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A Trust Model with Personality Factors for Information Dissemination in Social Networking Service

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Abstract

The rapid development of Social Networking Services (SNS) has generated numerous possibilities for human communication. The countless posts and messages uploaded daily can generate rumors that often evolve into fake news. This fake news can be deliberately spread, but most of it is accidental. Moreover, this false information can spread in many areas, including critical disaster-related information. To analyze and address these issues, understanding the trustworthiness of both users and the SNS in general can help in mitigating the spread of fake news. In this thesis, we propose a trust model consisting of identity-based, behavior-based, relation-based, feedback-based, and information-based trust factors, incorporating the Big Five personality traits. We conducted an agent-based modeling simulation for the proposed trust model, investigating user behavior according to the Big Five personality traits and several user aspects: knowledge level and psychopathy. The experiment is based on online surveys and related studies representing social network users' behavior. We compare the overall trust and trustworthiness in the numerical results to validate our proposed trust model. Furthermore, we systematically compare the occurrence of fake news under conditions where the initial news is either truthful or fabricated. Numerical results show that overall trust is sensitive to information-based trust, while it is not

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significantly affected by behavior-based trust. Additionally, openness, conscientiousness, and extroversion were correlated with overall trust, while the effects of agreeableness and neuroticism on overall trust were insignificant.

Keywords:

Social Networking Service, Trust, Big-five Personality Traits, Fake News, Disaster-related News, Agent-based Modeling

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1. Introduction

The increasing trends of social networking service (SNS) has opened the opportunities for the users in exchanging information online in real-time. This ignites numerous researchers in studying many aspects emerge in the SNS. With the freedom and its widely open system, the lack of understanding and knowledge might affect the general understanding of a specific rumor. This condition leads us to the emergence of fake news created by a malicious users, in which sparse the information, confuse the people about which is trustworthy. Its general characteristics that raise people occasion, creates a rumor spreading, which creates an epidemic effect of news dissemination. This phenomenon need to be analyzed in both understanding fake news as a unit and fake rumor spreading in general.

Fake news has become a common phenomenon in the social networking service. Following to the study performed by [1], 86% of SNS's users were at least once discover and believe fake news contents on the network. Moreover, most fake news sharing were accidental rather than deliberate. The news contents can be varied from; political stands to the public movements. [2]. The author of [3] states critical type information such as disaster and health pandemic related news are likely claimed to be misleading, do to lake of people's general understanding. Findings in [3] also further explain the COVID-19-related content becomes the number one topic. However, these news are often contain false and misleading information. Following the fake news engaging trends, the original, truthful information is found lacking attention. Subsequently, [4] reported that in disaster occasion, most users are refrain to contribute and add more context to the received news, where most of them are likely to seek and look for the current trends and update to news from someone else. These circumstances might be a burden for rescue teams or someone who needs help, if the fake news is distributed right after the events. Moreover, this might create a trust issue for everyone, doubting the trustworthiness of the receiving news in the SNSs. This is because fake news may steal the attention and prevent the true news to be distributed and, confusing anyone concerned and need an immediate updates about the disaster. In order to prevent this unhealthy uses of the sites, trustworthiness evaluation have been widely used in several decision-making tools [5]. The key point is to evaluate every news items trustworthiness, then further evaluates users trustworthiness scores. In order to fulfill this, social networks need to be consider from its complexity and vagueness stand points.

As in many disaster and social network cases, numerous research fields, including social computing, cognitive sciences, and data science, have been applied to elaborate on fake news and its dissemination on social networks. In [6], authors aimed to implement personality traits gathered from an online questionnaire of individuals to understand how each behaves and is connected in social networks. They also gathered information on the user behavior of the network using an online questionnaire. These questionnaire responses determined how individuals' personality traits created different responses while interacting with information, such as, likes, shares, and comments. These personality traits will be the key to identifying who is responsible for fake news creation and dissemination through social networking service. Furthermore, these personality traits were analyzed using agent-based modeling to show how messages are exchanged among users.

Social network is a form of a group of users which connected through relations. This relations includes patterns and visual representation which can be observed through social network analysis [7]. Regarding the fake news, if most of information spread in the network are fake, most users whose receiving the news will be deceived. Real time information dissemination can be examine through data visualization. However, investigating the nature of the incident in the real world is unpractical and time-consuming. Moreover, the social network data is dynamics, means, one single cause might have different outputs [7, 8]. One solution to understand this problem is to model trusting process works within users. By analysing trusting mechanism, we are able to construct a evaluation system based on trust, that is user-centered and free from the fake news biases.

In this research, we construct a framework of how SNS users trust news from other users. Prior to our work, Info-trust proposed in [5], have considered four trust-based approach of; the identity-based, relation-based, behavior-based, and feedback factor. We proposed an additional trust factor to the prior work with the information-based trust. Previously, the trust evaluations are fully centered to users. However, with information-based, news items also being considered by observing its semantic and surface features. The features are consists of the item's internal characteristic, which is the content accuracy, and the item's exterior characteristics, such as photo inclusion, logical degree, and popularity of the post [9]. Provided that, we construct the information-based trust by three characteristics of the content, the included photo, logic, and its popularity. From this extension, the posts created by users also affects the user's trustworthiness value.

To portray users' SNS usage behaviors and interactions, we consider personality traits as the user unique characteristics. Several personality models was introduces in analysing user behavior in SNS; the big-five personality traits, Myers-Briggs Type Indicator (MBTI), dark triad, and behavioral inhibition system and behavioral activation system (BIS/BAS) [6, 10–14]. In this research, we consider the big-five personality traits and psychopathy to understand the information dissemination mechanism. The big-five personality traits compromise; openness, conscientiousness, extroversion, agreeableness, and neuroticism. To perform and evaluate our proposed trust model, we consider an agent-based simulation model that integrates personality traits and trust in information dissemination in disaster situations. This work formulates and associate two factors, the trust modeling which formerly proposed by [5], and the personality modeling which proposed by [6]. This model enabled us to explore how information dissemination works based on individuals' trust and personalities. We developed a trust evaluation system by expanding the existing model with information-based trust by applying an agent-based model using NetLogo simulator. The dissemination process and user behavior were investigated using Big-Five personality traits.

This study aims to explore the nature of fake news sharing behavior among SNS users. The central research questions are as follows:

1. How do users decide which users are trustworthy based on the characteristics of the information and other users' aspects?

2. How does personality affect trusting behavior and users' actions towards information on social networking services?

3. How is information disseminated throughout the Twitter social network?

The research structure is organized as follows. We briefly present the related work in Chapter 2. The big-five personality traits in SNS usage is presented in Chapter 3, and the proposed model is presented in Chapter 4. The experiments and questionnaire are shown in Chapter 5. While the numerical examples and discussion are discussed in Chapter 6, followed by the conclusion of the research in Chapter 7.

2. Related Work

In this section, we show related work on three different aspects, fake news on SNS, trust evaluation, and the big five personality traits. We then discuss a practical way to measure user trustworthiness and to incorporate both cognitive and social features into the system model.

The study of fake news or dissemination starts with the upcoming trends of SNS usage. Fake news involves the deliberate creation and dissemination of false information intended to cause harm [15]. Several findings also state that fake news can be intentionally or unintentionally be misleading [16, 17]. In the case of daily rumors and conversation, news is generally formed in two ways; through verbal and indirect communication. In verbal communication, identifying a person whose lying is a skill can be learned through experience [18,19]. However, this mechanism may not apply in the case of social networking service, which users tends to evaluate how trustworthy both the issuer and message to accept or discard news. Thus, not only the issuer point of view, the message point of view is perspective that need to be considered [20].

Human cognition of opinions plays a crucial role in accepting and discarding messages [21–23]. Trust is one of the factors affected by human cognition, which can be achieved by either short or long-term interaction within a community [24, 25]. In a network, interaction builds cooperation, and each user benefits from the group. This interaction will build perceptions, and then form a trusting decision.

In social networking service, trust is gained from perceived information quality, perceived system reliability, and perceived trust [22, 26]. This implies that an SNS user will trust a rumor according to how they think about the information quality, system reliability, and rumors' trustworthiness. Since relationships in SNS are regarded as social capital established among society, forming groups follows multidimensional factors consisting of many aspects such as relations, family, and friends [25, 27]. This means that when users gain trustworthiness, they also form a multidimensional way of thinking towards other users. However, due to the complexity of the problems, such as knowledge, point of interest, and personality differences, it might be difficult for users to examine the reliability of online news, especially in the middle of a crisis.

During disaster phases, people are likely to seek the latest news rather than contributing to the information. Only a few groups of people will share the information they have received [4]. The ability to widely share critical information for coordination is the main advantage of using social networks during disasters [28]. However, most information shared by the social network user is regarded as a rumor, a piece of unproven information that can later be corroborated as trusted or fake news [29]. This unproven information quickly spreads because users will likely fail to collect the desired important facts [29, 30]. This situation splits users into two groups, the trusting group and the distrusting group, resulting from their personal information processing. This polarization among users may lead malicious users to spread rumors, which lead to the existence of fake news and misinformation. Fake news is false fabricated information or a statement in a report on social media [29, 31]. This news issued by an unreliable person is called a rumor, which is classified as a fact or a false rumor [29]. This false information aims to deceive people, raising trust issues concerning the accuracy and credibility of information.

The significance of trust in information dissemination is discussed in [24]. In [24], the authors proposed trust classification, which includes institution-based, knowledge-based, calculative-based, personality-based, and cognition-based in mass communication schemes. The authors pointed out that the research focused on social networking sites, specifically in mass, group, and interpersonal communication. [6] pointed out that the personality of an SNS user affects the information dissemination.

Gao *et al.* [5] proposed Info-Trust, a trustworthiness-eval-uation scheme with multi-criteria trust factors. Trust is classified into four types: identity-based trust, behavior-based trust, relation-based trust, and feedback-based trust. Info-

Trust provides an assessment of the trustworthiness of the information sources. However, the model does not consider the importance of the information for trust features, as pointed out in [9]. In this research, we extend the model of [5] to a model in which users' perception of the information source is considered.

Users' communication styles also depend on their perceptions, preferences, and behaviors [32]. This means that personalities also influence how users behave in social networking service. [6] proposed the Big-Five personality traits, dark triad, and regulatory self-efficacy to explain how users react differently towards fake news. The Big-Five personality traits model describes an individual with five characteristics. The model was first developed [33], consists of five personality traits: openness, conscientiousness, agreeableness, and neuroticism. Each personality trait is a spectrum that differentiates human behavior [33, 34].

Numerous researchers approach this problem by presenting new fact-checking algorithms, which are based on social properties data such as popularity and link structure, and context property such as the content of the tweet and meta-information [5, 35]. However, there is also a need to consider the personality and users' mental condition during unpredictable disaster crises, which can be very suitable by applying an agent-based modeling method [6, 36, 37].

Our contribution in this research is to add information-based trust into the trust model and the agent-based modeling implementation that includes both trust and personality traits of fake news emerging. Adding information-based trust into the trust model allowed us to examine the credibility of the news. Considering the news features and their types, we can evaluate the change in trend from regular news to fake news which is originally introduced in this research. This news-changing behavior was originally introduced in this research using the agent-based modeling method.

