Mitigating Risk in Web-Based Social Network Service Selection: Follow the Leader

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Abstract— **In the Service Web, a huge number of Web services compete to offer similar functionalities from distributed locations. Since no Web service is risk free, this paper aims to mitigate the risk in service selection using "Follow the Leader" principle as a new approach for risk-reducing strategy. First, we define the user credibility model based on the "Follow the Leader" principle in web-based social networks. Next we show how to evaluate the Web service credibility based on its trustworthiness and expertise. Finally, we present a dynamic selection model to select the best service with the perceived performance risk and customer risk-attitude considerations. To demonstrate the feasibility and effectiveness of the new "Follow the Leader" driven approach to alleviate the risk in service selection, we used a Social Network Analysis Studio (SNAS) to verify the validity of the proposed model. The empirical results incorporated in this paper, demonstrate that our approach is a significantly innovative approach as risk-reducing strategy in service selection.**

Keywords - Web service selection, credibility assessment, risk, web-based social networks, Follow the Leader.

I. INTRODUCTION

In the Service Web, Web services and Web-Based Social Networks will emerge to create an environment where users and applications can search and compose services in an automatic and seamless manner. The Service Web is expected to be a place where a huge number of Web services will compete to offer a wide range of similar functionalities. It is expected that Web services will fully leverage the Semantic Web to outsource part of their functionalities to other Web services [1]. In this case, some services may not have interacted before, while others may act maliciously to be selected. A key requirement is to provide trust mechanisms for quality access and retrieval of relevant Web services with perceived risk considerations.

In the Web service selection, reputation assessment mechanisms are used to establish trust between Web services. The notions of "trust" and "reputation" are both used to evaluate an entity's trustworthiness [2]. Recent research [3] shows that a good Web service reputation positively affects the consumer's trust and negatively affects the consumer's perceived risk. For example, consumers are hesitant to transact with a service provider who has a history of failing to honor its obligations, whereas it is relatively less risky to transact with a vendor who has a history of honoring its obligations.

Web service selection is a complex process where a service that best satisfies user preferences is selected from a set of candidate services based on user requirements [4] As per the selection criteria, various non-functional properties such as quality of service (QoS), can be used and expressed as user preferences. QoS such as response time, throughput, availability, reliability and privacy are difficult for the user to determine and control. Users are usually not willing to spend time describing their detailed preferences to the system. They are even less inclined to assign weights to them, especially if they do not have a clear understanding of the effects and results of this input. Moreover, users may not even be aware of their explicit preferences. Hence, risk-averse users who want to use Web services often seek help from their friends, peers, experts and business partners who may have relevant expertise or experiences.

In this paper, we propose a service selection approach based on a credibility framework that models user and Web service credibility with Web service perceived risk and user risk attitude. Our work is the first that uses a formal "Follow the Leader" model [5] based on web-based social networks and service credibility to mitigate risk in service selection using the most trustworthy and experienced users in the social network.

In order to simplify the paper, we will refer to customers / users as human users, and a Web service as an atomic service such as a home loan or a home insurance service. The proposed approach can be used as a module of Web services personalized recommender system where user behavior can be captured from his/her interactions in WBSN.

II. MOTIVATIONS AND CONTRIBUTATIONS

Decision making in risky complex situations has always been a very difficult task. Traditional decision models for Web service selection based on utility only are no longer adequate; service selection is more complicated with traditional approaches because the consumers may not even know with whom they are interacting.

To illustrate the challenges involved in Web service selection we provide the following example, which illustrates the key difficulties and at the same time motivates our approach.

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Motivating Example:

Bob just moved to the USA. By nature he is a risk-averse person. He is seeking an insurance company to insure his home. Bob lives in the same area as his friend Adam who has already taken out home insurance. This is Bob's first house, and he does not want to spend too much time on analyzing insurance features he would rather have the same insurance as his friend Adam. What if Bob did not know Adam? Can he get reasonable advice from somebody who lives in his area? If not, then he would have to embark on tedious and time consuming process of differentiating between the vast number of home insurance services in which all of them may match his request from a functionality perspective, but vary in their non-functional properties.

Using trust in social networks provides a promising approach to make recommendations to other users based on trust propagation in finding a friend or a friend of a friend with similar interests. However, even when the user relies on a trustworthy friend there is still an amount of perceived risk to be considered in adopting the Web service recommended. The quality of the selected Web service can be improved further by assessing its credibility by incorporating its trustworthiness and expertise at the same time. Our key contribution in this paper is threefold:

1. A user model with risk-attitude based on user credibility that captures trust relationships between users.
2. A Web service credibility metrics that incorporate trustworthiness, expertise and perceived risk.
3. A Web service selection approach based on the service credibility and Follow the Leader to mitigate the performance risk in service selection.

