Social Networks: Service Selection and Recommendation

Jebrin Al-Sharawneh

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Abstract

The Service-Oriented Computing paradigm is widely acknowledged for its potential to revolutionize the world of computing through the utilization of Web services. It is expected that Web services will fully leverage the Semantic Web to outsource some of their functionalities to other Web services that provide value-added services, and by integrating the business logic of Web services in the form of business to business and business to consumer e-commerce applications.

In the Service Web, Web services and Web-Based Social Networks are emerging in which a wide range of similar functionalities are expected to be offered by a vast number of Web services, and applications can search and compose services according to users' needs in a seamless and an automatic fashion. Web services are expected to outsource some of their functionalities to other Web services. In such situations, some services may be new to the service market, and some may act maliciously in order to be selected. A key requirement is to provide mechanisms for quality selection and recommendation of relevant Web services with perceived risk considerations.

Although the future of Web service selection and recommendation looks promising, there are challenging issues related to user knowledge and behavior, as well as issues related to recommendation approaches. This dissertation addresses the demanding issues in Web service selection and recommendation from theory and practice perspectives. These challenges include cold-start users, who represent more than 50% of the social network population, the capture of users' preferences, risk mitigation in service selection, customers' privacy and application scalability.

This dissertation proposes a novel approach to automate social-based Web service selection and recommendation in a dynamic environment. It utilizes Web-Based Social Networks and the "Follow the Leader" strategy, for a Credibility-based framework that includes two credibility models: the user Credibility model which is used to qualify consumers as either leaders or followers based on their credibility, and the service Credibility model which is used to identify the best services that act as market leaders.

Experimental evaluation results demonstrate that the social network service selection and recommendation approach utilizing the credibility-based framework and “Follow the Leader” strategy provides an efficient, effective and scalable provision of credible services, especially for cold-start users. The research results take a further step towards developing a social-based automated and dynamically adaptive Web service selection and recommendation system in the future.

Certificate of Authorship/Originality

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Jebrin Al-Sharawneh

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To the souls of my parents
who taught me to love learning

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List of Abbreviations

ABMS	Agent-based Modeling and Simulation
B2B	Business-to-Business
B2C	Business-to-Consumer
BPEL4WS	Business Process Execution Language for Web Services
CF	Collaborative Filtering
HITS	Hyperlink-Induced Topic Search
IOPE	Input, Output, Post-conditions and Effects
MAE	Mean Absolute Error
OWL	Web Ontology Language
P2P	Peer to Peer
QoS	Quality of Service
QoWS	Quality of Web Service
RDF	Resource Description Framework
RS	Recommender System
SLA	Service Level Agreement
SNA	Social Network Analysis
SNAS	Social Network Analysis Studio
SOA	Service Oriented Architecture
SOAP	Simple Object Access Protocol
SOC	Service Oriented Computing
SSSRM	Social-based Service Selection and Recommendation Model
SWS	Semantic Web Services
TECBF	Trustworthiness Expertise Credibility-Based Framework
UCrM	User Credibility Model
UDDI	Universal Description, Discovery and Integration
UDK	User Domain Knowledge
URI	Uniform Resource Identifier

W3C	World Wide Web Consortium
WBSN	Web-based Social Network
WS	Web Service
WSCrM	Web Service Credibility Model
WSDL	Web Service Description Language
WS-Policy	Web Services Policy Framework
XML	Extensible Markup Language

Chapter 1

Introduction

Service Oriented Computing (SOC) has emerged in recent years as a powerful paradigm for assembling complex Web applications from distributed simpler application components known as services [178, 208]. In the Service Web, Web services and Web-Based Social Networks (WBSN) are emerging in which applications can search and compose services according to users' needs in a seamless and an automatic fashion [148]. In the Service Web, a wide range of similar functionalities are expected to be offered by a vast number of Web services. Web services are expected to outsource some of their functionalities to other Web services [148]. In such situations, some services may be new to the service market, and some services may perform maliciously in order to be selected. Thus, to ensure high quality selection and retrieval of suitable Web services, it is essential to provide mechanisms to guarantee the trustworthiness of the selected service.

Semantic Web Services (SWS), as pointed out by Berners-Lee, Hendler and Lassila [20], extend Web services with an explicit representation of meanings using ontological structures and formal reasoning mechanisms. SWS provide advanced facilities for the automated discovery, selection, composition, contracting, and execution of dynamic Web services. SWS provide advanced facilities for automated discovery, selection, composition, contracting, and execution of dynamic Web services. Although Web services' main motivation is their interoperability, the 'automation of information use and dynamic interoperability are the objectives of the Semantic Web and Semantic Web Services' [153].

Web service selection is a complex process, whereby the best service that matches user preferences is selected from a set of candidate services usually provided by a service discovery process based on user requirements [215]. Users usually express their selection criteria in terms of a range of quality of service (QoS) attributes or non-functional properties such as service level agreement (SLA).

The non-functional properties of Web services such as availability, response time, security, privacy and reliability are difficult for the user to determine and control. According to Cantador and Castells [33], some users are usually reluctant to spend time expressing their detailed preferences to the recommender system. They are even less inclined to assign relative weights to each preference, especially when the effects the consequences of their input are unknown. Moreover, users may not even be aware of their implicit preferences. Consequently, a customer who wants to find a Web service often seeks help from friends, peers, experts and business partners who have relevant experiences. Capturing and specifying user preferences are among the most complex problems in the Web service selection process.

Web-Based Social Networks (WBSN) analysis has been subjected to increased attention in recent years. There are hundreds of WBSN consisting of hundreds of millions of members [69], and in many WBSN, members are allowed to express their trust in other members; consequently, members' social contexts can be recognized [67]. Identifying leaders in large scale WBSN is a difficult and important issue. The leaders in a social network are the most credible advisers for the rest of the population in the social network.

In the last few years, most service provision research work focused on service discovery techniques based on the functional requirements of Input, Output, Post-conditions and Effects (IOPE) and service invocation [74]. Another line of research has focused on Web service composition challenges. However, there is less research work that directly aims to tackle the Web service selection problem, and even less that considers Web service recommendation based on web-based social networks. Therefore, Web service selection and recommendation becomes a crucial issue in addressing the need to provide users with a credible service that is most likely fulfill their requirements.

Web service selection is one step beyond discovery. However, there are many research challenges ahead in the drive to achieve social-based automatic service selection and recommendation. Innovative methods to automate service selection and recommendation based on users' behaviors in social-based networks are therefore needed.

In this chapter, I explain what initiated my interest in the subject and identify related technologies. I also specify research problems under consideration, describe my method and contribution, and present the organization of the dissertation.

1.1. Motivations

This research has been motivated by the needs of everyday people making decisions about available choices from Web services. Decision-making in risky, complex and dynamic situations has always been a difficult task. Traditional decision models for Web service selection based on utility only are no longer adequate; Web service selection is increasingly more complicated than traditional approaches allow because consumers may not even know with whom they are interacting.

To illustrate the challenges involved in Web service selection and recommendation, I provide the following examples, which illustrate the key difficulties and, at the same time, the motivation behind my approach.

1.1.1. Scenario 1

Bob has just moved to Australia. Once he is settled, Bob decides to buy his first home and resolves to apply for a home loan. He works for the same company as his friend Adam who has already taken out a home loan. Additionally, Bob plans to undergo cataract surgery which places him in the same situation as his colleague Mary. This is the first time Bob has bought a house; he does not want to spend too much time analyzing home loan features and would like to have a similar home loan to that of his friend Adam. Furthermore, he prefers to seek Mary's recommendation for a skilful surgeon to carry out his cataract surgery.

Adam’s preferences in obtaining a home loan differ from Mary’s preferences regarding undergoing cataract surgery. These two sets of preferences in different contexts (home loan and cataract surgery) meet Bob’s needs.

What if Bob did not know Adam or Mary? Could he obtain reasonable advice from somebody who has expertise and knowledge in these issues? If not, he would need to embark on a tedious and time consuming process to differentiate between a vast number of home loan Web services which may match his request from a functionality perspective, but which may vary in quality and include non-functional properties.

Bob may need to consider the following preferences for the deemed home-loan: (1) Functional Preferences such as loan term, interest rate, redraw facility, establishment fee, application fee, legal fee, settlement fee and monthly service fees. (2) Non-Functional

Preferences (QoS), such as trust, reputation, security, reliability, privacy and response time.

1.1.2. Scenario 2

Jack has just moved to the USA. By nature, he is a risk-averse person. He is seeking an insurance company to insure his home. Jack lives in the same area as his friend Alice who has already taken out home insurance. This is Jack's first home, and he does not have time to spend on understanding and analyzing insurance features from a large number of insurance services; he would rather explore and be guided by the insurance option selected by his friend Alice. What if Jack did not know Alice? Could he get feasible advice from somebody who lives in his area? If not, he would have to go in a time consuming and a tedious process of making distinctions between a huge number of home insurance services which may match his needs from a functionality perspective, but which may vary in their qualities.

Jack can be either able to find a home insurance service or not; if Jack finally gets a suitable home insurance that satisfies his needs, to what extent does that service is trustworthy to be used? Even after its usage, to what extent does he receive the promised qualities? If Jack is aware about his information privacy and lately he found his personal information was revealed to other advertising companies, then he would be in a bad situation that leads to user late dissatisfaction.

On the other hand, if Jack was not able to make his mind to select a home insurance service, is there any possible approach to help Jack to find a home insurance service that match his needs?

Using trust in social networks provides a promising approach for making recommendations to other users based on trust propagation in finding a friend, or a friend of a friend, with similar interests. However, some users do not have friends with experience in the deemed issue. Furthermore, even when the user relies on a trustworthy friend, there is still an amount of perceived risk to be considered in adopting the recommended Web service. The quality of the selected Web service can be improved by assessing its credibility based on incorporating its trustworthiness and expertise at the same time. In this dissertation, I demonstrate that seeking advice from a trustworthy expert is more feasible and practical than seeking advice from a normal trustworthy user.

1.2. Problem Scope and Definition

Social-based Web service selection is a challenging problem in theory and practice. Utilizing trust in Web-Based Social Networks (WBSNs) provides a promising approach for making recommendations to other users sharing similar interests. Nevertheless, the quality of recommendations can be improved by incorporating users' expertise in the recommender, because trusted expert advice will lead to better recommendations. Current recommendation approaches cannot make reasonable recommendations for cold-start users, who represent more than 50% [157] of the population in most social networks, and they cannot not specify their needs precisely. Hence, seeking advice from a trustworthy expert is more feasible than seeking advice from an ordinary trustworthy user which leads to the question: how do we find trustworthy experts in the WBSN?

Cold-Start users

Cold-start users are one of the most important challenges in recommender systems; they also represent the largest user group. A cold-start user is described as a new user who has joined the recommender system and has provided only a few, or no ratings; in this case the recommender system is unable to generate good quality recommendations [154]. Since the cold-start user has provided only a limited number of ratings or failed to provide any ratings at all, similarity-based approaches are unable to find similar users sharing their interests. However, social network-based trust recommenders, can provide recommendations if the new user is linked to large number of users in the social network [90].

Formally, the problem addressed in this dissertation can be stated as: given a new user in the social network who has just registered with the system, he/she does not have any previous interaction opportunities from which his/her preferences and interests can be captured. Such customers are called "Cold-Start" users. The problem is: how to recommend to them the best Web service that matches their needs?

In the previous discussion, I have highlighted that traditional service selection cannot solve such problems. Several approaches targeting different domains seek to address this problem, such as:

1. Service selection approaches based on QoS: these approaches are effective for Web service selection using utility computations. Some users are usually reluctant to spend time expressing their detailed preferences to the system [33]. They are even

less inclined to assign relative weights to each preference, especially when the effects and consequences of their inputs are unknown. Moreover, users may not even be aware of their implicit preferences.

2. Service recommendations: trust propagation or inference algorithms as indicated by Golbeck [67] are effective at predicting trust and for improving recommendations, when there are paths in the social network connecting members, and the trust values on those paths are available. On the other hand, inference algorithms are inapplicable in many cases when trust values or links are not available.
3. Reputation-based service selection: this approach discovers misbehaving Web service providers, reports them, and maintains a set of metrics reflecting the past behaviors of other Web service providers in the network. According to Klein *et al.* [105], 52.1% of eBay[1] buyers comment on sellers. Ratings left by buyers are positive in 98.1% of cases. From this ratio, we can conclude that 47.9% of buyers either fear revenge or do not bother to give a seller rating. Thus, the insufficiency in ratings availability impacts the reputation system's accuracy [148].

These incentives solve part of the problem under specific conditions, but not all of them. The goal of trust and reputation systems is to enable users to make decisions about the best Web service to select within other sets of constraints.

For the Web service selection and recommendation problem in a dynamic environment, and based on the above discussion, the following questions framed this research:

- How can users searching for a service be identified, based on their service domain knowledge and behavior in a social network?
- How do users build their credibility to be promoted as network leaders in a specific domain? How are domain leaders that act as advisers for other users identified?
- How do service providers build their credibility to be promoted as market leaders in a specific domain? How can Web service provider leaders be identified?
- How can a Web service be recommended to a cold-start user or risk-averse customer?

[1] http://www.ebay.com/

- What sort of risks is associated with a selected Web service? How can these risks be alleviated?
- How can the proposed approach be utilized in the industry?

These questions are important, but they are difficult, if not impossible, to answer using the existing Web service selection and recommendation approaches.

1.2.1. Scope Limitations and Assumptions

The focus of this dissertation is to provide mechanisms, models, and algorithms to facilitate the augmentation of user requirements and preferences with semantic Web service selection and recommendation. I also consider how to address related issues associated with Web service selection and recommendation, such as privacy and scalability, from a practice-based perspective.

To ensure the focus on the outlined research questions, I provide the following assumptions to give a clear view about the context of this research. Some of these assumptions may already have efficient solutions, while some are under active investigation by others. Some of these assumptions may not be realistic at the moment, but they have already been targeted as future research focuses because of the expected growth in Web services technologies.

- Web services are "autonomous, platform-independent entities that can be described, published, discovered, and loosely coupled in novel ways" [177]. They are business modules, self-contained, self-describing and stateless; they accept one or more requests and return one or more responses through a well-defined, standard interface.
- "Users" in this dissertation refers to either human customers or software agents that interact in the WBSN and are able to perform required interactions.
- Web services use the Internet as a communication medium and open Internet-based standards, including the Web Services Description Language (WSDL) for defining services, the Simple Object Access Protocol (SOAP) for transmitting data and the Business Process Execution Language for Web Services (BPEL4WS) for orchestrating services [177].
- Non-functional property descriptions for all Web services are available using Web Ontology Language for Services (OWL-S) [153].

- Services are registered in a centralized repository such as the Universal Description, Discovery, and Integration (UDDI)[2] directory, which is used to register Web services descriptions, and categorize them by functional keywords.
- Web service discovery is a simple process such as keyword-based or ontology-based discovery focused on functional properties. In this dissertation, Web service selection is considered a step beyond service discovery; hence, I assume a suitable discovery mechanism to be in place using the methods of Klusch, Fries and Sycara [108], for example, or the discovery approach described in Sivashanmugam *et al.* [206].
- Service composition refers to instantiating abstract workflows, which is the next stage after selection. The service composition workflows are predefined using an orchestration language such as Business Process Execution Language for Web Services (BPEL4WS) for orchestrating services [177].

1.3. Significance

Service Web and Semantic Web Services (SWS) are widely acknowledged for their potential to revolutionize the world of computing, and to change the way knowledge and business services are provided and consumed on the Web [31, 209]. Cardoso [34] indicated that SWS promise to increase the level of automation and have the ability to integrate Semantic Web meaningful content with Web services business logic. SWS thus enables individuals and industries to communicate in an environment where various business activities are performed and value-added services are provided.

My contribution to this research is to facilitate the augmentation of Web-based social networks with semantic Web service selection and recommendation, particularly for cold-start users or risk-averse customers. Providing an automatic selection and recommendation mechanism of Web services will have a significant impact not only on end users, but also on the integration of Web services from an industrial perspective.

Cold-start users as indicated previously; are one of the most important challenges in recommender systems; they represent the largest user group. Due to the lack of cold-start user information that used to find similar users sharing their interests using similarity computations, similarity-based approaches fail to find such users.

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[2] www.uddi.org

Web service recommendation differs from product recommendation in that Web services have non-functional properties or QoS attributes that must be considered in addition to functional attributes. Although many works discuss Web service recommendation, to the best of my knowledge there are currently no such systems available. Therefore, one aim of this dissertation is to bridge the gap between theory and practice by evaluating the applicability of the proposed Web service selection and recommendation approach.

The significance of this research is drawn from the fact that current recommender approaches cannot satisfy cold-start and risk-averse users' needs. According to the literature, cold-start users constitute a significant percentage of the user population. According to Massa and Bhattacharjee [157], cold-start users are defined as users who have provided less than five reviews. Cold-start users represent 52.82% of the population in the network. Users who do not have friends represent 31.30% of the population, *i.e.*, nobody expresses trust in them, and the percentage of users with two friends or less represents 59.70% of the population.

Golbeck [67] uses trust values between users to make recommendations, indicating that trust inference algorithms are inapplicable in many cases, particularly when trust values or paths between members are not available. In Golbeck's FilmTrust system, more than 58% of users do not have friends; furthermore, more than 60% of the users are connected only via small clusters. Consequently, network-based trust algorithms are not effective for the majority of users, and users' privacy is always a concern.

Thus, users without friends or risk-averse users cannot receive proper recommendations about the deemed Web service because such users often tend to avoid the burden of explicitly stating their preferences and either leave the system, or rely upon "free-riding" [252].

According to the above mentioned facts, current approaches are not able to provide Web service recommendations or feasible solutions for cold-start users or risk-averse customers, who represent more than half of the population. In this dissertation, I provide an innovative approach to address these issues based on the "Follow the Leader" strategy. The significance of the proposed approach is reflected in the following:

1. Social-based service recommendation using the "Follow the Leader" strategy is significantly more computationally efficient than traditional collaborative filtering (CF) and trust-aware approaches, and can be implemented in WBSN communities and utilized in large-scale recommender systems.

2. The sound predictive power of social leaders indicates social influence on other users that explains the feasibility of the proposed approach.

1.4. Research Methodology

I use 'users cannot' case study-based research methodology. My research began with an analysis of real world Web service selection and recommendation scenarios. These scenarios represent real life cases. Based on the case studies, the Web service selection and recommendation requirements were represented and defined. To successfully achieve the requirements, I investigated currently proposed Web service selection and recommendation techniques in the literature. Augmenting Web service selection and recommendation techniques with Web-based social network analysis techniques led to a feasible solution of the defined problem.

To provide an evaluation of the proposed solutions, I first propose a formal framework for evaluation. I then design a Web service selection and social network analysis simulation tools, using the NetLogo [171] platform for testing Web service selection and recommendation. Finally, I evaluate the performance and outcomes of the proposed Web service selection and recommendation methods using data extracted from two commercial Web sites. In this way, I demonstrate how formal methods can be applied in practical cases. Furthermore, the evaluation scenarios indicate settings and applications in which automated Web service selection and recommendation are useful. I combine theoretical, practical and empirical results to answer the proposed research questions.

1.5. Publications Arising From This Thesis

Journal Papers

- Al-Sharawneh, J. and Williams, M.-A. 2011. "Social Based Service Selection and Recommendation: Follow the Leader", submitted to Transactions on Information Systems (TOIS), December, 2011.
- Al-Sharawneh, J., and Williams, M.-A. 2011. "Are Social Network Leaders Credible Advisers?", submitted to Transactions on Internet Technology (TOIT), December, 2011.

Conference Papers

- Al-Sharawneh, J. and Williams, M.-A. 2009. "ABMS: Agent-Based Modeling and Simulation in Web Service Selection". Proc. Management and Service Science, 2009. MASS '09. International Conference, Beijing, China, IEEE.
- Al-Sharawneh, J. and Williams, M.-A. 2009. "A Social Network Approach in Semantic Web Services Selection Using Follow the Leader Behavior". Enterprise Distributed Object Computing Conference Workshops, 2009. EDOCW 2009, Auckland, New Zealand, IEEE.
- Al-Sharawneh, J. and Williams, M.-A. 2010. "Credibility-aware Web-based Social Network Recommender: Follow the Leader". ACM RecSys 2010, Recommender Systems and the Social Web Workshop (RSWEB), Barcelona, Spain.
- Al-Sharawneh, J., Williams M.-A., and Goldbaum, D. 2010. "Web Service Reputation Prediction Based on Customer Feedback Forecasting Model". Enterprise Distributed Object Computing Conference Workshops (EDOCW), 2010 14th IEEE International, Vitória, ES, Brazil.
- Al-Sharawneh, J. and M. Williams 2010. "Credibility-based Social Network Recommendation: Follow the Leader." ACIS 2010 Proceedings. Paper 24. http://aisel.aisnet.org/acis2010/24: 1-10. **3rd best paper award.**
- Al-Sharawneh, J., Williams, M.-A., Wang, X. and Goldbaum, D. 2011. "Mitigating Risk in Web-Based Social Network Service Selection: Follow the Leader". Proc. of ICIW 2011: The Sixth International Conference on Internet and Web Applications and Services, St. Maarten, The Netherlands Antilles, The International Academy, Research and Industry Association (IARIA). **One of the top papers award.**

1.6. Dissertation Outline

In this chapter, I have discussed the main challenges of the dissertation in addressing the social-based Web service selection and recommendation problem. First, I presented my motivation and interest in the research topic through real life scenarios. Next, I defined the thesis problem, scope and associated limitations. The significance of the thesis was justified by reference to the claims (or witness) of other researchers who have made significant contributions in the research area. The research method was presented and a list of publications arising from this thesis was introduced. The remainder of this dissertation is organized as follows:

Chapter 2 surveys the social service selection and recommendation problem and identifies three key technologies that can be integrated to address it. The chapter begins with terminology and definitions related to Web services used throughout this dissertation. An overview of key technologies: Semantic Web Services, Web based social networks and recommender systems are then presented, as well as an outline of social-based service selection and the recommendation problem, highlighting current challenges. A review on the literature related to my proposed solution is presented; the related areas include Web-based social network analysis, Web-Based social networks and trust, trust-based Collaborative Filtering (CF), "Follow the Leader" strategy, and finding experts in a social network. Finally, a review is presented of three social service selection and recommendation approaches: reputation, recommender and referral.

Chapter 3 presents the proposed Credibility-based Web service social service selection and recommendation framework. Two new models of credibility are proposed: the user Credibility model and the Web service Credibility model. Each model uses two credibility components: the trustworthiness credibility component and the expertise credibility component. I then demonstrate how each model can be used in the social Web service selection and recommendation context.

Most of the current approaches adopt either trust or reputation as the basis for social service selection. Unfortunately, most of these approaches ignore the expertise component of the Web service or the recommender. My work differs from existing approaches in three major aspects. First, I adopt a social-based service selection approach using Web-based social networks. Second, I use a well-established social strategy "Follow the Leader" to infer and drive service selection. Third, my proposed approach is augmented with user behavior analysis to provide more effective performance.

The key contributions of Chapter 3 are:

1. A Trustworthiness Expertise Credibility-Based Framework (TECBF) is proposed.
2. A user model based on credibility that captures trust relationships between users.
3. A clustering approach based on the "Follow the Leader" strategy and user credibility to identify community leaders in the WBSN.
4. An effective means of generating high quality user-based collaborative recommendations based on user credibility and "Follow the Leader" strategy.
5. Web service credibility metrics that incorporate trustworthiness and expertise.

6. A social Web service selection approach based on user credibility, service credibility and “Follow the Leader” to make service selection and recommendation.
7. An evaluation framework to evaluate models, algorithms and approaches presented in TECBF.

Chapter 4 presents the recommendation, experimentation and evaluation of the proposed user Credibility model. I demonstrate the effectiveness of the proposed user Credibility-based clustering derived from “Follow the Leader” to identify Top-N recommenders, who are leaders in the context with the highest trustworthiness and expertise among all users. I demonstrate the effectiveness of the user Credibility model through visualization using my Social Network Analysis Studio (SNAS) on a subset extracted from the widely used EPINIONS[3] dataset. Then, I show how leaders act as expert recommenders by providing accurate predictions and benchmark them against the leading algorithms: conventional collaborative-based similarity and the social trust-based approaches. I demonstrate the effectiveness of the clustering approach by validating my approach using social network analysis measures, such as centrality measures where leaders show the highest average in-degree and the highest average out-degree centrality compared to other members (followers) in the network. Furthermore, I show that leaders are the most prominent and influential members in the network and demonstrate that there is a significant Interest Similarity between leaders and target users.

Chapter 5 presents Web service selection experimentation and evaluation of the proposed Web service Credibility model. I demonstrate the effectiveness of the Web service Credibility model by first providing experiments to validate the model, and then evaluating the proposed social service selection based on user credibility and Web service credibility. I benchmark the Credibility model against other well known utility-based and trustworthiness-based selection models. The key contributions of Chapter 5 are:

1. A review of recent social service selection approaches.
2. A simulation model that imitates Web services and users behaviors in a dynamic environment.
3. A Web service credibility bootstrapping algorithm to initialize service credibility for new services.
4. A user query model with preferences.

[3] http://www.EPINIONS.com/

5. Evaluation metrics for social service selection accuracy.
6. Benchmarking the Credibility-based approach against the utility-based approach.
7. Benchmarking the Credibility-based approach against the trustworthiness-based approach.

Chapter 6 proposes a new approach for mitigating risk in social service selection based on the "Follow the Leader" strategy. To demonstrate the feasibility and effectiveness of the new approach in alleviating the risk in Web service selection, I extend the functionality of the Social Network Analysis Studio (SNAS) to analyze user behavior in a social network, following which the SNAS is used to verify the validity of the proposed model. The empirical results incorporated in this chapter demonstrate that the proposed approach is a significantly innovative approach as a risk-reducing strategy in service selection.

The key contributions of Chapter 6 are threefold:

1. A user model with risk-attitude based on user domain knowledge and its credibility in the "Follow the Leader" context.
2. Web service performance risk metrics that reflect its credibility.
3. A social Web service selection approach based on service credibility and the "Follow the Leader" strategy to mitigate performance risk in service selection.

Finally, Chapter 7 concludes the thesis and presents the major future research directions.

Chapter 2
Research Background and Related Work

In Chapter 1, I presented the research motivations and challenges of the social-based Web service selection and recommendation problem. The proposed solution presented in this dissertation builds on my observation that the three powerful technologies: Semantic Web Services, Web based social networks and recommender systems possess the kinds of catalytic synergies required to address the complex problem of service selection and recommendation. All three technologies are currently enjoying unprecedented interest and investment in both research and practice. In this dissertation, I demonstrate the collective power of these technologies using an innovative and powerful agent behavior model "Follow the Leader" [70].

In this chapter, I first present the terminology and definitions related to Web services used throughout this dissertation; next, I present social-based service selection and recommendation problem highlighting current challenges. Then I present an overview of key technologies: Semantic Web Services, Web based social networks and recommender systems. Then, I review the literature related to my proposed solution; the related areas include: Web-based social network analysis, Web-Based social networks and Trust, Trust-Based Collaborative Filtering (CF), Follow the Leader, finding expert in a social network and clustering. Many of the reviewed articles cross multiple areas. Finally, I review three social service selection and recommendation approaches: reputation, recommender and referral-based approaches. For a general overview of the basics in service-oriented computing: semantics, processes, and agents, the reader is directed to Singh and Huhns

[202]; especially Chapter 20: Social Service Selection. An interesting survey on trust and reputation based Web service selection is available in Wang and Vassileva [223].

My work differs from existing studies in three major aspects. First, I adopt a social-based service selection approach using Web-based social networks. Second, I use a well established social strategy “Follow the Leader”. Third, the proposed approach is augmented with user behavior analysis. Furthermore, I focus on financial Web services such as home loans and insurance services. I recognize the importance of trust assessment for the financial services can provide feasible solutions. In the proposed approach, the trustworthiness and expertise of a service provider are also considered.

2.1. Terminology and Definitions

I adopt the following, well-established terminology in this dissertation:

A Web Service (WS): is defined as a self-contained, self-describing software application that can be advertised, located, and used across the Web using a set of standards [150, 177]. Web services are with public interfaces described in XML. According to World Wide Web Consortium (W3C) [217], Web services identified by a URI, their interfaces are defined in Web Service Description Language (WSDL), published in the Universal Description, Discovery and Integration (UDDI) directory, Web services can be discovered and invoked by other software systems. These systems interact with Web services using XML-based messages conveyed by Simple Object Access Protocol (SOAP) [112].

Web services are considered as a promising technology for Business-to-Business (B2B) and Business-to-Consumer (B2C) integration [112]. A group of services from different providers can collaborate and compose to form a new functionality. Business Process Execution Language for Web Services (BPEL4WS)[4] is used for Web service composition. BPEL4WS is a language used to describe service-based business processes and specify interaction protocols for involved services [112].

Quality of Service (QoS): Malik, Akbar and Bouguettaya [148] defined QoS as “a set of quantitative and qualitative characteristics of a system, necessary to achieve the required functionality of an application”. QoS is a broad concept that covers multiple non-functional properties, or dimensions, some of which can service specific aspects and others more general. Quality of Service (QoS) attributes are defined in public ontology and

[4] http://www.ibm.com/developerworks/library/specification/ws-bpel/

mapped to a set of ranges or values [148], examples of QoS attributes include response time, availability, privacy, security, and reliability.

Web service discovery: is the process of finding Web services, which satisfy specific requirements. Discovery is achieved by searching the service with a matching description and service profile on the UDDI. Due to the increase of the Web services availability with similar functionalities on the Web, this drives the need for more complicated Web service discovery mechanisms[119].

2.2. Web Service Selection

Web service selection is the process used to select a service implementation from the discovered services that best match user specified QoS requirements [97]. The cost of a service is another key factor that influences a service consumer's selection [223], a high quality service usually costs more than a low quality service with the same functionality. Thus, a service selection process needs to balance between the service cost and service quality.

Web Service Selection is a complex process, in which the service that best satisfies user preferences is selected from a set of candidate services, usually returned from a service discovery process based on specific user requirements [215]. As per the selection criteria, a varied number of non-functional properties or QoS attributes can be used as user preferences. Such QoS attributes can apply restrictions on the behavioral and the functionality of service descriptions [215], *i.e.,* QoS preference may control the service usage. As the competition between services providers is increasing dramatically, consumers are facing a huge number of available services; this has led to an issue called information overload problem [98].

Social Web service selection in this dissertation is designed to provide context-awareness, effective capture and identification of user preferences and high levels of re-usability of the best services and preferences based on the notion of the market leadership. The term *context* refers to the physical and social situation in which a user query is placed.

A considerable number of works in recent years have been devoted to studying various aspects of service selection and recommendation. These efforts vary in their dimensions [22]; service selection with or without QoS, service selection based on reputation or policies [178], or service selection based on trust. Research activities have focused on utilizing QoS metrics in Web service selection and assessing trust between interacting partners [159].

Trust and reputation play an important role in a service selection; it is natural that a service consumer would like to choose a trustworthy service or a service with a high reputation [223], where trust and reputation mechanisms are used for making a good service selection. The selection step involves a rational decision making to select the best service instance from many service providers [159]. Since the quality of service(QoS) attributes are changing over time, thus, it is mandatory to take these changes into consideration in reputation computation.

2.3. Overview of Key Technologies

The work presented in this dissertation builds on my observation that the three powerful technologies: Semantic Web Services, social networks and recommender systems possess the synergies required to address the complex problem of service selection and recommendation. All three technologies are currently enjoying unprecedented interest and investment in both research and practice. In Chapter 3, I demonstrate the collective power of these technologies using an innovative and powerful agent behavior model called "Follow the Leader" [70].

In this section, I provide an overview of the three research technologies, on which the proposed social-based service selection and recommendation approach is constructed. I emphasize both technical and philosophical issues that have inspired the "Follow the Leader" architectural design.

2.3.1. Semantic Web Services

Sir Tim Berners-Lee brought the vision of the Semantic Web [20] as a new form of Web content in which the semantics of information and services are defined and understood by computers. The Semantic Web provides a framework to share and reuse data and services across applications. The Semantic Web is anticipated to allow heterogeneous Web services to interact, exchange data and orchestrate complex processes on an ad-hoc basis.

Semantic Web services (SWS) require two main processes in order to execute, namely service discovery and service selection. Semantic Web service discovery seeks to find a match between service requirements and service advertisements based on the semantic metadata attached with the services. The use of ontologies allow richer descriptions of activity requirements providing efficient ways to locate services to perform these activities in the executable Web process [206].

A typical service-based applications architecture composed of three main components: a service provider, a registry and a consumer [86]. Providers advertise or publish their services on the registry, where consumers locate and invoke them. Since non-functional properties or QoS of Web service is not part of the UDDI, most of the discovery mechanisms do not consider quality of the advertised Web services; they consider only the functionality of the service description.

Web Service Selection is the process that chooses a single service that best satisfies user preferences from a set of candidate services which the service discovery process identifies [215]. Web service selection is a complicated task particularly if it takes different non-functional properties into consideration. The service selection involves (1) specifying user functional and non-functional requirements, (2) matching of service offerings against user requirements, and (3) selecting the best match through aggregation and evaluation matched results [215].

Several approaches have been employed in semantic Web services selection: semantics-based, policy-based and trust and reputation-based. The majority of semantic Web services selection approaches are based on the semantics of non-functional properties and QoS where Web Service Description Language Semantics (WSDL-S) and Web Ontology Language (OWL-S) are used to describe the non-functional properties and corresponding interdependencies and hierarchies of properties as shown in Maximilien and Singh [158]. Policy-based service selection approaches allow the user to specify the non-functional requirements by encoding these in a QoS policy model as in Liu, Ngu and Zeng [140]. Trust and reputation-based methods base the selection process on the classification of trust and reputation systems, where feedback is provided from communities or recognized agencies, *e.g.* methods in Maximilien and Singh [159].

For SWS to be successful, it is mandatory to have powerful mechanisms to capture user requirements that are both user friendly and expressive enough to capture a large quantity of complex preferences and the logical relations between preferences [241]. Preferences need to be prioritized and can be associated with a corresponding level of importance (weight). The preference information not only needs to be captured but also managed and matched automatically and effectively by the SWS selection process.

2.3.2. Web-based Social Networks

Web-Based Social Networks (WBSNs) have recently been receiving increased research attention; Web-based social networks are online communities: people, teams, or any social group [39, 200, 224] interacting on the web, and connected via social relationships, such as co-working, friendship or knowledge exchange in varied contexts such as entertainment, politics, religion, dating or business.

WBSNs currently play an important role in the life of millions of active Internet users; over the last few years, interest in WBSNs Websites such as Facebook[5], MySpace[6], Friendster[7], Twitter[8] and LinkedIn[9] has increased considerably, and the popularity of such sites has increased significantly [13, 25, 76]. WBSNs play an important role in people's daily interactions with their friends [168], for example, Facebook has more than 800[10] million users (as of November, 2011) who spend some 700 billion minutes on the site every month[11]. If Facebook were a country, it would be the third most populous in the world [25]. Furthermore, WBSNs played an important role in social revolution in the Middle East from Tunisia to Egypt, Yemen to Libya and Syria.

In WBSNs, users are driven to contact and befriend other users, create and publish their own content in the form of opinions, videos or photos, and share this content with other users, and rate or comment on content posted by other users. As a result, users are now treated as simple Web resources [57]. A person may create multiple identities, and may even create links between these identities [166], each of these identities considered as a separate user. The real-world social networks evolve over time; people and their social connections are constantly changing [83].