3. Big-Five Personality Traits

The information dissemination behavior of users depends on the user's characteristics. Behaviors such as sharing, receiving, posting, and commenting are generally can be traced back with personality traits [6, 10–14]. In [6], the Big-Five personality traits were used to explain how personalities affect users' behavior when using SNS. This finding also implicitly shows that personality and trust models should be considered when explaining information dissemination. Moreover, recent trends show many applications of user classifications and clustering based on interests, including Twitter [38]. Prior to this work, several studies have introduced the relationship between SNS activities and the big-five traits. It is varied from the SNS use and passive engagement [39] and motivation and mental use [40]. Applying personality traits to a trust evaluation system enables information propagation effectiveness and combating fake news. In this research, we assume that each user has his/her own personality that differentiates their ways of receiving information from and sending it to others.

In terms of the characterization of the personality of a user, the Big-Five personality traits were developed by [41], which identify individual differences in choosing the right words in Webster's Unabridged Dictionary. The Big-five personality traits comprise a taxonomy of psychology consisting of openness, extroversion, conscientiousness, agreeableness, and neuroticism.

In this research, we assume that user action depends on their personality, characterized by the Big-Five personality traits[1] We define $U(= \{1, 2, \ldots, N\})$ as

[1]In this research, we are not specifically focused on how each personality affects each other. However, according to Klimstra et al., the results found in studies by Allemand et al., 2007, Allemand et al., 2008, and Soto and John, 2012 have reported inconsistent results, since the concept itself consists of five different independent traits. This leads us to assume that personality is an independent factor that further affects users' interactions on SNS.

Table 3.1: User and Personality Notations.

Notation	Description
U	Set of users
N	Number of users
O_i	Openness of user i
E_i	Extroversion of user i
CS_i	Conscientiousness of user i
A_i	Agreeableness of user i
NR_i	Neuroticism of user i
Kn_i	Knowledgeability of user i
Ps_i	Psychopathy of user i

the set of users joining an SNS system. For user i ($\in U$), let O_i, E_i, CS_i, A_i, and NR_i denote user i's openness, extroversion, conscientiousness, agreeableness, and neuroticism, respectively. These variables were within the interval of [0,1]. For each variable, the higher the value, the greater is the corresponding characteristic. The parameters are listed in Table 3.1. In the following sections, we describe the details of personality traits.

3.1. Openness

Openness personality represents how a user opens towards any new source of information [33]. From the SNS use viewpoint, Openness has no relation to malicious or honest SNS use [40]. However, following [14], in this research, the openness users have the characteristics of being creative and tend to find a piece of new information. Openness users also often associated with popularity [40]. This tendency gives the openness users a faster reaction time for finding and receiving news than those with low openness traits. The role of openness users are explained in Algorithm 1

[42]

Algorithm 1 Simulation Algorithm for Openness

Require: generated U, N, O_i

Ensure: User i overall trust T_i

initialize population
for $i = 1, ..., N$ **do**
  calculate the $follower_i$ according to the Eq. 4.3
  for time slot $n = 1, ...$ **do**
    for $i* = \underset{i}{\text{argmax}}\{O_i\}$. **do**
      for $i* = \underset{i}{\text{argmax}}\{follower_i\}$. **do**
        initialize post creation
        add tweet $tw_k^{(i)}$ links to the neighboring $follower_i$ nodes
        Calculate the overall trust $T_i(n)$ according to the Eq. 4.26
for $i = 1, ..., N$ with $tw_k^{(i)}$ neighbor **do**
  if $O_i > P_{ol}$ **then**
    Like the received tweet

3.2. Conscientiousness

While receiving new information, users can derive information either rationally or emotionally. They form a rational decision by paying attention to the details of the information and being cautious not to get trapped by fake information that may spread widely in the social networks. This cautious act is a typical way of information processing of users with conscientiousness personality traits. Conscientiousness personality traits explain the user's tendency to follow rules and refrain from spreading rumors until they have the credibility to be trusted [14]. The role of conscientiousness users are explained in the Algorithm 2

3.3. Extroversion

Extroversion is considered an essential factor that represent the extent nof information spreads [13]. Extroversion users are willing to socialize, gather new information, and share positive emotions towards other users [14]. Previous researchers found that users with high extroversion are likely to support any infor-

Algorithm 2 Simulation Algorithm for Conscientiousness

Require: generated U, N, CS_i
Ensure: User i overall trust T_i

for $i = 1, ..., N$ with $tw_k^{(i)}$ neighbor **do**
    if $CS_i > P_{Csl}$ **then**
        Like the received tweet
    if $CS_i < P_{Css}$ **then**
        Share the received tweet
    Calculate the overall trust $T_i(n)$ according to the Eq. 4.26
    for $i = 1, ..., N$ with CS_i **do**
        if $tw_k^{(i)}$ neighbor = Fake **then**
            Unfollow

mation sent by their related persons [13, 43]. Extroverted users are also likely to have more SNS friends [44, 45]. In the SNS environment, if users followed each other, there is a high possibility that the information will be shared and provide high relation-based trust, as described in the following sections 4.3. The role of extroversion users are explained in the Algorithm 3

3.4. Agreeableness

During a disaster event, the manifestation of empathy and sympathy towards victims influences our decision to trust or distrust the disaster information. This emphatic response represents cooperation and altruism among users who have agreeableness. Agreeableness is typically related to cooperative and altruistic behavior [14]. These two aspects affect dissemination behavior. Agreeableness users tend to spread the news if they believe it and try to share the news with a user with many followers in the network [15, 46]. The role of agreeableness users are explained in the Algorithm 4

Algorithm 3 Simulation Algorithm for Extroversion

Require: generated U, N, E_i

Ensure: User i overall trust T_i

```
for i = 1, ..., N do
    initialize post creation
    Set Pictures(tw_k(i)) = { 0, if 0 ≤ E_i ≤ 0.3
                              1, if 0.3 ≤ E_i ≤ 0.4
                              2, if 0.4 ≤ E_i ≤ 0.5
                              3, if 0.5 ≤ E_i ≤ 0.6
                              4, if 0.6 ≤ E_i ≤ 1
    add tw_k^(i) links to the neighboring follower_i nodes
for i = 1, ..., N with tw_k^(i) neighbor do
    if E_i > P_El then
        Like the received tweet
    if E_i < P_Es then
        Share the received tweet
    Calculate the overall trust T_i(n) according to the Eq. 4.26
```

$$Pictures(tw_k(i)) \begin{cases} 0, \text{if } 0 \leq E_i \leq 0.3 \\ 1, \text{if } 0.3 \leq E_i \leq 0.4 \\ 2, \text{if } 0.4 \leq E_i \leq 0.5 \\ 3, \text{if } 0.5 \leq E_i \leq 0.6 \\ 4, \text{if } 0.6 \leq E_i \leq 1 \end{cases}$$

Algorithm 4 Simulation Algorithm for Agreeableness

Require: generated U, N A_i

Ensure: User i overall trust T_i

for $i = 1, ..., N$ with $tw_k^{(i)}$ neighbor **do**
    if $A_i > P_{Al}$ **then**
        Like the received tweet
    if $A_i < P_{As}$ **then**
        Share the received tweet
    if $A_i > P_{Ac}$ **then**
        comment the received tweet
        generate $r \sim Uniform(0, 1)$
        if $A_i > r$ **then**
            Set the comment Negative
        else
            Set the comment Positive
    Calculate the overall trust $T_i(n)$ according to the Eq. 4.26

3.5. Neuroticism

During a disaster event, being negative and anxious about the upcoming event might become a problem. Along with anger, feelings of frustration and depression may lead to the creation and dissemination of fake news across the network. This mental condition is characterized by the neuroticism trait. People with this personality trait are likely to be closed off, fearful, moody, and jealous of other users [14]. In SNS networks, neuroticism is related to sharing more information, presenting falsehoods, and pursuing personal objectives [13,47]. The desire to be at the center of attention leads this type of user to create fake news for others. The role of neuroticism users are explained in the Algorithm 5

Algorithm 5 Simulation Algorithm for Neuroticism

Require: generated U, N, NR_i

Ensure: User i overall trust T_i

```
for i = 1, ..., N with tw_k^(i) neighbor do
    if NR_i > P_Nrl then
        Like the received tweet
    if NR_i < P_Nrs then
        Share the received tweet
    for NR_i with PS_i and tw_k^(i) neighbor do
        initialize fake news creation
        add tw_k^(i) links to the neighboring follower_i nodes
    Calculate the overall trust T_i(n) according to the Eq. 4.26
```

3.6. Additional Personality Characteristics: Knowledgeability and Psychopathy

In addition to the Big-Five personality traits, we further consider two personality features: knowledgeability and psychopathy.

In general, knowledgeable users carefully consider the trustworthiness of disseminated news [48]. Prior studies show that the lack of careful thinking and decision-making is associated with insufficient and/or inaccurate prior knowledge [49]. We define $Kn_i \in [0, 1]$ as the knowledgeability of user i. A large Kn_i implies user i has high knowledgeability.

A situation similar to the creation of fake news also occurs if users have a high amount of extroversion, which makes them communicate well with other users. In this research, we refer to these personalities as psychopathic. Psychopathic users share fake news by distorting the contents and/or adding new information from previous news that might be important for the disaster victims. This type of user shares fake news knowing that the material is incorrect, instead of sending false information accidentally [15]. Psychopathic users also are likely to share fake news that they know is false. Therefore, users who have higher psychopathy level will have high likelihood of deliberately sharing fake news [46]. We define $Ps_i \in [0, 1]$ as the psychopathy of user i. A high Ps_i implies that user i has high psychopathy. As shown in the table 3.2, Neuroticism is the only personality traits that positively correlated with instability and psychopathy act.

Table 3.2: Correlation between personality traits.

Personality traits	Psychopathy	Source
Openness	-	[50]
Conscientiousness	-	[51]
Extroversion	+	[50]
Extroversion	-	[51, 52]
Agreeableness	-	[50–52]
Neuroticism	+	[50–52]

In the simulation, corresponding to the malicious and knowledgeability, each user's psychopathy and knowledge values were set randomly to the probability of 0.5. Furthermore, we introduce the probability of a malicious user to disseminate fake news, P. The value of P is taken from 0 to 1. If P is set to 0, then the malicious users will not disseminate the fake news. If the value is set to 1, then the malicious users will disseminate the fake news. In the simulation, we set $P = 0.5$. This means the malicious users will not always share fake news but will also disseminate true news.

4. Trust Model

Trust is a fundamental cognitive factor in believing and having faith in an object. This belief involves one party's interest with reliance on the other [53, 54]. Trust can develop over time as its value changes based on interactions between two or more people over time. Trustworthiness is considered a display of behavior by a party that acts in a trustworthy manner [54]. In this research, trust is considered as a property of users indicating how trustworthy they are, while trustworthiness represents the degree to which users accept news.