The rest of this paper is organized as follows: Section III presents a review of some related works. In Section IV we propose a credibility based framework, next in Section V we model perceived risk and risk attitude in Web service selection, followed by simulations. Finally, we conclude by summarizing our findings and future plans for further work.

III. RELATED WORK

In the following section, we present the synergies which are used in our framework.

A. Web-Based Social Networks and Trust

Web-based social networks (WBSNs) are online communities "people, organizations or other social entities" [6] connected by a set of social relationships, such as friendship, co-working or information exchange in varied contexts e.g., entertainment, religion, dating, or business.

Over the last few years, interest in social networking websites such as MySpace, Twitter and Facebook have increased considerably [7]. Hundreds of millions of people are members of social networks online and many of those networks contain trust data [8]. With access to this information, trust has the potential to improve the way recommendations are made and services are selected.

In WBSNs, the trust inference mechanism is becoming a critical issue when participants want to establish a new trust relation or measure trust values between connected users [9]. The idea is to search for trustworthy users by exploiting trust propagation [10] over the trust network.

B. Trust and Risk in Service Selection

Trust and risk are two tools for making decisions in uncertain environments [11]. In such environments, where the service consumer often has insufficient information about the service provider and the offered services, this forces the consumer to accept the risk of prior performance [12], i.e., to pay for services before receiving them, which can leave her in a vulnerable position. Trust comes into play as a solution for the specific problems of risk. Trust becomes the crucial strategy for dealing with an uncertain and uncontrollable future. So, trust is particularly relevant in conditions of ignorance or uncertainty with respect to the unknown actions of others.

There are only a few computational trust models that explicitly take risk into account. Studies that combine risk and trust include [13] and [11]. In PET, Liang and Shi [13] their conclusion highlights that risk is important in designing a personalized trust system.

Trust can be described as a positive state of mind caused by the perception that the risk resulting from collaborating with the trusted party is acceptable [14]. Trust systems enable parties to determine the trustworthiness of participating parties. Trust is relevant in situations where one must enter into risks but has incomplete control over the outcome, hence any act of trusting implies some bet and some risk [15]. A recent study [3] concludes that as trust increases, consumers are likely to perceive less risk than if trust were absent; i.e., the consumer's trust negatively affects the consumer's perceived risk of a Web service transaction.

C. Follow the Leader

As pointed out by social psychology theory [9], the role of a person in a specific domain has significant influences on trust evaluation if the person recommends a person or an object. Follow the leader in dynamic social networks [5], is a formal probabilistic model of opinion formation with dynamic confidence in agent-mediated social networks where the profiling of agents as leaders or followers is possible. An opinion leader is specified as a highly self-confident agent with strong opinions. According to [5], in a social network, a member is either a leader or a follower who adopted another leader's opinion to use a Web service. Subsequently this member adopts whatever her best friend adopted, otherwise the member has no active friends and consequently it acts as an independent user.

Ramirez-Cano and Pitt [16], define the relationship between two agents as a confidence function, such that: "an agent (i) increases its confidence in another agent (j) based on how well (j's) opinion meets the criteria specified in i's mind-set. A mind-set represents the set of beliefs, attitudes, assumptions and tendencies that predetermine the way an agent evaluates a received opinion".

IV. CREDIBILITY BASED FRAMEWORK

A. Web Based Social Network (WBSN) Interaction Model

In a WBSN, as shown in Fig. 1, let a set of users $\boldsymbol{U} = \{\boldsymbol{u_1}, \ldots, \boldsymbol{u_N}\}$ interacting in a set of contexts or domains $\boldsymbol{D} = \{\boldsymbol{d_1}, \ldots, \boldsymbol{d_L}\}$, such as categories in EPINIONS.com. In each domain there is a set of Web services (K), such that: $\boldsymbol{S} = \{\boldsymbol{S_1}, \ldots, \boldsymbol{S_K}\}, where\ \boldsymbol{S} \in \boldsymbol{D}$.

Each user *(u ∈ U)* rates a set of Web services M denoted by: $R_u^S = \{R_u^1, \ldots, R_u^i \ldots, R_u^M\}, where\ M \leq K$, and (R_u^i) is the rating value of user *u* for Web service S_i. The rating value can be any real number, but most often ratings are integers, e.g., in the range [1, 5].

In a trust-aware system, there is also a trust network amongst users. We define (T_u^v) to be the direct trust between user *u* and user *v*, trust value is a real number in the range [0, 1]: 0 means no trust and 1 mean full trust between users.