The significance of WBSNs can be emphasized in a number of ways [13]; for example, users may benefit from their interactions with other users to locate relevant information, or they may search existing connections in the WBSN to be linked with a user they may

5 http://www.facebook.com

6 http://www.myspace.com

7 http://www.friendster.com

8 http://twitter.com

9 http://www.linkedin.com

10 http://www.facebook.com/press/info.php?statistics

11 http://spectrum.ieee.org/computing/networks/social-networking-friended

benefit from the interaction with them. Many WBSN users indicate that they have been able to obtain a job through their interactions and connections in LinkedIn. Furthermore, WBSNs facilitate the dissemination of new information and knowledge in a widespread manner, to diffuse innovations and spread views and opinions, such as, political and social messages, between members and to announce new services and products [13, 107].

WBSN, to a great extent, reflects social trust between the individuals in a social group. Intuitively, when faced with overwhelming choices without specific domain knowledge, a user typically will refer to friends for opinions on a specific issue [70, 135]. Recently, the trust-based approach for making recommendations has emerged. This approach exploits the network of trust between users and generates recommendations utilizing individuals ratings and their relationships such as direct or indirect friends who are trusted by the user seeking a recommendation [168]. The trust network among users is very sparse [168]; hence trust inference approaches are used to compute trust values among indirectly connected users within the trust network.

Some members of WBSNs have considerable influence on other members and are known as leaders or pioneers [70, 235]. Newman [172] used the principle of "preferential attachment" to describe this phenomenon; where the nodes that have many links tend to be acquired more [172]. Recent research has shown how preferential attachment can lead certain nodes to act as highly connected hubs [107].

2.3.3. Recommender Systems and Collaborative Based Filtering

Recommender Systems (RS) aim to provide users with recommendations about items that people may have similar preferences or have appeared to have liked in the past [155]. Collaborative Filtering (CF) is considered as the dominant technique for recommender systems; it relies on the opinions expressed by other users. CF models can be divided into two subcategories according to how they incorporate consumer preference similarity [192]: memory-based and model-based [155].

Memory-based CF models utilize stated preference data (ratings) of other consumers (reference consumers) as predictors for target consumers' preferences; the most popular approach is the neighborhood model [27]. Furthermore, memory-based methods are either user-based or item-based [142, 195]. User-based methods try to find some similar users sharing the active user in their rating styles, and then use ratings similarity to predict the active user ratings for some item not rated by the active user. Item-based methods utilize items similarity to find similar items. However, defining similarity between users is a complicated task and computationally expensive; where the sparsity issue and noise in the data make limitations over similarity computations [9].

The model-based CF approach employs a variety of general models such as matrix factorization [90]. Model-based models differ from memory-based CF models in that they use model parameters to capture preference similarities via a learning model instead of directly using reference consumers' data.

Most CF based recommender systems build a neighborhood of likeminded customers who appear to have similar preferences [194]. The neighborhood formation scheme (clustering) is the learning process or model-building for the recommendation algorithm. The main purpose of neighborhood formation is to produce recommendations of two types: those that predict an opinion-score of a product for that user, or those that recommend Top-N products that the user has not already purchased and that they may like [49, 194].

In recent years, research on using recommender systems (RS) for Web service discovery and selection has emerged as an effective approach [38]. Kokash, Birukou and D'Andrea [111] adopt a so-called implicit culture framework, where it is possible to capture the community culture using people' interactions with the environment.

Lerman [123] showed that people within a social circle, are attracted to other people activities, and also like items their friends like. Therefore, user friends in WBSNs can be considered as reliable sources of recommendations [76]. Sinha and Swearingen [204] compared between recommendations quality made by users' friends and a recommender system. They found that users preferred recommendations from their friends more than recommendations made by a recommender system.

Traditional collaborative-based filtering (CF) approaches ignore the social or trust relationships between users [143]. CF approaches suffer from the cold-start and sparsity weaknesses; these problems have a similar cause, if the overlap between user ratings is too small, the CF approach cannot define a reliable neighborhood in order to generate recommendations [121].

In daily life, users usually prefer to receive advice or recommendations from trustworthy peers, where they utilize peers past interaction history to select the most trustworthy peer and to assess the quality of the received advice [76]. Furthermore, users prefer receiving recommendations from people they trust more; therefore, recommendations can be generated using the ratings provided by other users who are directly trusted by the user seeking recommendation, or indirectly trusted by another trusting user utilizing trust propagation mechanism [244].

A major drawback of the CF is that it is unable to differentiate between neighbors with similar tastes as friends or strangers [136]. Although CF utilizes neighbors to make recommendations, it is unable to demonstrate how people seek information using their friends in social networks.

It is important to note that the promise of social recommender systems is based on at least two assumptions as indicated by Lee and Brusilovsky [121]; first, the availability of social connections to define the similarity of users' interests, second, the source of the recommendation is an essential criterion for judging the quality of recommendations [121].

In the early days of the Internet, it was difficult to identify the close friends of a user [136]. Currently, WBSN sites such as Facebook, Twitter and Google+, provide tools to gather WBSN information, that enable researchers to integrate WBSN information and the CF mechanisms to generate recommendations. Finding a credible recommender is an important issue, therefore, one of the main objectives of this dissertation is to utilize social network information to make recommendations based on the credibility of users drawn from their trustworthiness and expertise. I argue that an intelligent recommender system should provide context aware recommendations of Web services, without the users having extensive personal expertise on all available choices.

Social networks have been used in CF, recently DuBois *et al.* [52] use trust as a basis for forming clusters. My work as shown in Chapter 3, is the first that uses a formal "Follow the Leader" strategy based on Web-based social network, and user credibility to generate a cluster of the most trustworthy and experienced users in the social network called leaders, and then, I show how leaders act as advisers to other users including cold-start users who do not have enough interactions to capture their similarity.

2.4. Web Service Selection and Recommendation Challenges

Although the future of Web service selection looks very promising, there are still challenging problems in the recommendation process. Some of these issues relate to user knowledge and behavior, and others relate to recommendation approaches to finding a trustworthy person to provide advice for the target user. In the following section, I provide an overview of these challenges.

2.4.1. Cold-Start Users Issue

In collaborative-based filtering, new items and new users to the recommender system do not have enough ratings data and thus cannot be used in recommendation [9].

Cold-start users represent one of the most important challenges in recommender systems. A cold-start user is described as a new user who has joined the CF-based recommender system and has not provided any ratings, or has provided a limited number of ratings. In such cases, the recommender system cannot make feasible and useful recommendations to cold-start users [154], and is unable to provide any recommendation at all if the target user has expressed no ratings. For the same reasons, similarity-based approaches are unable to find similar users [223]. However, social network-based recommendation approaches can generate recommendations provided the new user is linked to a large portion of the social network [90].

According to Massa and Bhattacharjee [157], cold-start users form a significant ratio of the entire user population, representing around 50% of the population. Furthermore, users who do not have friends represent 31.30% of the population, *i.e.*, their Web of trust is empty. In Golbeck's [67] FilmTrust system, over 58% of the users have no friends in the system, and our experimental analysis indicates that the percentages of users who do not have friends are 39.42% and 81.56% in Extended EPINIONS and FLIXSTER datasets respectively.

Current recommender approaches cannot satisfy the cold-start user's needs. Golbeck [67] has indicated that trust inference algorithms are effective at predicting trust and improving recommendations when there are paths in the social network connecting members, and the trust values on those paths are available. On the other hand, inference algorithms are inapplicable in many cases when trust values or links are not available. Thus, for the majority of users, network-based trust algorithms will be ineffective.

This means that all users without friends in the network fail to receive proper recommendations about the deemed Web service; such users often tend to avoid the burden of explicitly stating their preferences and either leave the system or rely upon "free-riding" [252].

Although some solutions have been reported in the literature for the cold-start recommendations issue [73, 118, 179], most of these efforts assume that the active user provides at least one rating, or that the active user provides complete profile information such as age, gender and job attributes to capture the user's interests and infer their similarities. However, what if the active user does not provide ratings or personal information to capture their interests?

Recently, Kavitha Devi and Venkatesh [98] addressed the cold-start problem in their model by considering the active user as a "novice user", and they provided the user with a set of items with high ratings as the default recommendation. Nonetheless, the cold-start issue reflects more than half of users in the population who need a feasible solution.

2.4.2. Sparsity Issue

Data sparseness is another challenge for collaborative-based filtering. The sparsity problem shares the cold-start problem in its cause, because it occurs when available data is insufficient to identify users or item similarities due to a vast number of users and items [193]. As reported in Sarwar *et al.* [192], the available ratings density in commercial recommender systems is frequently less than 1%. Thus, most CF algorithms suffer from the sparsity problem; consequently, they cannot handle users with a small number of ratings. According to Kavitha Devi and Venkatesh [98], the sparsity level of a rating matrix is computed as the ratio of the number of zero entries to the total number of entries. They conclude that when the sparsity level is greater than 90%, it is very difficult to compute the correlation between users; thus, the sparsity problem consequence is the lack of neighbors.

In practice, as indicated by Kim et al. [102], even though some users are extremely active, each user only provides ratings for a limited number of items; similarly, items that are considered very popular may received ratings from a small number of all users. Accordingly, in such cases when the intersection between two users is empty or the intersection between two items is also empty, the similarity between these users or items is not computed at all [157]. Even when it is possible to compute the similarity, it may be not reliable, because of the insufficiency of the processed information [176]. Moreover, some purchases are gifts and thus do not reflect the active user's interests [252] and users may not even be aware of their implicit preferences.

Many algorithms have been devoted to handling the sparsity problem through predicting the missing values. Wang, De Vries and Reinders [220] proposed a generative probabilistic framework that uses user-item matrix to predict the rating value. Xue *et al.* [236] proposed a framework for CF that utilizes the strengths of memory and model-based approaches.

Although some solutions are reported in the literature for the sparsity issue, such as [84, 176, 182, 232], most of these efforts assume that the active user provides at least enough rating to capture its similarity, or that they have at least one trusted friend to infer the user's interests. If the active user does not provide enough ratings or the user does not have friends to infer their interests, however, then to the best of my knowledge, no algorithm can provide a recommendation for the user in question. This issue reflects more than 50% of users who need a feasible solution.

2.4.3. Privacy Issue

Privacy has received considerable attention from industry and academia in the past few years. Web service providers offer services that increasingly require the revelation of users' personal information, which poses a growing privacy concern to their users. Web service providers utilize their customers' personal information to develop and generate personalized advertisements. Some providers may also release or sell their customers' information to third parties for a variety of purposes [113]. Moreover, Resnick and Varian [188] indicate that "people may not want their habits or views widely known".

In Web-based social networks, user profiles, preferences, ratings, interests and purchase history are used as valuable assets to make social recommendations, however, improved social recommendations come at a cost; they can potentially lead to privacy breaches by revealing users' sensitive information [147]. For instance, if the active user has only one friend, a social recommendation algorithm that recommends the products that friends buy might reveal the entire shopping history of that friend; information that the user probably did not intend to share. Moreover, a system that uses only trusted edges in friend suggestions may leak information about the lack of trust along specific edges, which would also constitute a privacy breach [147].

According to Kobsa [109], 70% of internet users are concerned about the privacy and security of their online personal information. On the other hand, 90% of people are concerned if online businesses share their information for purposes other than the main purpose for which that information was collected. Furthermore, 83% of online users believe that Web sites that share their personal information with other Web sites invade their privacy. These figures illustrate the significance of the privacy issue.

A considerable number of works in recent years have been devoted to studying various aspects of the privacy issue. Garcia *et al.* [64] present privacy protection mechanisms for Web services which use policies defined in the Web Services Policy Framework (WS-Policy). Kolter, Kernchen and Pernul [113] introduce a collaborative privacy community that enables related privacy information exchange. Calandrino *et al.* [32] demonstrate that algorithms that recommend products based on friends' purchases have practical privacy concerns. McSherry *et al.* [162] show how to build privacy preservation for movie recommendations. Toubiana *et al.* [211] propose a framework for privacy that preserves targeted advertising based on user history.

In highlighting a recent announcement from Google, Tuerk [212] indicates that one way to manage user privacy on social network sites is for the user to specifically decide who can see their information, determining whether it is visible to just a few friends, colleagues, family members or everyone on the Web based on the user’s various identity options in Google products.

In this dissertation, my focus is to preserve user privacy, and not reveal any personal information about the identity of the leader who provides advice to the target user without prior consent.

2.4.4. Scalability

The Scalability issue is considered to be performance problem [114]. Rana and Stout [186] define scalability as: "the ability of a solution to a problem to work when the size of the problem increases".

According to Sarwar *et al.* [192], computations in nearest neighbor similarity algorithms grow with the number of items and the number of users at the same time. Since there are millions of items and users in a recommendation system, then such algorithms suffer from serious scalability issues.

In traditional collaborative-based filtering CF, the neighbors are identified using model-based or memory-based approaches. The memory-based approach compares the active user with all other available users including new users; therefore, the computational complexity increases with the increase in the number of users. This computational complexity is considered to reflect the scalability issue.

In summary, similarity computation for a matrix of N users and M items is an $O(N^2M)$ problem [9]. Since new users and/or new items frequently enter the system, it is mandatory to update the similarity matrix on a regular basis. Consequently, CF-based approaches generally suffer from scalability restrictions. Although various mechanisms, such as k-means clustering, have attempted to address the scalability problem, scalability is still an open research issue in most CF-based systems [9].

2.4.5. Capturing Users' Preferences and Ratings

Web service non-functional properties or QoS such as availability, response time, security, privacy and reliability are difficult for the user to determine and control. Users are usually reluctant to spend time describing their complete preferences and providing ratings for the system [33, 202, 252], and are even less willing to assign corresponding relative weights to their preferences, especially when the consequences of their inputs are unknown or undetermined. Moreover, according to Ziegler [252], some purchases are gifts and thus do not reflect the active user's interests and users may not even be aware of their implicit preferences.

Existing works have studied a user's explicit interests as specified in their profile, or their implicit interests indicated by their prior interactions with various types of information on the Web [225]. Recently, the increase in online social networks has sparked an interest in leveraging social networks to infer user interests [226], based on the existence of social influence and correlation among neighbors in social networks [203]. For applications that can directly observe user behaviors (*i.e.*, logs of search engines), inferring interests from friends in social networks provides one extra useful enhancement [225]. For many other applications, however, it is difficult to observe sufficient behavior of a large number of users; in such situations, inferring their interests from their friends can be the only viable solution [225]. For example, for a new user in a social application, the application may only have information about friends who are already using it. To motivate the new user to actively participate, the application may want to provide personalized recommendations of relevant content; consequently, the application has to infer interests from friends, which is problematic if the user does not have friends.

On the other hand, user feedback can be either explicit or implicit depending on the mechanism used to capture user satisfaction. Although explicit approaches capture user satisfaction more accurately, these approaches are costly, and often users do not cooperate [116]. Resnick *et al.* [187] indicate that "people may not bother to provide feedback at all" and that it is "difficult to elicit negative feedback" and difficult to ensure honest reports.

Consequently, users tend to avoid the burden of explicitly stating their preferences and either leave the system or rely upon “free-riding” [252]. However, explicit ratings are difficult to achieve [187, 202] because they place extra overheads on the user.

The reputation approach only requires user evaluations, but in some cases, it may be difficult to obtain them. Research on eBay[12] reveals that ratings are submitted in only 50% of transactions [45]. However, the eBay example deals with human interaction. With automated ratings likely to be used with Web services, elicitation problems may still exist due to privacy issues [134] or disinterested users.

In a recent study, according to Klein *et al.* [105], eBay buyers comment on sellers 52.1% of the time. Ratings left by buyers are positive in 98.1% of cases. From this ratio, we can conclude that 47.9% of buyers either fear revenge, or they do not bother to give a seller rating. Dellarocas and Wood [48] investigated the consequences of non-random missing feedback on reputation scores; they found that dissatisfied consumers are reluctant to provide feedback. The feedback score generally is the most important indicator of Web service reputation. Since a significant ratio of members do not participate in the rating process, the lack of ratings can have a major impact on the quality of the reputation system [148].

A cold-start customer who wants to find a Web service often seeks help from their friends, peers, experts and business partners who have relevant experience. Capturing and specifying user preferences are among the most complex problems in the service selection process. Some approaches make selections based on the non-functional properties ontology or synthesize selection using previous queries of a similar situation. An alternative proposed by Singh and Huhns [202] is to obtain users’ ratings implicitly by inferring users’ ratings drawn from their actions on the Web site. Actions such as browsing, return visits and purchase history can be used to infer users’ implicit ratings. Nevertheless, data incompleteness is still a major challenge.

2.4.6. Top Authors addressing Challenges

In the previous sections, I discussed Web service selection and recommendation challenges (cold start, sparsity, privacy, scalability, and user’ preference capturing). In this section, I

[12] http://www.ebay.com/

provide a list of the authors who address at least three of these challenges as shown in Table 2.1 below. QoS indicates if the approach is based on Quality of Service or not.

Table 2.1: Recommendation approaches that address at least three challenges

Authors	Ref.	Cold-Start	Sparsity	Privacy	Scalability	Users' Pref. and ratings	QoS
Sarwar, Karypis et al. 2001	[192]	Y	Y		Y		No
Massa and Bhattacharjee 2004	[157]	Y	Y		Y		No
Ziegler 2005	[252]	Y	Y	Y	Y	Y	No
Amatriain, Lathia et al. 2009	[9]	Y	Y	Y	Y	Y	No
Kavitha Devi and Venkatesh 2010	[98]	Y	Y		Y		No

As we note from the above table, none of these approaches consider service selection and recommendation as shown in QoS column, they consider product recommendation only. Moreover, not all presented approaches are aware of all the challenges: cold start, sparsity, privacy, scalability, and user' preference capturing. For example, Ziegler [252] and Amatriain, Lathia et al. [9] address all five challenges. Kavitha Devi and Venkatesh [98] do not address privacy or user preferences, Massa and Bhattacharjee [157] address only cold-start and sparisty issue highlighting user credibility as malicious behaviors, Sarwar, Karypis et al. [192] do not address privacy or user preferences.

2.5. Related Works

This section reviews the literature on Web-based social network analysis, Web-based social networks and trust, trust-based collaborative filtering (CF). Next, I present the "Follow the Leader" strategy as the cornerstone of the proposed framework, and finally I review some works used in clustering and collaborative filtering. Clustering users has been used in collaborative filtering; my work is the first that uses credibility and the "Follow the Leader" strategy as the basis for forming the leaders' cluster. Finally, I describe some works related to clustering in collaborative-based filtering.

2.5.1. Web-based Social Network Analysis

Social Network Analysis (SNA) has emerged as a key technique in social and behavioral sciences, as well as in other major disciplines [224]. SNA exploits the link structure and examines the roles and behavior of nodes in the network, and on the network as a whole [41]. SNA makes use of a variety of statistical and visual analysis tools to achieve this.

SNA is a sociological approach to analyzing the patterns of interactions and relationships between social actors in order to determine underlying social structures such as central nodes that act as hubs, leaders or gatekeepers, highly connected groups, and patterns of interactions between groups [224].

SNA is increasingly being used as a structured way to analyze the extent of informal relationships among members within various formally defined groups [39]. SNA provides a means to analyze customers' relationships and has important implications for making e-commerce recommendations [235]. The links between the nodes are used as a means to indicate their relationships and to determine interactions that can potentially identify communities [41]. Berners-Lee *et al.* [19] point out that there is a tendency for authorities and hubs to appear as the focus of cyber communities.

Sociologists agree that power is a fundamental property of social structures [89]. People with higher social capital can attract more people than those with lower social capital. This is called preferential attachment [83], where a complex network exhibits a power-law degree distribution. The power-law degree distribution of social networks, which is due to the effect of preferential attachment, reflects our lived experience that the rich get richer. In the study of the distribution of wealth, Huang [83] indicates that 20% of the population in a given society holds 80% of the total wealth or power of the society.

Newman [172] justifies preferential attachment for in-degree by articulating that "Web sites are easier to find if they have more links to them, and hence they get more new links because people find them."

Recently, Gilbert *et al.* [66] proposed a Dynamic Social Network Analysis and Visualization (DySNAV) system. This system assists users in analyzing the community dynamics available in such social networks. Furthermore, individuals develop community structures by regularly collaborating or communicating with certain people rather than others.

In June 2011, Lefkow [122] reported that Google's senior vice president for engineering, Vic Gundotra, announced that the Google search engine had launched its rival to Facebook, a social networking service called Google+. In this application, Google has integrated Facebook social networks, and users are grouped according to the social circles that reflect their personal interests and relationships such as college friends, or family members, depending on the context of the user search within Google.

2.5.2. Web-Based Social Networks and Trust

Golbeck [67] defines trust in a person as “a commitment to an action based on a belief that the future actions of that person will lead to a good outcome”. Trust between two parties indicate a ‘subjective probability’ that one party, the ‘trustee’, will perform favorable actions to the other party, the ‘truster’, or will drive the trustee to behave appropriately with the truster [173].

In WBSNs, users can express how much they trust other users. Trust provides users with information about the people they share content with and accept content from. Since most WBSN users are unknown to one another, and they do not have any previous direct interactions on WBSN sites, trust inference is used to help them establish new relationships with other unknown users or to measure trust values between indirectly connected users [137]. The idea in trust inference differs from CF which is used to find similar users, because it is used to find trustworthy users over the network who are directly or indirectly trusted by the active user [155].

Users in WBSN are able to express how trustworthy other users are. In the context of RS, user trustworthiness is measured by the accuracy and the relevance of the ratings they provide [155]; therefore, trust statements expressed by users can be used to build a trust network. Moreover, trust metrics are used in predicting and assessing other users or their friends’ trustworthiness from the active user perspective.

In fact, users prefer to receive recommendations from the most trustworthy people [244]. Therefore, trust propagation approaches are used to find people who are directly or indirectly trusted by the current user to generate recommendations, utilizing other users’ expressed ratings. However, if the user does not have links to other users, *i.e.*, they are a cold-start user, it is problematic for RS to make recommendations to them.

2.5.3. Trust-Based Collaborative Filtering (CF)

The connection between user similarity and trust was established in Ziegler and Golbeck [253]. Using experiments, they demonstrated that a significant correlation exists between the trust that users explicitly express, and their corresponding similarities, utilizing the recommendations they have made in the RS. The more trust there is between two users in a specific context, the more similar are the users in that context.

In recommender systems, many research proposals have used trust information such as [52, 67, 68, 90, 127, 135, 143, 155, 156, 175, 218].

Ziegler [252] used trust network analysis to form a cluster of trusted neighbors. Golbeck's PhD thesis [69] focused on trust in WBSNs, including trust computations and applications. She deployed her FilmTrust recommender system, in which users are able to rate movies and write reviews about movie collections. The system also enables users express how much they trust other users' reviews or ratings based on a ten-level trust scale.

To provide accurate recommendations, similarity has been proved to be a key factor in neighbor selection. Furthermore, a neighbor's trustworthiness and expertise have been considered to be complementary criteria for selecting the best possible collaborative advice [117]. Similarity can be interpreted in several ways, such as similarity in interests or ratings or opinions. Golbeck [67] has explored the relationship between trust and profile similarity. This work shows through analyzing existing systems data and surveys that when a user expresses trust in other users, he/she captures different similarity facets with those users. Systems with trust components enable users to make direct trust statements about other people, and these trust statements can usually be used to generate a social network.

Empirical results demonstrate that using trust metrics in WBSNs can improve the quality of recommendations. O'Donovan and Smyth [175] used the MovieLens dataset to investigate how trust impacts the accuracy of recommender systems. They created trust-values used to estimate the prediction accuracy of a person in predicting the preferences of another. Using such trust values in a traditional CF algorithm showed significant improvements in recommendations accuracy.

There are hundreds of millions of members in WBSNs, and many of those networks contain accessible trust information. Trust has the potential to improve recommendation mechanisms [52]. Trust propagation can be used to establish trust in strangers [26] and such a mechanism enables trust relationships to be extended to unknown people who share the active user their interests (*i.e.*, similarity propagation).

2.5.4. Follow the Leader

Social psychology theory [137] points out that a person's role in a specific context has a significant influence on trust assessment if that person recommends another person or an object. Thus, the role of the user should be taken into consideration in making recommendations.

"Follow the Leader" in dynamic social networks [70, 185] is a model of opinion formation with dynamic confidence in agent-mediated social networks, in which the profiling of agents as leaders or followers is possible. Ramirez-Cano and Pitt [185] define an opinion leader as "a highly self-confident agent with strong opinions"; an opinion follower is attracted to other agents in whom he/she has more confidence [185]. The "Follow the Leader" model provides a formal probabilistic approach; Goldbaum's model [70] identifies three types of consumers who seek input from outside experts. Goldbaum defined the expert as, somebody who possesses better knowledge and information than the general public in a specific context, and gives three consumer scenarios as follows [70]:

1. The consumer has a predefined set of preferences but imperfect information about available products. Hence, the expert provides advice or information to the consumer about a specific product that maximizes the consumer's utility.
2. The consumer has innate preferences among available products but can be influenced by experts and peers opinions. The expert can provide advice consistent with the underlying preferences of a group of consumers.
3. The consumer has no innate preferences. Peers and experts influence the consumer's tastes, whereas the expert shapes the consumer's opinion

The expert in all previous cases can be considered as an experienced user who spends time and effort analyzing product features to finally make the decision on whether to use the product, and who provides high quality feedback on that product. Furthermore, they are in a position to strongly recommend the product to friends who have similar needs.

According to Goldbaum [70], a member of a social network is either a leader or a follower who adopts another leader's opinion or recommendation to use a product. Subsequently, this member adopts whatever his/her best friend has adopted; otherwise, the member has no active friends and acts as an independent (leader).

Ramirez-Cano and Pitt [185] define the relationship between two agents (users) as a confidence function, so 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". We conclude that user trust is the determinant relationship between two friends.

2.5.5. Finding Expert Leaders in a Social Network

Unfortunately, there is no consensus in the literature on the definition of an expert. Song *et al.* [207] refer to innovators and early adopters as the social leaders. Goldbaum [70] defines an expert as someone who possesses both better information than the general public, and can provide advice to others through education or charisma. According to Goldbaum [70], in a dynamic social network, experts are promoted to leaders if they have the greatest number of incoming links. Leaders are influencing the choice of others in the population. Amatriain *et al.* [9] define an *expert* as "an individual that we can trust to have produced thoughtful, consistent and reliable evaluations (ratings) of items in a given domain".

I define a leader as an expert in a specific domain who has advanced knowledge in that domain, influences other people to follow his/her opinion, builds a high reputation, provides continuous activity to be perceived as trustworthy by others and has up to date expertise; *i.e.*, has built adequate credibility to be a leader at all times. Leaders may lose their credibility if they cease to provide ratings, or behave inconsistently during their leadership period.

Identifying expertise in an organization is a challenging issue; it drives the development of new category of search engines called expert finders [240]. McDonald and Ackerman [161] identified various aspects of experts finding called expertise identification: 'Who are the experts on topic X?' and expertise selection 'What does expert Y know?'.

SmallBlue [132, 133] is a social networking application used to find the most knowledgeable people who are considered as experts within a specific community or network. It explores 'the valuable business intelligence' of 'who knows what?', 'who knows whom?' and 'who knows what about whom' within a community or an organization, without needing the explicit individuals involvement.

Amatriain *et al.* [9] consider professional raters as domain experts, who can predict the behavior of other users in the WBSN, using items ratings in a given domain produced by experts to recommend these items to other users. The experts in their model represent the highly raters among all users in the population.

Zhang, Tang and Li [247] proposed a propagation approach to find experts in WBSN. They used each member' information to compute their expertise level; then they select the top ranked members as candidate experts based on their expertise level.

Recently, Chung and Rao [43] present a recommendation approach for Internet services for experience products, they use a concept called ‘virtual experts’. Virtual experts represent a group of people who has previous experience with the product and evaluated it.

EPINIONS[13] is a product and shop review site where users can rate and review various products and items such as books, cars, movies, and computers. It uses a business model based on the cost-per-click online marketing [94], EPINIONS apply charges on advertisers based on the number of users’ clicks made when a user read reviews about advertisers’ products on EPINIONS' web site. Users can also rate reviews in EPINIONS; these reviews and ratings are public. Items are organized by categories, in each category, users are classified into 5 levels [221], ranging from category leaders, top reviewers, advisors, most popular reviewers, to ordinary members.

1. Category leaders are EPINIONS members who are in charge of a particular category; their major responsibilities include rating new reviews, selecting top reviewers and advisors for their category and working to increase high-quality reviews for the key products in their category.
2. Top reviewers in EPINIONS are those members who write high quality reviews to assist shoppers finding best products in a specific category, where their reviews are distinguished by the EPINIONS community, and received the highest rating.
3. Advisors in EPINIONS are those members who rate other members’ reviews, and provide advice to reviewers through comments to improve the quality of their generated content.
4. Most popular reviewers are EPINIONS members whose reviews attract a high number of visitors to their reviews.
5. Ordinary members are the default users.

Category leaders are selected quarterly by EPINIONS staff based on the members nominations [94]. Consequently, leaders are the most trustworthy and experienced users. This approach indicates that leaders are context specific, *i.e.*, for each product category.

2.5.6. Clustering and Collaborative Filtering

Users' clustering has been used in collaborative filtering; however, my work is the first to use credibility as the basis for clustering users based on their roles, identifying leaders

[13] http://www.epinions.com/

cluster and followers cluster. In this section, I describe the work that has been conducted using clustering for collaborative filtering.

Finding virtual community (clustering) in WBSN is an important and difficult task. A clustering algorithm is used to group users in some way that optimizes specific criteria [53]. Criteria can be trust relationships, ratings, reputation, preferences, expertise or credibility. Web search algorithms are used to extract communities [41]; for instance, Kleinberg [106] explored the structure of hubs and authorities communities, and identified authorities as topics' experts communities in the network.

Different researchers have used varied clustering approaches, such as graph-based approaches, link-based approaches and pattern and data mining approaches [13]. Graph-based approaches model the user community as a graph with nodes represent users, while link-based approaches use ranking algorithms such as PageRank.

Flake [60] used graph theory and connectivity to identify Web communities. Merelo-Guervos *et al.* [163] used Kohonen's Self-Organizing Map algorithm that utilizes patterns and data mining techniques to group communities into cells. Since the community formation is an evolutionary process, thus, communities' discovery can be improved by exploiting the time stamp of members joining the community.

Some researchers used a Bayesian approach to cluster users, for example, Breese *et al.* [27] cluster users based on their ratings. Ungar and Foster [213] cluster users based on their preferences. [52]. Other researchers used graph methods for clustering users based on their preferences as shown in Mirza *et al.* [165]. Sarwar *et al.* [194] used a scalable neighborhood algorithm to cluster users; their clustering method produced a higher Mean Absolute Error (MAE) than the CF standard approach.

Recently, DuBois *et al.* [52] have suggested clustering users based on their trust relationships. Such approach, coupled with a memory-based approach was able to produce high quality recommendations.

2.6. Social Based Service Selection

Social service selection is defined as finding the desired Web services by using information from other users based on their experiences [22]. Social service selection, sometimes referred to as social navigation [202], is characterized by its personalization, or how people act within a space, and dynamism [51]. Where personalization is defined in Adomavicius and Tuzhilin [3] as "the ability to provide content and services tailored to individuals based on knowledge about their preferences and behavior", and "the use of technology and customer information to tailor electronic commerce interactions between a business and each individual customer".

User Semantics as indicated by Scherp and Jain [197] is a concept of the user's perception of the real world based on their personal information and knowledge. Two factors influence user semantics: user's context (such as location and time) and user's social situation in the social network and their role such as leaders or followers. Consequently, personalization is context specific, *i.e.*, it depends on the receiver's situation and available information.

Social service selection techniques are how people make decisions in everyday life when concrete data is unavailable. In such cases, users rely on the input from friends, friends-of-friends, respected peers, experts, leaders and published ratings. Due to the network nature of Service Oriented Computing (SOC), social approaches can be utilized when selecting services [22]. In real life of the internet, the same notion of social navigation is applied when people buy a product or service from a Web site, such as Amazon.com. For example, when browsing for a book, a user has access to reviews left by other users as well as recommendations (people who bought book X also bought book Y).

Maximilien and Singh in [160] indicate that, Web services represent relationships reflected in their interactions with other participants such as the service consumer and the service provider. They view Web services as agents that enable users to augment Web services interaction styles between service consumer agents and service provider agents. Agents can provide mediation, negotiation, communication and collaboration between involved parties, *i.e.*, Web services and consumers, using trust and referral-style interactions [160]. Furthermore, Maamar *et al.* [144, 145] identify collaboration, substitution, and competition interactions between involved Web services.

According to Singh and Huhns [202], social-based service selection has three main approaches:

1. Reputation-based approach aggregates consumers' ratings of services at a central source to make recommendations to users in terms of their quality.
2. Recommender approach is used to make a prediction of a user's interests possibly based on users with similar characteristics or behaviors.
3. Referral approach utilizes trust among users and brokers in the network to obtain users ratings on services.

Each approach can use QoS or not, moreover, each approach has strengths and weaknesses for certain situations and contexts (these will be discussed in Sections 2.6.1 - 2.6.3); consequently, when the user is unable to make a decision about selecting a Web service from a vast number of services, then the user relies on social-based service selection approach. QoS is a set of measurable categories, both functional and non-functional, expressing the performance of a service [29]. Due to many users and service domains with different goals, there are no standardized QoS categories; some QoS categories are commonly seen in specific areas. However, with networked QoS, for example, it is common to see categories such as availability, latency and data rate [22].

In the following section, I review the three social service selection approaches.

2.6.1. Reputation Based Approaches

Reputation reflects what is generally believed about an entity character or behavior [94]. A reputation system collects, distributes, and aggregates feedback from other members about each member past behavior [187]. Reputation systems have been used to predict the trustworthiness of service providers [93]. In centralized reputation systems, a reputation centre collects information about participants in the market or community using feedback from other consumers. The reputation centre also provides an integrated user feedback mechanism through an evaluation of the product or the service [51, 134]. The reputation centre computes for each member a reputation score and makes all scores available for the public [183]. Members then can use others' scores to make decisions; thus, entities that attract most reputable members are likely to produce favorable outcomes [93].

User feedback can be either explicit or implicit depending on how to capture feedback. Although explicit approaches capture user satisfaction more accurately, they are costly and often users do not cooperate [116]. Resnick *et al.* [187] indicate that some people are reluctant to provide feedback, where it is difficult to elicit negative feedback, and it is difficult to assure honest reports. Research using eBay data revealed that only 50% of transactions have ratings submitted [45]. With automated ratings likely to be used with Web services, elicitation problems may still exist due to privacy issues [134], or disinterested users.

Wang and Vassileva [223] identify the following problems in reputation systems: 1. People are usually reluctant to give negative ratings since they can see each other's ratings and are afraid of revenge. 2. People can change their identities especially if they get a bad reputation. 3. A person's reputation is represented by a single numeric value, which makes it difficult to see different aspects of the reputation such as security or privacy. 4. The system computes the reputation treating all the ratings equally without taking into account the credibility of the raters.

Xiong and Liu [231] highlight the following problems in most reputation systems: 1. cannot differentiate between dishonest and honest feedback, 2. do not support contexts in the trustworthiness evaluation, 3. suffer from insufficient feedback because there is no incentives for peers provide feedback, 4. unable to deal with peers' strategic dynamic personality; as some peers act maliciously after they build good reputation.

For an interesting survey about trust and reputation systems for online service provision, the reader is directed to Jøsang, Ismail and Boyd [94] and Wang and Vassileva [223].

Reputation systems with QoS are commonly implemented with a single broker or QoS authority. Perhaps due to the simplicity, the majority of frameworks [37, 47, 96] involved a fixed set of QoS attributes to measure. The rationale for picking a fixed set was never adequately addressed other than indicating that previous studies had often selected them, although the attributes picked seemed reasonable for services. The common service attributes picked are as follows: reputation/trust, availability, execution time, cost, and bandwidth. It would be possible although not perfect, to add another set of general attributes to this list, such as, overall rating or miscellaneous rating that users could utilize for their business specific ratings [22].

