik ini	☐	☐	☐	☐	☐
Saya merasakan komunikasi saya bersama rakan saya berharga	☐	☐	☐	☐	☐

Saya rasa
berbaloi
berkomunikasi
dengan rakan
saya

☐☐☐☐☐

Apabila saya
berkomunikasi
dengan rakan
saya, perbualan
tersebut
memberi
input(ganjaran)
dan makna

☐☐☐☐☐

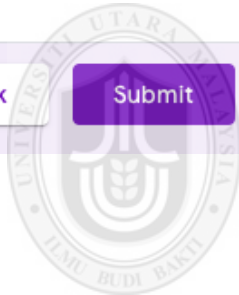
Saya dan rakan
saya bersetuju
perbualan kami
mempunyai
persamaan

☐☐☐☐☐

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