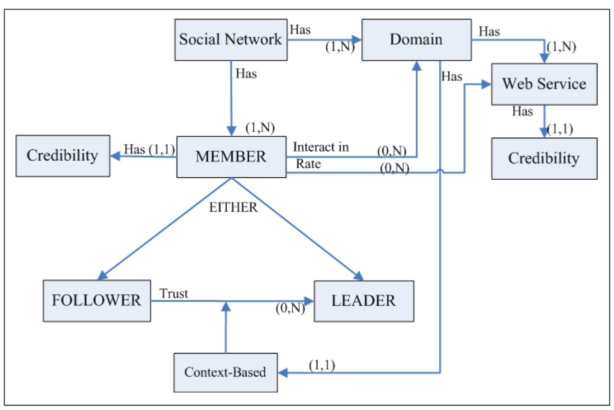

Figure 1. WBSN user interaction model

B. User Credibility Based Clustering - Follow the Leader

The "Follow the Leader" model [5], provides us with insights to identify users based on their roles in the WBSN i.e., either leaders or followers. Enriching the "Follow the Leader" model with trust, gives us the potential to analyze WBSN based on user's credibility. Fig. 1 shows the basis of our approach. User credibility measure reflects their trustworthiness and expertise and provides us with the means to identify users' roles in a specific context. Some users can be classified as leaders others can be classified as followers according to their credibility level.

User credibility is a synonym of believability [17]. Credibility of an agent can be measured by its trustworthiness, expertise, and dynamism [18]. The majority of researchers identify two key components of credibility: trustworthiness and expertise. In our previous work [19, 20] we derived a formula to express user credibility in a WBSN. This formula is expressed as:

$$\mathrm{Cr}(u) = \alpha * \mathrm{Cr}(R_u) + \beta 1 * \mathrm{Cr}(T_D^u) + \gamma * \mathrm{Cr}(T_I^u) \quad (1)$$

User credibility components consist of: (1) $\mathrm{Cr}(R_u)$ refer to user credibility expertise from user ratings component, (2) $\mathrm{Cr}(T_D^u)$ refer to user credibility trustworthiness from direct followers trust and (3) $\mathrm{Cr}(T_I^u)$ refer to user credibility trustworthiness from indirect followers trust, where $\alpha + \beta 1 + \gamma = 1$, and $\alpha, \beta 1, \gamma$ are system tuning parameters representing the importance of each credibility component. In our experiments, we use the values (5/9,3/9,1/9) respectively.

Credibility of Web service is a crucial part in service selection. In the following section we define Web service credibility and show how to compute it in a dynamic environment.

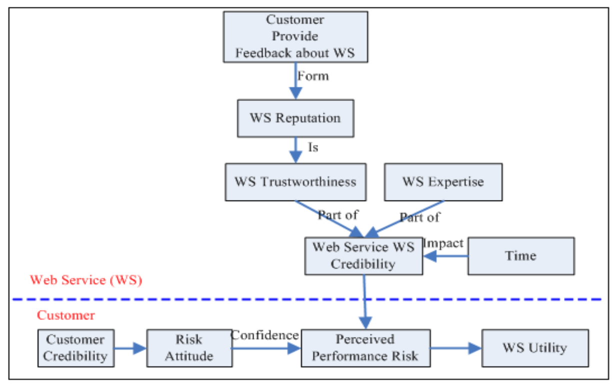

Figure 2. Web service Credibility Model

C. Web service Credibility Model

We define a credible Web service as a service that performed consistently, accurately, and has proven to be dependable over a period of time (t). Credibility of a Web service $\mathrm{Cr_t}(S)$ as shown in Fig. 2 can be measured by its trustworthiness $\mathrm{Cr_t}(T_S)$, expertise $\mathrm{Cr_t}(E_S)$ and dynamism [18]; so we address these components as follows:

1) Web service credibility from Trustworthiness

Trustworthiness is the property of an entity of being "able to be trusted", while trusting is "to have belief or confidence in the honesty, goodness, skill or safety of a person, organization or thing" [21]. Trustworthiness of a Web service is the property of being "worthy of confidence" and therefore related to past consistent reputation in specific context and time.

We define Web service trustworthiness $\mathrm{Cr_t}(T_S)$ as a measure of its reputation and is regarded as a predictor of its future behavior [1]. Reputation is what is generally said or believed about a person's or thing's character or standing [14]. It is a collective measure of the opinion of a community of users (humans or agents) regarding their actual experience with the service [22]. It is computed as an aggregation of users' feedbacks and reflects the reliability and trustworthiness of the service and its provider. Web service reputation is impacted by the following factors [23]:

1. Customer feedback: represents the extent of customer satisfaction from providers' performance based on the interaction with the Web service, and the opinion of the customer on the fulfillment of the service considering the agreement [22] between the user and the service provider.

2. Credibility of a rater: indicates how credible the rater is in providing feedback. Malik and Bouguettaya [24] define a credible rater as one who has performed consistently, accurately, and has proven to be useful (in terms of ratings provided) over a period of time. Ratings from highly credible raters weigh more than ratings from consumers with low credibility's.