Due to recommender techniques being personalized by definition, and due to the distributed approach of referral techniques, reputation techniques could benefit from storing user specific historical ratings as well [96]. Typically, brokers store the average rankings for each QoS attribute, albeit often a skewed or massaged averages based on some criteria; the issue with this approach is that the users' ratings is combined with the community data. Kalepu, Krishnaswamy and Loke [96] suggest convincingly that each user average ranking for each service should also be stored and factored in with the community data to avoid the disagreement with the majority.

2.6.2. Recommender Based Approaches

Recommender systems are the commonly used technique for product selection [97]. There are varied recommender systems categories, content-based, collaborative and hybrid recommender systems, in which each recommender system has its own strengths and weakness [4]. There are many e-commerce Web sites that use recommender systems to provide a recommendation to the user. Amazon, eBay, and EPINIONS all have recommendation services to ease the burden of product selection.

Employing collaborative-based filtering in Web service selection is a new emerging trend; most of Web service recommendation approaches use Web service ratings based on 'subjective opinions' of service consumers [99, 201]. Manikrao and Prabhakar [151] proposed a framework for Web service selection using service requirements semantic matching in the recommender system. Their approach utilizes users' feedback and CF. It is used to help users to select a service from a candidate set of Web services. Finally, the system requests the user to rate the service after the user invokes the selected service. However, users are reluctant to provide explicit ratings [187].

Unfair rating is typical problem in most recommender systems; nevertheless, there are some approaches used to eliminate malicious agents ratings [234]. The idea is to ignore ratings below a certain quality threshold, or received from an agent their credibility is below a certain credibility threshold. Sherchan *et al.* [201] infer users' ratings based on the analysis of user ratings behavior in a Web service environment.

Collaborative filtering [81, 154, 192, 195, 250] is one of the major technologies used in recommender systems to suggest items that users might like [196]. Typical collaborative filtering system is centralized, where a centralized node is responsible for collecting ratings from users, and storing them in a matrix with a row for each user and a column for each item. According to Massa and Bhattacharjee [157], standard collaborative filtering algorithm has three steps:

1. The similarity between a given user and every other user is calculated, based on the similarity of their ratings on the items that they have both rated before. The Pearson correlation coefficient is the most popular algorithm for measuring the similarity between two users.
2. The predicted rating of a user on an item that he/she has not rated is calculated as a function of the ratings from the other users, who have rated the item weighed by the similarity between the user and the other users.
3. The items with the highest predicted ratings are recommended to the user.

Although the algorithms of collaborative filtering systems and personalized reputation systems look similar, they are different in their focus [223]. Collaborative filtering systems emphasize the similarity of users' tastes, while personalized reputation systems focus on the trust between users. However, they are both used to measure the reliability of other users' opinions/ratings. According to some definitions, trust means similarity of users' tastes [26, 67, 120, 253] in some contexts. If two users are more similar in their tastes, they can trust each other's opinions more. Therefore, a collaborative filtering system can be regarded as a variation of a personalized reputation system.

Recently, Zheng *et al.* [250] proposed WSRec; a hybrid collaborative filtering method for Web services recommendation, where users' past experiences for Web service QoS information are collected to predict QoS of candidate services. Furthermore, Chiu, Leung and Lam [42] proposed a quantitative recommendation model utilizing utility, reputation, impression, trustworthiness, risk attitude, and persuasiveness.

A collaborative filtering based recommender system can make good quality recommendations when the system has enough required data. But it is vulnerable to the lack of data, which causes two problems, cold-start and data sparseness issues discussed early in Section 2.4 of this chapter.

Web service recommendation related research appears in efforts such as [23, 24, 103, 125, 127, 151, 250]; some of these efforts address the QoS attributes as user preferences.

Recently, Chung and Rao [43] present a recommendation approach for Internet entertainment services for experience products like movies and games, using a general consumer preference model when significant information on non-quantifiable attributes (*i.e.*, QoS is missing). They compute product utility from two components (observed and unobserved) based on QoS attributes availability; the unobserved component is evaluated using residuals of virtual experts. Their results show improvements in the prediction hit rate over collaborative algorithms.

2.6.3. Referral Based Approaches

Referral-based approaches are used to evaluate services and referrals to help users to find experts [22]; agents who provide information about other agents' trustworthiness are referred to them as a *witnesses* [14], and the provided information is called as *referral trust*. Sabater and Sierra [189] proposed how to combine reputation information from different agents in varied contexts; this approach can recognize trustworthy agents in each context. Referral trust is presented in "open networks" by Beth *et al.*, [21].

Abdul-Rahman and Hailes [2] classified agent' trustworthiness as *Very Trustworthy*, *Trustworthy*, *Untrustworthy* and *Very Untrustworthy*. The relying agent then can apply their perception about the referring agent trustworthiness before considering the referral agent in account. Other works consider referral trust such as Xiao and Benbasat [229], and O'Donovan and Smyth [175], describe reputation applications and their impact on recommenders. In summary, the trusted party recommends a party (who recommends a party) that can perform the function [190].

In real life, if a consumer needs to avoid a risky transaction, they may consult a trusted friend, what they think about that transaction. If this friend is unable to provide an opinion about that transaction, he/she can ask a friend of their friends, and so on until he/she finds someone (*i.e.*, a recommender) who can provide an opinion about that transaction [214], this scenario is shown in Figure 2.1 below.

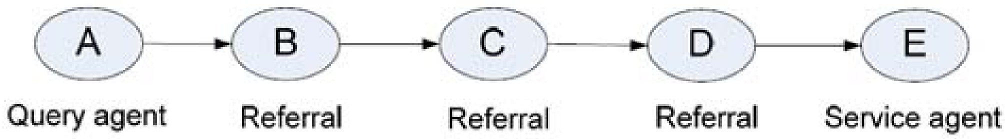

Figure 2.1. Referral Graph [223]

A referral system perform the following functions [22]:

- Evaluate services and referrals to help users to find experts.
- Maintain directories about other agents.
- Integrate interaction between agents [51].

The referral approach is characterized by an agent A querying about a service to another agent B among its neighbors. Agent B may not respond to agent A’s query, may respond by offering its service, or refer another agent C who may be able to perform the service requested by agent A. Moreover, each agent maintains expertise and sociability about other agents [202]. Expertise is the ability of an agent to perform a service while the sociability is the ability of an agent to refer other accurate agents. These two factors are updated based on service ratings [22].

Besides rating services, referral selection systems often rate reputation peers. Since reputation peers can be considered as services, QoS attributes can be applied here as well [85]; this can lead to an improved referral trust sub-networks that dynamically adjust quicker, and more accurately ultimately leading to an improved service rating [159].

2.6.4. Recommendation Approaches against Challenges

In the previous sections, I presented social-based service selection approaches, while in Section 2.4, I discussed Web service selection and recommendation challenges. In this section I provide a comparison between service selection approaches and how each of the challenges (cold start, sparsity, privacy, scalability, and user' preference capturing) impacts each of the selection approaches.

Table 2.2: Challenges addressed in recommendation approaches

	Reputation	Recommender	Referral
Scope	Aaggregates users' ratings of services at a central source to make recommendations to users in terms of their quality	Make a prediction of a user's interests based on users with similar characteristics or behaviors	Utilizes trust among users and brokers in the network to obtain users ratings on services
Operation	Centralized	Centralized	Decentralized
References	[94, 100, 130, 148, 199, 201, 216, 223]	[23, 24, 43, 103, 125, 127, 151, 250]	[2], [229]
Strengths	• Simple design overall	• Find services easily due to automated suggestions • In some cases, can avoid elicitation due to tracking user behavior	• No single point of failure • System dynamically restructures based on broker trust • Stores less data
Weaknesses	• Most vulnerable to collusion and retaliation • Difficulty eliciting ratings • Single point of failure • Difficult for low ranked service to promote itself	• Requires many ratings to make a recommendation • Complexity due to increase data storage and traversal • Single point of failure	• Trust issue among brokers/agents • Distributed system may be slower than stand alone • More complex due to distributed nature
Cold-Start	• Not considered for users	• lack of data implies could not find similarities with cold-start • some treated as naïve user	• Considered, user need to know at least one friend
Sparsity	• N/A – Since no similarity computation is needed	• lack of data causes data sparseness especially for cold start users	• N/A – Since no similarity computation is needed
Privacy	• Difficult to see different aspects of the reputation such as security or privacy	• Hot issue in rec. systems • 70% of internet users are aware about their privacy • Privacy breaches by revealing users' information.	• Not considered due to distributed nature.
Scalability	• Scalable based on number of services/products available.	• Since similarity computation increases, scalability is a challenge	• Distributed system may be slower than stand alone
Users' Ratings	• Implicit or explicit • Difficulty eliciting ratings • reputation is represented by a single numeric value • credibility of the raters not considered	• Implicit or explicit • Difficulty eliciting ratings • Unfair rating is typical problem • Raters' credibility issue in most approaches..	• More transactions and users needed for ratings • Unfair rating issue • Raters' credibility issue

As indicated previously, Web service recommendation differs from product recommendation in that Web services have QoS attributes that must be considered in addition to the functional attributes during the service selection and recommendation. Although adding QoS improves the quality of the recommended service and increases users' satisfaction as provides more accuracy in ratings; QoS systems must face additional issues that include [22]: added complexity, extra data storage, computations overheads, increased network traffic, and involved interface to express QoS attributes during the service selection. Thus considering QoS attributes is useful in handling privacy issue and user preferences at the selection process; and place extra overheads on scalability, user' rating and sparsity due to increased complexity.

It is also worth mentioning that almost all the work undertaken on recommender systems has varied approaches that address Web service selection and recommendation, notably not all presented approaches are addressing all these challenges: cold start, sparsity, privacy, scalability, and user' preference capturing.

2.7. Chapter Summary

Social service selection is a challenging problem in theory and practice. This field is incredibly immature; this argument is supported by the fact there is no automated public service selection system deployed in the commercial world at present. Although some approaches used to handle services as products; services have non-functional properties or QoS attributes that distinguish them from products.

This chapter has briefly introduced the social service selection and recommendation problem. Three powerful technologies can be integrated to address it have been identified and described: semantic Web services, Web based social networks and recommender systems. These technologies possess the catalytic synergies required to address the complex problem of service selection and recommendation. The challenges and research gaps associated with the social service selection and recommendation problem in a dynamic environment were identified. User behavior analysis indicates that cold-start users represent more than 50% of the users' population. Unfortunately, there is no solution that can effectively handle these users.

In summary, many trust and reputation systems have been developed to address the service selection problem. In this chapter, I presented a systematic overview of these diverse state-of-the-art approaches. A review of the literature related to the proposed solution is presented; the related areas include Web-based social network analysis, Web-based social networks and trust, trust-based Collaborative Filtering (CF), “Follow the Leader” strategy, finding experts in a social network and clustering and collaborative filtering. Finally, I presented three social service selection and recommendation approaches; reputation, recommender and referral-based approaches.

In the remainder of this dissertation, I propose a social service selection and recommendation approach based on a credibility framework that models user and Web service credibility with Web service perceived risk and user risk attitude. My work is the first that uses a formal “Follow the Leader” strategy, 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.

Chapter 3

Credibility-Based Social Service Selection and Recommendation

In Chapter 2, I presented the social-based service selection and recommendation problem highlighting current challenges. These include handling cold-start users, sparsity, privacy, capturing users' preferences and feedback, and scalability problems. Furthermore, I reviewed three social service selection and recommendation approaches: reputation, recommender and referral-based approaches. User behavior analysis indicates that cold-start users represent more than 50% of the users' population and represent new customers that services can attract. Current approaches do not provide effective solutions to handle the preferences of these users in selecting a Web service.

In this chapter, I present a credibility-based social service selection and recommendation framework. My work differs from the existing approaches in three major aspects. First, I adopt a social-based service selection approach using Web-based social networks. Second, a well established social strategy "Follow the Leader" is used. Third, I augment the proposed approach with user behavior analysis.

Most of the current approaches adopt either trust or reputation as the basis for social service selection. Unfortunately, most of these approaches ignore the expertise component of the agent, *i.e.*, the Web service or the recommender.

In this chapter, I introduce two models of credibility: a user Credibility model and Web service Credibility model. Each model uses two credibility components: trustworthiness and expertise. I show how each model can be used in the context of the social service selection and recommendation. Finally, I propose an evaluation framework to evaluate the models, algorithms and approaches presented in this chapter.

3.1. Introduction

In Web-Based Social Networks (WBSNs) users are influenced by published opinions, ratings and comments posted by other users. WBSN, to a great extent, reflects social trust between individuals in a social group. The presence of social connections defines the similarity of user interests [121]. Intuitively, when faced with overwhelming choices and lacking specific domain knowledge, a user will refer to the opinions of friends on a specific item or service [70, 135]. However, defining users' similarity is a complex and challenging task, particularly when the sparsity issue and noise in the data apply limitations over similarity computations, and consequently make computations more expensive [9].

Trust-based recommendation approaches exploit the trust relationships between users, and make recommendations for a user based on the ratings of other users who are directly or indirectly trusted by that user [168]. The trust network is very sparse; hence, trust inference approaches are used to infer trust values between users who are indirectly connected in the trust network. Although trust-based approaches have superior rating prediction coverage than traditional (CF) recommender systems, the conventional trust-based approach suffers from computational complexity [243]. Furthermore, the rating prediction coverage of the trust-based model can also be significantly worse for cold-start users. In summary, the conventional trust-based approach suffers from the following shortcomings: cold-start, sparsity, noise in the data and scalability issues [9].

Some members of WBSNs have a greater level of influence over other members and are known as leaders or pioneers [70, 235]. Finding a credible recommender is a challenging issue, therefore, the main objective of this chapter is to utilize social network information to make recommendations based on the credibility of users drawn from their trustworthiness and expertise.

Social networks have been used in Collaborative Filtering (CF). Recently, DuBois *et al.* [52] used trust as a basis for forming clusters. My work is the first to use a formal "Follow the Leader" strategy, based on web-based social networks and user credibility, to generate a cluster of the most trustworthy and experienced users in the social network called leaders. Leaders act as advisers to other users, including cold-start users, who do not have enough interactions to capture their similarity using trust approaches.

In the Service Web, as indicated by Malik, Akbar and Bouguettaya [148] a wide range of similar functionalities are expected to be offered by a vast number of Web services; moreover, different services from distributed locations can collaborate to create new value-added composite services. In such situations, some services may be new to the service market, while other services may perform maliciously in order to be selected. A key requirement is to provide credibility assessment mechanisms for quality access and retrieval of relevant Web services.

In Web service selection, reputation assessment mechanisms are used to establish trust between consumers and Web services, as indicated by Wang and Vassileva [223]. In a recent research, Kim, Ferrin and Rao [101] show that a good Web service reputation positively affects the consumer's trust. The Web service selection process involves rational decision-making to select service instances from a huge number of service providers [159]. Since QoS changes over time, it is also necessary to take these changes into account in the selection process.

Web service selection is a complex process in which the service that best matches customer preferences is selected from a group of candidate Web services based on customer requirements [215]. As per the selection criteria, various QoS attributes can be expressed as customer preferences. Web service non-functional properties or QoS attributes are difficult for the customer to determine; moreover, some customers are reluctant to spend time describing their complete preferences and providing ratings for the system [33, 202, 252], and are even less willing to assign relative weights to their preferences, especially when the effects and consequences of their inputs are unknown or undetermined [6]. Moreover, customers may not even be aware of their implicit preferences.

Consequently, a customer who wants to find a Web service will often seeks help from friends, leaders and business partners who have relevant experience. Capturing and specifying customer preferences is one of the most complex problems in the selection process [202, 252].

Many social service selection approaches based on trust and/or reputation have recently been presented, such as [63, 72, 124, 125, 138, 141, 152, 219, 239]. Nevertheless, few of them consider the impact of service expertise in the social service selection.

Other researchers have presented approaches for Web service recommendation such as [23, 24, 103, 125, 127, 151, 250]. Some of these efforts address the QoS attributes as user preferences. Some use trust, others use reputation, but unfortunately, none of them uses trustworthiness and expertise of the Web service at the same time.

In this chapter, I propose a social service selection approach based on a credibility framework that models user and Web service credibility. My work is the first to use a formal "Follow the Leader" strategy [70] based on Web-based social networks and service credibility to make service selection using the most trustworthy and experienced users or service providers in the social network as advisers to the rest of the population in the network.

Utilizing trust in Web-Based Social Networks (WBSNs) is a promising approach for making recommendations to other users based on trust propagation to find a friend, or a friend of a friend, with similar interests. However, some users do not have friends in the social network to infer a trustworthy person who can provide recommendation. Moreover, some users, such as leaders, do not want to rely on other friends. Current recommendation approaches cannot make reasonable recommendations for the cold-start users, who represent more than 50% of the population in most social networks.

I argue that seeking advice from a trustworthy expert is more feasible than seeking advice from an ordinary trustworthy user, which leads to the question: How do we find trustworthy expert users and service providers in the WBSN?

The key contributions of this chapter are as follows:

- A Trustworthiness Expertise Credibility-Based Framework (TECBF) is proposed.
- A user model based on credibility that captures trust relationships between users.
- A clustering approach based on the "Follow the Leader" strategy and user credibility to identify community leaders in the WBSN.
- An effective means of generating high quality user-based collaborative recommendations based on user credibility and "Following the Leader" strategy.
- Web service credibility metrics that incorporate trustworthiness and expertise.
- A social Web service selection approach based on the user credibility, service credibility and "Follow the Leader" to make service selection and recommendation.
- An evaluation framework to evaluate models, algorithms and approaches presented in TECBF.

3.2. TECBF: Trustworthiness Expertise Credibility-Based Framework

This section presents a framework called TECBF that is intended as an effective, efficient and feasible approach to make social-based service selection and recommendation in WBSN environments.

TECBF, as shown in Figure 3.1, is based on a trustworthiness component and an expertise component. Credibility is a synonym of believability [10] and refers to the objective and subjective components of the believability of an agent. I follow Malik and Bouguettaya [149] and define a credible agent as one who "has performed consistently, accurately, and has proven to be useful" over a period of time. The credibility of an agent refers to its quality of being believable or trustworthy and its capacity to be measured by its trustworthiness, expertise, and dynamism [115].

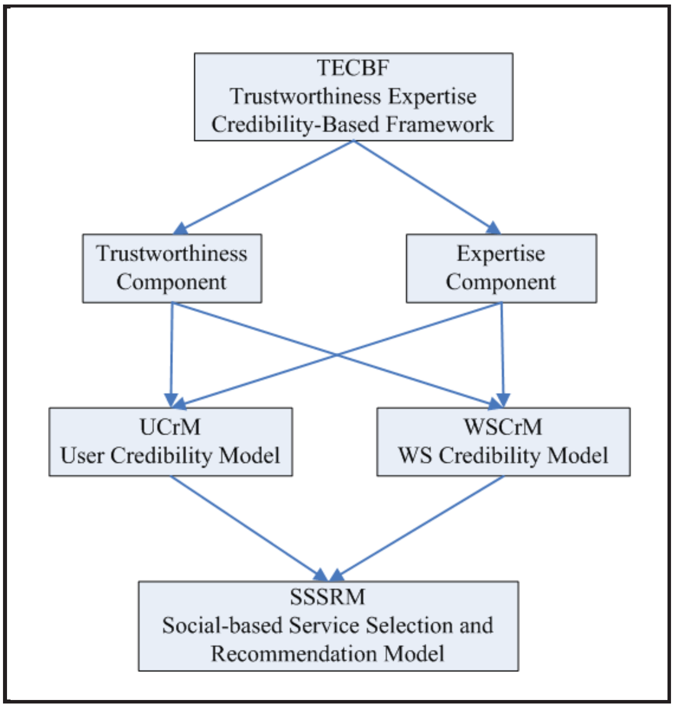

Figure 3.1. TECBF: Trustworthiness Expertise Credibility-Based Framework

Users and services in a WBSN interact in varied contexts. Pascoe [180] defines a context as "the subset of physical and conceptual states of interest to a particular entity", while Dey and Abowd [50] define context as: "any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves."

In each specific context, TECBF employs a user Credibility model (UCrM), adopting the trustworthiness and expertise components drawn from that context. UCrM reflects the behaviors of the users in that context. TECBF also employs a Web service Credibility model (WSCrM), adopting the trustworthiness and expertise components which are drawn from that context. WSCrM reflects the behaviors of the services in that context.

To achieve effective and efficient Web service selection and recommendations in WBSN, TECBF proposes a Social-based Service Selection and Recommendation Model (SSSRM) that utilizes both UCrM and WSCrM.

The following sections explore these models in details:

3.3. UCrM: User Credibility Model

In this section, I define the concepts to be used in the model, as shown in Figure 3.2.

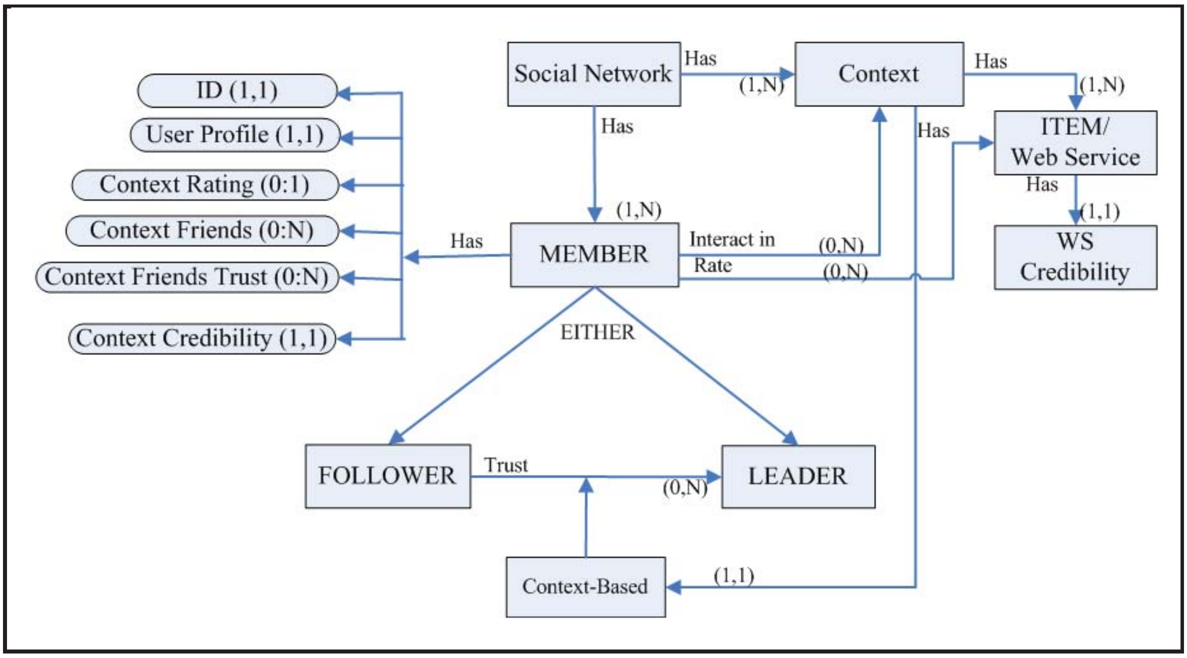

Figure 3.2. User Credibility Model (UCrM) in WBSN

Members in a WBN interact in a variety of contexts. I consider users as registered members in the WBSN; each registered user has a unique identity (ID) with a corresponding user profile that reflects personal information. If the user interacts in a specific context or category, then the user may provide ratings for an item or items (services) in that context. Moreover, users may specify their trust in other members' ratings. This generates a set of friends in that context (called Context Friends), with corresponding trust values for each friend. The model also shows that, at any point in time, a credibility score for each member and Web service (item) can be generated. Utilizing a "Follow the Leader" strategy, users can be qualified as either leaders or followers in that specific domain.

In WBSN, let U be a set of users, $U = \{u_1, \dots, u_N\}$ interacting in a set of contexts $C = \{c_1, \dots, c_L\}$, such as categories in EPINIONS[14] or Web services.

In each context or category there is a set of items I, so that: $I = \{i_1, \dots, i_K\}, where\ I \in C$, K is the number of items in the set I.

Each user $u \in U$ rates a set of items or Web services M denoted by: $R_u^I = \{R_u^1, \dots, R_u^i \dots, R_u^M\}, where\ M \le K$, and R_u^i is the rating value of user u for item i. The rating value can be any real number, but most often ratings are integers, in the range [1, 5]. 'User' here refers to either an online community member or a software agent that interacts in the WBSN and is able to perform the required interactions.

In a trust-aware system, there is also a trust network between users. I define (T_v^u) to be the direct trust between user *v* and user *u*; the trust value is a real number in the range [0, 1], with zero meaning no trust and 1 meaning full trust between users, or a value on a scale in the range [0, 5] adopted from Abdul-Rahman and Hailes [1], and used in the EPINIONS dataset, with zero meaning no trust and 5 meaning complete trust between users. Binary trust networks such as Amazon[15] and eBay[16], are the most common trust networks. In this model, I consider only positive trust; distrust or negative trust is not considered in this chapter to avoid the dilemma of 'the enemy of my enemy is my friend', or 'if A distrusts B and B distrusts C, to what extent does A trust C?'

I model a WBSN in a specific context as a direct graph:

$$G = \langle U, T \mid U\ is\ set\ of\ Nodes, T\ is\ set\ of\ edges \rangle$$

In this model, I am concerned with the following characteristics of trust [69, 91]:

1. Trust is context based, which means that if A trusts B to repair his/her car, this means A may not trust B to provide his/her with medical advice.

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14 www.epinions.com - is a general consumer review site that was established in 1999.

15 www.amazon.com

16 www.ebay.com

2. Trust is directed from source to target; meaning that if A trusts B to repair his/her car this does not mean B should trust A in the same context.
3. Trust is transitive: if A trusts B and B trusts C in the same context or area of expertise, then some degree of trust between A and C can be inferred.
4. Trust is dynamic and may increase or decrease with further observation or interactions (*i.e.*, experiences). Trust can also decay with time.

Goldbaum's "Follow the Leader" model [70] provides us with insights to cluster users based on their roles in the WBSN, whether they be leaders or followers. Enriching the "Follow the Leader" model with trust provides us with the potential to analyze WBSN based on user credibility. Figure 3.2 shows the basis of my approach. A credibility measure of users reflects their trustworthiness and expertise and provides the means to cluster users in a specific context; some users can be classified as leaders, while others can be classified as followers according to their credibility level.

Users' credibility, as defined previously, is a synonym of their believability [10]. The majority of researchers have identified two key credibility components: trustworthiness and expertise. To evaluate user credibility, I address these two components as follows:

3.3.1. Trustworthiness Component

In this chapter, I refer to "trust" and "trustworthiness" as different but related concepts. As pointed out by Jøsang, Ismail and Boyd [94]: "Trust is the extent to which one party (truster) is willing to depend on somebody (trustee), in a given situation with a feeling of relative security, even though negative consequences are possible". This definition acknowledges the subjective nature of trust through truster '*willingness*' to depend on the trustee with '*relative security*' that the trustee will perform a favorable action for the truster. The dependence aspect in their relationship is supported by three factors: '*possibility*' implies uncertainty, '*negative consequences*' implies associated risk and '*given situation*' implies the context of dependence.

Aquevegue and Ravasi [12] cite Barney and Hansen (1994) who differentiate explicitly between trust and trustworthiness, pointing out that "while trust is an attribute of *a relationship* between exchange partners, trustworthiness is an attribute of individual exchange partners". Therefore, a trustworthy entity is an entity in which we can place our trust with consideration of any perceived risk.

In trust-aware WBSN for a specific context, users act as Truster or Trustee. Truster users provide trust scores for other users (Trustees), based on their confidence level that trustees will provide reliable ratings for items in a specific context. Consequently, trustees gain a reputation for their trustworthiness, and the greater the number of trusters who either directly or indirectly trust a user, the higher their credibility. I represent this relation as follows:

$$Cr_t(T_T^u) = f(T_v^u, N_D^u, N_I^u, N_{DMax}, N_{IMax}, t) \qquad (3.1)$$

where $Cr_t(T_T^u)$ value is a real number in [0, 1] and refers to user credibility gained from its trustworthiness at a specific point in time t, T_v^u is a *scaled* trust score that user *v* assigns to user u as defined previously, N_D^u is the number of *direct friends* who trust u and N_I^u is the number of *indirect friends* of u, *i.e.*, friends of friends. To give the user with the maximum number of followers more weight than others, the user with the maximum direct followers N_{DMax} is considered as a reference point; furthermore, N_{IMax} refers to the maximum number of indirect friends in the set, considered as a reference point. The normalized trust score is defined as follows:

$$T_v^u = \frac{T_v^u(Given)}{T_{range}},$$

where the Trust score range (T_{range} = 5) is the maximum trust score that can be assigned to a trustee in the WBSN, as shown in EPINIONS.

3.3.1.1. Credibility from Direct Followers' Trust

The number and types of links that members in WBSN have are the keys to determining their importance in the network, which constrains their behavior, and the range of opportunities, influence and power that they have [78]. Direct followers (trusters) of a user enrich the user's credibility based on the amount of trust they put in the candidate trustee.

Direct followers/friends of a user provide trust scores specifying how much they trust the user. The aggregation of trust scores is a measure of the user's trustworthiness; consequently it is a measure of user credibility. Formally, the credibility from direct followers/friends trust is denoted by $Cr_t(T_D^u)$, and defined as follows:

$$Cr_t(T_D^u) = \frac{1}{N_{DMax}} \times \sum_{v=1}^{N_D} T_v^u \qquad (3.2)$$

where $Cr_t(T_D^u)$ value is a real number in [0, 1] and represents the gained credibility from direct followers at time t. N_{DMax} refers to the number of direct followers of the user with maximum direct followers in the context, considered as a reference point. The impact of N_D^u appears on the aggregation of trust values from direct followers (friends). As can be seen, the credibility from direct followers is normalized, hence if the most trustworthy user receives a trust score of 5 from all friends then, $Cr_t(T_D^u) = 1$ if that user has the maximum number of direct followers at time t.

3.3.1.2. Credibility from Indirect Followers' Trust

Using the trust transitivity feature of trust proposed by Golbeck and Hendler [68], friends of friends who trust their nearest friend, and also trust their friends' next friend, yield a trust score which is the product of the two scores. Formally, the credibility from indirect followers (friends of friends) trust at time t, is denoted by $Cr_t(T_I^u)$, and defined as follows:

$$Cr_t(T_I^u) = \frac{\mathbf{1}}{\boldsymbol{N_{IMax}}} \times \sum_{v=\mathbf{1}}^{\boldsymbol{N_D}} \left\{ T_v^u \times \sum_{v=\mathbf{1}}^{\boldsymbol{N_I}} T_v^u \right\} \qquad (3.3)$$

where $Cr_t(T_I^u)$ value is a real number in the range [0, 1] which represents the gained credibility from indirect followers at time t, and N_{IMax} refers to the maximum number of indirect followers of a user in the context. In the first part of the formula, T_v^u refers to the direct trust of direct followers to the target user N_D, while T_v^u in the second part of the formula refers to the indirect followers' trust N_I. Trust aggregation for each direct follower over indirect followers allows us to aggregate the trust associated with all friends of this follower. In Figure 3.3 for example, if F12 trusts F1 with a score (4) and F1 trusts U with a score 3 on a trust scale of maximum 5 (*i.e.*, T_{range} = 5), then F12 trusts U with score = (4 * 3) / (5 * 5) = 0.48 in normalized measure or 2.4 in scaled measure of 5.

Notably, the credibility gained from lower levels in the hierarchy is ignored, since their contribution to the users' credibility is very small compared to first and second level friends.

Example: I provide the following example to explain and illustrate the above concepts.

Figure 3.3 represents user U with three direct followers - friends (F1, F2, F3) with corresponding direct trust values (3, 4, 3) to user U in a specific context. Arrows in the diagram indicate the trust relationship directed from the truster to the trustee with corresponding amount of trust. Direct followers (F11, F12) of F1 and (F21, F22, F23) of F2 are also indirect followers to U. To compute the credibility of U from trustworthiness component gained from direct and indirect followers:

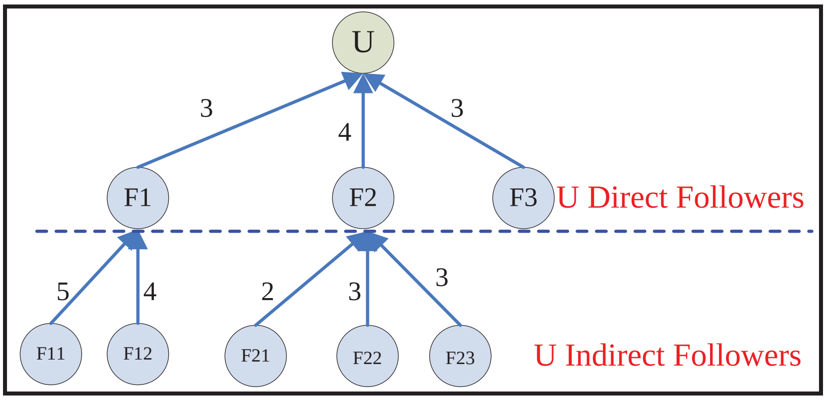

Figure 3.3. Direct and Indirect Followers' Trust

1. To normalize trust values, we divide each *trust value* by (5), thus trust values (3, 4, 3) for direct followers are normalized to trust values (0.6, 0.8, 0.6).
2. If user U has the maximum number of direct followers and indirect followers in this context, at that specific point in time t, then: $N_{DMax} = 3$, and $N_{IMax} = 5$.
3. Credibility from Direct Followers is computed as:
4. $Cr_t(T_D^u) = \frac{1}{3} * (0.6 + 0.8 + 0.6) = 0.667.$
5. Credibility from Indirect Followers is computed as:
6. $Cr_t(T_I^u) = \frac{1}{5} * \big(0.6 * (1 + 0.8) + \ 0.8 * (0.4 + 0.6 + 0.6)\big) \ = \ 0.472$

3.3.2. Expertise Component

Expertise, a key dimension of user credibility, is defined as the user competency degree in providing accurate ratings and demonstrating high activity [117]. The expertise dimension of the user credibility captures their perceived knowledge and skills in a given context. WBSN members vary in their knowledge and consequently their level of expertise; the more the knowledge a member has, the more power they possess, to the extent that "knowledge is power" [78]. The credibility of a user coincides with their reputation, which consequently coincides with their expertise level in a specific topic (context); in a WBSN as YouTube, for example, user reputation correlates with the content quality they generate [13].

Reputation is the public opinion about an entity, it generally reflects what is believed about the entity's standing or character [93]. It is a collective measure of the opinion of a community of users (humans or agents) regarding their actual experience with the entity in a specific context [130]. It is computed as an aggregation of users' feedback and reflects the reliability and trustworthiness of the agent. Agent reputation is impacted by the following factors: 1. Customer feedback, and 2. Credibility of a rater, which indicates how credible the rater is in providing feedback. Malik and Bouguettaya [149] 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 high credible raters carry more weight than ratings from consumers with low credibility.