In the case of SNS, trust can be formed through community interactions [1]. By engaging in communication that shapes perceptions, the decision to trust or distrust an object emerges within the human brain. Trust is established by at least two users: an information writer and a reader, the trustee and trustor. Because building trust quickly is difficult, we propose a trust evaluation system based on [5], which considers four trust factors: identity-based trust, behavior-based trust, relation-based trust, and feedback-based trust. We extend the model proposed in [5] by adding information-based trust to illustrate the significance of information factors that may mislead users.

In the following, we consider a discrete-time SNS system where time is divided into slots. We assume that at time slot n $(= 0, 1, 2, \ldots)$, user i $(\in U)$ has the overall trust $T_i(n)$, and that user i takes an action such as creating a news, distributing or discarding a forwarded news, according to the value of $T_i(n)$. Table 4.1 summarizes the notations used for the five trust factors.

We introduce the social popularity function of the variable associated with user i, Var_i, which was originally proposed in [5]

$$f(Var_i) = \frac{\log(Var_i + 1)}{\log(\max_{j \in U}(Var_j + 1))}. \tag{4.1}$$

Table 4.1: Notations for Trust Model.

Notation	Description
$tw_k^{(i)}$	The tweet issued by user i at time k
$D(tw_k^{(i)})$	The dissemination ratio of $tw_k^{(i)}$
$Ntw(n)$	Number of tweet that has been generated at time n
$T_i(n)$	Overall trust of user i at time n
$\overline{T}(n)$	Average trust at time n
IT_i	Identity-based trust of user i
BT_i	Behavior-based trust of user i
RT_i	Relation-based trust of user i
FF_i	Feedback factor of user i
IFT_i	Information-based trust of user i
$C(tw_k^{(i)}, n)$	Accuracy of tweet $tw_k^{(i)}$
$IP(tw_k^{(i)})$	Ratio of number of included pictures in $tw_k^{(i)}$
$PP(tw_k^{(i)}, n)$	The popularity of tweet $tw_k^{(i)}$
Kn_i	Knowledgeability of user i
Ps_i	Psychopathy of user i
$NC_i(n)$	Number of negative comments of tweets created by user i
$PC_i(n)$	Number of positive comments of tweets created by user i
$FP(n)$	Number of users who become the followers of users
$FN(n)$	Number of users who quit the followers of users

4.1. Identity-based Trust

Identity-based trust is the identity profile of the SNS users [5]. The identity-based trust is formed with the social popularity denoted by the number of followers, the authority factor, and the age factor. Let IT_i and AF_i denote the identity-based trust and the age factor of SNS user i ($\in U$), respectively. The age factor of user i, denoted as AF_i, corresponds to the account's age displayed on the social network profile. For instance, if a user registered on the network in 2019, the age value would be 4 in 2023. The formulation for the age factor of user i, AF_i, is defined as

$$AF_i = \frac{Ag_i}{\overline{Ag} + Ag_i}, \tag{4.2}$$

where Ag_i is the age value of user i and $\overline{Ag}$ is the average age of all the users.

At each time slot, each user decides to/not to be the follower of other users. We assume that for $i, j \in U$, user j follows user i if his/her overall trust $T_j(n)$ is greater than threshold θ_{trust}. We introduce the following two subsets of U:

$$FP(n) = \{j \in U : T_j(n-1) \leq \theta_{trust}, T_j(n) > \theta_{trust}\},$$
$$FN(n) = \{j \in U : T_j(n-1) > \theta_{trust}, T_j(n) \leq \theta_{trust}\}.$$

$FP(n)$ is the set of users that are new followers of any other users at time n, while $FP(n)$ is the set of users that stop to follow other users at n.

We also define $followers_i(n)$ as the number of followers of user i at time n. The value of $followers_i(n)$ is updated with $FP(n)$ and $FN(n)$ according to the following equation

$$followers_i(n) = followers_i(n-1) + |FP(n)| - |FN(n)|, \tag{4.3}$$

where $|\cdot|$ denotes the cardinality of a set.

Let $P_i(n)$ denote the popularity factor of user i at time slot n, defined by

$$P_i(n) = f(followers_i(n)), \tag{4.4}$$

where $f(\cdot)$ is the popularity function defined in (4.1).

Then, the identity-based trust, IT_i, is defined as

$$IT_i(n) = w_p \cdot P_i(n) + w_{au} \cdot Au_i + w_{af} \cdot AF_i, \tag{4.5}$$

where w_p, w_{au}, and w_{af} are weight parameters, and Au_i is the authority score of user i defined by

$$Au_i = \begin{cases} 1, & \text{if the verified badge exists in user } i\text{'s account,} \\ 0, & \text{otherwise.} \end{cases} \tag{4.6}$$

Here, the verified badge is a verification mark attached to the profiles of some legitimate users. $Au_i = 1$ implies that user i has verified badge on his/her account page.

4.2. Behavior-based Trust

Behavior-based trust reflects the cognitive processes that dictate how information spreaders behave on social networking service. This is related to the number of fake news items that the information spreaders follow, implying how controversial they behave in the social network. There are two behavioral responses on a social network that users can draw from a tweet: comments and mentions. Comments are responding to someone's tweet by placing a response tweet into the tweet comment section. On the contrary, mentions are actions of calling someone into another tweet.

In this model, we suppose that comments are more informative to examining trustworthiness than mentions, which was also pointed out in [5]. The main reason is that comments are placed within tweets, whereas mention is an action of sharing with another node that may not have any linked connection to a specific user. In behavior-based trust calculation, the primary focus is only on the factors that belong to the information spreaders, such as comments, shares, and likes, where mentions only show the actions made by the receivers. We also assume that the behavior of information spreaders is more important than the source of the post.

Let $BT_i(n)$ $(i \in U)$ denote the quantity of behavior-based trust of user i at time slot n. The evaluation is performed in two different point of view; the tweet creator perspective and the tweet receiver perspective. In terms of the tweet creator perspective, $BT_i(n)$ is calculated based on three factors; senders' likes, shares, and comments. We define $tw_k^{(i)}$ $(i \in U, k = 1, 2, \ldots, n)$ as the tweet generated by user i at time k.

Now we define the following variables associated with the tweet $tw_k^{(i)}$.

$lk(tw_k^{(i)}, n)$: The number of likes that $tw_k^{(i)}$ receives by time slot n.

$sh(tw_k^{(i)}, n)$: The number of shares that $tw_k^{(i)}$ receives by time slot n.

$co(tw_k^{(i)}, n)$: The number of comments that $tw_k^{(i)}$ receives by time slot n.

Let $Inf(tw_k^{(i)}, n)$ denote the influence value of a single tweet $tw_k^{(i)}$ at time slot n, which is defined by

$$Inf(tw_k^{(i)}, n) = \frac{f(lk(tw_k^{(i)}, n)) + f(sh(tw_k^{(i)}, n)) + f(co(tw_k^{(i)}, n))}{3}. \quad (4.7)$$

Then, Influence creator factor $IC_i(n)$ is defined as

$$IC_i(n) = \frac{1}{\#_i^{tweet}(n)} \sum_{k=1}^{\#_i^{tweet}(n)} Inf(tw_k^{(i)}, n), \quad (4.8)$$

where $\#_i^{tweet}(n)$ is the number of tweets created by user i until time slot n.

From the viewpoint of the users who received the tweet from user i, they want to understand how often user i interacted with fake news and true news. This can be evaluated by measuring the number of fake tweets liked, shared, and discarded by user i compared to true news.

Let $Tlk_i(n)$ (resp. $Flk_i(n)$) denote the number of likes on true (resp. fake) news by user i at time slot n. We define $LK_i(n)$ as the degree of likes by user i at time slot n, which is given by

$$LK_i(n) = \frac{f(Tlk_i(n))}{f(Tlk_i(n)) + f(Flk_i(n))}. \quad (4.9)$$

In order to characterize the share behavior of users, we introduce the degree of share for user i, Sh_i. Let $Tsh_i(n)$ (resp. $Fsh_i(n)$) denote the number of shares on true (resp. fake) news by user i at time slot n. We also define $Tds_i(n)$ (resp. $Fds_i(n)$) as the number of discards on true (resp. fake) news by user i at time slot n. Then Sh_i is defined as

$$Sh_i(n) = \frac{f(Tsh_i(n)) + f(Fds_i(n))}{f(Tsh_i(n)) + f(Fsh_i(n)) + f(Tds_i(n)) + f(Fds_i(n))}. \quad (4.10)$$

Let $IR_i(n)$ denote the influence receiver factor of user i in time slot n, defined by

$$IR_i(n) = \frac{LK_i(n) + Sh_i(n)}{2}. \tag{4.11}$$

With the influence creator factor $IC_i(n)$ and influence receiver factor $IR_i(n)$, the behavior based trust of user i in time slot n, $BT_i(n)$, is defined as

$$BT_i(n) = \frac{IC_i(n) + IR_i(n)}{2}. \tag{4.12}$$

4.3. Relation-based Trust

In general, users are likely to trust the information provided by family members and friends. The relation-based trust is a measure of how closely a user is related to his/her colleagues who provide information. We adopt the relation-based trust of [5] in which the degree of closeness is characterized by the betweenness centrality and number of shortest paths between users. The major difference between this model and that in [5] is that users with high extroversion personality trait tend to have high interaction with others, causing high relation-based trust value [43]. The relation-based trust of user i, RT_i, consists of two factors: the local clustering coefficient of user i, LC_i, and the betweenness centrality of user i, $\sigma(i)$. The local clustering coefficient quantifies of how close a node, in this case, a user, is to its neighbors. This was proposed by [55] with the main goal of determining the proportion of the current number of links divided by the maximum possibility of links that could exist between the nodes. Following [5], the local clustering coefficient of user i, LC_i is calculated according to the following equation:

$$LC_i = \frac{2Ln_i}{No_i(No_i - 1)}, \tag{4.13}$$

where Ln_i is the number of links between user i's neighboring users, and No_i the number of user i's neighboring users.

In contrast, the betweenness centrality addresses the centrality of a graph by measuring the shortest path of every vertex. The betweenness centrality of user

i, $\sigma(i)$, is defined as follows:

$$\sigma(i) = \sum_{s \neq i \neq t} \frac{\varsigma_{st}(i)}{\varsigma_{st}}, \tag{4.14}$$

where $\varsigma_{st}(i)$ $(s, t, i \in U)$ is the number of the shortest connection paths between users s and t via user i, and ς_{st} is the number of the shortest connection paths between users s and t.

With LC_i and $\sigma(i)$, RT_i is defined as

$$RT_i = \frac{LC_i + (1 - \sigma(i))}{2}. \tag{4.15}$$

4.4. Feedback Factor

The feedback factor accounts for the trust given by the receiver of a tweet by providing reviews or rating the information source [5]. The more positive comments posted in the comment section of the tweet, the more trustworthy the information becomes. The feedback factor was evaluated from the viewpoints of tweet creators and tweet receivers.