3. Customer preference weight: each customer has a specific preference weight for each QoS attribute j denoted by W_i^j in the range [0,1]. Reputation of attribute j at time t denoted by $REP(S_t^j)$; is the weighted average of all feedbacks from all customers N who rated attribute j. For the (j^th) attribute, reputation in time (t) can be defined as:

$$REP(S_t^j) = \frac{\sum_{i=1}^{N} FEEDBACK(S_i^j) * Cr_i^j * W_i^j}{N^j * W_a^j * Cr_a^j} \quad (2)$$

where $FEEDBACK(S_i^j)$ is received about attribute j from the rater i in the range [0, 1] at time t, Cr_i^j is the rater i credibility in the range [0, 1]. For the (jth) attribute: N^j, W_a^j and Cr_a^j represent number of customers who rated attribute j, average of user preference weights and average raters' credibility respectively.

Web service Global Reputation is the aggregation of all attributes' reputation of the Web service, and defined as:

$$REP(S_t) = \frac{\sum_{j=1}^{n} REP(S_t^j) * W_a^j}{\sum_{j=1}^{n} W_a^j} \quad (3)$$

where n is the total number of Web service attributes and (t) is the time stamp. W_a^j is the average of user preference weights for the jth attribute. We model Web service credibility from Trustworthiness component $\mathrm{Cr_t}(T_S)$ as:

$$\mathrm{Cr_t}(T_S) = \frac{\sum_{j=1}^{n} REP(S_t^j) * W_a^j}{\sum_{j=1}^{n} W_a^j} \quad (4)$$

2) Web service Credibility from Expertise component

Expertise, a key dimension of Web service credibility is defined as the degree of a Web service competency to provide accurate results as promised and exhibit high activity [25]. The expertise dimension captures the perceived interoperability and skills of the Web service. QoS monitoring for Web services described in Zeng, Lei et al. [26] can be used as a reference model. We model Web service credibility drawn from its expertise component as:

$$\mathrm{Cr_t}(E_S) = \frac{\mathrm{N_t^S}}{\mathrm{N_{Max}^t}} * P_s^t \quad (5)$$

where ($\mathrm{N_t^S}$) refers to engagement frequency in a specific period t, and defined as the number of times the Web service was engaged in an execution process. ($\mathrm{N_{Max}^t}$) is the maximum service frequency in that domain; considered as a reference point. (P_s^t) is the performance of service [0, 1]; and computed as the aggregation of all QoS performance. Considering that a quality management system provides temporal information about each attribute performance (P_s^j), i.e., the extent of the service meet the SLA between the user and the provider for that attribute; then we define QoS attribute performance from one transaction P_s^j for the (jth) attribute as follows:

$$P_s^j = \begin{cases} 1 \ if \ Q_s^{jAdvertised} \le Q_s^{jPerceived} \ (Maximize\ attribute\ j) \\ 1 - \frac{|Q_s^{jAdvertised} - Q_s^{jPerceived}|}{Q_s^{jAdvertised}}, \ Maximize\ j\ Otherwise \\ 1 \ if \ Q_s^{jAdvertised} \ge Q_s^{jPerceived} \ (Minimize\ attribute\ j) \\ 1 - \frac{|Q_s^{jAdvertised} - Q_s^{jPerceived}|}{Q_s^{jPerceived}}, \ Minimize\ j\ Otherwise \end{cases} \quad (6)$$

where ($Q_s^{jAdvertised}, Q_s^{jPerceived}$) in the range [0, 1] and refer to the advertised and perceived quality values respectively. When the QoS attribute is maximized, means the higher value over the promised (advertised) value is the better, such as security. When the attribute is to be minimized, means the lower value below the promised (advertised) value is the better such as response time and duration. For example, if the advertised response time which needs to be minimized; is (0.8 ms) and the perceived response time is (0.95 ms), then the performance of the response time is (0.8125). While when the perceived response time is (0.75 ms), then the performance of the response time is (1).

Taking the average performance of each attribute from its (N) previous performances as:

$$P_{s,t}^{jAvg} = \frac{\sum_{\mathrm{j=1}}^{\mathrm{N}} P_s^j}{\mathrm{N_t^S}} \quad (7)$$

Then over-all performance of the service is the weighted mean of all attributes, formally given by:

$$P_{s,t}^t = \frac{\sum_{t,j=1}^{n} P_s^{jAvg} * W_a^j}{\sum_{t,j=1}^{n} W_a^j} \quad (8)$$

where (n) is number of QoS attributes, (W_a^j) is the average preference weight of all users for the jth attribute for all services in that domain over time t.