If item i receives ratings from N users at time t, and each rater provide R_u^i for that item then the average of ratings of item i is given by:

$$R_{t_{avg}}^{\ i} = \frac{1}{N} \times \sum_{u=1}^{N} R_u^i \tag{3.4}$$

In order to avoid current user rating (R_c^i) influence on $R_{t_{avg}}^{\ i}$ and for a small number of raters *e.g.* N < 10, current user rating is excluded from $R_{t_{avg}}^{\ i}$ calculations; this yields:

$$R_{t_{avg1}}^{\ i} = \frac{\{\sum_{u=1}^{N} R_u^i\} - R_c^i}{N-1} \tag{3.4.a}$$

Thus user trustworthiness in providing rating R_u^i for item i is measured by comparing the provided rating R_u^i with $R_{t_{avg}}^{\ i}$; the smaller the difference between the two ratings, the higher the user's expertise and consequently their credibility. Thus, user credibility of one rating is defined as the difference between two ratings, and is given in the following formula as:

$$Cr_t\left(R_u^i\right) = 1 - \frac{|R_u^i - R_{t_{avg}}^{\ i}|}{R_{t_{Max}}^{\ i}} \tag{3.5}$$

where $R_{t_{\mathrm{Max}}}^{\ \mathrm{i}}$ is the maximum rating scale. Although researchers such as O'Donovan and Smyth [175] use other approaches to penalize ratings too far from reference rating $R_{t_{avg}}^{\ i}$, I argue that this formula works for binary ratings and scaled ratings as well, and I provide the following example to prove this empirically.

Example: consider that three users (a, b, c) provide ratings for item i, that has a maximum rating scale $R_{t_{\mathrm{Max}}}^{\ \mathrm{i}}$ = 5, and the average rating of item i is $R_{t_{avg}}^{\ i}$ = 4 from the total population in the network. Each user provides a rating for item i, as (5, 2, 4). If each user rating credibility is computed based on Formula 3.5, then the credibility of users (a, b, c) is (0.8, 0.6, 1) respectively. Notably, user c rating is the most credible user rating among the three users. This example demonstrates that user expertise in rating is penalized by the relative deviation from the population average rate.

If user u provides ratings for M items/services, then the accumulated user credibility expertise component from rating M items is denoted by $Cr_t(E_u)$, where the value is in the range [0, 1], formally is given by:

$$Cr_t(E_u) = \frac{1}{M} \times \sum_{i=1}^{M} Cr_t(R_u^i)$$

$$Cr_t(E_u) = \frac{1}{M} \times \sum_{i=1}^{M} \left\{1 - \frac{|R_u^i - R_{t_{avg}}^i|}{R_{t_{Max}}^i}\right\} \tag{3.6}$$

In order to differentiate between users who provide more ratings for different items, user expertise and consequently their credibility increases if the number of ratings increases. To consider the impact of this factor, I model user contributions as a weight factor for user ratings credibility; hence users who contribute more than others are rewarded with higher credibility. If the user with the maximum number of ratings over all items K is considered as a reference point $N_{t_{Max}}^{K}$, then the user contribution weight = (number of ratings of the user / maximum number of ratings among all users), formally given by:

$$R_u^w = \frac{M}{N_{t_{Max}}^{K}} \tag{3.7}$$

Using equation (3.7) in (3.6) yields the user credibility from the expertise component,

$$Cr_t(E_u) = \frac{1}{N_{t_{Max}}^{K}} \times \sum_{i=1}^{M} \left\{1 - \frac{|R_u^i - R_{t_{avg}}^i|}{R_{t_{Max}}^i}\right\} \tag{3.8}$$

It is clear from the above equation that if a user does not make any rating contributions, then the reward from the expertise component equals zero. The more credible contributions are made, the larger is the expertise reward received.

3.3.3. Computing User Credibility

By aggregating the credibility components, *i.e.* expertise component and trustworthiness (credibility from direct followers and indirect followers) component, the user credibility $Cr_t(u)$ at time t is given by:

$$Cr_t(u) = \alpha Cr_t\left(E_u\right) + \beta Cr_t(T_D^u) + \gamma Cr_t(T_I^u) \qquad (3.9)$$

where $\alpha + \beta + \gamma = 1$, and α, β, γ are model tuning parameters that represent the importance of the expertise credibility component, and the trustworthiness credibility (from direct followers and indirect followers) component. These parameters can be normally set or using automated machine learning techniques.

3.3.3.1. Impact of system tuning parameters

System tuning parameters can be determined according to the implementation circumstances. For example, when the system has no ratings, *i.e.*, the system with trust statements only, then the expertise credibility component α = 0. On the other hand, if the system has ratings statements only, then the trustworthiness credibility components β, γ = 0. When the ratings and trust statements are both available, however, then depending on the density of each component, the system administrator can tune these parameters based on either the frequency or the importance of each component.

3.3.4. Credibility Dynamism

Credibility may increase or decrease with further observation or interactions (*i.e.*, experiences), thus, it can also decay with time [7]. New experience draws more importance than old experience [222]; hence, all credibility data that refer to the past either with no or small importance. Adopting the decay factor $f_d(t)$ from Khosravifar *et al.* [100] to control this impact, given that all transactions are time stamped, to give a credibility that decays over time if the user is inactive, then equation (3.9) can be rewritten as:

$$Cr_t(u) = \frac{\sum_{t=t1}^{t2} Cr(u_t) \times f_d(t)}{\sum_{t=t1}^{t2} f_d(t)} \qquad (3.10)$$

The decay factor is given by: $f_d(t) = e^{-\lambda(t2-t1)}$, where each time period has its decay factor, λ ∈ [0, 1], and t2 – t1 is the time interval between the current time and the observations time, where ratings were provided by the raters. It is clear that all interactions or observation within a specific period have the same decay factor. For the current period t2 – t1 = 0, then $f_d(t) = 1$. For old observations when $f_d(t) < \lambda$, then observations are not considered because they are outdated. As shown in Figure 3.4, lower values of λ give a higher range of reference time.

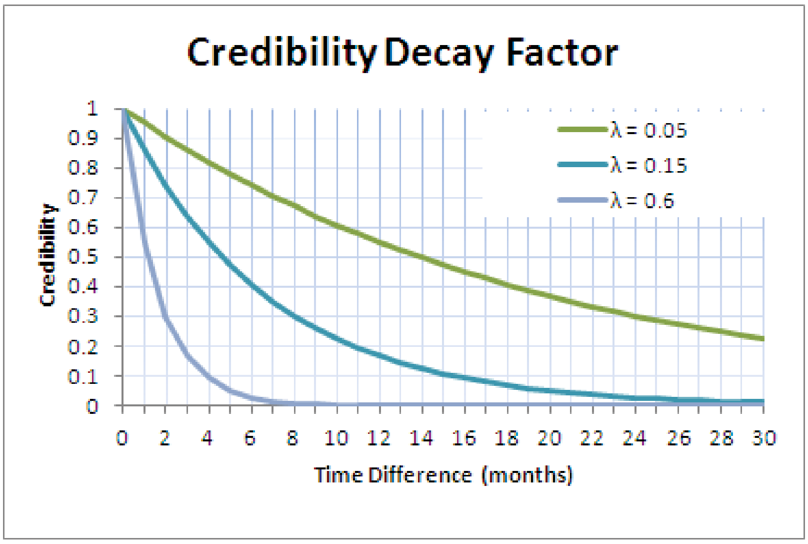

Figure 3.4. Impact of Decay Factor (λ) on Credibility

3.3.5. Clustering Users Based on Credibility

According to DuBois, Golbeck and Srinivasan [53] a "clustering algorithm takes a set of points in a metric space and groups them in a way that tries to optimize some criteria". Our clustering criteria is selected to achieve the objective of finding the most trustworthy and expert users who can act as advisers for the rest of the community in the network.

In this model, I define a *credibility threshold* from which leaders and followers are identified, and is given by (3.11) below:

$$\begin{cases} if\ Cr_t(u)\ \geq\ Cr_{t_{Threshold}},\ then\ user\ is\ Leader \\ if\ Cr_t(u)\ <\ Cr_{t_{Threshold}},\ then\ user\ is\ Follower \end{cases} \quad (3.11)$$

$Cr_{t_{\text{Threshold}}}$ refers to the *Credibility Threshold,* which is a system parameter that identifies users based on their credibility, and it is used to promote an adequate number of leaders from the target set based on the power-law degree distribution of social network, which is due to the effect of preferential attachment, Huang [83] indicate that 20% of the population in a given WBSN holds 80% of the total power of the society, which I consider them as leaders in the social network.

Notably, the credibility threshold is time dependent; for example, in the early stages of implementation, the credibility threshold can be set to a small value in order to promote higher number of leaders from the target set, while at later stages of implementation, the credibility threshold can be increased to higher values in order to promote adequate number of leaders from the target set.

3.3.5.1. How to identify the Credibility Threshold?

After computing user credibility, users can be sorted according to their credibility in descending order. The Top-N credible users are considered to be leaders; N here refers to the number of leaders to be promoted. By pointing the credibility of the N^{th} leader the Credibility Threshold is obtained. The Credibility Threshold can be slightly increased or decreased based on the circumstances. For example, for small datasets, a percentage of leaders in the range 10% to 20% is feasible, while for large datasets, a percentage of leaders in the range 5% to 10% is also feasible. I demonstrate the impact of varying leaders' ratio in Section 4.5.3.

Leaders usually have the knowledge and power to provide trustworthy advice by recommending the most trustworthy items for other users.

To build a "Follow the Leader" hierarchy, user credibility is used to identify users' roles, *i.e.*, whether they are leaders, followers, or independents [70]. Followers usually follow the most credible friend in a given context. If a follower finds their credibility higher than the credibility of all friends, using the confidence relation [185], the user acts as either a leader (if qualified as leader) or as an independent. Due to the dynamism of the network created by its natural evolution, some leaders may lose their credibility over time if they behave dishonestly, or if they stop making contributions or their trustworthiness drops.

3.3.5.2. Extended Example

In the following section, I provide an extended example to address the whole process of identification leaders and followers. This example was extracted from the Epinions dataset that is used in Chapter 4.

Consider a social network with 49,289 users, I extracted 10 users with varied ratings activity and varied number of direct followers and indirect followers, as shown in Table 3.1. The headings in Table 3.1 are defined and computed as follows:

1. User ID: is the reference number that identifies the user.

Table 3.1: User Credibility computation example

User ID	No. of Direct Followers	Cr. From Direct Followers	No. of Indirect Followers	Cr. from Indirect Followers	No of Ratings	User Ratings Average	Cr. From Rating	User Credibility	L/F
Notation	N_D	$Cr_t(T_D^u)$	N_I	$Cr_t(T_I^u)$	M	$R_{t_{avg}}^{u}$	$Cr_t(E_u)$	$Cr_t(u)$	
Formula	(3.2)	(3.2)	(3.3)	(3.3)	(3.6)	(3.5)	(3.6)	(3.9)	
23	1024	0.396	101335	0.824	598	4.0485	0.539	0.523	L
65	569	0.220	65061	0.529	1023	4.3832	0.952	0.661	L
298	181	0.070	33829	0.275	352	3.3551	0.300	0.221	L
341	959	0.370	99448	0.809	901	3.6260	0.807	0.662	L
6468	72	0.028	3279	0.027	144	3.7014	0.118	0.078	L
19191	2	0.001	5	0.000	8	3.6250	0.000	0.000	F
19495	1	0.000	0	0.000	4	4.2500	0.000	0.000	F
22427	2	0.001	5	0.000	12	2.7500	0.000	0.000	F
23951	1	0.000	0	0.000	1	5.0000	0.000	0.000	F
25379	1	0.000	0	0.000	14	2.5714	0.000	0.000	F

2. No. of Direct Followers: is the number of users who are directly following the user. Each number refers to the number of trust statements placed in that user, as the trust in this dataset is binary trust.

3. Cr. From Direct Followers: is the credibility from direct followers/friends trust, and computed as shown in formula (3.2)**;** N_{DMax} refers to the number of direct followers of the user with maximum direct followers considered as a reference point. In this dataset N_{DMax} value is 2589.

4. No. of Indirect Followers: is the number of users, who are indirectly following the user, i.e., indirect followers are (friends of friends).

5. Cr. from Indirect Followers: is the credibility from indirect followers (friends of friends), and computed as shown in formula (3.23)**;** N_{IMax} refers to the maximum number of indirect followers of a user in the dataset; $N_{IMax} = 122983$.

6. No of Ratings: is the number of ratings M provided by the user for M items/services,

7. User Ratings' Average: is the average of all items' ratings provided by the user, where the maximum rating in this dataset $R_{t_{Max}}^{\boldsymbol{i}}$ = 5, and the average item rating in the dataset is 3.99. This column is presented to show the deviation of users' rating from average rating in the dataset, it is not used in the calculations, and it is presented for demonstration purposes.

8. Cr. From Rating: is the accumulated user credibility expertise component from rating M items is denoted by $Cr_t(E_u)$, it reflects user trustworthiness in providing rating R_u^i for each item i and measured by comparing the provided rating R_u^i with $R_{t_{avg}}^{i}$ for that item

from all users who rated that item. The maximum number of ratings over all items K is considered as a reference point $N_{t_{Max}}^{K} = 1023$. The actual calculation follows formulas (3.5) and (3.6).

9. User Credibility: is the aggregation of the credibility components, i.e. expertise component and trustworthiness (credibility from direct followers and indirect followers) component as shown in formula (3.9). Where the system tuning parameters α, β, γ are assigned the values (5/9, 3/9, 1/9) respectively.

10. L/F: based on the credibility threshold that already defined in Section 3.3.5, the value of 0.019 is considered as credibility threshold for this dataset as discussed in section 4.5.3.

From Table 3.1, we note that:

- Top 5 users are identified as leaders based on their final credibility compared to the credibility threshold, while lower 5 users are identified as followers.
- When user' rating deviates from average item rating, the expertise credibility suffers from such behavior especially for users with small rated items such as user 23951.
- When the user has a small number of trustors, then the user credibility from direct followers suffer as well, this conclusion is also applied for indirect followers trust.
- Although the expertise credibility calculations are not shown in the above example, the computations performed as per Section 3.3.2. Please refer to the example presented in that section.

3.3.6. Using Leaders as Potential Top-N Recommenders

In order to make recommendations, my approach relies on leaders as the Top-N credible and trustworthy users in a specific context of providing recommendations. The number of leaders is determined by previously defined credibility threshold.

3.3.6.1. Prediction for experienced users

We compute the predicted rating by user a for unknown item i using the following formula proposed by Massa and Avesani [155] replacing similarity weight with credibility weight:

$$Pred(a,i) = R_a^{Avg} + \frac{\sum_{u=1}^{K} Cr(u) \times (R_u^i - R_u^{Avg})}{\sum_{u=1}^{K} Cr(u)} \qquad (3.12)$$

where K is the number of leaders who rated item i, R_u^i represents the rating for item i provided by leader u with a corresponding credibility $Cr(u)$, R_u^{Avg} represents leader ratings average and R_a^{Avg} represents average ratings provided by user a.

3.3.6.2. *Prediction for cold-start users*

Cold-start users are one of the most important challenges in recommender systems. Because cold-start users are more dependent on the social network compared to users with more ratings, the effect of using trust propagation becomes more important for cold-start users. In the Credibility model, notably, each cold-start user ends up with a leader in their trust graph. Moreover, in many real life social rating networks, a large portion of users do not express any ratings, and only participate in the social network [90]. Hence, using a user Credibility-based model can be an effective approach to making recommendations using leaders as advisers to other users. I show the effectiveness of this through the evaluation experiments described in the next chapter.

Cold-start users are new users to the recommender system who have expressed only a few ratings. When the target user (a) does not have ratings or their ratings number is less than 5, *i.e.*, they are a cold-start user, the following formula is used, replacing the trust weight proposed by Golbeck and Hendler in [68] by credibility weight Cr(u) of a leader:

$$R_{Pred}^i = \frac{\sum_{u=1}^{K} Cr(u) \times R_u^i}{\sum_{u=1}^{K} Cr(u)} \tag{3.13}$$

where K is the number of leaders who rated item i, R_u^i represents the rating for item i provided by leader u with a corresponding credibility $Cr(u)$.

3.4. WSCrM: Web Service Credibility Model

Figure 3.5 represents a Web service Credibility model. It shows that Web service credibility is aggregated from Web service (WS) trustworthiness component and expertise component. These two components are impacted by a time factor that determines the recent data from the old ones. WS trustworthiness is reflected by its reputation which is drawn from customers' feedback that represents their satisfaction with the usage of the WS.

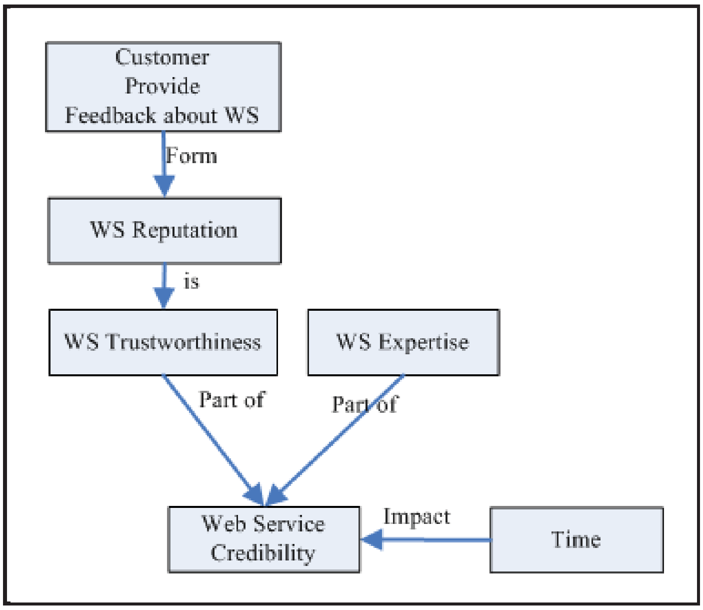

Figure 3.5. Web service Credibility Model (WSCrM)

A credible Web service is defined as a service that performed accurately, consistently, and has proven to be dependable over a period of time (t). Credibility of a Web service $\mathrm{Cr_t}(S)$ as shown in Figure 3.5 can be measured by its trustworthiness $\mathrm{Cr_t}(T_S)$, expertise $\mathrm{Cr_t}(E_S)$ and dynamism [115]; so I address these components as follows:

3.4.1. Web Service Credibility from Trustworthiness

According to Chiu, Leung and Lam [42], 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". A trustworthy entity is an entity in which we can place our trust or an entity that is worthy of confidence; this is applicable to the service provider and the Web service. This means trustworthiness of a Web service indicates its worth of confidence, thus, it entails its past consistent reliability, experience and reputation in a specific context and time. Hence, trustworthiness is used as an indicator of the extent that we can depend on the service provider in providing a service even though there is some perceived risk associated with that service.

Web service trustworthiness $\mathrm{Cr_t}(T_S)$ is defined as a measure of its reputation at any point of time t, and is regarded as a predictor of its future behavior [148]. Reputation reflects the public opinion about an entity's character or behavior [93]. It is a collective measure of the opinion of a community of users (humans or agents) regarding their actual experience with the service [130]. It is computed as an aggregation of users' feedback and reflects the reliability and trustworthiness of the service and its provider. Web service reputation is impacted by the following factors:

1. Customer feedback: represents the extent of customer satisfaction with providers' performance based on the interaction with the Web service. Additionally, it represents the opinion of the customer on the fulfillment of the service considering the service level agreement - SLA [130] between the user and the service provider.

2. Credibility of a rater: indicates how credible the rater is in providing feedback. Malik and Bouguettaya [149] 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 raters with high credibility weigh more than ratings from raters with low credibility.

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

$$REP(S_t^j) = \frac{\sum_{i=1}^{N} FEEDBACK(S_i^j) \times Cr_i^j \times W_i^j}{N^j \times W_a^j \times Cr_a^j} \qquad (3.14)$$

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 the number of customers who rated attribute j of service S, average of users' preference weights and average raters' credibility, respectively.

Web service reputation is computed as an aggregation of users' feedback and reflects the reliability, trustworthiness and credibility of the service and its provider. We view different reputation aspects as components of the over-all reputation; each reputation aspect is an aggregation of all feedback that addresses that aspect. Some aspects may address provider behavior, others address Web service behavior. While some aspects can be considered on the attribute level such as response time of Web service, other aspects considered as an aggregation of multi-attributes; such as provider reliability or service security.

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

$$REP(S_t) = \frac{\sum_{j=1}^{n} REP\left(S_t^j\right) \times W_a^j}{\sum_{j=1}^{n} W_a^j} \qquad (3.15)$$

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 j^{th} attribute. Since Web service reputation reflects its credibility, I model Web service credibility from Trustworthiness component $\mathrm{Cr_t}(T_S)$ as:

$$Cr_t(T_S) = \frac{\sum_{j=1}^{n} REP\left(S_t^j\right) \times W_a^j}{\sum_{j=1}^{n} W_a^j} \qquad (3.16)$$

3.4.2. Web Service Credibility from Expertise Component

Expertise, a key dimension of Web service credibility, is defined as the Web service competency degree in providing accurate results as promised and demonstrating high activity [117]. The expertise dimension captures the perceived inter-operability and skills of the Web service. QoS monitoring is out of the scope of this chapter; monitoring the QoS for Web services presented in Zeng *et al.* [246] or Xiaoying *et al.* [230] can be used as reference models for QoS monitoring, where these models can capture the advertised and the delivered QoS values on attribute level. I model Web service credibility drawn from its expertise component as:

$$Cr_t(E_S) = \frac{N_t^S}{N_{Max}^t} \times P_{s,t} \qquad (3.17)$$

where $\mathrm{N_t^S}$ refers to service engagement frequency in a specific period t, and is defined as the number of times the Web service was engaged in an execution process. $\mathrm{N_{Max}^t}$ is the maximum service engagement frequency in that domain; considered as a reference point. $P_{s,t}$ is the performance of service in the range [0, 1] at time t; and computed as the aggregation of all QoS performances. 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 I define QoS attribute performance from one transaction P_s^j for the j[th] attribute as follows:

$$P_s^j = \begin{cases} 1 \;\; if \;\; Q_s^{jAdvertised} \leq Q_s^{jPerceived} \; (Maximize\ attribute\ j) \\ 1 - \frac{|Q_s^{jAdvertised} - Q_s^{jPerceived}|}{Q_s^{jAdvertised}}, \; Maximize\ j\ Otherwise \\ 1 \;\; if \;\; Q_s^{jAdvertised} \geq Q_s^{jPerceived} \; (Minimize\ attribute\ j) \\ 1 - \frac{|Q_s^{jAdvertised} - Q_s^{jPerceived}|}{Q_s^{jPerceived}}, \; Minimize\ j\ Otherwise \end{cases} \tag{3.18}$$

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, it means the higher value over the promised (advertised) value is the better, such as security. When the attribute is to be minimized, it 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. When the perceived response time is 0.75 ms, then the performance of the response time is 1.0.

Taking the average performance of each attribute from its N previous performances, average performance of attribute j is given by:

$$P_{s,t}^{jAvg} = \frac{\sum_1^N P_s^j}{N_t^S} \tag{3.19}$$

Over-all performance of the service is the weighted mean of all attributes n, formally given by:

$$P_{s,t} = \frac{\sum_{t,j=1}^n P_s^{jAvg} \times W_a^j}{\sum_{t,j=1}^n W_a^j} \tag{3.20}$$

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

Using equation 3.20 in equation 3.17 yields expertise credibility at any point of time as:

$$Cr_t(E_S) = \frac{N_t^S}{N_{Max}^t} \times \frac{\sum_{t,j=1}^n P_s^{jAvg} \times W_a^j}{\sum_{t,j=1}^n W_a^j} \tag{3.21}$$

3.4.3. Computing Web Service Credibility

Web service credibility is computed by aggregating the credibility components: trustworthiness component from reputation and expertise credibility component.

Web service credibility at current time t is given by:

$$Cr_t(S) = \beta Cr_t(T_S) + (1 - \beta) Cr_t(E_S) \qquad (3.22)$$

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

3.4.4. Web Service Credibility Dynamism

In Web service selection, recent credibility components trustworthiness and expertise attract more importance than old ones. Web service may increase or decrease with further observation or interactions (*i.e.*, experiences), thus, it can also decay with time [7]. As dynamism of users' credibility discussed in Section 3.3.4., the same concept applied here for Web services. Recent experience draws more importance than old one [222]; hence, all credibility data that refer to the past either with no or small importance. Adopting the Decay factor $f_d(t)$ from Khosravifar *et al.* [100] to control this impact, given that all transactions are time stamped, credibility of service s can be defined as:

$$Cr(s) = \frac{\sum_{t=t1}^{t2} Cr_t \times f_d(t)}{\sum_{t=t1}^{t2} f_d(t)} \qquad (3.23)$$

The decay factor is given by: $f_d(t) = e^{-\lambda(t2-t1)}$, as defined and discussed previously in Section 3.3.4.

3.4.5. Web Service Credibility Characteristics

In this model, my focus is in the following characteristics of Web service Credibility, drawn from trust characteristics [69, 91]:

1. Credibility is context specific: for example, we can use a home insurance service (A) to insure our home in Sydney because it is worthy of being trusted for its excellent reputation and experience, on the other hand we cannot use service (A) to

insure a home in Washington D.C. using the same insurance service. This example shows that Web service Credibility defined in the context of the user's needs.

2. Credibility is aspect specific: to illustrate this point, consider the following situation. There are two payment services, S1 and S2, both of which have the same global reputation and experience. S1 has better security procedures than S2. If the customer gives security higher preference over other capabilities, then S1 is better than S2 for that customer. This example shows that Credibility has multiple aspects; each aspect can play a role in assessing the service trustworthiness and its usage suitability.
3. Credibility is dynamic: since service reputation and its expertise may decrease or increase with further interactions (*i.e.*, experiences), credibility also decays with time. Recent experience draws more importance than old experience, because old experience may become irrelevant or outdated after a specific period of time. So, in order for users to trust a Web service, its worth and integrity must be constantly proven over time.

3.4.6. Web Service Credibility Model - Flexibility and Robustness

The following section presents the features that demonstrate the flexibility and robustness of the Web service Credibility model.

3.4.6.1. Model Components Initialization and Simplification

Some researchers may dispute the complexity of the model, especially in managing the Web service expertise component. I argue that there is a tradeoff between accuracy and simplicity. We can simplify the model on the account of the level of accuracy; therefore, I provide the following formula to calculate the expertise component of Web service credibility that replaces equation (3.21), if monitoring Web service performance is difficult to attain.

$$Cr_t\left(E_S\ \right) = \frac{N_t^S}{N_{Max}^t} \times \frac{\sum_t Trans_{success}}{\sum_t Trans_{all}} \qquad (3.24)$$

where $Trans_{success}$ refers to successful transactions performed by the service, $Trans_{all}$ represents total transactions of the service, and other parameters as defined previously in equation (3.17).

If the expertise component is hard to monitor, or not achievable in the initial stages of system implementation, *i.e.*, system bootstrapping, then the model can rely on the trustworthiness component only, by setting $\beta = 1$, which ignores the expertise component; consequently this emphasizes the robustness of the model.

System bootstrapping/initialization, or new services are a critical issue in using the service Credibility model. For the trustworthiness component, we have two options: (1) setting the trustworthiness of each service to 0.5, or (2) using the capability measure described in Section 5.2.3., to generate a value in the range [0, 1] that represents service relative capability compared to other services in the domain.

3.4.6.2. Web Service Credibility Aspects

I argue that trustworthiness and expertise components, and consequently service credibility are context specific, particularly for selection and composition. For each context, differentiated credibility evaluations for different service credibility aspects must be established [222]. For example, a user may evaluate the Web service from various QoS aspects, for instance security or privacy aspects. The global credibility is the aggregation of the credibility from each aspect. This shows that Credibility has multiple aspects; each aspect can play a specific role in assessing the service trustworthiness and its usage suitability for the purpose of selection and composition.

In summary, any aggregation of related attributes can form an aspect in the credibility model. For example, in a home loan service, we can consider redraw facility, availability Y/N and whether the loan is transferable Y/N as a flexibility aspect of the home loan, which is an aspect of the credibility of a home loan service.

3.5. SSSRM: Social-based Service Selection and Recommendation Model

In service selection, there may be several Web service instances that can be selected by a consumer and used in the composition process at run-time. If one service instance from these instances does not match the consumer’s needs during run-time, it should be replaced by another similar service [238]. This emphasizes that top M services should be returned to the consumer. In most utility-based service selection approaches, the most common metrics used are cost and QoS attributes advertised by the service provider; this is not sufficient for effective social service selection.

According to user Credibility model, users are categorized based on their roles in the WBSN *i.e.*, either leaders or followers. We can consider a leader to be an expert in a specific domain if he/she has adequate knowledge and influences other people to follow his/her selected choices and has built enough reputation with continuous activity to be considered trustworthy by others, and has up-to-date expertise, *i.e.*, has built adequate credibility to be a leader at all times. By nature, leaders use their own knowledge and expertise to select a Web service. Followers usually do not have adequate knowledge to make a selection; they rely on a friend, or a friend of a friend, with similar interests they can trust.

Since the proposed user Credibility model shows that each trust hierarchy graph ends with a leader at the root, and that seeking advice from a trustworthy expert leader is more effective than seeking advice from an ordinary trustworthy friend; moreover, some users do not have friends in the social network to infer a trustworthy person who can provide recommendations. Hence, a feasible solution is to rely on leaders to provide recommendations for other followers in the network.

A follower customer prefers to select a service from a credible service provider because it has been used by other leaders. A leader customer prefers to select services with high utilities [42]. In the context of "Follow the Leader", followers usually follow leaders or experts and base their decisions on the tradeoff between the expected utility from the recommended service and their confidence about available choices.

In the proposed service Credibility model, I assume that n is the number of QoS attributes of Web services in a specific domain. In this section, I assume the customer provides a free term query specifying the functionality of the service, and the customer also provides a number of QoS as the terms of his/her query. Query analysis and semantics are beyond the scope of this thesis. We assume that one or more terms of the query refer to the functionality of the service, *e.g.*, home loan, home insurance. We also assume that the system can capture user preferences from free terms semantically or provide the customer with a form to express their preferences.

According to Wildemuth [227], user domain knowledge (UDK) is the user level of knowledge in that domain (*i.e.*, subject area) that is the focus or topic of the search. In the context of documents searches, according to Zhang *et al.* [248], three behavior variables can be used as UDK predictors: the number of documents saved, the average query length, and the average ranking position of the documents opened. The first and the third variables are included in the proposed user Credibility model and mapped to the number of items rated and their corresponding rating score. The second parameter represents user query expressiveness.

In the context of Web service selection and the "Follow the Leader" strategy, I identify three query scenarios that reflect UDK. Customers provide their preferences in their queries, which are related to the number of QoS attributes of the Web service (WS). User preferences in a query can be expressed in any of the following ways: (1) Where user preferences represent 60% or more of WS QoS attributes, I define this query as an "expressive query", *i.e.*, the user knows what he/she wants, or (2) Where user preferences represent 20% or less of WS QoS attributes, I define this query as a "non-expressive query", *i.e.*, the customer does not know exactly what they want, or (3) Where user preferences represent more than 20% and less than 60% of WS QoS attributes, I define this query as a "partial-expressive query". Since query expressiveness indicates UDK; it reflects user behavior and confidence in the service selection process.

Jindal *et al.* [92] indicate that a customer's domain knowledge reflects his/her expertise, and entails the amount and content which is developed from prior individual involvement with a product. I define user domain knowledge (UDK) as the level of expertise exhibited by the user that reflects user expertise in that service domain, which includes service functionalities [191] and service qualities. The expertise defined in Jindal *et al.* [92], and can be mapped to the expertise component in the user Credibility model; UDK can be expressed as a function of user credibility as the first indicator of UDK and the level of expressiveness of the user query, *i.e.*, user preferences expressed in their query as the second indicator of UDK. I propose the following formula that satisfies these two indicators:

$$UDK = \frac{Cr(u)}{Cr_{Max}(u)} \times \frac{QoS_P}{n_{Tot}} \qquad (3.25)$$

where UDK refers to the user knowledge in a category of Web services such as home loan or home insurance services, $Cr(u)$ represents user credibility in the social network and $Cr_{Max}(u)$ represents the maximum user credibility in the social network as a reference point. QoS_P represents the number of user preferences QoS entered in his/her query and n_{Tot} is the total number of QoS attributes n in that service category. Notably, user knowledge in functional properties in the domain is mapped to user credibility, while other indicators reflect user efficiency in providing efficient and reasonable queries. If a user is qualified as a leader, for example, he/she provides preference values that select a service with high utility.

Algorithm 1 in Figure 3.6 presents a social service selection with UDK, user credibility and expected utility using the service Credibility model described in Section 3.4. In this algorithm, M refers to the number of candidate services to be returned to the user to make their selection, ordered by their highest expected utility.

In Algorithm 1, UDK(LT) refers to leaders' threshold domain knowledge, when UDK $\geq$ UDK(LT) then the user is qualified as a leader. UDK(FT) refers to followers' threshold domain knowledge, where UDK $\leq$ UDK(FT) qualifies the user as a follower. Leaders' threshold UDK(LT) is a system tuning parameter related to the Web service publicity; for example, new Web service categories may require a lesser UDK leader threshold than older categories. In this section, UDK(FT) = 0.2 is proposed for illustrative purposes to qualify followers, where if UDK $\leq$ 0.2, then the user qualifies as a follower because their level of knowledge in this domain is limited and they need help from other leaders.

Algorithm 1. Social Service Selection Based on UDK, Credibility & WS Utility

```
1.  Capture user query, preferences and weights
2.  Identify functionality of the service, number of QoS attributes stored in the system (n).
3.  Identify expressiveness of the query.
4.  Identify user domain knowldge(UDK) based on number of entered preferences k; and user Cr(u)
5.  If UDK => UDK(LT) // user act as Leader if UDK => UDK Leader Threshold
6.    CandidateList =  given user preferences k, Get top-M services with highest credibility
7.    For each service in CandidateList compute Expected Utility (EU)
8.    Return Top-M services sorted by highest Utility to select from
9.  Elseif UDK <= UDK(FT) // user act as Follower if UDK <= UDK Follower Threshold
10.   Recommend to the user Top-M services used by leaders
11. Else // UDK > UDK(FT) and UDK < UDK(LT)
12.   (1)  Recommend to user Top-M credible services used by leaders, and
13.   (2)  Return Top-M services sorted by highest Utility to select from, steps (6-8)
14.   If customer self-confidence > confidence in others then
15.       Act as Independent and select a service from option (2)
16.   Else
17.      Act as a Follower and select a service from option (1)
18.   End If
19. End
```

Figure 3.6. Social Service Selection Based on UDK and Service Credibility Algorithm

Lines (6-8) represent the mechanism used to select the services based on user preferences and UDK. Line 6 obtains the Top-M services that maximize user utility based on their preference weights; for a set of user preferences (k, k $\leq$ n) each with a preference normalized weight W^j, such that $\sum_{j=1}^{k} W^j = 1$, the expected utility of a Web service based on user preferences denoted by $EU_P(S)$, as viewed by that customer with UDK > UDK(FT), is given by:

$$EU_P(S) = \sum_{j=1}^{k} \frac{Cr(S_t^j) * W^j}{Cr_{Max}(S_t^j)} \tag{3.26}$$

where $Cr_{Max}(S_t^j)$ represents the maximum credibility of attribute j among all candidate services considered as a reference point. $Cr(S_t^j)$ represents the credibility of attribute j, and W^j represents the user preference weight for attribute j. Cost is considered to be one of the QoS attributes.

The CandidateList in line-6 includes the Top-M services that maximize user utility based on user preference weights. Line-7, for each service in the CandidateList, computes Expected Utility, as shown in Formula 3.26.

Lines (9-10), represent the mechanism used to select the services for followers, where it recommends the user Top-M services used by leaders. When the UDK ≤ 0.2, then the expected utility of a Web service based on leaders recommendation denoted by $EU_R(S)$, is given by:

$$EU_R(S) = \frac{Cr(S_t)}{Cr_{Max}(S_t)} \tag{3.27}$$

Where $Cr_{Max}(S_t)$ represents the service with maximum credibility between all Top-M recommended services considered as a reference point, and $Cr(S_t)$ represents the credibility of each recommended service *i.e.*, the Top-M services recommended.