From the tweet creator's viewpoint, the feedback factor is measured as the number of positive comments that user i created for true tweets over fake tweets. We define $FC_i(n)$ as the feedback creator factor of user i at time slot n, given by

$$FC_i(n) = \frac{TPC_i(n) + FNC_i(n) + 2}{(TPC_i(n) + 1) + (FPC_i(n) + 1) + (TNC_i(n) + 1) + (FNC_i(n) + 1)}, \tag{4.16}$$

where $TPC_i(n)$ (resp. $TNC_i(n)$) is the cumulative number of positive (resp. negative) comments on the true tweets created by user i, counted at time slot n, and $FPC_i(n)$ (resp. $FNC_i(n)$) is the cumulative number of positive (resp. negative) comments on the fake tweets created by user i, counted at time slot n.

On the other hand from the tweet receiver viewpoint, it is important to measure the number of positive comments received by user i received over the negative comments. Let $FR_i(n)$ denote the feedback receiver factor of user i at time slot n, which is defined as

$$FR_i(n) = \frac{PC_i(n) + 1}{(PC_i(n) + 1) + (NC_i(n) + 1)}, \tag{4.17}$$

where $PC_i(n)$ (resp. $NC_i(n)$) is the cumulative number of positive (resp. negative) comments on the tweets created by user i, counted at time slot n.

With $FC_i(n)$ and $FR_i(n)$, the feedback factor of user i $FF_i(n)$ is formulated as

$$FF_i(n) = \frac{FC_i(n) + FR_i(n)}{2}. \tag{4.18}$$

4.5. Information-based Trust

In social networking service, the information feature plays an important role in information trust during disaster. For instance, the presence of photos significantly improves trustworthiness [9, 56]. Based on the 3S-model of information trust [9], the information features considered here are semantic features, which represent content accuracy and surface features that include photos, logic, and post popularity.

We focus on the dissemination of tweets, and we need to characterize the trustworthiness of each tweet created by a user. Let $C(tw_k^{(i)}, n)$ denote the content accuracy of tweet $tw_k^{(i)}$ at time slot n, which is defined by

$$C(tw_k^{(i)}, n) = \frac{PF(tw_k^{(i)}, n) + 1}{PF(tw_k^{(i)}, n) + NF(tw_k^{(i)}, n) + 2}, \tag{4.19}$$

where $PF(tw_k^{(i)}, n)$ (resp. $NF(tw_k^{(i)}, n)$) is the cumulative number of users who give positive (resp. negative) feedback to tweet $tw_k^{(i)}$ until time slot n. We define the accuracy for the contents generated by user i, $C_i(n)$, as the average of $C(tw_k^{(i)}, n)$ taken by all the tweets issued by user i

$$C_i(n) = \frac{1}{\#_i^{tweet}(n)} \sum_{k=1}^{\#_i^{tweet}(n)} C(tw_k^{(i)}, n). \tag{4.20}$$

Similarly, we define $IP(tw_k^{(i)})$ as the ratio of the number of pictures included in tweet $tw_k^{(i)}$ to the maximum number of pictures in a tweet, which is given by

$$IP(tw_k^{(i)}) = \frac{Pictures(tw_k^{(i)})}{4}, \tag{4.21}$$

where $Pictures(tw_k^{(i)})$ is the number of pictures in $tw_k^{(i)}$. Note that on Twitter, the maximum number of pictures in a tweet is four. Let $IP_i(n)$ denote the average number of pictures included in a tweet by user i. Here, the average is taken by user i's tweets generated until time slot n. $IP_i(n)$ is given by

$$IP_i(n) = \frac{1}{\#_i^{tweet}(n)} \sum_{k=1}^{\#_i^{tweet}(n)} IP(tw_k^{(i)}). \tag{4.22}$$

In terms of the popularity of a tweet generated by a user, let $Likes(tw_k^{(i)}, n)$ denote the number of users who gave their likes to tweet $tw_k^{(i)}$ until time slot n. We define the popularity of tweet $tw_k^{(i)}$, $PP(tw_k^{(i)}, n)$, as

$$PP(tw_k^{(i)}, n) = \begin{cases} 1, & \text{if } Likes(tw_k^{(i)}, n) \geq N/2, \\ 0, & \text{otherwise.} \end{cases} \tag{4.23}$$

Then, the popularity value of $user_i$, $PP_i(n)$, is defined as

$$PP_i(n) = \frac{1}{\#_i^{tweet}(n)} \sum_{k=1}^{\#_i^{tweet}(n)} PP(tw_k^{(i)}, n). \tag{4.24}$$

With these features, we define the information-based trust for tweets by an SNS user i at time slot n, $IFT_i(n)$, as the following equation

$$IFT_i(n) = w_c \cdot C_i(n) + w_{ip} \cdot IP_i(n) + w_l \cdot LT_i + w_p \cdot PP_i(n), \tag{4.25}$$

where w_η's ($\eta \in \{c, ip, l, p\}$) are weighting factors of variables.

4.6. Overall Trust

Finally, we define the overall trust of user i at time slot n, $T_i(n)$, as the following equation

$$T_i(n) = w_{it} \cdot IT_i(n) + w_b \cdot BT_i(n) + w_r \cdot RT_i + w_f \cdot FF_i(n) + w_{if} \cdot IFT_i(n), \tag{4.26}$$

where w_ξ's ($\xi \in \{it, b, r, f, if\}$) are weighting factors of component trust values.

To achieve a balance between all trust models, we determined the weights according to the questionnaire results shown in the following section of Simulation and Questionnaire.

5. Simulation and Questionnaire

In this section, we present the agent-based simulation experiment for our proposed trust model. First, we illustrate the procedure of the agent-based simulation and explain how the overall trust for each user is calculated. Then, we present the questionnaire conducted to set the parameters of our simulation model.

5.1. Agent-based Simulation

We developed an agent-based modeling environment for the SNS on NetLogo 6.0.4. In the simulation, SNS users were modeled as agents, and tweets were represented as the delivered materials. Trust changes were observed through the agents' overall trust values.

Our agent-based simulation consisted of four phases. The first phase is user generation, where users are generated and linked according to the Barabási Albert model of scale-free network [57]. Then, each user is characterized with personality traits explained in chapter 3.

Figure 5.1 shows a sample of a user relation network generated by the Barabási Albert model. Each users assigned to the personality based on the big-five personality worldwide distribution shown in the Table 5.3 [58]. In this figure, each user is characterized by the maximum personality attribute in a specific color. For example, the user with the highest openness value is colored red, while the user with the highest conscientiousness value is colored blue. The network relation illustrates how information is disseminated among users. In social networks, these relations are described as social links. For instance, if user 1 follows user 2, the information will propagate from user 2 to user 1.

The second phase involved tweet creation. Figure 5.2 illustrates this phase,

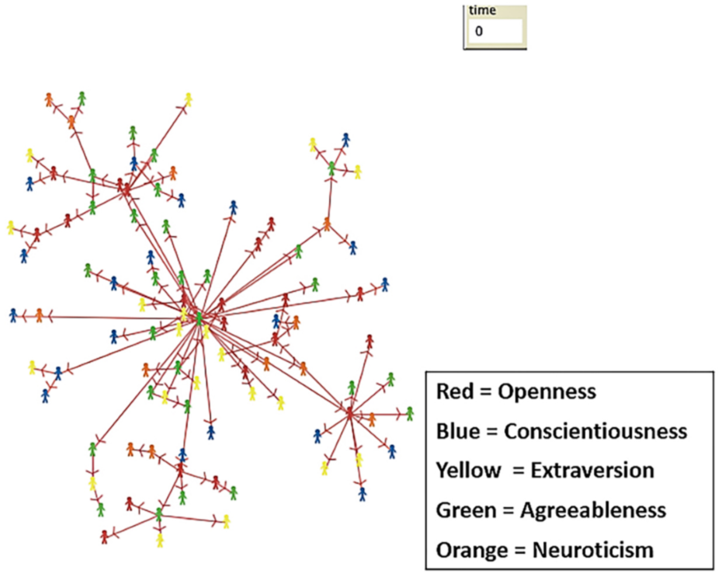


Figure 5.1: *Netlogo* Interface: Users are generated and assigned with personalities.

where several tweets are created in the network. In the figure, the blue edges represent the direction of tweet information, while the social links between users are depicted in red. As shown, if user i has no followers, the tweet will not be propagated to other users. During this phase, a limited number of users receive the news, and each of them examines the trustworthiness of the news according to the trust model. Subsequently, the news will be disseminated further through the network. We assume the news sharing depends to the news sharing probability which is also depending to the news rejection probability. This adoption mechanism will generate an R-shape news diffusion representation in the simulation program.

The third phase is the fake-news creation. When the news becomes popular, a fake news appears, as shown in Figure 5.3.

The fourth phase is the dissemination process of fake news. The users will receive the information and decide to share according to the CS_i value. When the knowledgeable users received the fake news, he/she will establish clarification based on the news, telling that the news is not correct. This creates social rejection towards all news related to the same topic. Then, the fake news will be disappeared. See Figure 5.4.

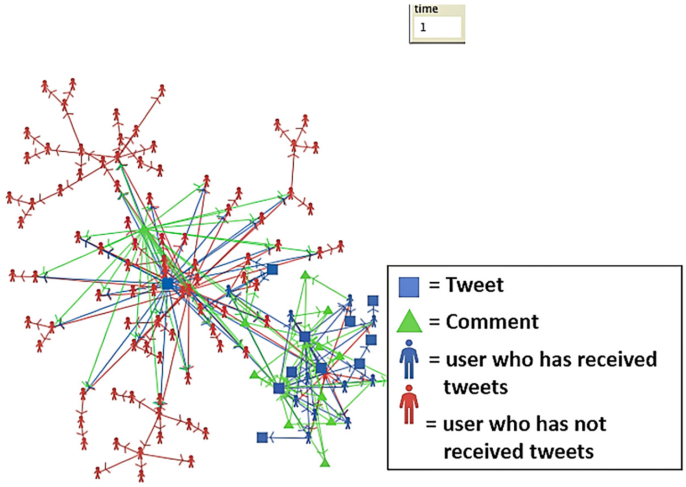


Figure 5.2: *Netlogo* Interface: Tweets are generated.

Our simulation is a discrete-time simulation with time slot $n \in \{0, 1, 2, \ldots, 50\}$. In one simulation experiment, the initialization process is executed at $n = 0$, then the above four steps are performed and terminated at $n = 50$. This experiment is repeatedly executed 100 times with different seeds, and the average values of performance measures are calculated.

5.2. Trust Calculation Procedure

In this sections, we describe the procedure of trust calculation in our agent-based simulation.