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Using equations (7, 8) in equation (5) this yields expertise credibility at any point of time as:

$$\mathrm{Cr_t}(E_S) = \frac{\mathrm{N_t^S}}{\mathrm{N_{Max}^t}} * \frac{\sum_{t,j=1}^{n} P_s^{jAvg} * W_a^j}{\sum_{t,j=1}^{n} W_a^j} \quad (9)$$

3) *Computing Web service Credibility*

Web service credibility is computed by aggregating the credibility components: trustworthiness component from reputation and expertise credibility component; hence Web service credibility at current time (t) is given by:

$$\mathrm{Cr_t}(S) = \beta * \mathrm{Cr_t}(T_S) + (1 - \beta) * \mathrm{Cr_t}(E_S) \quad (10)$$

where β in the range $[0, 1]$, represents the importance of each credibility component. For example; when ($\beta < 0.5$) the system relies on trustworthiness less than expertise credibility component.

4) *Credibility Decay*

In Web service selection; recent credibility components: trustworthiness and expertise attract more importance than old ones; considering the decay factor $f_d(t)$ to control this impact; credibility of service (s) can be defined as:

$$\mathrm{Cr(s)} = \frac{\sum_{t=t1}^{t2} \mathrm{Cr_t} * f_d(t)}{\sum_{t=t1}^{t2} f_d(t)} \quad (11)$$

where $f_d(t) = e^{-\lambda 1(t2-t1)}$, and λ1 in the range [0, 1], (t2 – t1) is the time interval difference between the present time and the time in which the credibility data were collected.

V. Perceived Risk And Risk Attitude In Web Service Selection

Since no Web service is risk free, there is always some degree of risk or uncertainty associated with Web service selection decisions. In the following section we explore the perceived risk of Web service performance and show how customers have varied risk attitudes towards handling the perceived risk.

A. *Perceived Performance Risk in Web service selection*

During Web service selection consumers often act on information that is incomplete and far from perfect [3]. As a result, they are often faced with some degree of risk or uncertainty in their selection decisions. Kim, Ferrin et al. [3] formally define perceived risk as a consumer's belief about the potential uncertain negative outcomes from the online transaction. Featherman and Pavlou [27] view perceived risk as "a combination of uncertainty plus seriousness of outcome involved". Perceived risk is commonly viewed as uncertainty regarding possible negative consequences of using a Web service.

In Web service selection, perceived risk has different dimensions such as reliability, availability, response time, security and privacy; we refer to these dimensions as performance risk. When the service provider does not respect the SLA in any of advertised QoS attributes the Web service performance suffers from such behavior; which in turn increases the severity of the associated risk. For example, when a consumer submits credit card information through a transaction she can feel the threat of the possibility of credit card fraud or even disclosure of consumer information to non-authorized people when the security or privacy performance is low or unknown.

In this paper, we follow [28] and define perceived Performance Risk (PR) in [0,1] as: Consumer assessment of potential performance problems, malfunctioning, transaction processing errors, reliability and/or security problems, that cause the Web service not perform as expected.

B. *Risk Attitude and Perceived Risk*

Risk attitude represents how willing the customer is to take on the perceived risk which is largely dependent on the character of an individual [21] and their position, e.g., financial position or their role such as followers or leaders. Different factors affect risk attitude such as personality type, gender, age, culture, etc. Furthermore, we believe that risk attitude is context based; for example, a customer can use a Web service without any monetary transaction or even a cheap service with a high attitude to accept the risk, while when using a monetary Web service with payment she would usually have different trade-offs between utility and perceived risk in making her decision.

Consumer risk attitude determines the courses of action to be followed. Consumers who are cautious by nature may avoid risky situations and fail to capture opportunities as a consequence. Since all decisions have an element of uncertainty about them, all decision-makers are risk takers [29]. The degree to which decision-makers enjoy taking risk depends upon individual attitudes.

The risk attitude of the customer plays a vital role in selecting the most attractive choice. However, in Web service selection users may have different risk attitudes; the risk attitude (RA) of a customer is given by a real number in [0, 1]. Customers with risk attitude 0 are the most risk-averse customers, while customers with risk attitude being 1 are the most risk-seeking customers.

C. *Perceived Risk from Risk Attitude Perspective*

Risk evaluation involves the consumer determining the possibility of the failure of the interaction with the Web service and the subsequent possible consequences for their resources involved in the interaction. In general, it is accepted that the higher the perceived risk the lower the likelihood of the transaction. We believe that credibility, perceived risk and expected utility of the Web service from risk-averse customer perspective are related according to the following the axioms:

1. When WS credibility goes to zero, perceived risk goes to one consequently utility goes to zero.

2. When WS credibility increases, perceived risk decreases and consequently utility increases.
3. When WS credibility goes to one, perceived risk approaches zero, consequently utility goes to the maximum value depending on the customer risk attitude [0, 1].