Customer self-confidence assessment is the final determinant in the selection decision process, as shown in lines (11-18). Customer domain knowledge enriches customer confidence; when customer domain knowledge increases, customer self-confidence increases and when customer domain knowledge decreases then the customer self-confidence decreases. The following scenarios describe different customers' behavior in service selection:

1. Customers with high domain knowledge (Leaders): select the service that maximizes their expected utility based on Web service credibility; they usually

provide an expressive query to select the service with the highest expected utility score. Leaders may adopt new services that have never been used before in order to gain higher utility.

2. Customers with low domain knowledge (Followers): benefit from their social relations and their trust in others; they usually prefer to use a service even if it is expensive, because it has been used by other trusted leaders or friends with proven successful performance. They prefer to follow trustworthy advice from other leaders or friends rather than acting themselves.
3. Other customers make their decisions based on their self-confidence in their domain knowledge and the expected utility from Web services in hand. They make their decision either to follow other leaders (as in case 2), or to act as independents (leaders) if they are confident that their selection preferences lead to better utility than those proposed by other leaders, or if their self-confidence in their domain knowledge is higher than other friends' domain knowledge.

3.6. Evaluation Framework

In the previous sections, a Trustworthiness Expertise Credibility-Based Framework (TECBF) was presented which to use as the basis for a Social-based Service Selection and Recommendation Model (SSSRM) utilizing the User Credibility Model (UCrM) and Web Service Credibility Model (WSCrM).

To evaluate the proposed TECBF framework, the proposed models, algorithms and approaches need to be evaluated. Since there is currently no evaluation framework for the TECBF framework, the best choice available is to propose a new evaluation framework that adopts some ideas from Hayes *et al.* [80] and Zibin and Lyu [251] combined with trust-based recommendation [68], social network analysis [225] and Web service selection [216].

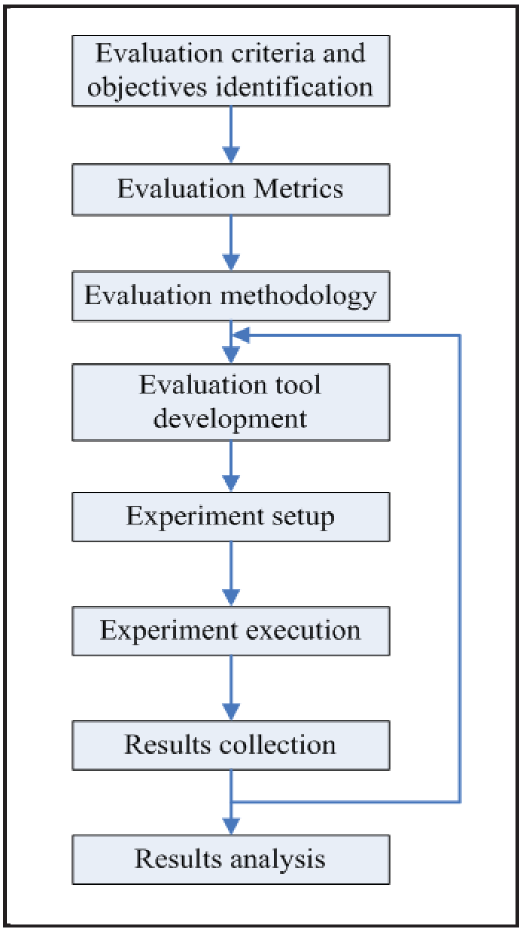

Figure 3.7. TECBF Evaluation framework

The proposed framework is designed to: (1) confirm that using the "Follow the Leader" strategy in the credibility-based framework is an effective and efficient approach in Web service selection and recommendation using Web-based social networks, and (2) verify the proposed credibility-based algorithms and approaches presented in this dissertation by investigating their effectiveness and efficiency. 'Effectiveness' here refers to doing the right thing to produce the intended or expected results, while 'efficiency' refers to performing or functioning in the best possible manner with the least resources.

As shown in Figure 3.7, the proposed evaluation framework is applicable for each model or algorithm in the TECBF framework, and it includes a set of steps that determine the evaluation process flow. These steps are described as follows.

1. Evaluation criteria and objectives identification: this step identifies the evaluation criteria and objectives of the model, algorithm or approach. For example, how can we demonstrate that the credibility-based approach is an effective recommendation approach? This entails a set of experimental evaluations to be performed to investigate the effectiveness and efficiency of the proposed approach.

2. Evaluation metrics: the metrics are used to measure the performance efficiency and effectiveness of the algorithm or approach. For example, in most recommender systems, coverage and accuracy metrics are used to evaluate the performance of recommendation algorithms [4].
3. Evaluation methodology: this step determines the evaluation methodology to be implemented from the following two methodologies:
   a. Simulation: since there are no services available on the Web for testing purposes, simulation methodology is used as the best available choice for service or user behavior evaluations. The simulation approach can be used to imitate the behaviors and activities of users and Web services in a social network environment.
   b. Off-line experimentation: for recommendation approaches, the most common evaluation approaches are performed off-line using existing datasets [80].
4. Evaluation tool development: in the case of simulation as the selected methodology, the evaluation algorithm/approach is developed using NetLogo platform to perform the required functionalities and interaction behaviors of the participating agents (users and services), while for off-line experimentation, the evaluation algorithm/approach is developed using SQL and VB platforms.
5. Experiment setup: in this step, a test dataset is prepared for each specific scenario using off-line datasets, or in the case of simulations, test data are generated randomly then imported to the simulator or generated randomly during the simulation session.
6. Experiment execution: this step executes the algorithm or the specified approach (using the evaluation tool described in step 4), on the test data for the specified experiment.
7. Results collection: test results are collected for each scenario. Steps 4-6 are repeated to execute additional experiments on other test cases if needed.
8. Results analysis: test results are presented either in tables and/or graphs, providing analysis of the achieved results.

To identify the evaluation criteria and the objectives presented in steps 1-3 of the proposed evaluation framework, the following section presents the associated evaluation objectives of the TECBF models.

A. User Credibility Model (UCrM) evaluation:

To evaluate the UCrM, I define the following evaluations to be achieved by UCrM using off-line experimentation methodology:

1. How can we demonstrate that the proposed credibility clustering approach is an effective approach to identifying leaders in the dataset?

   The proposed UCrM uses the “Follow the Leader” strategy to qualify leaders as the most prominent and influential actors in the dataset. The following two indicators can be evaluated for the leaders’ community and the followers’ community which represent members’ trustworthiness and expertise in the social network:

   a. Use members’ degree centrality to answer the question: to what extent are leaders’ prominent and influential actors in the social network?
   b. Use members’ average rating to answer the question: to what extent do leaders exhibit strong expertise in the social network domain?

2. How can we demonstrate that the credibility-based approach is an effective recommendation approach?

   Benchmarking the proposed credibility-based approach against the leading prediction approaches, CF-Similarity based [155] and Social Trust [68], can provide a significant evaluation means on large datasets, through evaluating the following metrics:

   a. Mean Absolute Error.
   b. Prediction Coverage.
   c. Prediction confidence.

3. How can we show that the credibility-based approach is an efficient recommendation approach?

   Benchmarking the proposed credibility-based prediction approach against the trust-based prediction approach can provide a significant evaluation means on large datasets by conducting the following evaluations:

   a. The extent to which users trust the leaders' community to provide advice for recommendation compared to first and second level friends.
   b. Demonstrate the efficiency of the proposed prediction algorithm by benchmarking the credibility algorithm prediction time against the trust algorithm prediction time.
   c. Evaluate the scalability of the UCrM using small and large datasets.

d. Evaluate the flexibility of the UCrM by exploring the trustworthiness and the availability of expertise components.

B. Web Service Credibility Model (WSCrM)

To evaluate the WSCrM, I define the following evaluations to be achieved by WSCrM using the simulation methodology:

1. Demonstrate the impact of trustworthiness and expertise dynamism on WS credibility.
2. Demonstrate the sensitivity of the WSCrM model to malicious Web service behavior.

C. Social-based Service Selection and Recommendation Model (SSSRM)

To evaluate the effectiveness and efficiency of the SSSRM, I define the following evaluations to be achieved by SSSRM using the simulation methodology:

1. The extent to which the user domain knowledge (UDK) acts as the determinant of leaders' and followers' behavior.
2. The extent to which SSSRM can provide an efficient service selection for leaders and recommend top services to followers. To evaluate the algorithm, I use the following metrics to verify its efficiency:
    a. Evaluate the R-precision of the SSSRM by investigating the number of services returned in the top-M candidate services.
    b. Assess whether the returned candidate services are of the highest available quality.
3. Benchmark the proposed SSSRM with other leading service selection approaches:
    a. Utility-based selection approaches
    b. Trustworthiness-based selection approaches

In the next two chapters, I demonstrate the effectiveness and the efficiency of the proposed TECBF framework, using steps (4-8) of the evaluation framework for each evaluation objective specified above for each model, algorithm or approach.

3.7. Chapter Summary

This chapter introduced a Trustworthiness Expertise Credibility-Based Framework (TECBF). It includes two models of credibility; the user Credibility model and the Web service Credibility model. Each model uses two credibility components: the trustworthiness credibility component and the expertise credibility component.

Since leaders are the most credible users in the WBSN, we rely on leaders to provide advice to other users in the network. Identifying leaders such as service providers, political leaders and terrorist leaders in large Web-Based social networks is a difficult and important issue. Leaders in a social network are the most credible advisers for the rest of the population in the network.

First, I proposed a new clustering approach based on the “Follow the Leader” strategy and user credibility to identify the leaders’ community in the WBSN. The proposed approach consists of two steps. The first step makes use of user trustworthiness and expertise to compute user credibility, and in the second step, it selects the top ranked credible users as domain leaders.

Second, I proposed a new approach to making recommendations based on leaders’ credibility as Top-N recommenders in the “Follow the Leader” strategy by incorporating social network information into user-based collaborative filtering. The credibility-based clustering approach can be used for recommenders that are embedded in social networks where users’ trust statements and items ratings are accessible.

Third, I proposed a new Web service Credibility model based on service reputation as a trustworthiness indicator and service performance as an expertise indicator. The aggregation of these two components represents Web service credibility at any point in time.

In Section 3.5, I proposed a social service selection algorithm utilizing user credibility, user domain knowledge and Web service credibility whereby users can be identified as leaders or followers based on their credibility and knowledge of the domain as expressed in their queries. Leaders usually select a service that maximizes their utility, while followers rely on leaders (experts) to select the most credible service from the services recommended by those leaders.

Finally, in Section 3.6, I proposed a framework to evaluate the proposed models, algorithms and approaches of the TECBF framework. In the next two chapters, I demonstrate the effectiveness of the proposed framework.

In Chapter 4, I demonstrate the effectiveness of the proposed user credibility-based clustering derived from “Follow the Leader” to identify Top-N recommenders, who are leaders in the context with the highest trustworthiness and expertise among all users. I demonstrate the effectiveness of the user Credibility model through visualization using my Social Network Analysis Studio (SNAS) in a specific context extracted from the widely used EPINIONS dataset. Then, using three large public datasets, I show how leaders act as expert recommenders by providing accurate predictions and benchmarking them against the leading algorithms: CF-Similarity based [155] and Social Trust [68] approaches. I demonstrate the effectiveness of the clustering approach by validating my approach using social network analysis measures *i.e.*, centrality measures where leaders show the highest average in-degree and the highest average out-degree centrality compared to other members (followers) in the network. Furthermore, I demonstrate that leaders are the most prominent and influential members in the network and show interest similarity with target users.

In Chapter 5, I demonstrate the effectiveness of the Web service Credibility model. I provide experiments to validate the model and use the proposed social service selection based on user credibility and Web service credibility to benchmark the selection model against other well known utility-based and trustworthiness-based selection models.

Chapter 4
Experimentation and Evaluation - Recommendation

In Chapter 3, I presented the user Credibility model which uses two credibility components: trustworthiness credibility component and expertise credibility component. First, I proposed a new clustering approach based on the "Follow the Leader" strategy and user credibility to identify leaders' community in the WBSN. The Credibility-based approach consists of two steps: in the first step, it makes use of user trustworthiness and expertise to compute user credibility, and in the second step, it selects users with the highest credibility ranking as candidate leaders.

Second, I proposed a new approach to making recommendations based on leaders' credibility in the "Follow the Leader" strategy as Top-N recommenders by incorporating social network information into user-based collaborative filtering.

In order to prove the effectiveness of the proposed user Credibility model, in this chapter, I demonstrate the effectiveness of the proposed user credibility-based clustering derived from the "Follow the Leader" to identify Top-N recommenders, who are leaders in the context with the highest trustworthiness and expertise among all users. I demonstrate the effectiveness of the user Credibility model through visualization using my Social Network Analysis Studio (SNAS) in a specific context extracted from the widely used EPINIONS dataset. Then, I show how leaders act as expert recommenders by providing accurate predictions and benchmarking them against the leading algorithms: CF-Similarity based [155] and with Social Trust [68]. Furthermore, experiments demonstrate the effectiveness of the clustering approach by validating the approach using social network analysis measures *i.e.*, centrality measures where leaders show the highest average in-degree and the highest average out-degree centrality compared to other members (followers) in the network.

Moreover, I conduct several experiments to demonstrate the efficiency of the proposed model in terms of interest similarity, prediction coverage, accuracy and response time measures.

The empirical results incorporated in this chapter, demonstrate that the Credibility-based approach is a significantly innovative approach to identifying leaders and making effective recommendations especially for cold-start users.

4.1. Introduction

To demonstrate the feasibility and effectiveness of an innovative user Credibility model using the “Follow the Leader” strategy to analyze the WBSN and make recommendations, I first introduce three datasets: EPINIONS, Extended EPINIONS and FLIXSTER, that are used in implementing the user Credibility-based model. Second, I developed a Social Network Analysis Studio (SNAS) to analyze and build “Follow the Leader” hierarchies that express Web based Social Network visualization. To test and evaluate the model, real data were captured from the three datasets and used to verify the proposed model. In this chapter, I discuss the datasets, experimental design and the results, which demonstrate that the idea of “Follow the Leader” as a means to build a credibility model that can make and improve the accuracy of recommendations over previous methods.

To prove the scalability of the model, I conducted extra experiments on three large datasets to identify leaders. First, the degree centrality of leaders was investigated compared to other members in the network; second, the interest similarity of the target user with the leaders’ community was compared with other friends’ communities. The results show that the leaders’ community exhibits greater similarity to the target user than the first level friends’ community.

The empirical results incorporated in this chapter demonstrate that the proposed user Credibility model is a significantly innovative approach to identifying leaders and making effective recommendations, especially for cold-start users.

4.1.1. Experiments Setup

I used Microsoft Access (2007) as the database platform, and all datasets were loaded to Microsoft Access (2007) on a PC Pentium(R) Dual-Core CPU E5200 @2.50GHZ 2.49 GHz, 1.99 GB of RAM. SQL queries were used to analyze the datasets and create a members table with a summary of trust and ratings statistics, and to identify members as leaders or followers based on their credibility. Microsoft Visual Basic 6.0 was used as a platform to run all batch jobs that generating all predictions and evaluating degree centrality and interest similarity measures.

4.1.2. Datasets Selection

Since the user Credibility model is based on the aggregation of the expertise and the trustworthiness of each user, I set the selection criteria for the datasets that satisfy experimental needs as follows:

1. Dataset must have identified users interacting in a social network environment.
2. Dataset must have identified items that represent the issues of interaction.
3. Dataset must show trust relationships between users with corresponding trust ratings between members.
4. Dataset must show ratings of items provided by the members of the social network.
5. Dataset must be large enough to perform scalability experiments.

Due to the sensitive nature of social network data, there are few public social rating network datasets. In the experiments, the following three datasets that satisfy the selection criteria were used:

1. EPINIONS[17] is a product and shop review site where customers can rate various items such as books, cars, movies, and computers. Users rate reviews provided by other users in EPINIONS; these reviews represent trust values in other reviewers, and the reviews and ratings are public. Items are organized by categories. Please refer to a detailed description about EPINIONS in Section 2.5.5. I use a dataset from EPINIONS, collected in 2005, which is available online from trustlet.org[18]. I refer to this dataset as EPINIONS in the experiments.

[17] http://www.EPINIONS.com/

[18] http://www.trustlet.org/wiki/Downloaded_EPINIONS_dataset

2. Extended EPINIONS is an extended version of the EPINIONS dataset; also obtained from the Trustlet website[19]. I refer to this dataset as Extended EPINIONS or EXT. EPINIONS in my experiments.
3. FLIXSTER[20] is a social networking service in which users can rate movies and create a social network. This large scale dataset was crawled from FLIXSTER.com by Jamali and Ester [90]. I refer to this dataset as FLIXSTER in the experiments.

In EPINIONS users rate products, and each rating represents product quality. However, the majority of other recommender systems such as FLIXSTER operate in an environment where ratings represent user taste or interest in that item. Although FLIXSTER does not entirely match the dataset selection criteria because users' ratings represent their tastes and interests, and the relationships between users indicate the level of agreement on the published opinion. Nevertheless, this dataset is considered to be representative of item ratings, and there is an implicit trust amongst users for their opinions. Trust refers to the similarity of users' tastes [26, 67, 120, 253] in a given context; therefore, if two users have similar tastes, they are better able to trust each other's opinions.

4.1.3. Dataset Pre-Processing Preparation

The following procedure was conducted to validate the dataset content before proceeding to implement the user Credibility model to identify leaders in each dataset.

1. Self-trust elimination: some users act maliciously and seek to increase their trustworthiness by trusting themselves. I believe self-trust statements must be eliminated during this stage. I noticed that the Extended EPINIONS dataset contains 573 self-trust statements which were eliminated.
2. Validity of data: the FLIXSTER dataset contains 625 ratings with rate value = 6. Since rate value should be in the range [1, 5], these ratings should either be excluded or adjusted to the highest rate value of 5. I adopted the latter choice in handling these records.
3. Distrust statements: as noted in Chapter 3, in this model, I am interested only in positive trust; distrust or negative trust is outside the scope of this thesis to avoid the dilemma of 'enemy of my enemy is my friend'.

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[19] http://www.trustlet.org/wiki/Extended_EPINIONS_dataset

[20] http://www.flixster.com/ was provided by (Jamali & Ester 2010), and available from http://www.sfu.ca/~sja25/datasets/

Table 4.1: Datasets summary

Statistics	EPINIONS	Extended EPINIONS	FLIXSTER
No. of Unique Users	49,289	139,573	787,213
Trust Statistics			
No. of Trust records	487,002	841,372	7,058,819
Self Trust Statements	0	573	0
No. of valid Trust Statements	487,002	840,799	7,058,819
No. of DisTrust Statements	0	123,705	0
No. of Unique Users with Trusters	49,288	84,550	145,135
Avg. No. of Trusters/User	10	6	9
Max. No. of trusters of a User	2,589	3,478	1,045
Max. No. of trustees of a User	1,760	2,070	543
Ratings Statistics			
No. of Ratings' Records	664,823	1,048,576	8,196,077
No. of Unique Items	139,738	74,302	48,794
Avg. item rate-value	3.99	4.62	3.61
Avg. Ratings/Item	5	14	168
Avg. Ratings/User	13	8	10
No. of Unique Users with Rating	40,163	39,849	147,612
Max. No. of Items Rated by a User	1,023	19,129	30,977
Cold-Start Statistics			
Cold-start users < 5 Ratings	26,036	126,360	717,728
% Cold-start users < 5 Ratings	52.82%	90.53%	91.17%
Cold-start items < 5 Ratings	116,153	21,874	23,035
% Cold-start items < 5 Ratings	83.12%	29.44%	47.21%

4.1.4. Datasets Summary

Three datasets EPINIONS, Extended EPINIONS and FLIXSTER as shown in Table 4.1 are used to validate the applicability of the proposed approach. These datasets provide us with the required information: trust relationships between users, the corresponding trust ratings between individuals and the ratings of items by the members of the social network. Using such huge datasets of different sizes enable us to demonstrate the scalability of the model and provide us with the means to assess different issues such as the centrality of leaders in the network, the interest similarity of leaders with respect to other members in the network and prediction coverage, accuracy, and response time.

Analysis of the datasets: Table 4.1 provides a summary of the dataset analysis. The following section introduces important remarks about the datasets:

1. Average number of trusters per user is: 10, 6 and 9 for the three datasets EPINIONS, Extended EPINIONS and FLIXSTER respectively; these figures indicate strong friendships established in the three datasets.
2. Average item rate-value in each dataset is: 3.99, 4.62 and 3.61 respectively for the three datasets, which indicates that the item rate-value in Extended EPINIONS is higher than the other two datasets with a value of 4.62 out of 5. This indicates over rating for all items in this dataset and impacts credibility-based ratings predictions compared to other datasets.
3. Average number of ratings per item is: 4.76, 14.11 and 167.97 respectively for the three datasets, which indicates that the items in FLIXSTER dataset are heavily rated.
4. Average number of ratings per user is: 13.49, 7.51 and 10.41 respectively for the three datasets. These figures enrich the user expertise credibility component.
5. Percentage of cold-start users *i.e.*, (users with < 5 Ratings) is: 52.82%, 90.53% and 91.17% respectively for the three datasets. These figures indicate that the Credibility-based model using leaders can serve as a perfect solution to predict items for cold-start users.
6. Percentage of cold-start items, *i.e.*, (items with < 5 Ratings) is: 83.12%, 29.44% and 47.21% respectively for the three datasets, which indicates that the EPINIONS dataset has the highest number of cold-start items.
7. For Extended EPINIONS, the average number of trusters per user and the average number ratings per user is the lowest among all three datasets. These figures impact the credibility-based ratings predictions for Extended EPINIONS compared to other datasets.

4.1.5. Items not appearing in Leaders' Scope Analysis

Table 4.2: Items not appearing in leaders' scope analysis

Dataset and Leaders Statistics	EPINIONS	Extended EPINIONS	FLIXSTER
No. of Unique Items in Dataset	139,738	74,302	48,794
AVG item rate_value in Dataset	3.99	4.62	3.61
No. of Unique Items rated by leaders	112,082	73,545	48,323
% of Unique Items rated by leaders	80.21%	98.98%	99.03%
Followers Only (FO) Item Rating Statistics			
No. of (FO) Items not rated by leaders	27,656	757	471
% of (FO) Items not rated by leaders	19.79%	1.02%	0.97%
No. (FO) Items with 2 or less ratings	26,228	628	469
% (FO) Items with 2 or less ratings	94.84%	82.96%	99.58%
No. of (FO) ratings (over Dataset Average Item rate value)	21,701	498	277
% of (FO) ratings (over Dataset Average)	78.47%	65.79%	58.81%

Why some items do not appear in leaders' rated items

I conducted analysis on items that do not appear in the leaders' scope as provided in Table 4.2, with the following interesting results:

1. Percentage of items that do not appear in the leaders' scope in the user Credibility model, *i.e.*, rated only by followers in datasets: EPINIONS, Extended EPINIONS and FLIXSTER are 19.79%, 1.02%, 0.97% respectively. This assures that these items represent a very small ratio for the last two datasets.
2. Items that do not appear in the leaders' scope are rated by followers only; these items have the following characteristics:

    a. Most of these items are rated by cold-start users; the percentage of followers with a rating of 2 Items or less rating is: 94.84%, 82.96% and 99.58% respectively for the three datasets.

    b. Most of these items are overrated; the percentage of these items with ratings greater than the dataset average rating is: 78.47%, 65.79% and 58.81% respectively for the three datasets.

Since these items are overrated (*i.e.*, there is a bias in their ratings) and are rated by cold-start users, we conclude that these items are cold-start items and are either rated by their providers or rated by malicious raters. The proposed credibility model excludes these items and shows sensitivity to such behavior.

4.2. WBSN Visualization

Social networks visual analysis is an integral component of social network analysis [62]. It provides a means to visualize members' links, relationships and community structures imbedded in the WBSN. It is used also to identify members based on their roles and activities in the WBSN, and can reveal a variety of information such as temporal relationships evolution [66].

The visualization of WBSN enables the study of social connections patterns that link sets of actors. Social network analysis exploits the link structure and examines the roles and influence of members on other members in the network, and on the network as a whole [41]. In the "Follow the Leader" strategy, members are identified as leaders or followers based on their credibility. The hierarchies are in multi level style, as shown in Figure 4.2, and express that for any member – in a specific branch – the credibility of the upper level member is higher than the credibility of the lower level member in that branch.

4.2.1. The EPINIONS Subset

For the purpose of the visualization experiments, a random subset extracted from the EPINIONS dataset [7] is used to validate the applicability of the proposed approach because it is not feasible to visualize all the links in the EPINIONS dataset. To represent a context in the model, a subset was extracted containing the users who rated 25 items selected randomly from the EPINIONS dataset. These items include (106, 515, 698, 18560, 619, 1081, 2164, 3010 and 6147).

I include the users' ratings history of 16 additional items to enrich users with a more extensive items ratings history; hence we can consider the subset refers to any item in the 25 items, which we consider as a context in the proposed approach. The subset includes 830 users with 2883 trust statements and 1672 ratings for the 25 items.

4.2.2. Social Network Analysis Studio (SNAS)

Utilizing the NetLogo [171] platform, I have developed a Social Network Analysis tool inspired by Goldbaum [70], and an extension for our previous work [5]. The user interface for EPINIONS subset is shown in Figure 4.1. Although NetLogo was used as a simulation tool, it has the facility to capture real data, this facility is used to analyze and evaluate the validity of the proposed approach. Figure 4.2 shows the "Follow the Leader" hierarchy for the social network associated with a single item in the dataset. The first row represents available items\services for selection. The black and red nodes refer to leaders and potential leaders respectively, the green nodes refer to followers and the blue nodes refer to independents. The hierarchy represents the dependency of the lower level users on the higher level; where each user either selects one item\service or follows only one of his/her best friends who has make item selection.

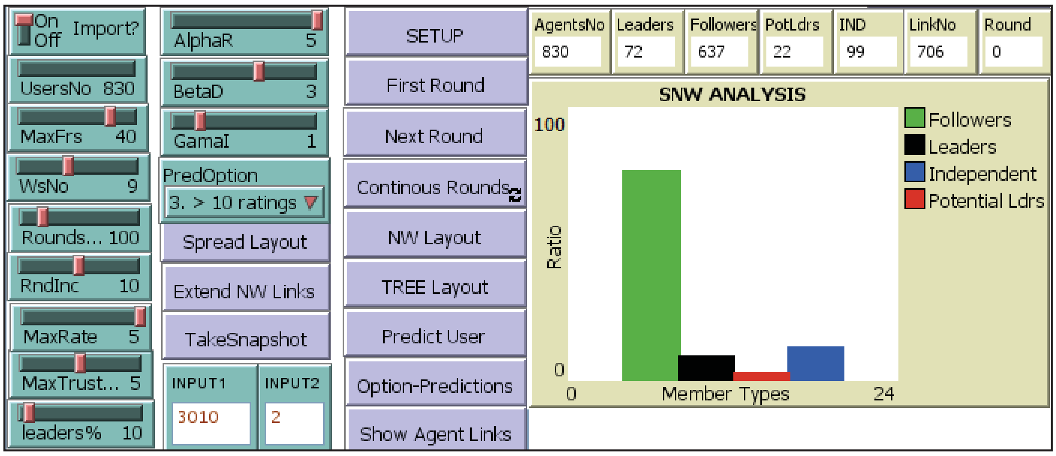


Figure 4.1. Social Network Analysis Studio (SNAS) – Graphical User interface

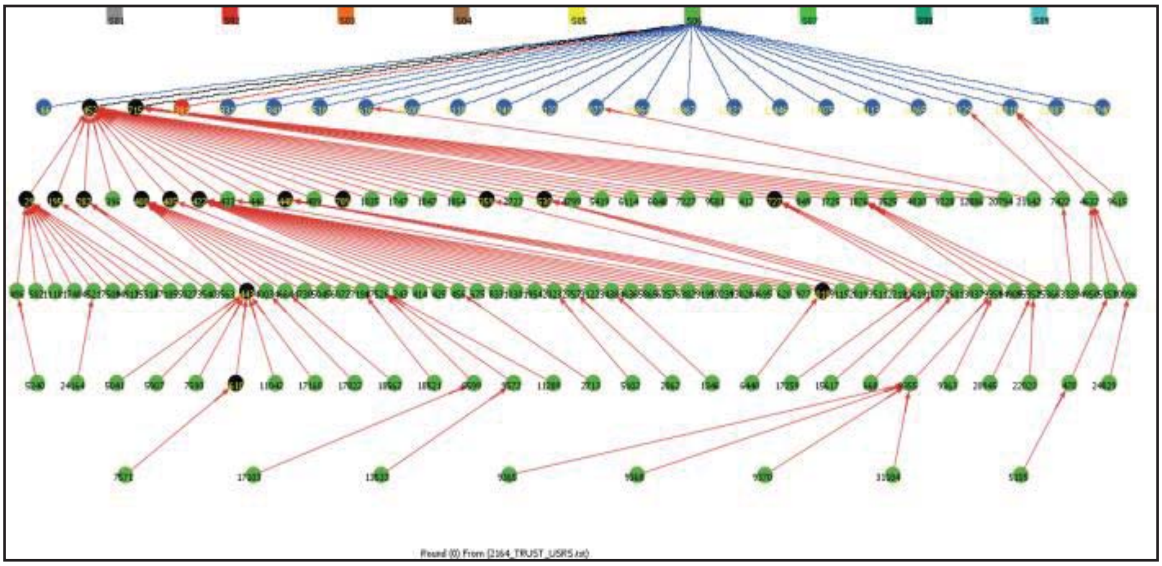


Figure 4.2. “Follow the Leader” Model for Social Network in Item 2164

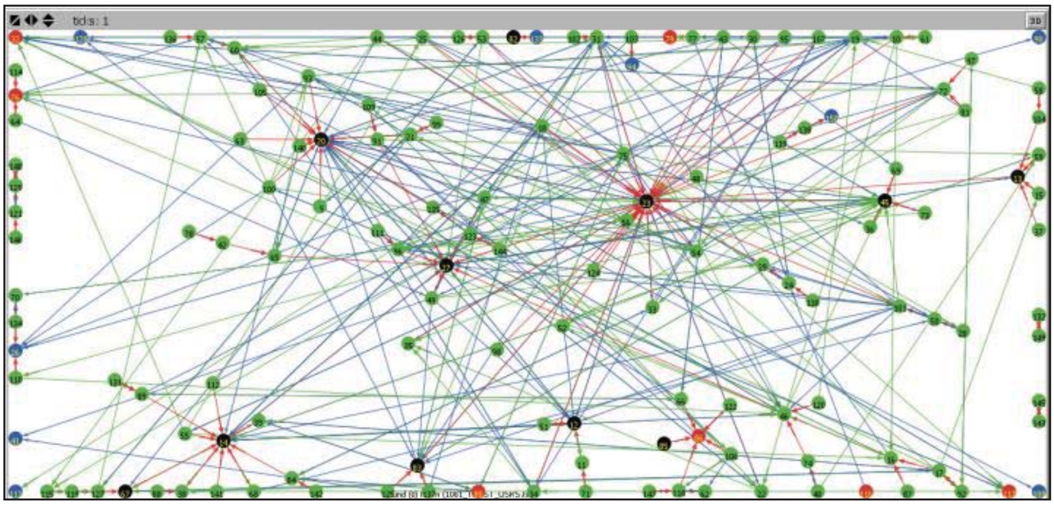


Figure 4.3. Social Network Relations in Item 2164

The blue links in Figure 4.3 are links to user friends, the red link refers to the best friend, and green links refer to links from followers to other friends.

Potential leaders are normal followers who have more confidence in themselves than in their friends; their credibility is below the credibility threshold and they usually have an adequate number of followers. Independents are users with higher self-confidence in themselves than in others, but they do not possess enough credibility to be considered as leaders.

4.2.3. Cyclic Trust in SNAS

One of the interesting issues in building the "Follow the Leader" hierarchical model is the cyclic trust. This phenomenon appeared when members trust each other in a reciprocal or cyclic mode; for example, A trusts B, B trusts C, C trusts D and finally D trusts A. To build the "Follow the Leader" hierarchical model, it was necessary to avoid such cycles; hence, the confidence relation [185] is used to resolve this issue. Simply, the cycle for the highest credibility member scanned, then the link from that member to the member with lower credibility was broken; for example, if C is the highest credibility member, then the hierarchy should be in the form: D linked to A, A linked to B, B linked to C, meaning that C is the highest credible member in the cycle.

4.3. Recommendation Prediction Using EPINIONS Subsets

In the following sections, I present benchmark recommendation prediction algorithms, followed by recommendation prediction evaluation metrics used. Then, I use the subset extracted from the EPINIONS dataset described in Section 4.2.1 and introduce prediction results. Finally I present my findings and discuss concluded results.

4.3.1. Benchmark Recommendation Prediction Algorithms

I use the following algorithms to verify and benchmark the proposed prediction accuracy of the proposed approach, using the EPINIONS Subset:

1. CF-Credibility (CF-1): based on the proposed prediction Formula 3.12.
2. Neighbors Trust (CF-2): based on Golbeck and Hendler [68] formula, outlined in Section 3.1 of the FilmTrust. This algorithm is used as a benchmark to the proposed CF-Credibility (CF-1). Credibility-based model provides the means to identify the nearest neighbors easily.
3. CF-Similarity(CF-3): this is the conventional CF prediction algorithm outlined in the Motivation section – formula (1) of Massa and Avesani [155], with the consideration that the similarity is based on leaders in the dataset. This algorithm is used as a benchmark for the proposed CF-Credibility.

In the conducted experiments, CF-1C and CF-2C refer to cold-start users, using CF-Credibility (CF-1) and Neighbors Trust (CF-2) algorithms respectively.

4.3.2. Recommendation Prediction Evaluation Measures

To validate the hypothesis that using the user credibility approach is an applicable approach to improve the accuracy of recommendations; ***leave-one-out*** [155] is used as my testing strategy. Using a known dataset where users' ratings are known, Leave-one-out as shown in Herlocker *et al.* [81] is an approach used to evaluate the prediction efficiency of a specific algorithm, by hiding one user rating for a specific item, then applying that algorithm to predict it. The predicted rating then is compared with the actual rating of the hidden item. The prediction error then is computed as the absolute value of the difference between the actual value and the predicted one. The procedure is repeated for all hidden ratings N. Then the Mean Absolute Error (MAE) of the algorithm is computed as the average of all prediction errors over that dataset. Notably, the smaller the MAE value, the higher is the performance. In this section, I use MAE1 to be used for experienced users, and MAE2 for cold-start users.

MAE1 is computed with respect to the actual rating by the user for the hidden item i; MAE1 is given by the following formula:

$$MAE1 = \frac{\sum_{i=1}^{N} |R_i^{Actual} - R_i^{Predicted}|}{N} \tag{4.1}$$

For cold-start users without ratings history or with a small number of ratings, MAE2 is computed with respect to the average of the item rating by all cold-start users N who rated that item, which reflects the population opinion about the item and reflects the leader's reliability in providing ratings. MAE2 is given by the following formula:

$$MAE2 = \frac{\sum_{i=1}^{N} |R_i^{Average} - R_i^{Predicted}|}{N} \tag{4.2}$$

Coverage is the second prediction performance measure and refers to the percentage of ratings after hiding them, the prediction algorithm is able to generate predicted ratings over all requested predictions [155]; Coverage is given by the following formula:

$$\text{Coverage} = \frac{\text{Number of Returned Predictions}}{\text{Number of Requested Predictions}} \times 100\% \tag{4.3}$$

Since the most useful measures are used for prediction evaluation and benchmarking, *i.e.*, MEA and coverage, other measures such as precision and recall measures could not provide a better means to show the effectiveness of the predicted results. Furthermore, the leave-one-out is selected as our testing strategy rather than 5-fold or 10-fold cross-validation [225], because such strategies should include leaders among the test dataset, and our concern is to emphasize the prediction performance of the model for cold-start users and not for experienced leaders.