First, a randomly selected user with openness personality creates a news and spreads it to the linked users. The main reason for this selection is that a high level of openness, coupled with extroversion, indicates increased usage of social networking sites (SNS) [6,43]. Furthermore, it has been observed that individuals who are open to experiences generally participate in more groups, resulting in a higher number of followers [6]. Therefore, selecting users with high openness is anticipated to generate greater information propagation, which will show the performance of our proposed model. Then, the users who have received the news will examine the trustworthiness of the news according to the trust model. The trustworthiness of the news is examined according to the trust model with five

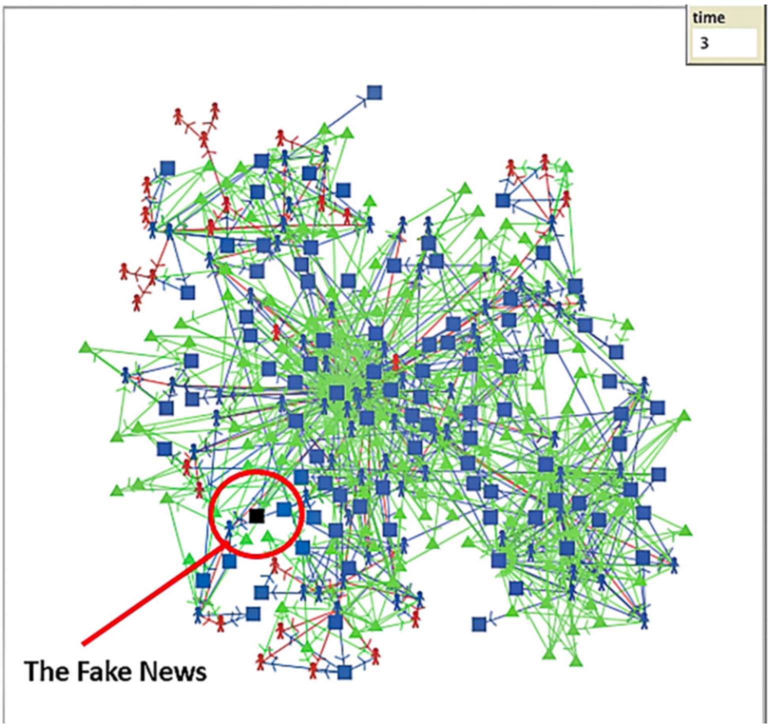


Figure 5.3: *Netlogo* Interface: Fake news are generated.

factors of trust: identity-based, relation-based, behavior-based, feedback factor, and information-based.

Assume that user i receives the news at time slot $t = n$. If the conscientiousness of user i, CS_i, is greater than or equal to 0.8, user i rejects the news. The action taken to disseminate the news depends on user's other personality traits. Users with openness, agreeableness, and extroversion are likely to share the received information. If CS_i is smaller than 0.5, user i accepts the news and shares it with his/her followers. If the value of CS_i is equal to or greater than 0.5 but less than 0.8, users will receive the information without sharing it with others.

In terms of the creation of fake news, we assume that a user with psychopathy creates a fake news from a receiving information. Let $D(tw_k^{(i)})$ denote the ratio of the number of users who received tweet $tw_k^{(i)}$ to the number of users N. We call $D(tw_k^{(i)})$ the dissemination ratio of the kth tweet issued by user i.

Consider the case where $D(tw_k^{(i)})$ reaches the value greater than 0.7 and user

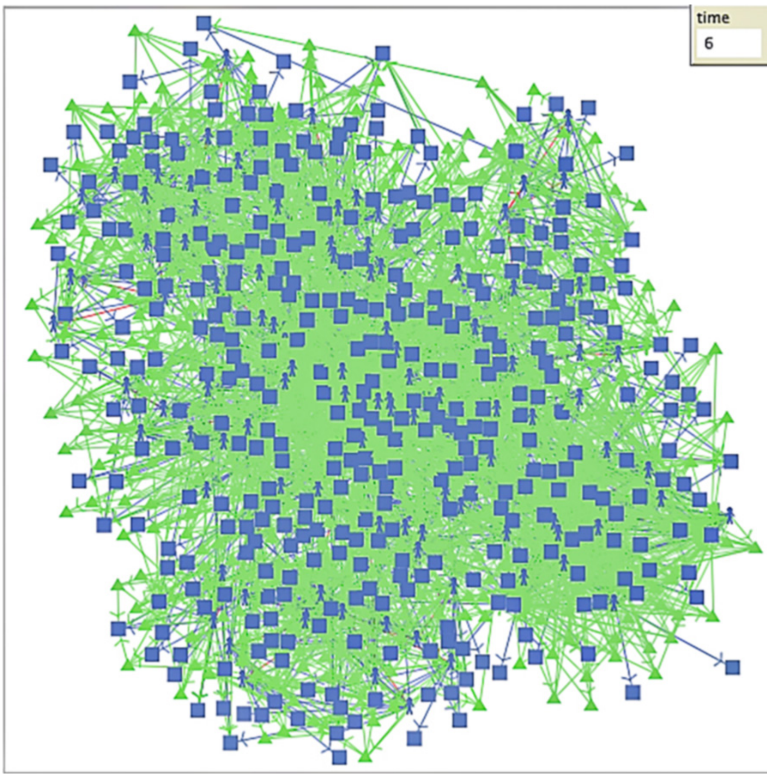


Figure 5.4: *Netlogo* Interface: Fake news disappearance.

j ($\neq i$) receives the tweet $tw_k^{(i)}$. If user j is psychopathy ($Ps_j = 1$) and his/her overall trust $T_j(n)$ is greater than or equal to 0.5, user j creates a fake news and disseminates it, independently of $tw_k^{(i)}$. The fake news will be removed if the number of negative comments added to the news is greater than $N/2$. The increase in negative comments is the result of clarification actions by knowledgeable users. The more negative comments are added to the fake news, the more users will counter the fake news.

In order to evaluate the information dissemination over the SNS, we consider the average of the overall trust values of all users, $\overline{T}(n)$.

5.3. Questionnaire

To set the simulation parameters of the trust model, we performed a questionnaire survey of 150 university students in Indonesia. We gathered our respondents' opinions about fake news. We achieve this by presenting questions in two parts, the users‘ opinion on how fake information spread and which factors affect their trusting behavior in social networking service. Examples of the questionnaire are presented below:

- According to this piece of information, what is your opinion?
- According to your experience which factors below, affect your decision on trusting or neglecting the news?

The questionnaire results will be used to determine the weight factor of the trust model evaluation. This online survey was taken from April to May 2020 with the target respondents being mainly Twitter users, who use Twitter frequently daily. We believe that determining this weight factor, in the beginning, will help us evaluate the trustworthiness of users according to what the group of people thinks about how to evaluate a piece of information.

In this survey, we successfully gathered 150 responses, taken from Google Forms, a questionnaire-taking platform.

The results of the questionnaire are shown in Figure 5.5. In this figure, 62% of the users believe that information quality is the key factor towards information acceptance. Note that information quality is the main feature off the proposed information-based trust. Then, the other resulting ratio of Identity, behavior, relation, and feedback are 18%, 8%, 8%, and 4%, respectively. These values are used for the weight parameters of the overall trust (4.26). "Generally, the weight factor can be changed dynamically by the SNS manager; in the case of Twitter, the administrator may adjust it. However, with the current progress of Twitter as a community-based service, providing a simple public questionnaire in the community is essential.

5.3.1 Parameter Settings

The weights of the overall trust in (4.26) were determined according to the questionnaire result shown in Figure 5.5. We call the weight-value set the baseline value. In order to investigate the impact of each trust factor on the overall trust, we formed five different scenarios to eliminate one trust factor. These scenarios

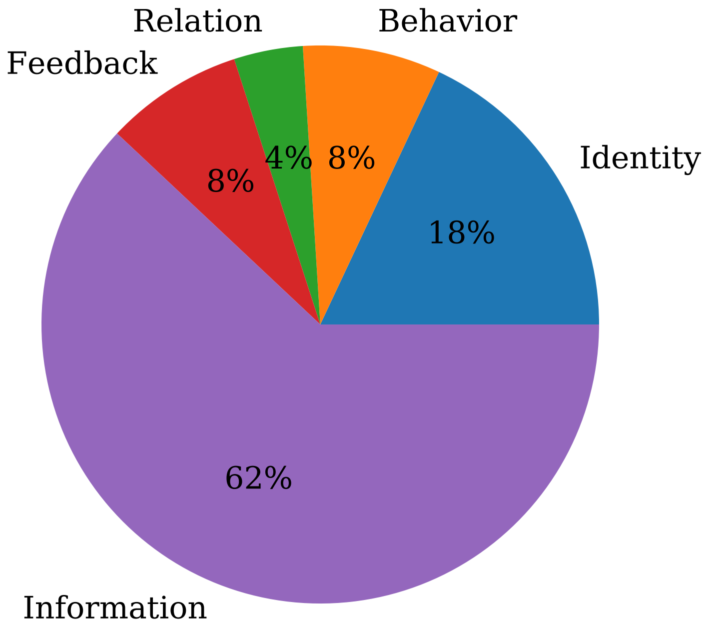


Figure 5.5: Questionnaire results for trust model.

aim to understand how the trust model works on SNS networks. We considered scenarios in which one of the trust factors was set to zero, while the remaining weights were normalized proportionally to the questionnaire result. For example, when the weight of the identity-based trust, w_{it}, is set to 0, w_b is given by

$$w_b = \frac{0.08}{0.08 + 0.04 + 0.08 + 0.62} \approx 0.097.$$

Similarly, w_r, w_f, and w_{if} are set to 0.048, 0.097, and 0.756, respectively. Table 5.1 shows the six scenarios: 1) baseline, 2) case without identity-based trust (wo IT_i), 3) case without behavior-based trust (wo BT_i), 4) case without relation-based trust (wo RT_i), 5) case without feedback factor (wo FF_i), and 6) case without information-based trust (wo IFT_i).

In terms of the Big-Five personality traits, we also consider the six scenarios. In the baseline scenario, all weights of the five traits were the same and equal to 0.2. For the remaining scenarios, the weight of one personality was set to one, and those of the other four personality traits were set to zero. (See Table 5.2.)

Table 5.1: Trust Simulation Scenarios.

Weight	Baseline	wo IT_i	wo BT_i	wo RT_i	wo FF_i	wo IFT_i
w_{it}	0.18	0	0.195	0.187	0.195	0.473
w_b	0.08	0.097	0	0.083	0.0869	0.210
w_r	0.04	0.048	0.043	0	0.043	0.105
w_f	0.08	0.097	0.086	0.0833	0	0.210
w_{if}	0.62	0.756	0.673	0.645	0.673	0

(wo: without)

Table 5.2: Big-Five Personality Simulation Scenarios.

Argument of UP	Baseline	Openness	Extroversion	Conscientiousness	Agreeableness	Neuroticism
openness	0.2	1	0	0	0	0
Extroversion	0.2	0	1	0	0	0
conscientiousness	0.2	0	0	1	0	0
agreeableness	0.2	0	0	0	1	0
neuroticism	0.2	0	0	0	0	1

The number of users was set to $N = 100$. Personality traits were assigned according to a previous study [58]. Following [58], the personality traits of a user were determined according to normal distributions. (See Table 5.3.) For each personality trait, we generated N positive samples from the corresponding normal distributions. Then, the samples are normalized with the maximum value of the N samples so that the resulting samples are in [0,1]. We conducted 100 simulation experiments with different seeds, taking the averages of the performance measures over 100 samples.