To model the relation between service credibility, perceived risk and risk attitude, we propose the following formula that satisfies the above axioms:

$$\mathrm{PR}(s) = \mathrm{e}^{-\mu \mathrm{Cr}} \quad (12)$$

where μ is customer risk attitude coefficient in the range [1, 5] and given by $\mu = 4RA + 1$. For a risk-averse customer with risk attitude RA = 0, $\mu = 1$; while for a risk-seeker with RA = 1, $\mu = 5$.

In [30], Sitkin and Weingart (1995) argue that the higher the perceived risk, the greater the perceived chance of experiencing a loss, therefore, the lower the consumer's expected utility from the transaction. Thus we can model the relation between perceived performance risks (PR) from a Web service (S), and associated utility U(s) as:

$$\mathrm{PR}(s) + \mathrm{U}(s) = 1 \quad (13)$$

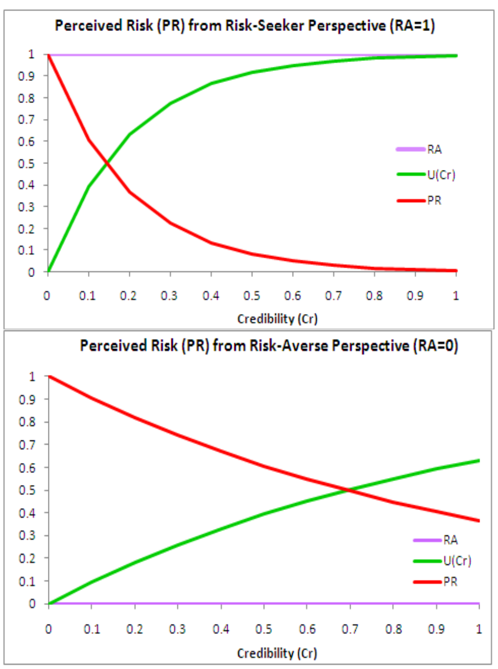

Figure 3. Perceived Risk variation with Different risk attitudes

Fig. 3 shows how the perceived risk (PR) related to the credibility and varies with risk attitude (RA) for the following cases: (1) RA = 1 for risk seeker, (2) RA= 0 for risk-averse customer. From the above formula we conclude that risk-seeker customers gain more utility than risk-averse customers as shown in Fig. 3, consequently risk-averse customers perceive more risk than risk-seeker customers.

In summary, we believe that the perceived risk is a reflection of user risk attitude i.e., how much risk is the customer ready to take as shown in Fig. 3. For example, if the credibility of the service = 0.7, then from a risk-averse customer perspective with risk attitude = 0 the perceived risk is 0.5, while from a risk-seeking customer perspective with risk attitude = 1 the perceived risk is 0.03.

VI. Service Selection with Risk Attitude and Perceived Risk

Customer self confidence assessment is the final determinant in the selection decision process. We argue that customer risk attitude enrich customer confidence-when customer risk attitude increases then customer confidence increases and when customer risk attitude decreases the customer's confidence decreases. The following scenarios describe different customers' behavior in service selection:

1. Risk-seekers customers (Leaders): select the service that maximizes their utility based on Web service credibility and accepting the perceived risk; they usually select the service with the highest credibility score when the perceived risk is within the customer risk attitude. Risk-seeking customers may adopt new services that have never been used before, or they can use a service that they know the perceived risk is high because they have a high risk attitude and choose to accept the perceived risk in order to gain higher utility.
2. Risk-averse customers (Followers): benefit from their social relations and their trust in others, they usually prefer to use a service even if it is expensive it was used by other friends with a proven successful performance. Risk-averse customers usually like to avoid risky situations; they prefer to mitigate the risk by following other trustworthy advice from leaders or other friends than acting themselves.
3. Risk-neutral customers make their decisions based on their risk attitude and the perceived risk from a Web services in hand. They make their decision either to follow other friends to mitigate a high perceived risk or acting as independents if they are confident that they can accept the perceived risk from the transaction.

VII. Simulation And Evaluation

To demonstrate the feasibility and effectiveness of "Follow the Leader" as a new approach to alleviate the risk in service selection, first we developed a Social Network Analysis Studio (SNAS) using NetLogo platform [31] that analyze user and Web service behaviors in a social network based on our simulation tool "4S: Service Selection Simulation Studio" [32] inspired by Goldbaum (2008). User interface is shown in Fig. 4. We use it to evaluate the validity of our approach. In the following sections we outline the testing environment and outcomes.

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A. Simulation Model

Our simulation model is composed of a fixed number of atomic services (9) with the same functional properties and varied in their QoS attributes. Each atomic service maintains a list of QoS attributes and promised values, where QoS is static during any simulation session. Web service credibility is dynamic and computed after each round.