4.3.3. The EPINIONS Subsets Prediction Results

Using SNAS, the following procedure is followed for each subset from EPINIONS:

1. Generate the "Follow the Leader" model for each subset, as shown in Section 4.2.2, using the Social Network Analysis Studio (SNAS).

2. Select users to predict item ratings for them, based on the following test options. The number of ratings indicates the expertise level of the customer, it is not necessary it reflects their credibility.
   - **Option-1:** for users who rated 4 items or less – these are usually followers in the model and cold-start users.
   - **Option-2:** for users who rated 5 items and up to 8 items, who are considered as experienced users in the subset.
   - **Option-3:** for users who rated 9 items or more – these are usually leaders in the model for the selected subset.
3. Generate a predictive rating for each user for a specific item based on the leave-one-out strategy.

Using the EPINIONS Subset described in Section 4.2.1, Table 4.3 provides the experimental results of the prediction algorithms for cold-start users, while Table 4.4 provides the experimental results of the prediction algorithms for experienced users. Figure 4.4 shows the MAE average for all predictions over all in the EPINIONS Subset.

Table 4.3: Experimental results of prediction algorithms: cold-start

			MAE-1		MAE-2		
DATASET	Testing Option	No. Test Cases	CF-1C Credibility	CF-2C Trust	CF-1C Credibility	CF-2C Trust	Coverage (1)
Subset-1	OPTION-1	200	0.990	0.980	0.291	0.753	59.50%
Subset-2	Cold Start	488	0.877	0.878	0.276	0.696	76.02%
Subset-3	< 5 ratings	669	0.934	0.903	0.301	0.709	72.50%
Over-All	Average	452	0.922	0.905	0.291	0.711	71.85%

Table 4.4: Experimental results of prediction algorithms: experienced users

			MAE-1			MAE-2			
DATASET	Testing Option	No. Test Cases	CF-1 Credibility	CF-2 Trust	CF-3 Similarity	CF-1 Credibility	CF-2 Trust	CF-3 Similarity	Coverage (1)
Subset-1		24	1.028	0.900	1.354	0.689	0.748	1.129	41.67%
Subset-2	OPTION-2	132	0.981	0.940	1.178	0.640	0.650	0.941	56.82%
Subset-3	5-8 ratings	145	0.959	0.944	1.197	0.605	0.654	0.962	55.86%
Subset-1		5	0.957	N\A:Leaders	1.525	0.211	N/A	0.694	0.00%
Subset-2	OPTION-3	14	0.914	0.991	1.160	0.333	0.572	0.606	64.29%
Subset-3	> 8 ratings	16	0.870	1.092	1.383	0.298	0.701	0.782	62.50%
Over-All	Average	56	0.967	0.948	1.213	0.593	0.658	0.938	55.89%

Note (1): Coverage here refers to the ratio of returned valid predictions over all predictions for CF-2. This value is (100%) for CF-1 and CF-3, as indicated in the coverage column for the Trust-based approach.

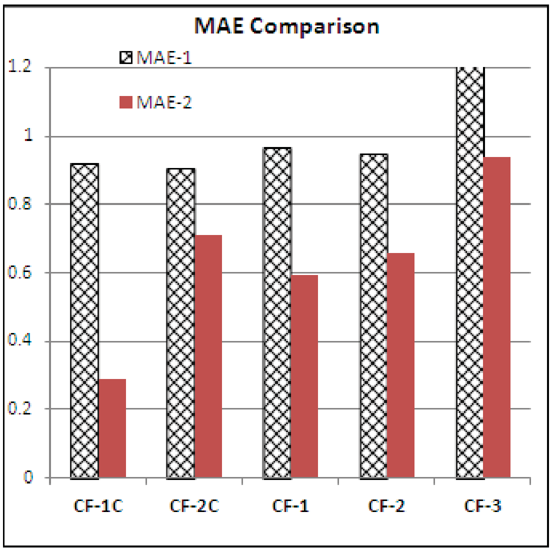


Figure 4.4. MAE Average for all Predictions over all Subsets

Results Discussion:

1. For the selected subset, leaders can provide recommendations with (100%) coverage in the Credibility-based prediction algorithm, while the Neighbors Trust algorithm (CF-2, CF-2C) cannot, simply because users in the Neighbors Trust do not have sufficient friends to reliably apply the Trust algorithm.
2. The Credibility algorithm for cold-start users (CF-1C) outperforms Neighbor Trust in two dimensions: first, the coverage of the Credibility model for cold-start users is 100%, while for Neighbor Trust the average coverage is 72%. Second, the quality of recommendations (MAE2) of cold-start Credibility is 0.291, while for Neighbor Trust (MAE2) is 0.711. This result emphasizes that normal users (followers) possess less credibility than leaders in providing recommendation.
3. CF-Credibility (CF-1) outperforms CF-Similarity (CF-3) by 25%; this difference shows that the Credibility-based approach provides more accurate results even when using the same leaders to measure similarity with them.
4. In OPTION-3: for users who rated 9 items or more, we observe that the Neighbor Trust algorithm provided poorer prediction in Subset-1, and predictions are too far from average algorithm performance to be of value because most of the users in OPTION-3 are leaders. Leaders usually do not act as Trusters; they are trusted by

other users. In other words leaders are not necessarily good judges of credibility or good at developing trust.

5. In OPTION-3: for users who rated 9 items or more, credibility based (CF-1) outperforms other approaches because leaders have enough ratings to compute the average.

4.4. Further Experiments on Large Datasets

The following sections present the findings from the experiments on the three large datasets. First, I provide the test options; next, I provide details of the experimental results from prediction algorithms. Finally, I present prediction coverage and response time, followed by prediction confidence based on the number of predictors.

4.4.1. Test Options on Large Datasets

The test options on large datasets are presented and described as follows:

Test Option	**Description**
Test1_1642	Users with ratings items (16-42), usually highly experienced users.
Test2_0915	Users with ratings items (9-15), usually experienced users.
Test3_0508	Users with ratings items (5-8).
Cold-Exp. < 5	Cold-start users with ratings items (2-4), old users in the dataset.
Cold-New < 5	Cold-start users with ratings items (2-4), new users in the dataset. These users are identified based on their user id in the dataset.

For each test option, all test cases are extracted from the main ratings dataset based on the number of items rated by the user, and then a subset with a specific number of cases is randomly selected from the extracted cases, and then used for prediction computation.

4.4.2. Definitions

In the following section, a description of the headings used in Table 4.5 is introduced:

1. Cred. Coverage: is the percentage of successful ratings predictions produced by the Credibility-based model as defined in Formula (4.3).

2. Cred. AVG Raters: is the average number of leaders who rated the predicted item in the sample test.
3. Cred MAE1: MAE1 calculated based on the Credibility prediction algorithm as defined in Formula 4.1.
4. Cred MAE2: MAE2 calculated based on the Credibility prediction algorithm as defined in Formula 4.2.
5. Trust. Coverage: is the percentage of successful ratings predictions produced by the Trust based model as defined in Formula 4.3.
6. Trust AVG Raters (K12): is the number of (1st and 2nd) level friends who rated the predicted item in the sample test.
7. Trust MAE1: MAE1 is calculated based on the Trust prediction algorithm as defined in Formula 4.1.
8. Trust MAE2: MAE2 is calculated based on the Trust prediction algorithm as defined in Formula 4.2.
9. Cred-Time / Trans (Sec): Time in seconds to process one prediction transaction in the Credibility-based model.
10. Trust-Time / Trans (Sec): Time in seconds to process one prediction transaction in the Trust based model.
11. % Time Cr/Trust: is the ratio of credibility prediction time to the trust prediction time for the same transaction.

Table 4.5: Detailed MAE comparison for all datasets: Credibility Algorithm vs. Trust Algorithm prediction for all test options

		Credibility-based approach					Trust-based Approach				Performance Measures		
DATASET	Test Option	No. Test Cases	Cred. Coverage	Cred. AVG Raters	Cred MAE1	Cred MAE2	Trust. Coverage	Trust AVG Raters(K12)	Trust MAE1	Trust MAE2	Cred-Time /Trans(Sec)	Trust-Time /Trans(Sec)	% Time Cr/Trust
EPINIONS	**Test1_1642**	300	100%	211	0.898	0.367	92.67%	64	0.907	0.392	0.600	1.860	32.26%
	Test2_0915	300	100%	150	0.744	0.378	90.00%	40	0.750	0.439	0.593	1.853	32.02%
	Test3_0508	300	100%	146	0.892	0.475	84.33%	28	0.854	0.565	0.593	1.840	32.25%
	Cold-Exp. < 5	300	100%	9	0.681	0.542	33.10%	3	0.732	0.631	0.595	1.832	32.48%
	Cold-New < 5	300	100%	94	0.668	0.545	9.33%	3	1.005	0.752	0.527	1.600	32.92%
	Average	**300**	**100%**	**122**	**0.776**	**0.461**	**61.89%**	**28**	**0.850**	**0.556**	**0.582**	**1.797**	**32.38%**
Extended EPINIONS	**Test1_1642**	300	100%	82	0.456	0.283	74.00%	30	0.311	0.293	1.383	4.203	32.91%
	Test2_0915	300	100%	42	0.392	0.275	69.33%	17	0.248	0.265	1.357	4.176	32.48%
	Test3_0508	300	100%	13	0.557	0.388	65.00%	4	0.315	0.444	1.364	4.170	32.70%
	Cold-Exp. < 5	300	100%	20	0.518	0.397	63.20%	7	0.381	0.410	1.360	4.182	32.52%
	Cold-New < 5	300	100%	24	0.462	0.370	61.00%	9	0.239	0.280	1.364	4.157	32.81%
	Average	**300**	**100%**	**36**	**0.477**	**0.342**	**66.51%**	**13**	**0.299**	**0.338**	**1.365**	**4.178**	**32.69%**
FLIXSTER	**Test1_1642**	200	100%	11,948	0.648	0.453	94.50%	59	0.651	0.498	11.550	59.395	19.45%
	Test2_0915	200	100%	10,553	0.818	0.566	85.50%	53	0.817	0.574	11.550	59.395	19.45%
	Test3_0508	200	100%	9,309	0.643	0.676	86.50%	41	0.684	0.715	11.550	59.395	19.45%
	Cold-Exp. < 5	200	100%	9,191	0.542	0.762	85.50%	43	0.566	0.787	11.649	50.061	23.27%
	Cold-New < 5	200	100%	8,047	0.531	0.871	78.50%	32	0.606	0.883	11.649	50.061	23.27%
	Average	**200**	**100%**	**9,809**	**0.636**	**0.666**	**86.10%**	**46**	**0.665**	**0.691**	**11.590**	**55.661**	**20.98%**

Table 4.5 presents a comparison between all datasets: Credibility Algorithm versus Trust Algorithm prediction for all test options. The last three columns in the table represent the prediction response time for the Credibility algorithm and Trust algorithm, and the percentage of credibility prediction time to trust prediction time.

The following sections discuss the results presented in this table.

4.4.3. Benchmark: MAE Comparison between Credibility and Trust

Table 4.6: Credibility Algorithm vs. Trust Algorithm prediction for all datasets

a. Prediction for cold-start users

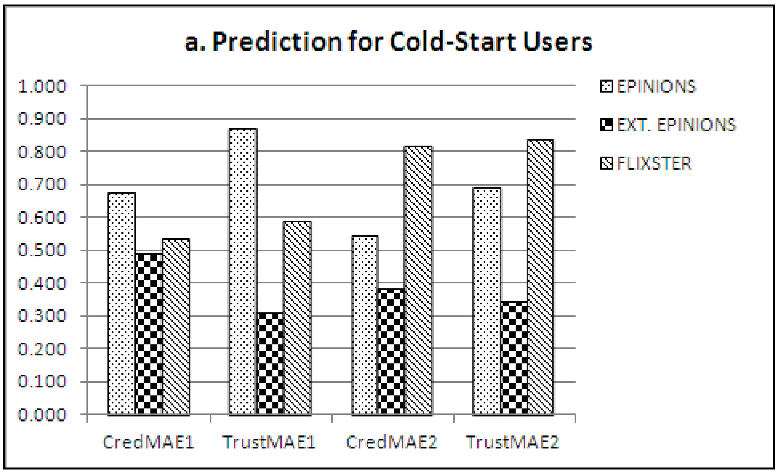
DATASET	CredMAE1	TrustMAE1	CredMAE2	TrustMAE2
EPINIONS	0.674	0.869	0.543	0.691
EXT. EPINIONS	0.490	0.310	0.384	0.345
FLIXSTER	0.536	0.586	0.817	0.835

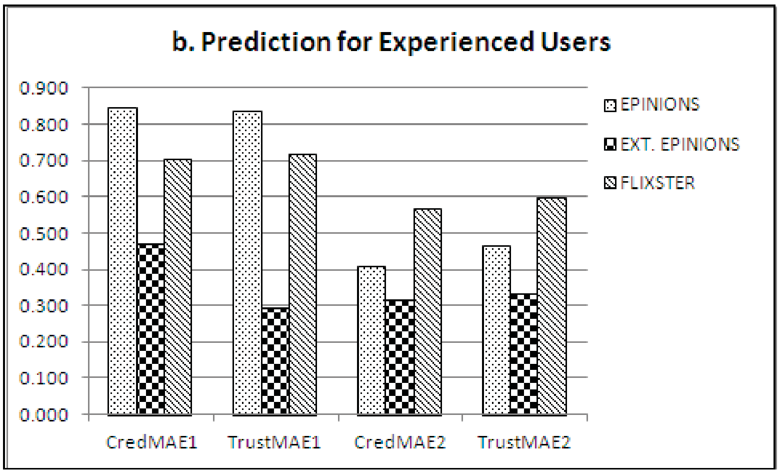
b. Prediction for experienced users

DATASET	CredMAE1	TrustMAE1	CredMAE2	TrustMAE2
EPINIONS	0.845	0.837	0.407	0.465
EXT. EPINIONS	0.468	0.292	0.315	0.334
FLIXSTER	0.703	0.717	0.565	0.596

c. Over-all prediction for the three datasets

DATASET	CredMAE1	TrustMAE1	CredMAE2	TrustMAE2
EPINIONS	0.776	0.850	0.461	0.556
EXT. EPINIONS	0.477	0.299	0.342	0.338
FLIXSTER	0.636	0.665	0.666	0.691





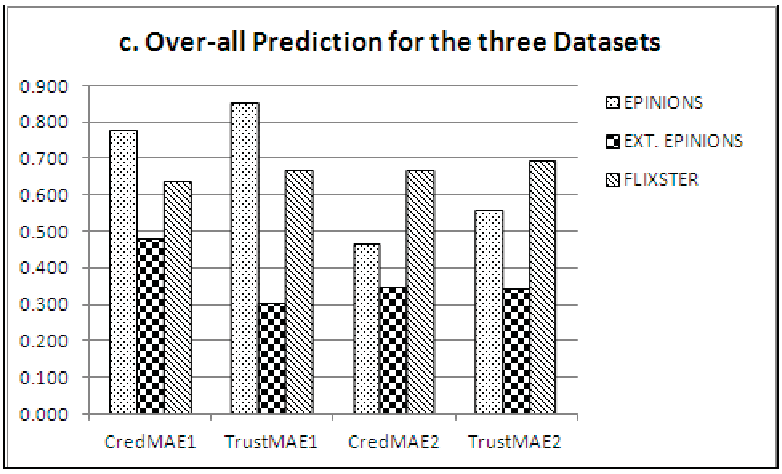


Figure 4.5. Credibility Algorithm vs. Trust Algorithm Prediction for all Datasets

Table 4.6 and Figure 4.5 show a comparison for all datasets between the Credibility Algorithm and the Trust Algorithm prediction. First, the headers in Table 4.6 are defined as follows:

1. MAE1 and MAE2 as defined previously in Section 4.3.2.
2. Cred: refers to proposed credibility model.
3. Trust: refers to Trust-based model.
4. For experienced users we used Formula 3.12 to make a credibility prediction. The same formula was used for trust-based replacing credibility with trust values for (1st and 2nd) level friends who rated the predicted item in the sample test.
5. For cold-start users we used Formula 3.13 to make a credibility prediction. The same formula was used for trust-based replacing credibility with trust values for (1st and 2nd) level friends who rated the predicted item in the sample test.

Results and discussion: From Table 4.6 we observe that:

A. For cold-start users:

1. The Credibility prediction algorithm using (MAE1 and MAE2) measures outperforms the Trust prediction algorithm for EPINIONS and FLIXSTER datasets in all prediction cases. Cold-start users do not have enough friends to compute reliable Trust based predictions. These results support our claim that leaders can provide feasible solutions for cold-start users, because leaders are the most credible users for providing advice.
2. The Trust prediction algorithm using (MAE1 and MAE2) measures outperforms the Credibility prediction algorithm for Extended EPINIONS for all prediction cases. Although the difference is not excessive, it is considerable. Since the average item rating for this dataset is 4.62 out of 5, thus, leaders provide more reliable advice than nearest friends.

B. For experienced users:

1. The Credibility prediction algorithm using MAE1 measure provides predictions similar to the Trust prediction algorithm for EPINIONS and FLIXSTER datasets in all prediction cases. The difference in the averages is approximately 0.01 for trust in EPINIONS and 0.01 for credibility in FLIXSTER. Experienced users have enough experienced friends to compute the predictions. The results in these experiments indicate that most experienced friends are leaders. These results support our claim that leaders also can provide reliable advice for experienced users; leaders are the most credible users for providing advice.
2. The Credibility prediction algorithm using MAE2 measure provides better predictions than the Trust prediction algorithm for EPINIONS and FLIXSTER datasets in all prediction cases. Although the experienced users have enough experienced friends to also compute the prediction, and most experienced friends are leaders, leaders can provide more reliable advice compared to experienced nearest friends, and they can provide reliable predictions comparable to the average rating of the items by the total population in the dataset.
3. The Trust prediction algorithm (MAE1 and MAE2) outperforms the Credibility prediction algorithm for Extended EPINIONS for all prediction cases. Although the difference is small, it is considerable. Since the average item rating for this dataset is 4.62 out of 5, the results from EPINIONS and FLIXSTER demonstrate that leaders provide more reliable advice than nearest friends.

C. The over-all prediction for the three datasets

Taking the averages of cold-start and experienced users for the EPINIONS and FLIXSTER datasets, the Credibility-based approach outperforms the Trust-based approach, whereas the Trust-based approach outperforms the Credibility approach for Extended EPINIONS due to the previously-discussed over rating items in this dataset.

From the above results, we conclude that the Credibility prediction algorithm using leaders as advisers is a feasible approach in making recommendations for the rest of the population in the dataset, especially for cold-start users.

4.4.4. Prediction Coverage

Prediction Coverage [155] as shown in Formula 4.3, refers to the percentage of ratings after being hidden, the prediction algorithm is able to generate predicted ratings over all requested predictions. The Credibility-based prediction approach produces 100% coverage for all datasets, while the Trust based prediction approach produce coverage of: 61.89%, 70.31% and 86.10% for EPINIONS, Extended EPINIONS and FLIXSTER datasets respectively, as shown in Figure 4.6. Since the average number of ratings per item is (5, 14, 168) for the three datasets respectively, the results show that when the average number of ratings per item increases then the prediction coverage increases as the probability that nearest friends have already rated such items increases as well. The Credibility-based approach is not sensitive to the average number of ratings per item, because leaders rate the most credible items.

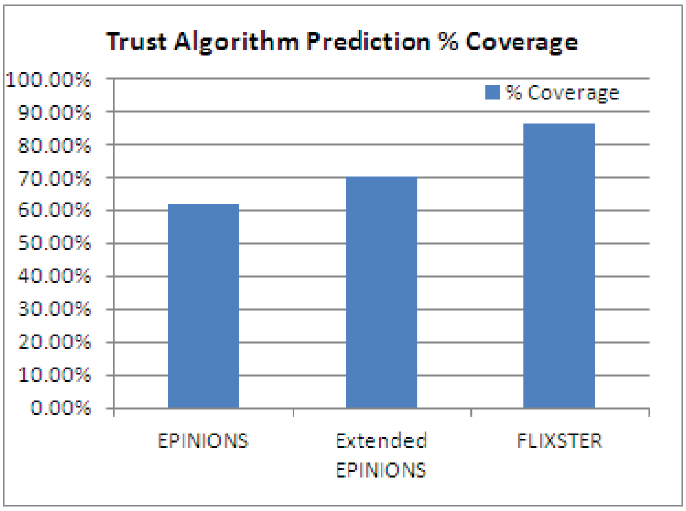
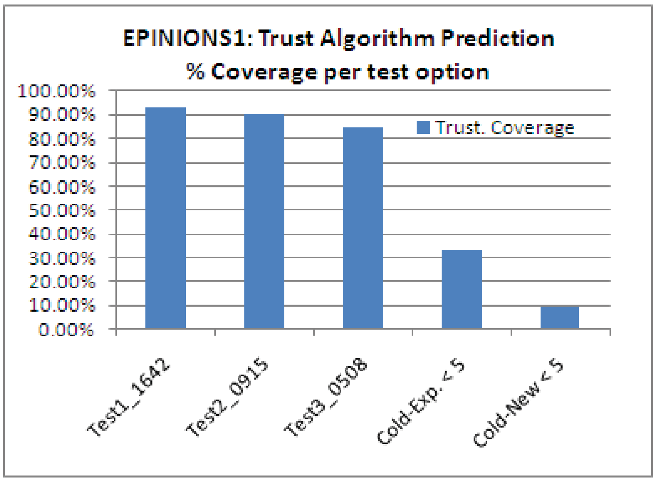
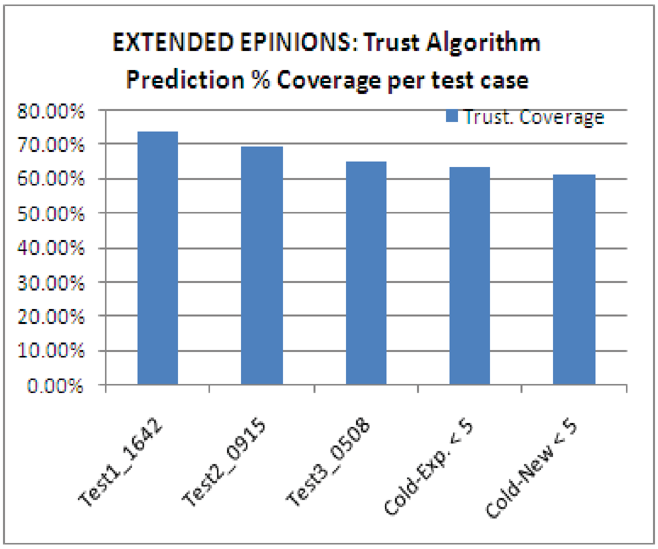


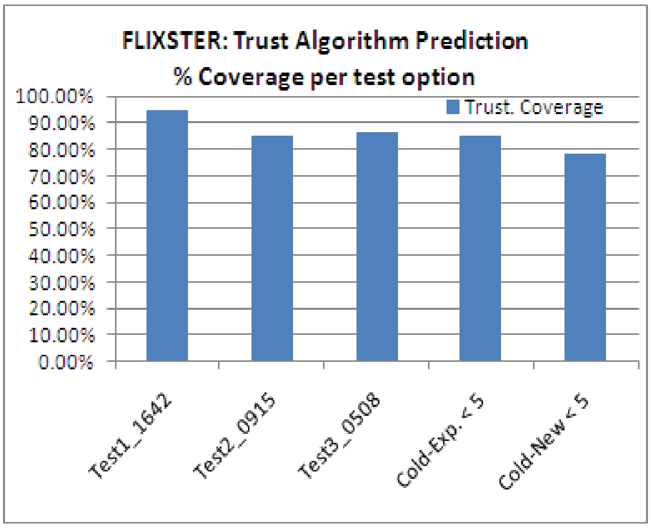
Figure 4.6. Trust Algorithm Prediction % Coverage for all Datasets



a: EPINIONS1 dataset



b: Extended EPINIONS dataset



c: FLIXSTER dataset

Figure 4.7. Trust Algorithm Prediction Coverage per Test Option for all Datasets

From Figure 4.6 and Figure 4.7, we conclude that:

1. The Credibility-based approach coverage outperforms the Trust-based approach, simply because leaders are available at all times, and they have rated most of the items in the dataset. On the other hand, the Trust-based approach provides more coverage for experienced users than cold-start users, which is because the Trust-based approach cannot ensure the availability of nearest friends especially for cold-start users.
2. When the size of network increases, trust prediction coverage increases.
3. Trust prediction coverage decreases when the average number of user ratings decreases; this indicates that the Trust prediction algorithm is not feasible for making recommendations for cold-start users.

Why is Credibility coverage 100% in the Credibility-based approach?

As mentioned previously, the selected test cases must have at least 2 items rated, one item to be hidden and the system computes predicted rating for it, Fortunately all randomly selected items are rated by leaders, but in the worst-case scenario, we can consider the coverage ratio from EPINIONS, Extended EPINIONS, and FLIXSTER as the percentage of items rated by all leaders as shown in Table 4.2, which represent 80.21%, 98.98% and 99.03% respectively, and these values are greater than the corresponding average of trust coverage.

4.4.5. Prediction Response Time

To what extent is the proposed Credibility-based model response time efficient compared to the Trust-based prediction algorithm?

The experiments were conducted on different machines: a dual-processor PC and a laptop. The notable findings from this experiment show that the Credibility-based prediction algorithm outperforms the Trust-based prediction algorithm in prediction response time. As shown in Figure 4.8, Credibility-based prediction algorithm time is 32.38%, 32.69% and 20.98% of the corresponding Trust-based prediction algorithm time from (1st and 2nd) level friends for the three datasets respectively. This ratio should decrease if the trust circle is expanded to the third and fourth level friends. These ratios demonstrate that the Credibility-based prediction algorithm is more efficient even in prediction response time.

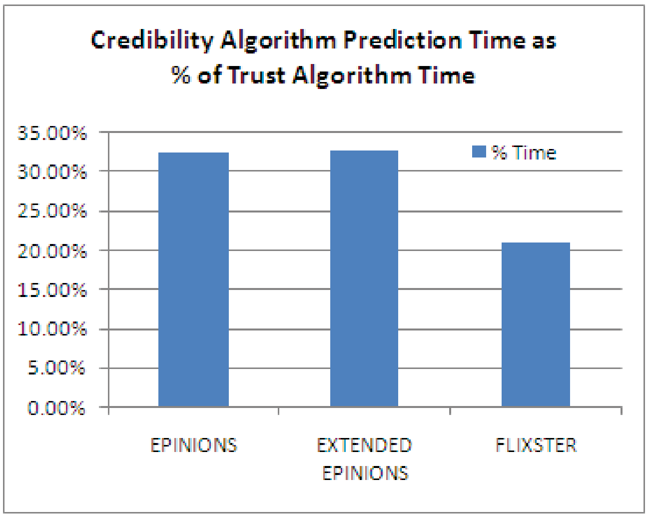


Figure 4.8. Credibility Algorithm prediction time as % of Trust Algorithm time

4.4.6. Prediction Confidence Based on Average Number of Predictors

Although measures such as Mean Absolute Error (MAE) and coverage are the most useful measures in assessing the accuracy of the prediction, Prediction Confidence is introduced as a measure of certainty of the prediction. Prediction Confidence is defined as the certainty for a prediction strategy [210], *i.e.*, the average number of raters per prediction strategy (Credibility-based or Trust-based). Table 4.7 summarizes the average number of raters for the Credibility-based approach and the Trust-based approach for the three datasets.

Table 4.7: Credibility average raters vs. Trust average raters

DATASET	Cred. AVG Raters	Trust AVG Raters(K12)	Cred/Trust Raters Ratio
EPINIONS1	121.9	27.7	4.4
EXTENDED EPINIONS	36.1	13.5	2.7
FLIXSTER	9809.4	45.5	215.5

As shown in Table 4.7, if we compare the average number of predictors who contribute to the prediction process between the Credibility-based prediction and the Trust-based prediction, using (1st and 2nd) level friends, we notice that in EPINIONS (first row), the average number of leaders who provided predictions is 121.9 rater, while the number of (1st and 2nd) level trusted friends (K12) who provided prediction is 27.7 rater; with the Credibility to Trust Raters Ratio being 4.4. These figures indicate that the prediction confidence produced by the Credibility model is 4.4 times compared to the Trust model.

The last column shows that the Credibility/Trust Raters Ratio over the three datasets is 4.4 times, 2.7 times and 215.5 times respectively. This indicates that the prediction confidence generated by leaders is more than the prediction confidence generated by (1st and 2nd) level trusted friends; this shows that Credibility-based prediction generates more confident prediction results than Trust-based predictions in terms of the number of predictors.

4.5. WBSN Leaders Clustering and Identification Evaluation

To evaluate the efficiency of the proposed Credibility approach in identifying leaders properly, I adopt the centrality measure as a means to demonstrate this argument.

Centrality measures have been used as a proxy for power and influence and have allowed the investigation of brokerage relations [30]. Centrality reveals how influential and powerful a node is, which reflects the roles of individuals in the network [235]. Degree centrality is measured as the number of links of a given node [61]. A node with a high degree centrality maintains numerous links and can be viewed as popular [39, 46]. Hanneman and Riddle [78] differentiate between in-degree and out-degree; if an agent receives many links, they are said to be *prominent*, or to have *high prestige*; this justifies, why many other agents seek to direct links to them, consequently, this may indicate their importance. Agents who have a significant high out-degree are able to exchange opinions with many others, or make many others aware of their views. Agents who show high out-degree centrality are often said to be *influential* agents [78]. So, to what extent leaders are prominent and *influential* agents?

In-degree Centrality

For a directed network, the in-degree [225] of a particular node represents the trustworthiness of that node, which consequently reflects its prominence and power. The in-degree centrality of a particular node (i) is defined as the number of in-links (truster statements) this node received [233]. A node i's in-degree centrality $D_{in}(i)$ can be formulated as:

$$D_{in}(i) = \sum_j T_{ji} \tag{4.4}$$

where $T_{ji} = 1$ if there is a trust between nodes j and i exists, and $T_{ji} = 0$ if there is no trust.

Out-degree Centrality

The out-degree of a particular node represents the activity of that node [225], which consequently reflects its influential behavior. The out-degree centrality of a particular node (i) is defined as the number of out-links (trust statements it issued) from this node [233]. A node *i's* out-degree centrality $D_{out}(i)$ can be formulated as:

$$D_{out}(i) = \sum_j T_{ij} \tag{4.5}$$

where $T_{ij} = 1$, if there a trust statement issued from node i to node j exists, and $T_{ij} = 0$ if no trust statement was issued.

Based on the above definitions, in-degree centrality and out-degree centrality are computed for leaders and followers for the three datasets, and the results are presented in Tables 4.8 and 4.9, and Figure 4.9.

4.5.1. Centrality Measures for Three Datasets

The following experiments are conducted to measure the Centrality Degree and the average ratings for all datasets; the results are shown in Tables 4.8 and 4.9, and Figure 4.9.

Table 4.8: Leaders vs. followers' centrality degree and average ratings for all datasets

Dataset	Member Type	No of members	Ratio (%)	Avg InDegree	Avg OutDegree	Avg Ratings
EPINIONS	Leaders	4,930	10.00%	68.08	55.69	77.59
	Followers	44,359	90.00%	3.41	4.79	6.36
	ALL	49,289	100.00%	9.88	9.88	13.49
Extended EPINIONS	Leaders	8,181	5.86%	63.48	60.56	117.57
	Followers	131,392	94.14%	2.45	2.63	0.66
	ALL	139,573	100.00%	6.03	6.03	7.51
FLIXSTER	Leaders	58,827	6.21%	86.17	30.89	114.36
	Followers	728,386	93.79%	2.73	7.20	2.02
	ALL	787,213	100.00%	8.97	8.97	10.41

Table 4.9: Leaders vs. followers' in-degree and average ratings for all datasets

DATASET	Leaders Avg. InDegree	Followers Avg. InDegree	Leaders Avg. Ratings	Followers Avg. Ratings
EPINIONS	68.08	3.41	77.59	6.36
EXT. EPINIONS	63.48	2.45	117.57	0.66
FLIXSTER	86.17	2.73	114.36	2.02

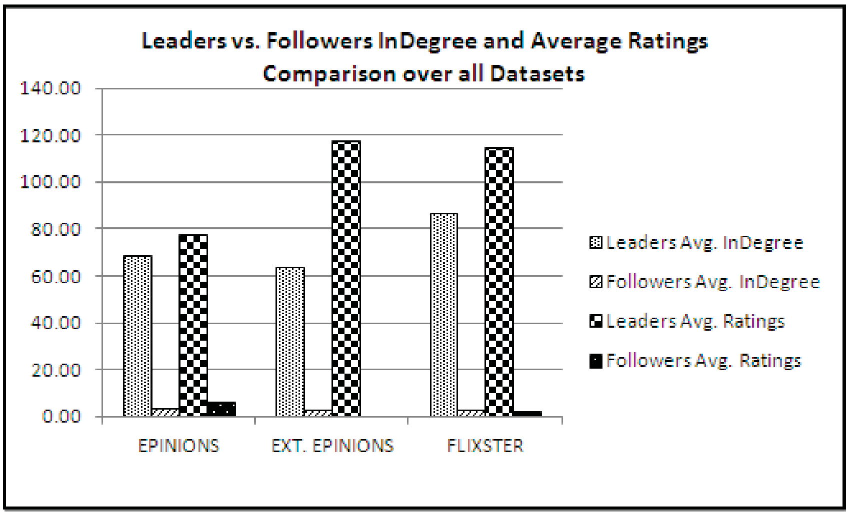


Figure 4.9. Leaders vs. Followers In-Degree and Average Ratings for all Datasets

From Table 4.8, Table 4.9 and Figure 4.9, we conclude the following:

1. Since the leaders' in-degree is much higher than the in-degree of followers, leaders are the most *prominent*, or they have high *prestige*. That is, many other members seek to direct ties to them, and this may indicate their importance and popularity [78].
2. Since the leaders' out-degree is much higher than the out-degree of followers, then leaders are *influential* actors [78].
3. Since the leaders' in-degree is higher than their out-degree, then leaders are the most *prominent*, or they have high *prestige* among the total population in the datasets.
4. Since the leaders' average ratings are much higher than the average ratings of followers, then leaders are the most experienced members in the network.

These conclusions show that the Credibility-based model is capable of identifying leaders efficiently.

To answer the question: ***to what extent are leaders prominent and influential actors?***

Since leaders possess high average in-degree and high average out-degree, which in both cases is more than followers and more than the average member in the network, leaders are the most prominent and *influential* members in the network. This outcome is drawn from their trustworthiness and expertise; leaders possess the highest trustworthiness and the highest average rated items in the network, which reflects their expertise level.

4.5.2. Interest Similarity

To what extent do users trust the leaders' community to provide advice for recommendation?

Previous research shows there is a correlation between interest similarity and trust among members in the network [121, 253]. The similarity and consequently the trust is the highest for directly connected users, and it decreases with the increase of the distance (K) between members.

I extend this idea to measure the interest similarity between the target user and leaders' community from one angle, and compare this with the interest similarity between the target user and 1st level community friends with distance K=1 from the target user and (1st and 2nd) level community friends with distance K=1 and distance K=2 from the target user from another angle, and investigate the ratio of K12 community friends who act as leaders.