In the simulation, we introduce the probability of a malicious user to disseminate fake news, P. The value of P is taken from 0 to 1. If P is set to 0, then the malicious users will not disseminate the fake news. If the value is set to 1, then the malicious users will disseminate the fake news. In the simulation, we set $P = 0.5$. This means the malicious users will not always share fake news, but also keep the true news disseminated.

Table 5.3 summarizes the parameter setting of the simulation experiments.

Table 5.3: Parameter Settings.

Description	Value	Source
Age: Ag_i	Sampled from Poisson distribution with mean 3.5	assumption
Number of users with $Au_i = 1$	Sampled uniformly from $[0, 100]$	assumption
Number of users with $Kn_i = 1$	Sampled from Normal distribution $N(49.82, 8.85)$	[59]
Probability of psychopathy users sending fake news: P	0.5	assumption
Number of users: N	100	assumption
Ratio of psychopathy users	20%	assumption
Openness: O_i	Sampled from $N(48.01, 08.95)$	[58]
Extroversion: E_i	Sampled from $N(51.25, 8.81)$	[58]
Conscientiousness: CS_i	Sampled from $N(47.19, 11.24)$	[58]
Agreeableness: A_i	Sampled from $N(46.38, 9.02)$	[58]
Neuroticism: NR_i	Sampled from $N(49.73, 9.66)$	[58]
Threshold: θ_{trust}	0.5	assumption

6. Results and Discussion

In this section, we present our simulation results. We first show our trust model validation and sensitivity, then discussing the effect of Big-Five personality traits on trust values.

6.1. Trust Model Validation

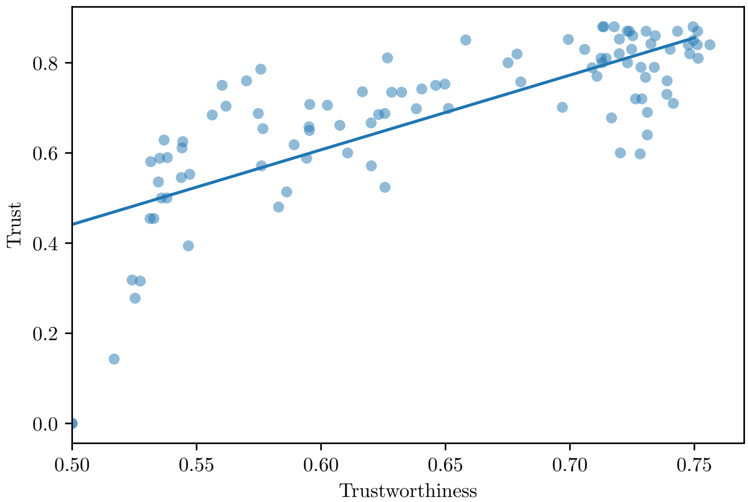


Figure 6.1: The overall trust T_i and trustworthiness comparison.

To validate the model, we introduce the trustworthiness of a user defined by

$$Trustworthiness(i) = \frac{N^{AN}(i)}{N^{AN}(i) + N^{DN}(i)}, \quad i \in U, \tag{6.1}$$

where $N^{AN}(i)$ (resp. $N^{DN}(i)$) is the number of news items accepted (resp. discarded) by user i. We consider the baseline scenario whose parameter setting is shown in Tables 5.1 and 5.2. We also set $P = 0$, following [60].

Figure 6.1 shows the relation between the trustworthiness and overall trust of 100 users at time slot $n = 10$ for one simulation experiment. In this figure, each point represents $(Trustworthiness(i), T_i(20))$ for user i ($i \in \{1, \ldots, 100\}$), while the line is the result of the linear regression analysis for those points. We observe from this figure that the overall trust grows with increase in the trustworthiness value. This tendency is supported by [60], validating our trust and system models.

6.2. Component Sensitivity of Trust Model

Figure 6.2 illustrates the evolution of the mean overall trust for the six scenarios in Table 5.1. It is observed in this figure that the overall trust values for all cases slightly increase. The mean overall trust in the case without behavior-based trust BT_i achieves the highest, while that in the case without information-based trust IFT_i is the lowest. Note that the case without information-based trust is equivalent to the system of Info-Trust [5].

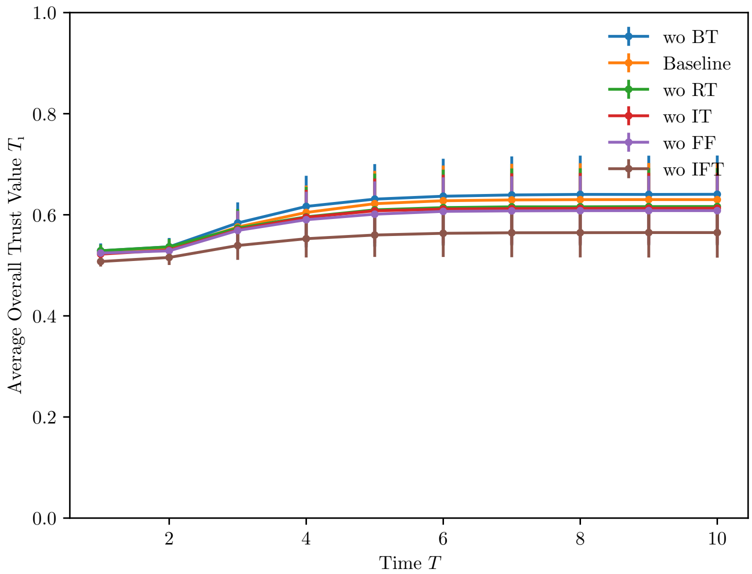


Figure 6.2: The overall trust T_i over the time of the trust scenarios.

In the parameter settings, we set the weights of the overall trust according to the questionnaire results, which gives the information-based trust the highest weight value. In terms of behavior-based trust, the weight value is similar to feedback factor, but has a lower trust value compared to the feedback factor evaluation.

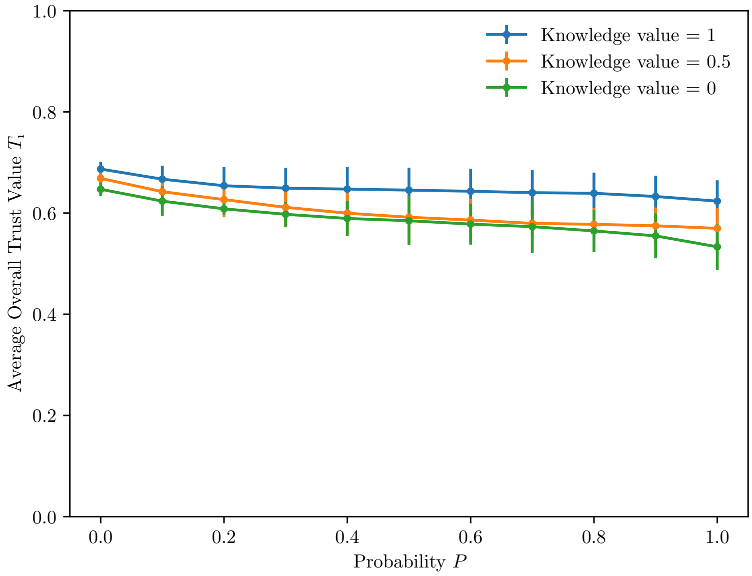


Figure 6.3: The overall trust T_i against the probability of a malicious user sending fake news P.

Figure 6.3 shows the average along with its standard deviation of the overall trust against P, the probability of a malicious user sending fake news. We conducted simulation experiments in cases with the user i's knowledgeability Kn_i equal to 0, 0.5, and 1 for $\forall i \in U$. In this figure, the average overall trust $\overline{T}(n)$ decreases with increase in P for the three knowledgeable cases. This is because a large probability of sharing fake news P increases the appearance of fake news. This causes negative comments created by knowledgeable users, making the spreading speed of the tweet slow. The higher number of negative comments $NC_i(n)$ affects a lower value of feedback factor $FF_i(n)$, while the lower number of tweet shared $sh(tw_k^{(i)}, n)$, and likes $lk(tw_k^{(i)}, n)$, affect a lower value of $BT_i(n)$.

Figure 6.4 shows how the number of malicious users affects the average overall trust $\overline{T}(n)$. In this figure, the overall trust decreases with increase in the number of malicious users, as expected. A remarkable point in the figure is that the overall trust values for three knowledgeability cases decrease similarly. This suggests that

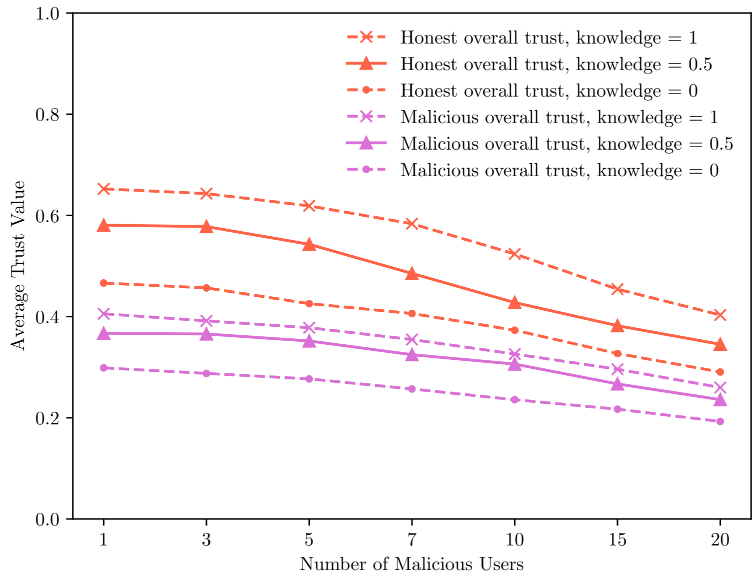


Figure 6.4: The comparison between Overall Trust T_i and number of malicious users.

the knowledgeability itself is not effective in preventing a decline in the users' overall trust. This decreasing value matches overall trust value decreases in [5] which shows how the trust degree react to malicious act.

6.3. Effect of Big-Five Personality Traits

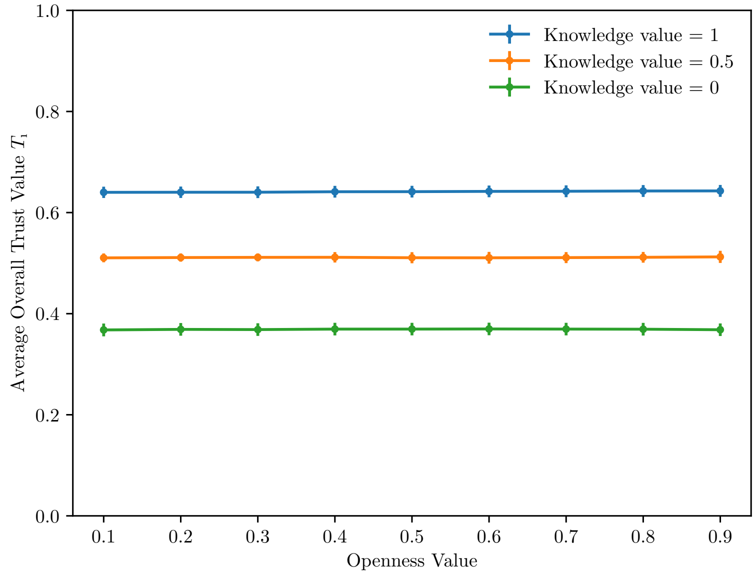
In this section, we investigate how the Big-Five personality traits affect the overall trust. Since our trust model is heavily performed based on users interactions, the different on Big-Five personality traits will affect the overall-trust value. In this experiment, we set the values of the targeted personality traits between 0.1 and 0.9, keeping all the other parameters same as those in [58]. In openness scenarios, if an open-to-experience user is not generated based on the parameter settings, the system will select a user with the highest betweenness centrality $\sigma(i)$, as shown in equation 4.14 , to ensure the dissemination of information to the majority of users in the network.