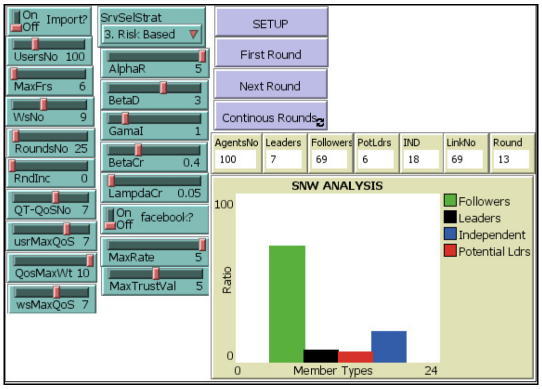

Figure 4. SNA Simulation Tool – User Interface

Each simulation session is composed of a fixed set of rounds (25). Each round represents a time unit e.g., one day. In each round a fixed number of customers (100) enter his/her queries into the system. Each customer has a varied list of preferences and corresponding values and weights. Each customer has a random number of friends (1-6) with corresponding trust values. By the end of each transaction, the system implements credibility computation based on service performance. Each service has an initial credibility at the beginning of each session based on its capabilities.

Each simulation session starts by importing the services and setting customers with their corresponding information. In each round every customer passes its query to the system. The system identifies leaders based on their credibility level and expressive queries. If the customer qualifies as a leader, then the system enables the leader selecting the best service from available services based on the expected utility. If the customer acts as a follower, then the system either: (1) Selects the best friend with highest credibility from the customer's friends, i.e., the confidence in that friend is higher than the confidence in herself, or (2) Allows the customer to act as independent if the confidence in herself is higher than any of her friends. By the end of each round, each customer provides a feedback to the system about their satisfaction from the service; this feedback is used to derive service reputation which has impact on service credibility.

B. Simulation Results

To test the hypothesis that using the "Follow the Leader" approach is an applicable approach to mitigate the perceived risk in the service selection we perform the following experiments:

1. Impact of Trustworthiness and Expertise on WS Credibility: in this experiment we show how Web service credibility varies with Trustworthiness and Expertise credibility components over time. Fig. 5 shows how credibility components Trustworthiness CR(T) and Expertise CR(E) vary with time, with importance weight ($\beta = 0.4$) for CR(T) and ($1 - \beta = 0.6$) for CR(E) to give CR(Global) for each round.

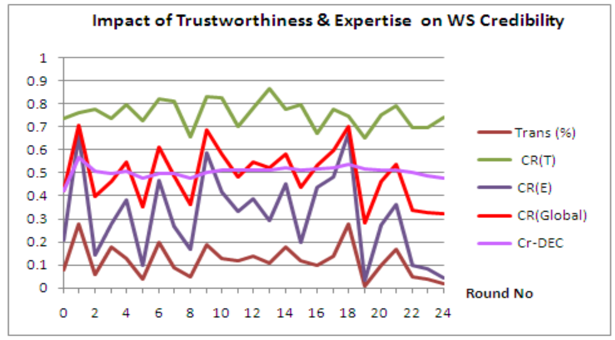

Figure 5. Impact of Trustworthiness and Expertise on WS Credibility on WS (S04

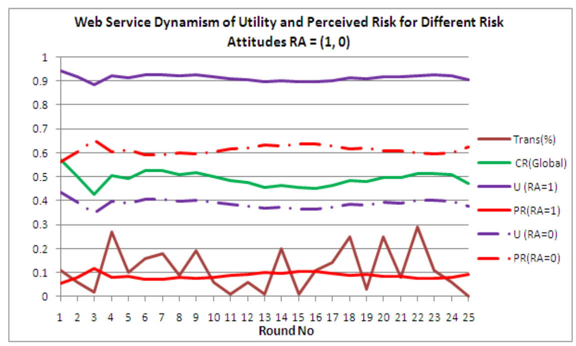

Figure 6. Dynamism of utility and Perceived Risk for Different Risk Attitudes RA = (1, 0)

2. Utility based Credibility vs. Perceived Risk for Different Customers Risk Attitudes RA = (1, 0.5, 0); in this experiment we show how different customers with varied risk attitudes perceive the risk PR from 9 services. In Fig. 6, WS=1 shows the highest credibility (0.73). From a risk-seeker perspective with RA = 1, the perceived risk PR is the lowest (0.026) with the highest utility (0.974); while from a risk-averse perspective with RA = 0, the perceived risk PR is the highest (0.481) with the lowest utility (0.519). This emphasizes the relationship between utility and perceived risk as (U + PR = 1), from any customer perspective (i.e., when the utility increases the perceived risk decreases) and vice versa.
3. Dynamism of Utility and Perceived Risk for Different Risk Attitudes RA = (1,0); Fig. 6 shows how credibility and corresponding utility of Web service varies with time from a customer varied perspective (i.e., with risk

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attitude as risk-seeker RA=1 and risk averse customer with risk attitude RA=0).