The Interest Similarity *Sim(a, C)* between the target user *(a)* and the community *(C)* is defined as the ratio of the number of the shared items rated *(IR)* between the target user and the community to the number of items rated by the target user [121], and expressed as:

$$\mathrm{Sim}(a, C) = \frac{\mathrm{IR_a} \cap \mathrm{IR_C}}{\mathrm{IR_a}} \tag{4.6}$$

The EPINIONS dataset is used to compute the following Interest Similarity measures for the target user with the following communities: (1) leaders' community (LDRS), (2) 1st level friends' community (FRNDS-K1), and (3) (1st and 2nd) level friends' community (FRNDS-K12). The percentage of the (1st and 2nd) level friends who act as leaders (% FRNDS-K12 AS LDRS) is also calculated, this percentage shows how leaders and nearest friends exhibit a common interest similarity with the target user.

Table 4.10 shows the Interest Similarity between the target users and the previously defined communities in the EPINIONS dataset. The target user is drawn from five test cases as shown in the first column that represent the expertise of the target user.

Table 4.11 shows the Interest Similarity between the target users and the previously defined communities in all datasets.

Table 4.10: EPINIONS dataset: Target user Interest Similarity measure with (leaders and friends) communities

DATASET	Test Case	LDRS Sim	FRNDS-K1 Sim	FRNDS-K12 Sim	% FRNDS-K12 AS LDRS
EPINIONS	Test1_1642	0.389	0.217	0.979	78.97%
	Test2_0915	0.449	0.172	0.979	90.74%
	Test3_0508	0.487	0.267	0.968	76.01%
	Cold-Exp. < 5	0.434	0.447	0.973	43.05%
	Cold-New < 5	0.593	0.417	0.976	11.93%

Table 4.11: All datasets: Target user Interest Similarity measure with (leaders and friends) communities

DATASET	LDRS Sim	FRNDS-K1 Sim	FRNDS-K12 Sim	% FRNDS-K12 AS LDRS
EPINIONS	0.470	0.304	0.975	60%
EXTENDED	0.680	0.583	0.887	74%
FLIXSTER	0.998	0.424	0.998	74%

Results: from the outcomes presented in Table 4.10 and Table 4.11, we conclude that:

1. The average target user's Interest Similarity with EPINIONS leaders (LDRS Sim) is 0.470, while the average target user's Interest Similarity with EPINIONS 1st level friends (FRNDS-K1 Sim) is 0.304 and the average target user's Interest Similarity with EPINIONS (1st and 2nd) level friends (FRNDS-K12 Sim) is 0.975. These figures indicate that the average target user's Interest Similarity with EPINIONS leaders (LDRS Sim) is more than the user Interest Similarity with the 1st level friends but less than the user Interest Similarity with (1st and 2nd) level friends, simply, because leaders rate most of the items while nearest friends provide ratings for a limited number of items.
2. Some (1st and 2nd) level friends of the target user act as leaders and their ratio increases when the target user's experience increases as shown in Table 4.10 last column for the EPINIONS dataset. When the target users are cold-start users (i.e., for cold-new the % FRNDS-K12 AS LDRS = 11.93%) while for experienced users (i.e., Test1-1642 who has rated more than 16 items, the % FRNDS-K12 AS LDRS increases to 78.97%).
3. FLIXSTER dataset leaders show Interest Similarity with target users similar to the Interest Similarity of (1st and 2nd) level friends with the target user as shown in Table 4.11. This is because leaders in the FLIXSTER dataset have the highest

average leaders' In-Degree of the three datasets which represents the trustworthiness of leaders in the dataset.

4. Target user average Interest Similarity with Leaders, and the percentage of (1st and 2nd) level friends who act as leaders, increases with the increase of the average in-degree of leaders and the increase in dataset size as shown in Figure 4.11. This is because most of (1st and 2nd) level friends act as leaders especially for experienced users in the dataset.

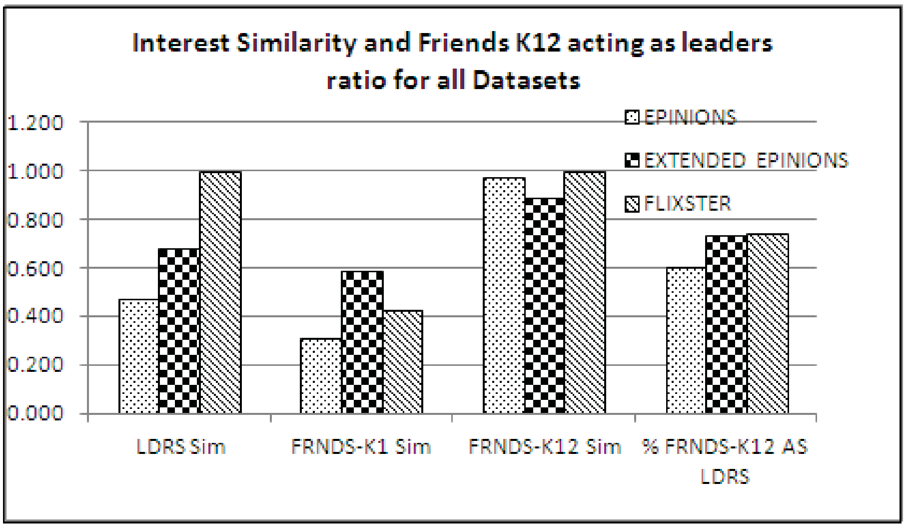


Figure 4.10. Interest Similarity and Friends K12 Acting as Leaders - Ratio for all Datasets

Conclusion: the leaders' community exhibits Interest Similarity with the target user more than the 1st level friends' community; this proves that leaders are more credible advisers than the 1st level friends. Furthermore, (1st and 2nd) level friends show Interest Similarity with target user more than leaders, simply because the nearest friends share more interests and taste with the target user for products such as movies.

4.5.3. Leaders' Credibility Threshold Analysis

In this section, I provide some highlights on the impact of selecting an optimum Credibility threshold for the model. For this purpose, Table 4.12 is generated to analyze the Credibility threshold for the EPINIONS dataset.

Table 4.12: Credibility threshold analysis for EPINIONS dataset

Case	CrThreshold	No. Leaders	% Leaders	Leader Avg Ratings	Rated Items	%Rated Items	Avg InDegree	Avg OutDegree
1	0.037	2090	4.24%	124.08	94,472	67.61%	124.03	83.91
2	0.019	4930	10.00%	77.59	112,082	80.21%	68.08	55.69
3	0.009	5202	10.55%	74.78	112,629	80.60%	66.19	55.57
4	0.005	5828	11.82%	68.34	113,827	81.46%	62.58	55.08
5	0.002	7263	14.74%	57.76	116,365	83.27%	53.63	49.45

The shaded row represents the credibility threshold used in the previous experiments, with a value of 0.019, where the maximum credibility = 0.661661 in the EPINIONS dataset was traced. From the above table, when decreasing the credibility threshold by 50% of the previous value, we note that:

1. The number of the leaders increases almost linearly; when the credibility threshold goes to zero, this means all members in the dataset are leaders.
2. The number of the items rated by leaders increases significantly in case 2 with respect to case 1, showing an increase of 17%, while for other cases an increase in the order of 1% is noticed. Since increasing the number of leaders does not provide a significant improvement in the prediction accuracy, and will create extra overheads in computations, I believe that selecting 10% of the population is an optimum choice for this dataset. Furthermore, most of the items that are not rated by leaders are either cold-start items or rated by their provider, or these items are rated by cold-start users and most of them are over rated, as discussed in Section 4.1.5.
3. Leaders' average in-degree and out-degree decreased significantly in case 2 with respect to case 1, while for other cases, a very small decrease was noticed. Since increasing the number of leaders does not provide the leaders' community with a significant increase in their influence and power, thus, selecting 10% of the population as leaders is a feasible choice for the EPINIONS dataset.
4. Leaders' average rating also decreased significantly; notably, increasing the number of leaders does not mean increasing the number of rated items.

In summary, we can conclude that selecting 10% of the population as leaders is a feasible choice in the EPINIONS dataset. When the size of the social network increases, a lower percentage of leaders is more appropriate as shown in the Extended EPINIONS and FLIXSTER. In general, a percentage of leaders less than 20% of the population is feasible and coincide with the power-law degree distribution of the social network [83], where 20% of the population can be considered as leaders in the social network.

4.6. Flexibility, Scalability and Applications

Using the Credibility-based approach on the various sizes of the three datasets EPINIONS, Extended EPINIONS and FLIXSTER shows the scalability of the model. The model can be applied to small and extremely large networks at the same time. The prediction response time increases when the size of the network increases as shown in the FLIXSTER dataset, especially when leaders' raters are in the order of tens of thousands. To overcome this weakness, the model can use a specific number of leaders in the order of tens who have rated the questioned item to participate in the prediction process.

In CF based systems, similarity computation for a matrix of N users and M items is an $O(N^2M)$ problem. Since new users and/or new items frequently enter the system, thus, it is mandatory to update the similarity matrix on a regular basis [9]. Consequently, CF-based approaches generally suffer from scalability restrictions. The proposed Credibility-based approach is scalable, as we have seen from previous experiments; it can be used in a huge datasets.

What if there are no ratings in the network?

Some networks do not have ratings, or the ratings are not relevant in the domain of the application; the Credibility model is capable of identifying leaders with trust relations only, simply by ignoring the expertise component in the model; *i.e.*, setting the system tuning parameter ($\alpha = 0$), that represents the importance of expertise component.

What if there are no explicit trust statements in the network?

In some networks, explicit trust statements are not always available [243], or the trust statements are not necessary in the domain of the application. The user Credibility model is capable of identifying expert leaders with items' ratings only, simply by ignoring the trustworthiness component in the model; *i.e.*, by setting the system tuning parameters that represent the importance of trustworthiness components to zero, *i.e.*, ($\beta = 0$ and $\gamma = 0$). In such scenario leaders are considered as experts among all population.

Since the proposed Credibility model relies on the number of items rated and on the ratings quality in qualifying expert leaders, the proposed Credibility-based approach is more efficient and reliable than other approaches that use the number of ratings only to qualify experts. Furthermore, extracting implicit trust using users' similarity in their rating [243] is an alternative to establishing trust in the model.

Since user Credibility-based model outperforms other prediction approaches especially in terms of prediction coverage, response time efficiency and handling cold-start users effectively, thus, the user Credibility-based model using the "Follow the Leader" strategy can be used in recommender systems as an alternative to the Trust-based prediction model. Moreover, a leaders' Credibility model is simpler than other approaches. Furthermore, the proposed Credibility model can be used as a mechanism to identify leaders in a network such as service providers, political leaders and terrorist leaders or similar applications.

4.7. Results Summary

In a Web based social network, user behavior is the determinant of their credibility; the credibility of users in a specific domain/context is the predictor of their role. Users with high credibility usually act as leaders, while users with lower credibility act as followers.

Increasing the number of users in the social network can produce more credible prediction results; it scales well. This behavior is more obvious in the three large datasets used to verify the Credibility model. The reason is that when increasing the size of the network, the number of genuine leaders also tends to increase.

How can we demonstrate that proposed the credibility clustering approach is an effective clustering approach?

I used degree centrality as a metric in measuring the effectiveness of the proposed clustering approach, based on the credibility of the members in the social network. Leaders in the network are identified based on their credibility, which is drawn from their trustworthiness and expertise. Since leaders possess the highest average in-degree and highest average out-degree, which in both cases is more than followers' and more than the average member in the network, they are the most prominent and *influential* members in the network. This effect is drawn from their trustworthiness and expertise; leaders possess high average rated items in the network.

How can we demonstrate that the credibility-based approach is an effective recommendation approach?

I used the following metrics to assess the accuracy of the prediction: (1) Mean Absolute Error (MAE), (2) Prediction coverage and (3) Prediction confidence as a measure of certainty of the prediction. The Credibility prediction algorithm using leaders as advisers is a feasible approach in making recommendations for the rest of the population in the dataset. The following metrics support this argument:

1. Mean Absolute Error (MAE): the Credibility prediction algorithm outperforms the Trust prediction algorithm for EPINIONS and FLIXSTER datasets in most prediction cases. This shows that leaders can provide quality recommendations for cold-start users as well as for experienced users.
2. Prediction Coverage: the Credibility-based prediction approach produces 100% coverage for all datasets, while the Trust based prediction approach produces coverage of 61.89%, 70.31% and 86.10% for EPINIONS, Extended EPINIONS and FLIXSTER datasets respectively. In the worst case scenario for the Credibility model, we can consider that the coverage ratio from EPINIONS, Extended EPINIONS, and FLIXSTER is 80.21%, 98.98% and 99.03% respectively, which represent the percentage of items rated by all leaders, and which is significantly greater than the corresponding average coverage of the Trust based model. This shows that leaders can provide better recommendation coverage for cold-start users, as well as experienced users, than the Trust based model.
3. Prediction confidence: based on the results presented in Section 4.4.6, when we compare the number of predictors who contribute to the prediction process between Credibility-based prediction and Trust-based prediction using (1st and 2nd) level friends, we find that the number of leaders who provide prediction is 4.4 times, 2.7 times and 215.5 times respectively for the three datasets. This highlights that prediction confidence produced by leaders is more than the prediction confidence produced by (1st and 2nd) level friends; consequently, this concludes that Credibility-based predictions generate more confident prediction results than Trust-based predictions in terms of the number of predictors.

How can we show that the credibility-based approach is an efficient recommendation approach?

A Credibility-based approach using leaders as recommenders shows performance efficiency in terms of scalability, interest similarity and prediction response time.

1. Scalability: using the user Credibility-based approach on varied sizes of the three datasets shows the scalability of the model. The model can be applied to small networks and large networks at the same time. The model can support networks

with ratings only, or with trust statements only, or with both ratings and trust statements. This shows that Credibility-based clustering is scalable for small datasets as well as for large datasets. The model can provide recommendations for cold-start users as well as for experienced users.

2. Interest Similarity: this measure reflects the extent of similarity between the leaders' community and the target user in providing recommendation. In Section 4.5.2, I showed that target user Interest Similarity with leaders is more than user Interest Similarity with 1st level friends but less than user Interest Similarity with (1st and 2nd) levels friends. Since some (1st and 2nd) level friends of the target user act as leaders, then the leaders' community exhibits more Interest Similarity with the target user than 1st level friends' community. This proves that leaders are more credible advisers than 1st level friends.
3. Prediction Response Time: from experiments presented in Section 4.4.5, I showed that the Credibility-based prediction algorithm outperforms the Trust-based prediction algorithm in prediction response time. The Credibility-based prediction algorithm response time is 32.38%, 32.69% and 20.98% of the corresponding Trust-based prediction algorithm time from (1st and 2nd) level friends for the three datasets respectively. These ratios demonstrate that the Credibility-based prediction algorithm is more efficient than Trust-based prediction algorithm even in prediction response time.

4.8. Conclusions

In this chapter, I evaluated the effectiveness and efficiency of the proposed user Credibility model using a set of experiments. First, visualization using the Social Network Analysis Studio (SNAS) is employed in a specific context extracted from the widely used EPINIONS dataset. The results presented in this chapter show that the proposed user Credibility-based clustering based on the "Follow the Leader" strategy is a highly effective approach in identifying Top-N recommenders, who are leaders in the context with the highest trustworthiness and expertise among all users.

Second, the effectiveness of the proposed user Credibility model is demonstrated by validating the model using social network analysis measures, *i.e.*, centrality measures where leaders show the highest average in-degree and the highest average out-degree centrality compared to other members (followers) in the network. Leaders are the most prominent and influential members in the network; this result is drawn from their trustworthiness and expertise, where leaders possess high average rated items in the network.

Third, the proposed new approach is used to make recommendations based on leaders' credibility in the model as Top-N recommenders by incorporating social network information into user-based collaborative filtering. The Credibility-based clustering approach can be used for recommenders that are embedded in social networks, where users' trust statements and/or items ratings are accessible. I have shown that using the user Credibility model is an effective approach to cluster users based on their credibility. In addition, trust relations can be extracted easily from the model, and user credibility is a valuable parameter in calculating items reputation.

Finally, the effectiveness of the proposed user Credibility model is demonstrated in providing accurate predictions and benchmarking its prediction performance against the leading algorithms: CF-Similarity based [155] and the Social Trust [68]. The results of the experiments presented in this chapter show the scalability and performance in terms of MAE, coverage, interest similarity and response time of the proposed user Credibility model based on the "Follow the Leader" strategy. The proposed model shows significant measurable performance enhancements over other approaches.

Chapter 5
Experimentation and Evaluation - Service Selection

In Section 3.4, I proposed a new dynamic Web service Credibility model with two credibility components: a trustworthiness component drawn from users' feedback about their satisfaction with the service aggregated as reputation, and an expertise component drawn from service performance and its conformance with its promised qualities. The aggregation of these two components represents Web service credibility at any point in time. In Section 3.5, I proposed a social service selection algorithm utilizing user credibility, user domain knowledge and Web service credibility where users can be qualified as leaders or followers, based on their credibility and their knowledge of the domain expressed in their queries. Leaders usually select a service that maximizes their utility, while followers rely on leaders (experts) to select the most credible service from the services recommended by those leaders.

In this chapter, I will demonstrate the effectiveness of the Web service Credibility model. First I provide experiments to validate the applicability of the model, and then I show the effectiveness of the proposed social service selection based on user credibility and Web service credibility, through benchmarking the social selection approach against other leading utility-based and trustworthiness-based selection approaches.

The empirical results incorporated in this chapter demonstrate that the proposed approach is an innovative means to identify users based on their behavior and knowledge, and make an effective service selection. The results also show that the proposed service Credibility model outperforms utility-based selection approaches.

5.1. Social Service Selection Approach

In the Service Web, a huge number of services compete and offer a wide range of similar functionalities [148]. Web service selection is a complex process, in which the best service that matches user preferences is selected from a set of candidate services based on user requirements [215]. As per the selection criteria, various non-functional properties or Quality of Service (QoS) attributes, can be used and expressed as user preferences. Web services' non-functional properties or QoS, such as availability, response time, reliability, security and privacy are difficult for the user to determine. Some users are reluctant to spend time describing their detailed preferences and providing ratings for the system [33, 202, 252], and are even less willing to assign relative weights to their preferences, especially when the effects or consequences of their inputs are unknown or undetermined. Moreover, users may not be explicitly aware of their own preferences or able to translate their preferences into an abstract form suitable for automated reasoning.

Based on the proposed social service selection approach presented in Section 3.5, a user can be recognized either as a leader or a follower. Leaders are experts in the service domain, and capable of providing rich functional and non-functional selection criteria.

I assume that the discovery and the matching process have been conducted over published service advertisements, and that all functional selection criteria have been met. The outcome from this process returns the set of matched services considered for the social service selection process.

Web service discovery is typically a simple process, featuring keyword-based or ontology-based discovery, or similar, focused on functional property. Web service selection is considered to be a step beyond service discovery, and a suitable discovery mechanism is considered to be in place using the methods of Klusch, Fries and Sycara [108], for example, or the discovery approach described by Sivashanmugam *et al.* [206].

5.1.1. Motivation and Contributions

Recall the motivation scenario presented in Section 1.1, where Bob does not have enough knowledge about home loans in Australia. He can rely on his friend Adam to provide advice for a home loan, but what if Bob does not know Adam? Could he get reasonable advice from an expert in home loans in Australia? If not, he would need to embark on a tedious and time consuming process to differentiate between the vast number of home loans, which may match his request from a functionality perspective, but may vary in their qualities, including non-functional properties.

In either case, finding the most trustworthy and experienced service is a challenging issue; different users have varied levels of knowledge in each service domain. A Web service Credibility model coupled with social service selection can provide an effective solution for both expert customers and cold-start users.

The key contributions of this chapter are as follows:

- A review of recent social service selection approaches.
- Development of a simulation model that imitates Web services and user behaviors in a dynamic environment.
- A Web service credibility bootstrapping algorithm to establish service credibility for new services.
- A user query model with preferences.
- Evaluation metrics for social service selection accuracy.
- Benchmarking the Credibility-based approach against the utility-based approach.
- Benchmarking the Credibility-based approach against the trustworthiness-based approach.

5.1.2. Social Service Selection Related Works

In Section 2.6, I presented three approaches used in social service recommendation: reputation, recommender and referral approaches. In this section, I present some important work that uses either trustworthiness components or an expertise component in the selection model; unfortunately, none of these efforts addresses both types of component at the same time. As opposed to previous works on service selection, where credibility is either neglected by Yu, Zhang, and Lin [242] or dealt with as any quality parameter as shown in Zeng *et al.* [245], service credibility is considered in this dissertation as a predictor for the future service behavior and reflects its trustworthiness and expertise at the same time.

Qi *et al.* [184] recently proposed a Credibility-based service selection, where the credibility evaluation is based on the QoS information from execution logs and users' QoS constraints. The authors use an approach called "Technique for order performance by similarity to ideal solution, (TOPSIS) method" and employ it to calculate the credibility of

QoS dimensions, including reputation as a QoS dimension. The credibility of each attribute is calculated as the average of its actual performance compared to the advertised performance. This measure to a certain extent reflects the expertise component in our model, while our model handles the trustworthiness credibility component which is ignored in their model.

Yang *et al.* [237], Shaikh-Ali *et al.* [199] and Wishart *et al.* [228] used trust and reputation to assess services that can be considered as candidates for the selection process, and focus on the representation and computation aspects of service reputation.

Yang *et al.* [237] use a multidimensional-trust model to assess different QoS aspects such as credibility, reliability and quality. They generate a trust vector that represents users' experience with the QoS aspects. In their model, service trustworthiness is considered to be the confidence level in that service; they employ 'Hypothesis Evaluation Theory' to estimate service trustworthiness. Notably, they use credibility as one QoS attribute. In Shaikh-Ali *et al.* [199], service reputation is linked to an execution context; two contexts are identified (user type and application domain), then services are assessed in either context. The reputation of the service is computed as a weighted mean of the feedback using the time decaying within the context. Again, their approach handles the trustworthiness component to a certain extent as in the proposed credibility model.

Vu, Hauswirth and Aberer [216] use trust and reputation assessment mechanisms to predict service quality. They use report evaluation system to assess the credibility of reports. They consider a limited number of trusted parties who can provide credible reports about the service's conformance compared to the advertised capability. They use credible reports to assess the credibility of other reports; in the selection process, false reports are identified and rejected. Service future behavior is then predicted utilizing linear regression technique on the previous QoS conformance and credibility reports. Since the trusted monitoring agents constantly provide the required assessments, there is no need for other users' reports.

Limam and Boutaba [131] propose a framework for service rating and selection based on quality and reputation. Their selection algorithm uses reputation, quality and cost constraints. Reputation is used to predict the trustworthiness of the offer quality and the extent to which this offer matches the delivered quality. The service ranking function aggregates the quality, cost, and reputation parameters into a single metric score that is used to evaluate service offerings against one another. In their model, they consider a more general reputation computation model where the trustworthiness of a service provider is evaluated with conformance to the terms enclosed in the offer *i.e.*, SLA. Their model ignores the expertise component of the service which has an impact on service credibility and usage in dynamic configuration.

In summary, some approaches use a trustworthiness component as described in Vu, Hauswirth and Aberer [216], Yang *et al.* [237], Shaikh-Ali *et al.* [199] Limam and Boutaba [131]. Other approaches use an expertise component as described in Qi *et al.* [184], but none of these works combines both components, which the proposed service Credibility model will do. Combining both components can produce a more reliable solution by considering consumer feedback and the service's performance to measure service credibility, as demonstrated in this chapter.

5.2. Notations and Definitions

In the proposed framework, I assume that n is the number of QoS attributes of Web services in the domain category. In the following section, a user query (request) model is introduced, then, a mechanism for predicting missing quality values for Web service is provided. Finally, I propose a Web service credibility bootstrapping approach.

5.2.1. User Query Model

Let U_p be a set of user preferences captured from user query (request).

Let m be the number of non-functional (QoS) attributes that appeared in user query and considered as constraints over the selection process, where $m \leq n$, then user preferences U_p can be defined as:

$$U_p = \{q_r^1, \dots, q_r^j \dots, q_r^m\}, (1 \leq j \leq m) \qquad (5.1)$$

q_r^j represents the j^th user preference (QoS) attribute, and given by:

$$q_r^j = \{q_N^j, q_O^j, q_V^j, q_w^j\} \qquad (5.2)$$

where N is the QoS attribute Name, O refers to the operator constraint ($\leq$,$\geq$), V refers to the value constraint and W refers to the weight constraint.

For example a user might search for: (home loan interest rate $\leq$ 6.5%, with weight 8)

Each QoS attribute is to be maximized or minimized based on the operator constraint. For example, the user is looking for the highest interest rate on a bank deposit while he/she is looking for the minimum home loan interest rate or ticket cost.

5.2.2. Predicting Missing Quality Values

Although some atomic services satisfy functional requirements and some QoS attributes are not available or not offered explicitly by the service provider, we can use the worst offered value for non-available attributes in the service. The value of a missing QoS attribute can be predicted by using either the worst-case values q_{max} or q_{min} or the average value q_{avg} as shown in Yu, Zhang, and Lin [242], where q_{avg} is more representative for the service behavior.

5.2.3. Web Service Credibility Bootstrapping

When a new service enters the market, setting its initial credibility is a challenge. Some approaches use a value of 0.5 or a random number in the range [0, 1] for a new service reputation or trustworthiness. To be fair in assessing a new service, setting the credibility of a new service should correlate with its advertised qualities. Accordingly, I introduce a service *capability measure*, as a relative measure of the new service with respect to other available services in the domain, assuming the weight of each attribute is drawn from other customers' average weight for that attribute. If no weights are available, especially at the system initialization, we can consider that all attributes are of similar weight, or that they can be set according to the system administrator's prior knowledge. We then define the attributes to be maximized and those to be minimized; *capability measure* C_i, for service i, with n QoS attributes is defined as follows:

$$C_i = \sum_{j=}^{n} W_a^j \times Q_i^j \, , (1 \leq \text{j} \leq \text{n}) \tag{5.3}$$

Where,

$$Q_i^j = \begin{cases} \frac{q_i^j - Min^j}{Max^j - Min^j} & if\ Maximize, op = " \geq " \\ \frac{Max^j - q_i^j}{Max^j - Min^j} & if\ Minimize, op = " \leq " \\ 1 & if\ Max^j - Min^j = 0 \end{cases} \tag{5.4}$$

W_a^j is the average preference weight of all users for the j^{th} attribute based on previous users queries, for all services in that domain as shown previously in Formula 3.20, such that,

$0 < W_a^j < 1$, and the average weights are normalized such that: $\sum W_a^j = 1$. Max^j, Min^j are the maximum and minimum values of the j^th attribute for all available services in the domain category.

Preference weights can be predicted based on the experience of the recommender system with user queries by computing the average weight of each attribute over a specific period of time. The recommender system initializes all weight values with equal values. Although this prediction is based on different users' behaviors, it gives a better indication than equal weights given to all attributes.

5.3. Benchmark Service Selection Algorithms

Since leaders and experts show high levels of domain knowledge, they can provide an expressive query that reflects their preferences. In this section, two approaches are presented to benchmark the proposed Credibility-based approach against these approaches: the Utility-based service selection presented in Yu, Zhang and Lin [242] and the Trustworthiness-based service selection proposed by Limam and Boutaba [131].

5.3.1. Utility-Based Selection Approach

Since utility-based selection approaches are the most useful approaches in service selection, the following utility-based selection approach presented in Yu, Zhang and Lin [242] is used for *benchmark purposes.* The procedure as follows:

1. Match user preferences with the advertised QoS attributes and ignore those services that do not match user preferences.
2. Compute the utility function for each atomic service.
3. Select the atomic service with the highest utility function as the best candidate. If two or more services have the same utility value, then select randomly from them.

The utility function U_i from service S_i as adopted from Yu, Zhang and Lin [242], for m user preferences; is defined as:

$$U_i = \sum_{j=1}^{m} W^j * Q_i^j, (1 \leq \text{j} \leq \text{m}) \quad (5.5)$$

Where,

$$Q_i^j = \begin{cases} \frac{q_i^j - \mu^j}{\sigma^j} & if\ Maximize, op = "\geq" \\ 1 - \frac{q_i^j - \mu^j}{\sigma^j} & if\ Minimize, op = "\leq" \\ 1 & if\ \sigma^j = 0 \end{cases} \quad (5.6)$$

Where Q_i^j represents the j^th^ attribute capability of service i.

W^j is the user preference normalized weight for the j^th^ attribute such that, $0 < W^j < 1$, and user preference weights are normalized such that: $\sum W^j = 1$.

μ^j, σ^j are the average and standard deviation of the j^th^ attribute for all candidates.

$Q_i^j = 1$ if $\sigma^j = 0$, *i.e.*, when all values of the same attribute are equal, this case is likely to occur if all services offer the same value for that attribute.

The service with the highest utility is returned to the customer.

5.3.2. Trustworthiness Based Selection Approach

Limam and Boutaba [131] use the Trustworthiness approach for service selection, and trustworthiness is defined in the proposed service Credibility model as one component besides the expertise component. The proposed service Credibility model computes service trustworthiness similarly to the Limam and Boutaba [131] approach in static service configuration *i.e.*, QoS attributes values are not changed during the simulation process.

I consider the trustworthiness component of the proposed service Credibility model to be similar, to an extent, to the trustworthiness described in Limam and Boutaba. In the following section, I present Limam and Boutaba's selection approach to be used for benchmark purposes; their approach is composed of the following steps:

1. Reputation of each service is computed.
2. Match Making: in this step, service offers are compared to user preferences expressed as cost and quality constraints. All offers that do not match user requirements are ignored.
3. Evaluation: this step identifies qualified services that offer affordable costs with quality level equals or better than the requested. Quality Q offers are evaluated using $scale_i(q_i)$, a function used to evaluate each QoS attribute i and the service cost, and computed as shown in Formula (5.7).

Service quality Q(s) is computed as:

$$Q = \sqrt{\sum_{i=1}^{m} W_i * scale_i(q_i)^2} \tag{5.7}$$

where Q represents the weighted root-mean-square of all QoS attributes (1,.., m). In this model, m also represents the number of user preferences, each with a corresponding preference normalized weight W_i.

4. Ranking: This is the final step, where Reputation (R), Quality (Q), and Cost (C) are combined into Score(s), the final selection metric. The service with the highest Score(s) is then selected.

$$Score(s) = e^{\lambda(R-1)} + e^{-\lambda}(w_q Q + w_c C - 1) \tag{5.8}$$

Where $\lambda = 2.6, w_q = 0.4 \; and \; w_c = 0.6,$ are model constant parameters defined in Limam and Boutaba's [131] model.

5.4. Experimental Evaluation

The proposed testing approach imitates the behaviors and activities of users in a social network environment, where different users have varied levels of knowledge in a specific service domain (category), such as home loans. Since there are no services available on the Web for testing purposes, the simulation methodology is used as the best available choice for evaluation.

In the following sections, I provide an overview of Agent-based Modeling and Simulation (ABMS). Subsequently, the test environment is presented using the SNAS tool, and is used to verify the proposed social service selection with UDK considerations model. Then I benchmark the proposed social service selection approach against the state of the art utility-based selection approach proposed in Yu, Zhang and Lin [242] and trustworthiness-based selection approach presented in Limam and Boutaba [131].

5.4.1. Agent-based Modeling and Simulation (ABMS) Overview

Simulation is the imitation of a real-world process or a system over time. Simulating something involves model development; the model should represent certain key characteristics or behaviors of a selected physical or abstract process or system. Computer simulations are used to solve concrete problems utilizing agent-based modeling [146].

Agent-based Modeling and Simulation (ABMS) is a new approach to modeling systems comprised of autonomous, interacting agents, where the simulation model is composed of real world entities with a corresponding representation of structures and behaviors [54]. ABMS provides a wide range of advantages, such as the fact that results are repeatable, and simulation models can be shared between scientists for further reuse and analysis.

ABMS can be used as a powerful tool to recreate and predict the actions of complex phenomena, especially in domains which need long time to evolve such as social networks. A simulation process consists of implementing the model with specific conditions defined as control parameters, and then analyzing the outcome. The simulation usually aims to build a model in which behaviors match real entities in specific aspects. By building the model, researchers can develop and draw conclusions about the behaviors of the real world entities or phenomena; simulation modeling is usually exploratory. Simulation may also be used also to confirm predicted behavior reliability under specific conditions; such conditions may not be under direct control [181].

Agent based modeling is the cornerstone of the ABMS process. Agents represent entities in the simulation model and agent relationships represent the interaction of the processes of entities. Agents are computer programs, autonomous and able to perform independent actions in unpredictable and dynamic environments [249]. Agents represent entities in ABMS and are used to generate model behaviors in the simulation.

In this thesis, NetLogo [171] was chosen over other simulation platforms such as RePast[21] and Swarm[22]. NetLogo is a multi-agent programming and modeling environment based on JAVA platform. NetLogo was conceived for simulating complex phenomena, specifically for large-scale patterns which arise from the complex interactions of several independent lower scale micro-agents [8]. Such emerging patterns are available in social sciences and real life. Despite its simplicity, NetLogo is used as a powerful simulation tool in various research fields and education. It is suitable for modeling a large collection of agents evolving over time.

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[21] http://repast.sourceforge.net

[22] http://www.swarm.org

NetLogo layout is composed of a main graphic window called the Virtual World which is used to present interacting agents. User controls are drawn from a set of choosers, buttons, sliders, switches, monitors and charts, all of which can be used in the user interface. As shown in Figure 5.1, in the upper left corner, the user can set the parameters of the model and choose combined scenarios to run the simulation. NetLogo enables users to import and export data from/to other sources; users can also easily handle data and visual results of the simulation using dynamic charts, monitors, print statistical data for test proofing and later analysis, take a snapshot of the Virtual World or record a movie [8].

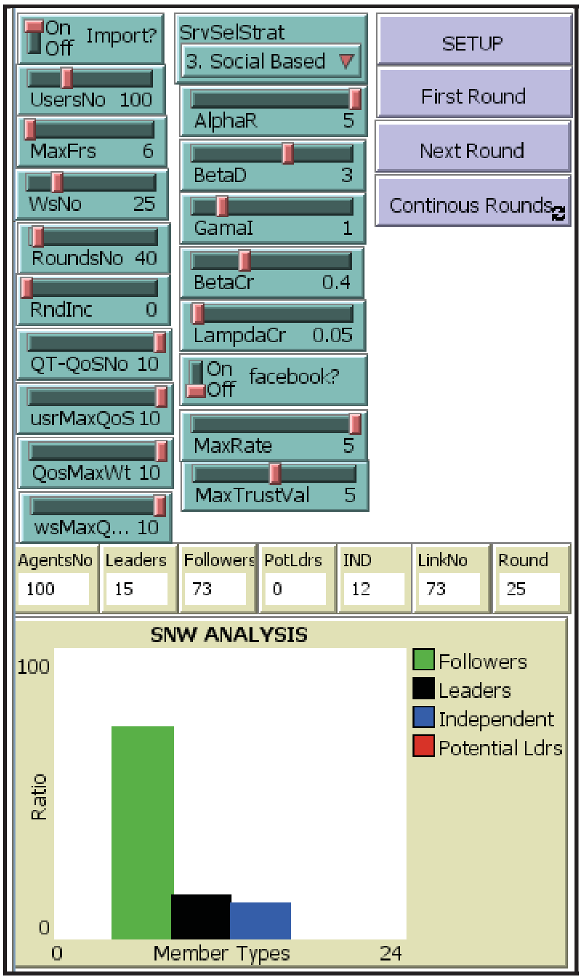

Figure 5.1. SNA Simulation Tool – User Interface

5.4.2. Simulation Model

To demonstrate the feasibility and effectiveness of the Web service Credibility model and the proposed social service selection proposed in Section 3.5, I extended the Social Network Analysis Studio (SNAS) using the NetLogo platform [171] to handle social service selection; it is used to analyze user and Web service behaviors in a social network, based on our simulation tool "4S: Service Selection Simulation Studio" [5] inspired by Goldbaum [70]. The user interface shown in Figure 5.1 is used to evaluate the validity of the proposed Web service Credibility model and the proposed social service selection approach.