Figures 6.5 to 6.9 show the overall trust against the Big-Five personality traits of openness, conscientiousness, extroversion, agreeableness and neuroticism, respectively. The results shows that openness, conscientiousness and extroversion personality traits increase the overall trust value, while larger values of agreeableness and neuroticism make the overall trust value small. These results conform to [13], which claims that neuroticism and agreeableness less correlate with trustworthiness, while the openness, conscientiousness and extroversion are highly related to trust.

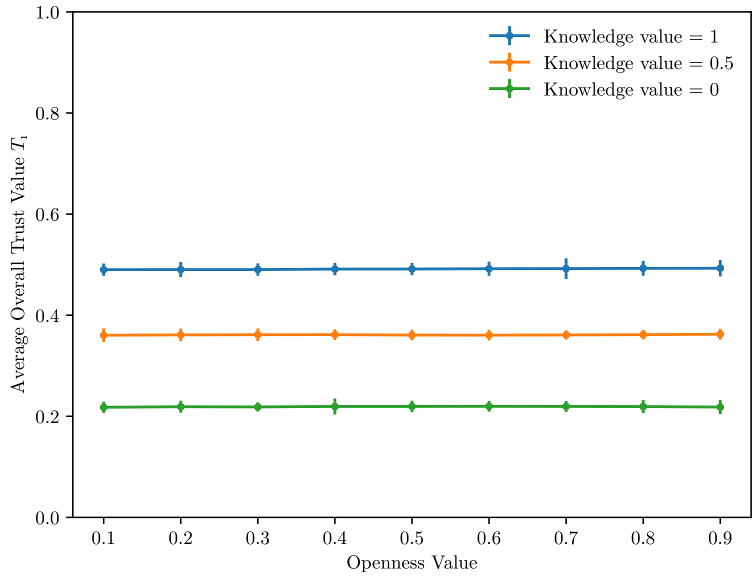
Figure 6.5 shows the relation between the overall trust and openness. We conducted the experiments in cases of the knowledgeability Kn_i = 0, 0.5 and 1. We also investigate the cases where the first news created is normal and fake. In this figure, the overall trust values for three cases of knowledgeability are almost similar when the openness value is between 0.1 and 0.3. With the increase of openness value, however, the overall trust values with Kn_i =0.5 and 1 slightly increase, while in case of $Kn_i = 0$, the overall trust remains constant. This result is consistent with [49] which reported that users with more knowledge act carefully and have higher overall trust value. Figure 6.5 also shows that the overall trust is insensitive to the openness. This is because the openness does not take into account likes and comments. However, the openness has the role in information spreading and creating.

Figure 6.6 shows the overall trust against the conscientiousness. We observe the monotonic growth of the overall trust with increase in the conscientiousness value in different knowledge values. Users with high conscientiousness value is very cautious and not trapped with fake news while the news is disseminated in the initial phases, and tend to gather more opinions from the other users in the feedback section, then deciding to trust or not to trust the information. This finding aligns with [61], which shows conscientiousness users are more successful in detecting fake news. Therefore, our trust model can evaluate conscientiousness users with high overall trust values based on their cautious characteristics.

Figure 6.7 shows the overall trust against the extroversion. In Figure 6.7 (a) where the fist news is normal, the overall trust monotonically and gradually grows with increase in the extroversion value. Users with high extroversion are likely to share positive comment and likes in a single tweet, therefore it will increase the trust value when the fake news is few. Note also that high extroversion users are likely to attach a high number of pictures in a single tweet. This affects

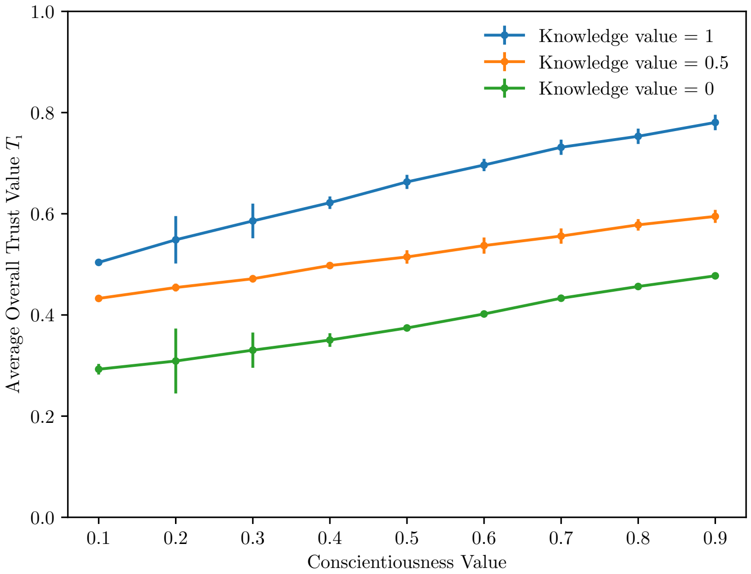


(a) The first news is normal.

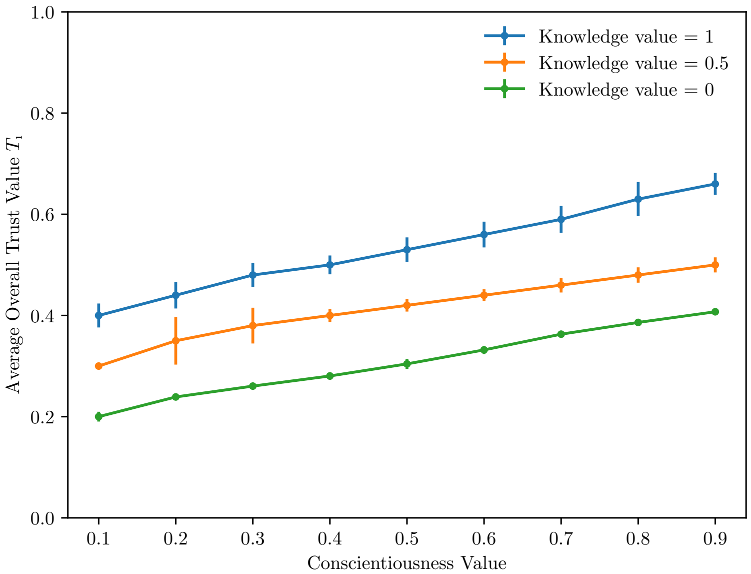


(b) The first news is fake.

Figure 6.5: Comparison of overall trust and openness personality rait.

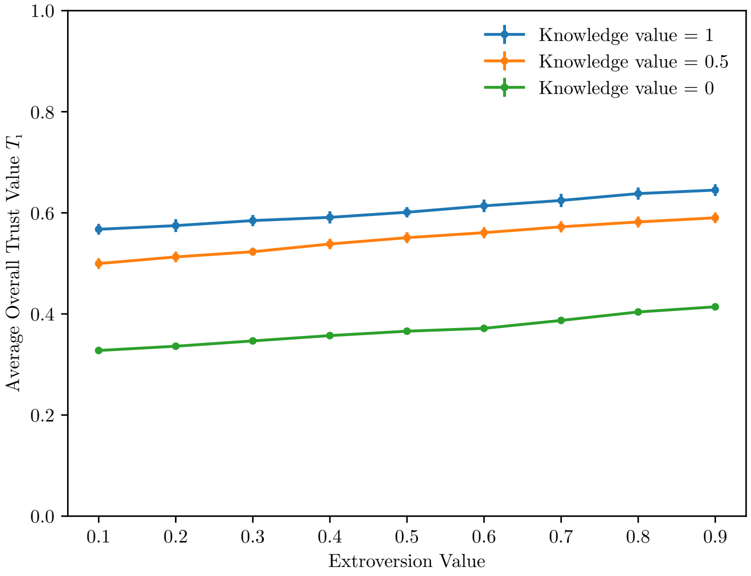


(a) The first news is normal.

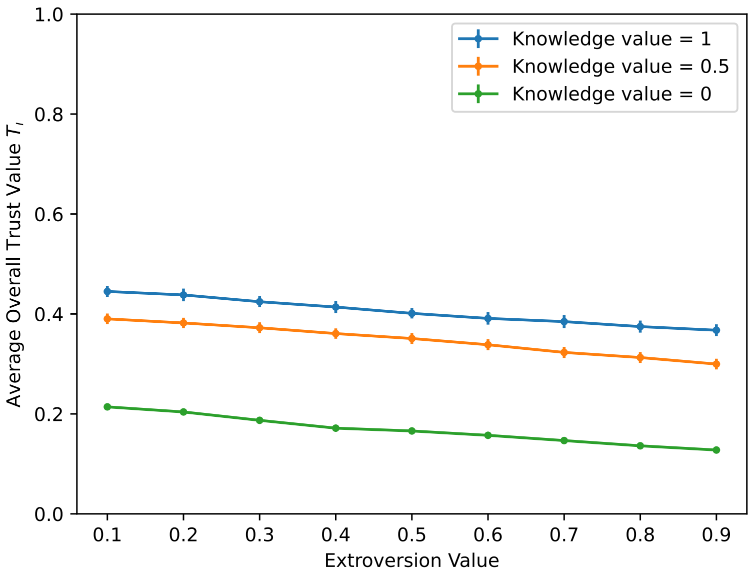


(b) The first news is fake.

Figure 6.6: Comparison of Overall Trust and Conscientiousness Personality Trait.



(a) The first news is normal.



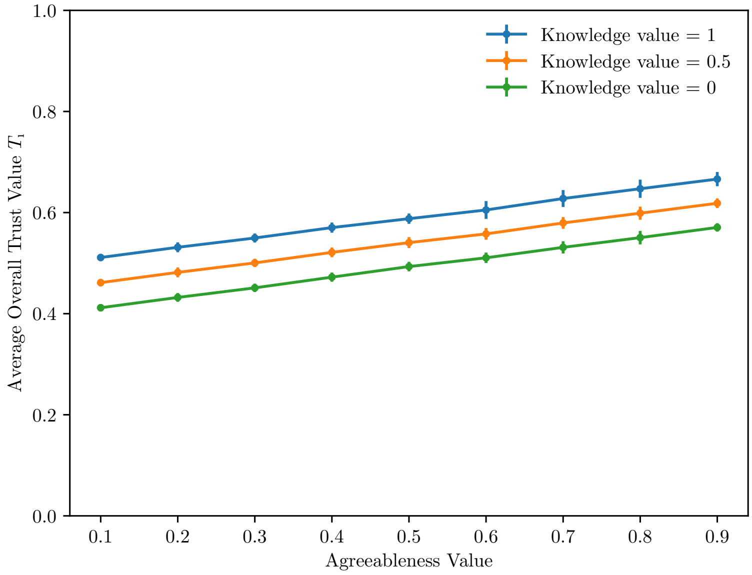
(b) The first news is fake.