4. Malicious Web service behavior – (Facebook' Privacy Scenario): In this experiment we simulate malicious service behavior after its approved credibility over a specific period of time (first 11 rounds) then acts maliciously by performing inadequately with one of its QoS such as privacy issue [33] for Facebook users. Fig. 7 shows how the service behaves consistently in the first 11 rounds with the highest credibility overall other services, but when one attribute of its QoS suffers, then associated credibility suffers as well. By calculating the impact of this change, we note that Round Credibility (RND-CR) decreased from an average of (0.59) in the first 11 rounds to an average of (0.35) in the rest of simulation rounds, with overall loss in its credibility of (39%). These figures reflect the sensitivity of the model against malicious behavior of Web service.

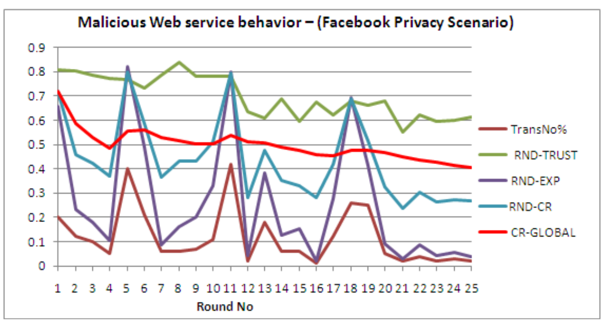

Figure 7. Malicious WS behavior: (Facebook' Privacy Scenario)

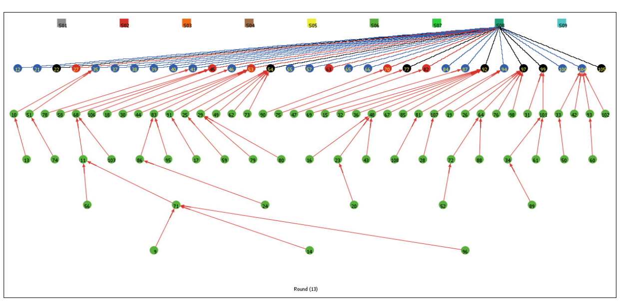

Figure 8. Service Selection based on customer Risk attitude and Service credibility –Follow the Leader Model

5. In Web service selection with risk considerations as shown in Fig. 8, Leaders (Black and Red agents) make their selection choice based on their risk attitude and Web service utility. Since leaders risk attitudes are high, they select the service with the highest credibility, whereas for customers with low risk attitude they make their decision based on the confidence that one of their friends selected a high utility service to follow (Green agent). If their confidence in themselves is higher than any of their friends then they take the risk and act as independent (Blue agents). Consequently they select their best service based on service credibility.

C. Results Summary

We summarize our observations from the previous experiments as follows:

1. In a Web based social network (WBSN), customer credibility is the determinant of its behavior. Credibility of a customer in a specific domain/context is the predictor of her risk attitude. Usually customers with high credibility act as leaders, while customers with lowest credibility act as followers.
2. Web service credibility is the determinant of its behavior; different services in a specific domain have same functionalities and vary in their QoS attributes. Each service has its unique credibility computed based on trustworthiness and expertise. Trustworthiness component is drawn from its reputation while its expertise represents to what extent the service provides promised QoS according to the SLA.
3. Proposed Web service credibility model shows its sensitivity to Trustworthiness and expertise. Web service Credibility drops significantly when one or more of its QoS attributes behave maliciously.
4. Proposed Web service selection based on risk attitude approach is an efficient approach to alleviate the risk of Web service selection for customers with low risk attitudes i.e., followers. This approach explores the confidence relation between the follower and her friends which is a function of customer credibility.

VIII. Conclusions And Future Works

In this paper, we proposed a centralized credibility based framework for users in WBSN and for Web services in a specific domain which are similar in their functionality but vary in their QoS. Credibility in both models is drawn from trustworthiness and expertise components of users and Web services. Users' credibility is an indicator of their risk attitude and self confidence; while service credibility is an indicator of its consumption.

We showed how risk-averse customers make their decisions in Web service selection and follow the best trustworthy friend in their social network; in order to reduce the perceived risk from the available choice based on "Follow the Leader" approach.

We proved the feasibility of our proposed framework in providing accurate Web service selection through simulation. The results of the experiments included in this paper show the applicability and scalability of the proposed credibility assessment based on "Follow the Leader" Model to mitigate the risk in service selection. We have shown how different users with varied risk attitudes make their decisions in the Web service selection process with the perceived performance risk and utility considerations.

Although we handle the risk for followers with low risk attitude in the service selection by following one of their best friends who selected a service that increase the follower utility, considering the confidence relation as the determinant to which is the best friend to follow, notably the omission of social influences between WBSN members is a limitation which will be explored in a future study.

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