Figure 6.7: Comparison of Overall Trust and Extroversion Personality Trait.

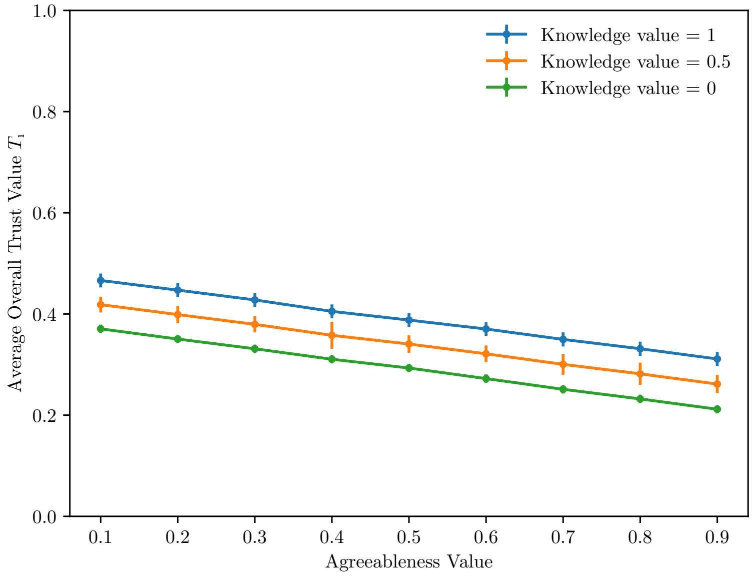
the included pictures value of the information-based trust [13]. Furthermore, the overall trust will decrease while the fake news appears more, since the extroversion users tend to give high positive comment even to fake news. This finding is supported by [61] showing that introverted users are reliable on detecting fake news.

Figure 6.8 illustrates the overall trust against the agreeableness. In terms of agreeableness, users with high agreeableness value are likely to share information without careful verification. In our simulation, the agreeableness users tend to have high level of tweet sharing and create positive comments. In Figure 6.8 (a) where the first news is normal, the overall trust values for three cases of knowledgeability are growing with increase in the agreeableness value. This result is supported by [44], which reporting that with increase in the amount of shared information, the overall trust value will increase. When the first news created is fake, the overall trust monotonically decreases with increase in agreeableness. When user i has high agreeableness, user i is likely to share the news regardless of its trustworthiness, increasing the number of shares of fake news Fsh_i for the behavior-based trust $BT_i(n)$, as well as the number of positive comments $FPC_i(n)$ for the feedback factor $FF_i(n)$. This behavior resulted in a decrease in both $BT_i(n)$ and $FF_i(n)$.

Figure 6.9 shows the overall trust against neuroticism. Users with high neuroticism value tend to share fewer posts in SNS [44]. In Figure 6.9, the overall trust values in three cases of knowledgeability are decreasing with increase in neuroticism value. This is because neuroticism is correlated with high fake news sharing and low logic value. Therefore this behavior decreases the information-based trust value. When the first news is normal, the differences among three curves is getting decreased with increase in the neuroticism value. Note that neuroticism users have higher likes probability and shares probability, but having less comment creation behavior. This makes the behavior-based trust $BT_i(n)$ large, while decreasing the feedback factor $FF_i(n)$ and information-based trust $IFT(n)$. When user i's knowledgeability is $Kn_i = 1$, user i is likely to create more comments than users with small knowledgeability. When the initial news is fake, the spread and engagement with likes on the fake news negatively impact user feedback, decreasing both behavior-based trust and feedback factor of the

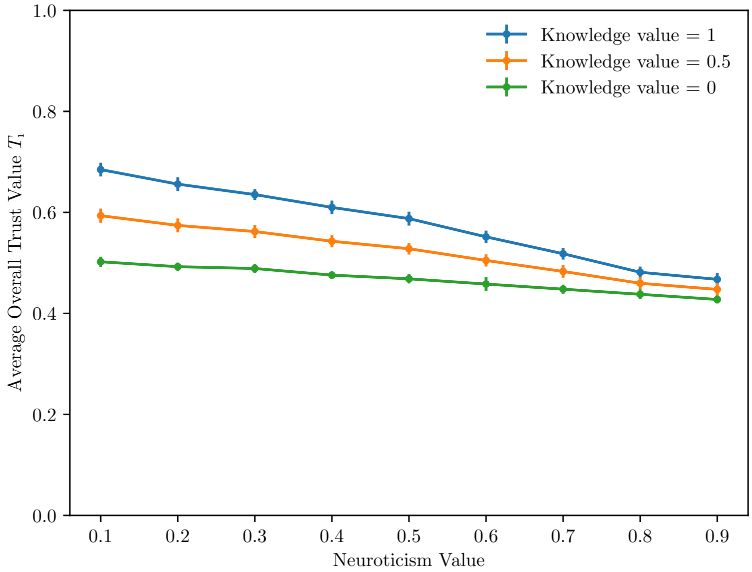


(a) The first news is normal.

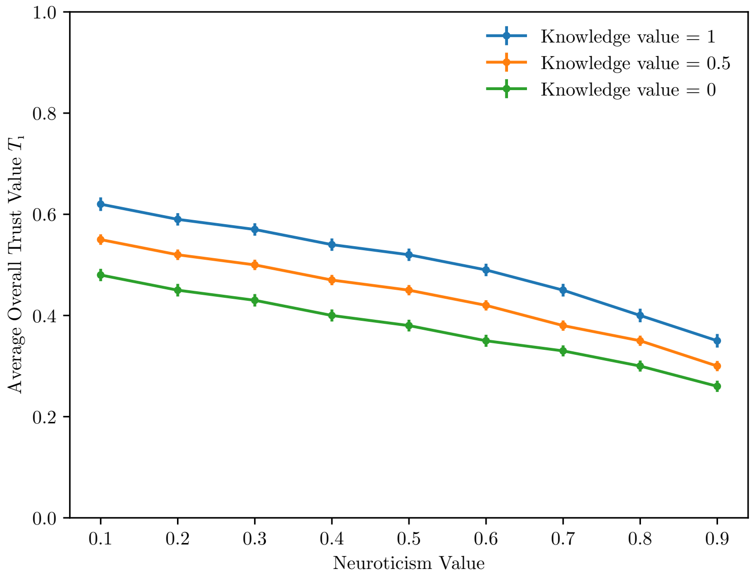


(b) The first news is fake.

Figure 6.8: Comparison of Overall Trust and Agreeableness Personality Trait.



(a) The first news is normal.



(b) The first news is fake.

Figure 6.9: Comparison of Overall Trust and Neuroticism Personality Trait.

users.

Based on the findings shown above, we can conclude that when the users' probability of sharing fake news is low, the high level conscientiousness and extroversion increase the overall trust value. On the contrary, the high level openness and neuroticism are correlated with decreasing the overall trust value.

In our simulation model, we introduce individuals into the social network who act maliciously independently. In the world of mass media communication, media plays a role in spreading information and shaping public opinions. In the context of social networking service, opinions from leaders or users with a high number of social links are highly influential compared to traditional media. As introduced by [49], individual agendas have a significant correlation with leaders' agendas and are not dependent on media agendas. In this research, we consider highly centralized users to be the most influential among the network. Although this is not directly correlated with leaders' agendas, we can see there is a possible relation among them. In this research, we are only interested in how personality traits affect fake news dissemination, and addressing this issue will be an important point for future work.

7. Conclusion

In this research, we proposed an analysis of how the information in SNS are disseminated using the factor of trust, Big-Five personality traits and agent-based modeling. In the proposed trust model, Big-Five personality traits were used for characterizing the personality of SNS users. The trust model was formed by five types of trust; identity-based, behavior-based, relation-based, feedback factor, and information-based. In order to evaluate the proposed trust model, we developed an agent-based simulation, conducting simulation experiments for the information dissemination in SNS. The overall trust value is low when the information-based trust is neglected while it is high when the behavior-based trust is neglected. The overall trust value is positively correlated with the trust level of the users. The overall trust value is decreasing when the probability of malicious users sharing fake news is high, while it is also decreasing when the number of malicious user increasing. Openness, conscientiousness, and extroversion are the attributes of the overall trust being increased, while the agreeableness and neuroticism decrease the overall trust of users.

Finally, our study addresses a valuable insight into how information is disseminated throughout the social network, and how personality can affect the reception of fake news.The research explores how personality changes and user characteristics might affect the overall trust value within the context of trust evaluation mechanisms in SNS. This study offers valuable insights into how SNS providers should design trustworthiness evaluation mechanisms by considering various user aspects. Moreover, in coordination with regulators, SNS providers can design systems that limit the spread of fake news. However, it is important to note the limitations of our research. In understanding the nature of information diffusion, the future work will focus on contrasting the propagation rates of fake news and true news. The existing survey was conducted among a biased group, and the number of responses was relatively small. Therefore, there is a need for future work to conduct a survey that includes not only a large number of people but also a diverse range of individuals. Furthermore, this study is based on the topology of a scale-free network generated from the Barabási–Albert model, which may not fully capture the inherent realistic randomness trends within social networks. Therefore, future work should focus on directly capturing the dynamics of social networks through various fake news cases, including disasters-related cases. Additionally, addressing the dissemination of fake news remains a significant issue. In future research, we aim to develop a system that effectively controls the dissemination of misinformation.

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Publication List

Reviewed Journal

1. Muhammad, R. F., and Kasahara, S., “Agent-based Simulation of Fake News Dissemination: The Role of Trust Assessment and Big Five Personality Traits on News Spreading,” Social Network Analysis and Mining, vol. 14, article no. 75, 2024. doi:10.1007/s13278-024-01235-8

International Conferences

1. Muhammad, R. F., and Kasahara, S., “An Agent-Based Model for Social Networking Service Users in Exchanging Information,”2023 International Conference on Emerging Technologies for Communications (ICETC2023), P1-17, November 29, 2023. doi: 10.34385/proc.79.P1-17.

2. Muhammad, R. F., and Kasahara, S., “Agent-based Simulation Approach to Information Dissemination in Social Networking Service: The Impact of Big Five Personality Traits on User Trust,” 2022 International Conference on Emerging Technologies for Communications (ICETC2022), S3-2, November 29, 2022. doi: 10.34385/proc.72.S3-2.

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Domestic Conferences

1. Muhammad, R. F., and Kasahara, S., “The Role of Trust and Personality in Social Networking Services’ Information Dissemination,” IEICE 2nd Global Net Workshop, 2022.3.25.