Simulation model parameters are shown in the user interface of Figure 5.1; any change in any of these parameters is expressed in the corresponding experiment.

The simulation model is composed of a variable number of atomic services N, which have the same functional properties, but varied in their QoS attributes; each atomic service maintains the following information: service code, a list of QoS attribute' codes and corresponding advertised values, where the advertised QoS is static during any simulation session. Web service credibility is dynamic and is computed after each round.

Each simulation session is composed of a fixed number of rounds (currently 25 in Figure 5.1). Each round represents a time unit *e.g.*, one day. In each round, a fixed number of customers (100) enter their queries into the system. Each customer has the following information: ID, and a varied list of QoS codes as preferences with corresponding preferred values and weights. Since NetLogo treats services and customers as agents with a unique id starting from 0, the first customer id starts from the number of services; for example, if we have 30 services then the services are labeled as ("S01",…, "S30"), and the customers' IDs start from 30. Each customer has a random number of friends (1-6) with corresponding trust values also randomly chosen. Each service has an initial credibility at the beginning of each session based on its capabilities as described in Section 5.2.3. By the end of each round, the system implements service credibility computations based on leaders' feedback and service performance.

Each simulation session starts by importing predefined services with corresponding QoS attributes, or generates services randomly, then sets customers with their corresponding information. Each round starts with a new set of random customer preferences drawn from the Web services' advertised QoS attributes and within minimum and maximum advertised values. In each round, every customer passes their query with preferences to the system. The system identifies leaders based on their credibility level and their UDK, which represents the expression of their queries as described in Section 3.5. If the customer is qualified as a leader *i.e.*, UDK ≥ 0.6, then the system enables the leader to select the best service from the Top-M services returned to the user based on the expected utility derived from service credibility Formula 3.26. If the customer acts as a follower, *i.e.*, UDK ≤ 0.2, then the system returns to the user the Top-M services used by leaders. When the user domain knowledge is in the range 0.2 < UDK < 0.6, the system provides two lists for the user; List-1, as for leader and List-2 as for follower. The user then either: (1) follows the best friend with highest credibility from the customer's friends, *i.e.*, when the confidence in that friend is higher than the confidence in himself/herself, or (2) allows the customer to act as independent if the confidence in himself/herself is higher than any of their friends.

By the end of each round, each leader customer provides feedback to the system about their satisfaction with each QoS attribute in their preference list; this feedback is used to derive a new trustworthiness value for the service as described in Section 3.4.1. Service performance also is assessed based on the advertised values and estimated delivered values that are generated randomly, as described in Section 3.4.2. Service credibility is computed from trustworthiness and expertise components with decay considerations; consequently, service credibility impacts the service selection performance in the next rounds.

5.4.3. Evaluation Metrics

The quality of the selection results produced by the proposed social service credibility approach can be measured by recall, precision, F1 Score, and R-precision; R-precision is sometimes called Top-K precision [87]. R-precision is recognized by the Information Retrieval community as the most useful quality parameter measure [216]. In the context of social service selection, R-precision represents the ratio of the most relevant services to the user from all returned services based on their credibility. Notably, selection results would be the best in the ideal case, *i.e.*, where recall, precision, F1, and R-precision measures are all equal to 1.0. Therefore, the result of the ideal case is considered as a reference point for comparing the quality of the returned services.

Since our main objective in the proposed social service selection based on service credibility is to provide the user with the Top-M credible services ranked by the highest credibility from which to select, we have to find:

1. The number of services returned in the top-M candidate services.
2. The available returned candidate services among the highest quality services.

To compute R-precision for a ranked list (Top-R), where R is the number of services relevant to the user query [15], the R-precision R_p of this ranked list is the precision at rank R. Rp is formally given by:

$$R_p = \frac{Relevant\ services\ in\ R}{R} \tag{5.9}$$

At rank R, the ranked list has both precision and recall equal to R_p. For example if the algorithm returned 4 services in the 5 top-ranked services, then R-precision = $\frac{4}{5}$ = 0.8.

5.5. Experiments and Simulation Results

In the following section, a set of experiments is provided to verify the following issues: first, the ability of the Credibility model to analyze services and customers behaviors, and then the proposed social service selection with UDK considerations is evaluated. Finally, I provide the results from benchmarking the proposed Credibility-based approach against other utility and trustworthiness-based approaches.

5.5.1. Validity of Web Service Credibility Computational Model

In this section, I present the following experiments that verify the applicability of the Web service Credibility model:

- Impact of Trustworthiness and Expertise on WS Credibility.
- Sensitivity of the model to malicious Web service behavior.

5.5.1.1. Impact of Trustworthiness and Expertise on WS Credibility

This experiment demonstrates how Web service credibility varies with trustworthiness and expertise credibility components over time.

Setup: In this experiment, WS Selection strategy is chosen randomly from all given services, *i.e.*, the customer selects a Web service randomly from the given services, in order to show the variation in the Web service behavior for a specific service (WS=S04) over the simulation period 25 rounds.

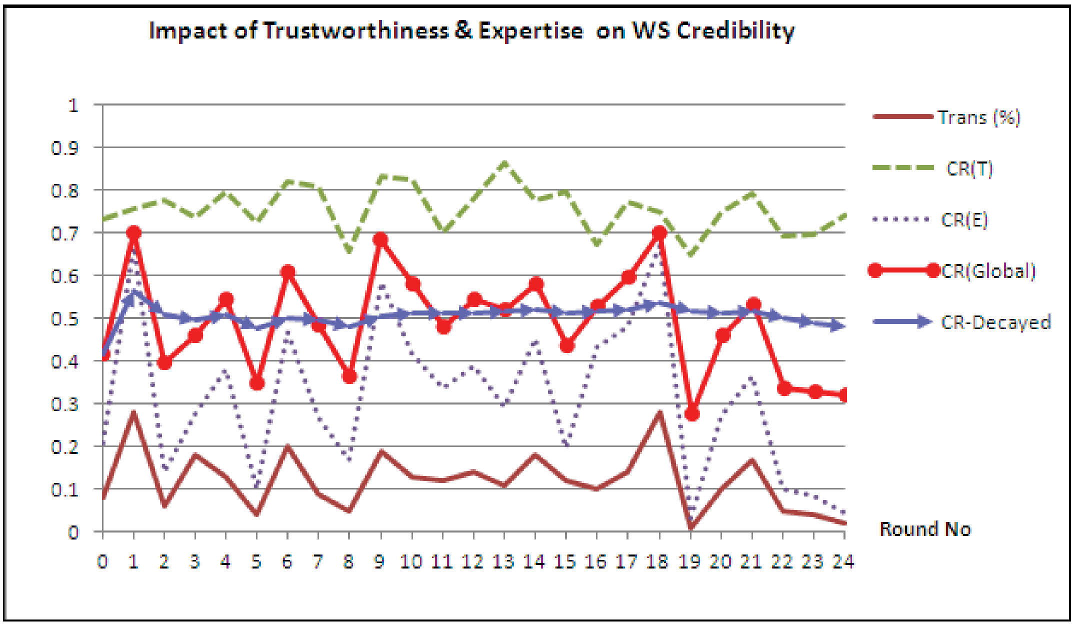

Figure 5.2. Impact of Trustworthiness and Expertise on WS Credibility for WS (S04)

Results: Figure 5.2 shows how credibility components: Trustworthiness CR(T) and Expertise CR(E) vary with time. The Trustworthiness component depends on reputation (how customers rate the service) and the Expertise component depends on Web service performance and number of transactions for each Web service each round. These two components are aggregated with an importance weight $\beta = 0.4$ for trustworthiness credibility CR(T), and $1 - \beta = 0.6$ for expertise credibility CR(E) to give CR(Global) for each round. Since credibility decays with time, the system computes the decayed-credibility (CR-Decayed) as the determinant credibility factor for service selection in the "Follow the Leader" selection strategy.

This experiment demonstrates the validity of the proposed Web service credibility computation model and shows the dynamism of service credibility over simulation rounds; service credibility is drawn from trustworthiness component represented by users' feedback and expertise component represented the degree of the service competency in providing accurate results as promised.

5.5.1.2. Model Sensitivity to malicious Web service behavior

In this experiment, malicious Web service behavior is simulated after its approved credibility over a specific period of time, then performs badly with one of its QoS such as the privacy issue presented in Bright [28] for Facebook users.

Setup: In this experiment, WS Selection strategy is chosen as randomly from all given services, with the same settings of the model parameters as in the previous experiment, in order to show the proposed Web service Credibility model detects malicious behavior. We allow the Web service to act honestly (*i.e.*, Web service provided QoS as promised) in the first 11 rounds, then from round 12 to the end of simulation the Web service provided unexpected performance for their users privacy.

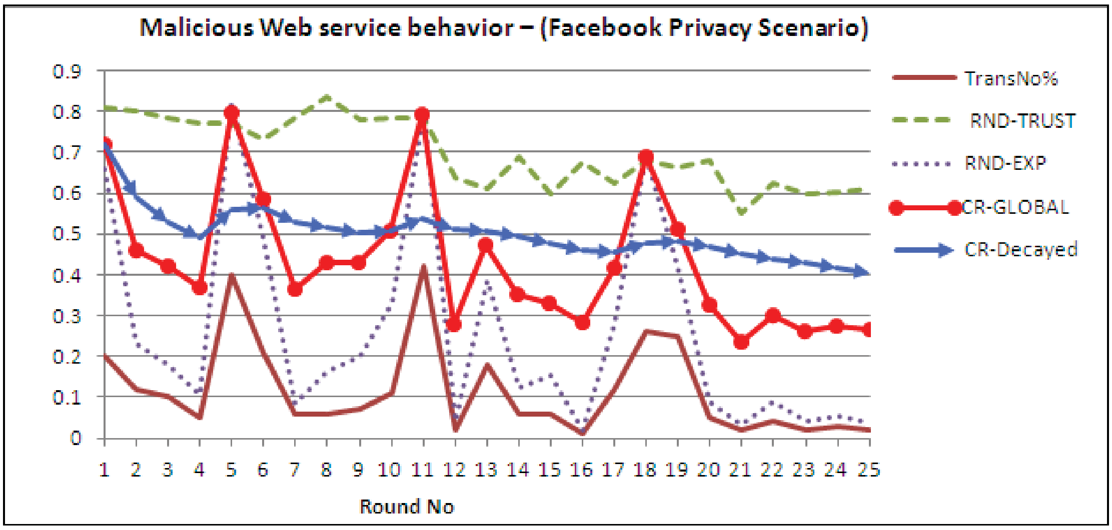

Figure 5.3. Malicious Web service behavior – (Facebook Privacy Scenario)

Results: Figure 5.3 shows how the service behaves consistently in the first 11 rounds with the highest credibility over all 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 service round Credibility decayed (CR-Decayed) decreased from an average of 0.54 in the first 11 rounds to an average of 0.36 in the rest of the simulation rounds, with overall loss in its credibility of 33%. The average percentage of transactions decreased from 16.3% to 8.1% with 50% loss in its customers. These figures reflect the sensitivity of the model against malicious behavior of Web service. The impact of this behavior is drawn from customers rating of the Web service and its corresponding expertise and reflected by the decrease in number of customers who adopted the service.

5.5.2. Social Service Selection with User Domain Knowledge (UDK) Considerations

To test the hypothesis that the “Follow the Leader” is an effective strategy for social service selection with user domain knowledge (UDK), as presented in Algorithm 1 of Section 3.5, where leaders have a high level of UDK in a specific domain: the system presents for the leaders Top-M services based on their preferences expressed in their queries, ordered by the highest expected service utility computed as shown in Formula 3.26. For followers, the system presents the user Top-M services used by leaders in the social network.

I present the same Algorithm 1 of Section 3.5, this time as a flowchart, as shown in Figure 5.4. For each query, the algorithm proceeds as follows:

1. Capture User Query & Preferences: In this step, the system captures user preferences specified in the query; these include QoS names, operators, values and preference weights. For example, in a home loan service, one term can be expressed as: “home loan establishment fees ≤ 100$, with weight = 7”.

2. Evaluate User Domain Knowledge (UDK) as shown in Formula 3.25. For example if the system maintains 10 QoS attributes for home loan services n, and the query includes 8 QoS attributes, then the expressiveness of the query is 0.8. In a social network settings user credibility can be known and can be used to calculate UDK. In this scenario we assume that user credibility initially unknown; consequently we can consider user credibility = 1, and UDK = entered terms / n.
3. If UDK ≥ UDK(LT), means that user domain knowledge is greater than or equal the leaders’ threshold domain knowledge 0.6, then the user is qualified as leader, and the system provides top-M services based on user preferences and the expected utility EU(s) computed as in Formula 3.26.

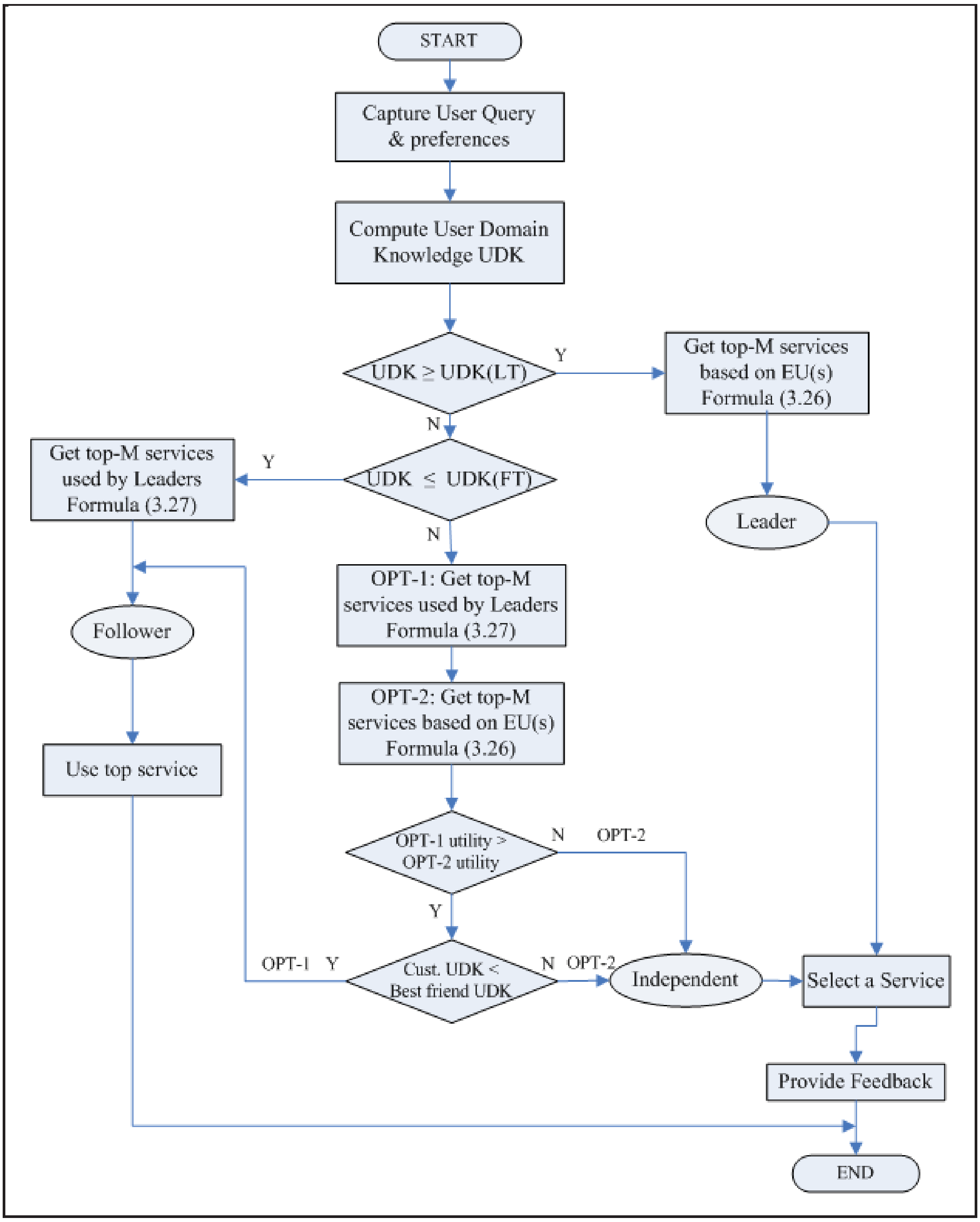

Figure 5.4. Social service selection Flowchart – Algorithm 1

4. If UDK $\leq$ UDK(FT), means if the user domain knowledge is equal or less than the followers' threshold domain knowledge 0.2, then the user is qualified as a follower, and the system provides top-M services used previously by leaders and currently maintain high credibility.
5. Otherwise, UDK(FT) < UDK < UDK(LT) *i.e.*, 0.2 < UDK < 0.6, then the system presents two options for the user: (1) a list of top-M services used previously by

leaders, and (2) a list of top-M services based on the user preferences and the expected utility EU(s), computed as in Formula 3.26. In this case, the user compares the top service utility in the two available options; if the utility from option 2 (leader case) is higher than Option 1 utility (follower case); or the user self-confidence is higher than the confidence in any of their friends (*i.e.*, user domain knowledge is higher than the friend with the highest UDK), then the user act as independent (leader); otherwise the user act as follower.

6. After the service consumption, each leader or independent customer provides feedback about their satisfaction about each QoS received.

Table 5.1: List of home loan services

Service Templates / Services Details				Code	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
				Name	EstFee	IntRate	Term	RespTime	MonFees	MaxAmt	ETermFee	RedFee	Transf?	Privacy
				Unit	$	%	Years	Day	$	$K	$	$	Y/N	%
				OP	<=	<=	>=	<=	<=	>=	<=	<=	>=	>=
				Min	0	5.25	15	4	4	250	110	6	0	95.15
				Max	300	7.75	30	14	12	750	200	24	1	100.00
Serv-CD	**Init-Cred**	**Last Cred**	**Last Trust**	**Last Exp.**	**Q1-Val**	**Q2-Val**	**Q3-Val**	**Q4-Val**	**Q5-Val**	**Q6-Val**	**Q7-Val**	**Q8-Val**	**Q9-Val**	**Q10-Val**
S01	0.489	0.000	0.000	0.000	180	6.5	20	14	5	750	140	22	1	95.15
S02	0.470	0.000	0.000	0.000	290	7.75	25	12	7	450	150	20	1	100.00
S03	0.449	0.000	0.000	0.000	270	7.75	20	9	12	750	200	14	1	100.00
S04	0.647	0.607	0.560	0.294	0	6.5	30	6	4	300	170	14	1	96.02
S05	0.632	0.000	0.000	0.000	130	7.75	30	12	5	550	160	8	1	98.77
S06	0.590	0.000	0.000	0.000	140	5.75	20	5	4	500	140	12	0	97.57
S07	0.647	0.658	0.580	0.338	75	5.25	15	8	4	700	170	8	0	100.00
S08	0.510	0.000	0.000	0.000	270	5.25	20	6	5	750	180	24	0	98.87
S09	0.485	0.000	0.000	0.000	240	6.35	30	10	10	250	160	6	0	99.96
S10	0.509	0.000	0.000	0.000	290	7.75	30	5	11	600	140	12	0	100.00
S11	0.466	0.000	0.000	0.000	120	5.65	30	9	12	250	170	22	1	96.51
S12	0.761	0.645	0.587	0.318	170	5.75	20	4	5	500	130	8	1	100.00
S13	0.518	0.000	0.000	0.000	0	7.75	20	6	8	300	190	10	1	97.85
S14	0.261	0.000	0.000	0.000	190	7.15	20	7	12	400	160	22	0	95.72
S15	0.658	0.665	0.587	0.340	250	5.55	15	4	8	600	150	10	1	100.00
S16	0.372	0.000	0.000	0.000	280	5.5	20	13	12	300	150	12	0	100.00
S17	0.561	0.000	0.000	0.000	160	6.25	20	10	5	650	130	18	1	95.27
S18	0.537	0.000	0.000	0.000	200	6.15	20	10	6	750	200	22	1	99.04
S19	0.581	0.000	0.000	0.000	0	7.75	30	8	6	750	160	18	0	98.46
S20	0.348	0.000	0.000	0.000	300	7.06	15	13	5	700	200	18	0	100.00
S21	0.345	0.000	0.000	0.000	300	7.5	20	12	10	750	120	14	0	95.73
S22	0.389	0.000	0.000	0.000	180	7	25	5	12	450	150	22	0	97.84
S23	0.384	0.000	0.000	0.000	150	7	15	10	11	550	110	20	0	98.49
S24	0.670	1.000	0.795	0.570	140	6.5	25	5	4	400	120	24	1	99.58
S25	0.442	0.000	0.000	0.000	80	7.75	20	7	9	500	200	10	0	100.00

Experiment Setup:

In this experiment, 25 predefined home loan services were imported to the system as shown in Table 5.1; each service has 10 QoS attributes. Although some attributes can be considered as functional attributes, for the purpose of this experiment, all attributes considered as QoS attributes to demonstrate the complexity facing customers in service selection. 100 users are generated randomly by the system then set their corresponding information: QoS preferences values and weights and friends. Each round starts with the same set of customers with new random preferences. The simulation in this experiment is composed of 40 rounds. In order for Web services to develop their credibility, in the first 30 rounds, leaders select services from the top five credible services randomly, then in the last 10 rounds users select services based on social-based service selection presented in Section 3.5.

5.5.2.1. List of home loan services items description

In the following section, a description of the headers in home loan is provided in Table 5.1.

A. Service Templates:

1. Name: Refers to QoS Attribute Name.
2. Unit: Refers to QoS Attribute Unit.
3. OP: Refers to QoS Attribute OP to be maximized (≥) or to be minimized (≤).
4. Min: Refers to the minimum QoS value advertised among all services. Users usually take this with Max as references to set their preferences' values.
5. Max: Refers to the maximum QoS value advertised between all services. Users usually take this with Min as references to set their preferences' values.

B. QoS Names Description:

1. EstFee: Establishment fee of the loan.
2. IntRate: Introductory interest rate of the loan.
3. Term: Loan term in years.
4. RespTime: Response time for the provider to respond, *i.e.*, approval time.
5. MonFees: Loan monthly fees.
6. MaxAmt: Maximum loan amount the provider can provide.
7. ETermFee: Early loan termination fee.
8. RedFee: Redraw fee per transaction.
9. Transf?: Is the loan transferable to others?
10. Privacy: Loan privacy level providers maintain for their clients; this attribute may be provided by a third party.

C. Service Details:

1. Serv-CD: Code of home loan service.
2. Cred: Credibility of the service as shown in the last round computed in Section 3.4.
3. Init-Cred: Initial credibility at bootstrapping described in Section 5.2.3.

4. Trust: Trustworthiness of the service as shown in the last round computed in Section 3.4.
5. Exp.: Expertise of the service as shown in the last round computed in Section 3.4.
6. Q-Val: Value of QoS attribute as advertised by the provider at round 0; these values are static during the simulation session.

5.5.2.2. Social service selection analysis

In the last 10 rounds of this experiment, the system implemented social service selection with UDK considerations. As shown in Figure 5.5, services are aligned in the top row. Leaders (Black agents with UDK ≥ 0.6) make their selection based on their UDK levels, available Web services credibility and associated utilities. Since leaders' UDK level is high, they select the service with the highest expected utility, which is drawn from its credibility. Customers with a low UDK level act as followers (Green agents with UDK ≤ 0.2); they make their decision and follow one of their trustworthy best friends (*i.e.*, the friend with the highest credibility among all friends).

Finally, for customers with user domain knowledge in the range $0.2 < \text{UDK} < 0.6$, the system provides two options: (1) the top credible service used by leaders, and (2) the top credible service with the highest expected utility based on their query preferences. Those customers make their decision based on their confidence in their UDK; if their UDK is less than their best friend, *i.e.*, the friend with highest UDK, then the customer elects to follow that friend (who already followed leaders advice) and act as follower (Green agent); otherwise, this customer has higher confidence in himself/herself than the confidence in any of their friends and acts independently (Blue agents), selecting their best service based on service credibility as leaders. When an independent agent is followed by others, then it is promoted to a leader. Independent agents can be promoted to leaders if their credibility is within the leaders' threshold.

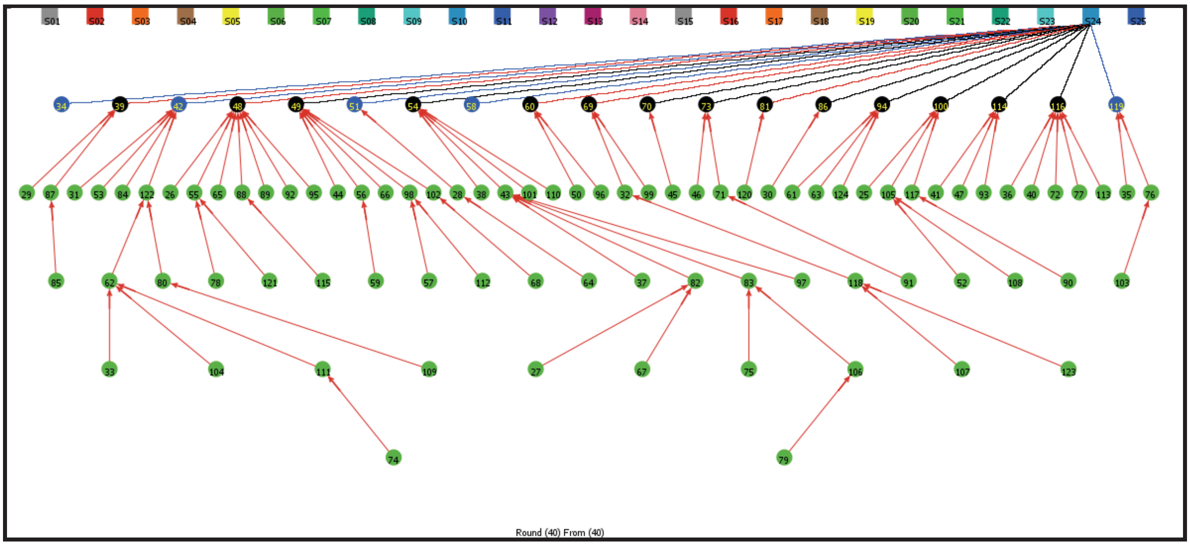

Figure 5.5. Social Service Selection based on customer UDK and service credibility – Follow the Leader Model

Table 5.2: Top-5 services' credibility at last round

Serv-CD	Init-Cred	crDecayed
S04	0.647	0.401
S07	0.647	0.435
S12	0.761	0.426
S15	0.658	0.439
S24	0.670	0.660

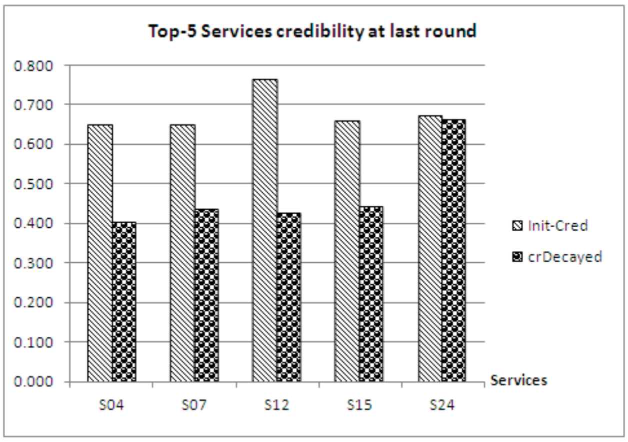

Figure 5.6. Top-5 services' credibility at last round

Since the simulation session started with selection from top-5 services randomly in the first 30 rounds, although service S12 started with the highest credibility between all other services at round 0, *i.e.*, credibility initial value as shown in Figure 5.6 and Table 5.2; unfortunately, S12 did not maintain its credibility all times. S24 maintained its credibility in most rounds. Figure 5.7 presents a comparison between S12 and S24 behaviors and shows in the first round S24 was selected by 36% of the users, while S12 was selected by 9% of the users, which reflects the difference in the service credibility (crDec) for the two services.

When the service performs properly as reflected by users' satisfaction and actual performance monitoring, then its credibility increases and it attracts more customers in the next round than its previous round. When the service performs poorly as reflected by users' satisfaction and actual performance monitoring, then its credibility decreases and it attracts less customers in the next round than its previous one. For example, credibility of S24 at round 33 decreased and attracted fewer customers in the next round than its average. When the system applied social service selection and selected the best service S24 for leaders and followers, then S24 becomes the dominant service and its credibility increases over time until the end of simulation, *i.e.*, round 40.

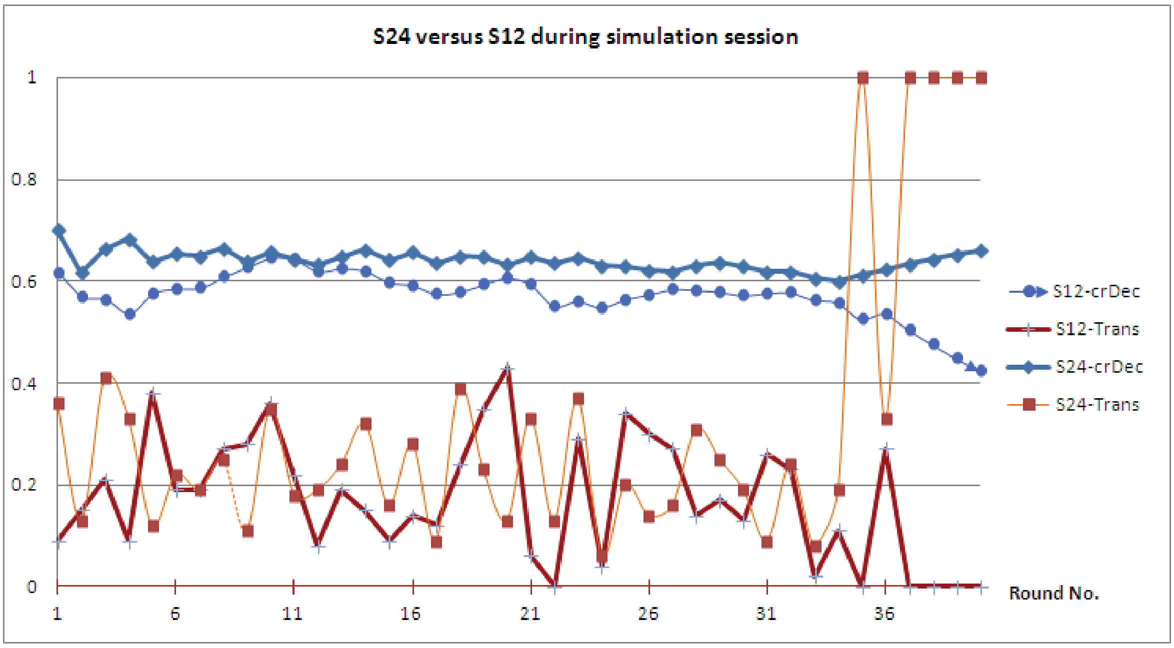

Figure 5.7. S24 versus S12 during simulation session

It is worth noting that the most selected service during the selection, S24, is the second in its initial credibility, comes with medium establishment fees, a low interest rate, response time and exit termination fees, the lowest monthly fees, and is transferable with a high term and privacy.

5.5.2.3. UDK Threshold Analysis

User domain knowledge threshold is a system tuning parameter that aims to determine a cut-off for users to be qualified as leaders or followers. In Algorithm 1, UDK(LT) refers to leaders' threshold domain knowledge, where UDK $\geq$ UDK(LT) qualifies the user to be a leader. UDK(FT) refers to followers' threshold domain knowledge, where UDK $\leq$ UDK(FT) qualifies the user to be a follower. In general, UDK(LT) is related to the Web service category publicity; *i.e.*, when a Web service is new to the market, then the smaller value of UDK(LT) is preferred to promote enough expert leaders in that category.

In this section, UDK(FT) = 0.2 is proposed as an effective value that strikes a good balance in qualifying followers, where if UDK $\leq$ 0.2, then the users are qualified as followers, whereas their level of knowledge in this domain is limited and they need help from other leaders. UDK(LT) = 0.6 is also proposed for illustrative purposes to qualify leaders, where if UDK $\geq$ 0.6, then the users are qualified as leaders as their level of knowledge in this domain is feasible to make service selection and recommendation.

5.5.3. Benchmarking Credibility-Based Approach with Utility-Based Approach

The aim of this experiment is to benchmark the Credibility-based approach against the Utility-based approach, and compare between the efficiency and effectiveness of the two approaches.

5.5.3.1. Experiment setup

This experiment used 99 services, each with 10 QoS attributes and 100 users, each user with a variable number of preferences generated randomly. Each user passes their query to the system, and the system implements Algorithm 1 to select the best services with user UDK, credibility of Web service and expected utility considerations, as shown in the flowchart, Figure 5.4.

By the end of each round, and for each user, the system also implements Utility-based selection approach described in Yu, Zhang and Lin [242], as follows:

1. A set of services that satisfy all user preferences are selected; we call this set the candidate services list.
2. The utility from each service is computed as defined in the benchmark model in Section 5.3.1.
3. A service with the highest utility in step 2 is selected as the best service from the top-5 services.

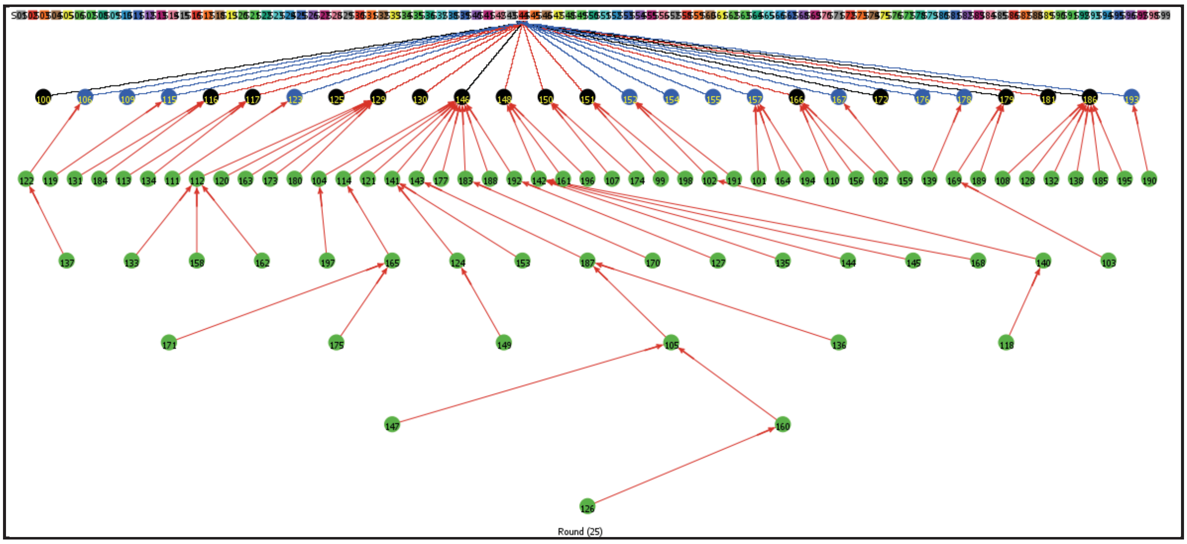

Figure 5.8. Social Service Selection with Credibility and UDK – Follow the Leader

Figure 5.8 shows "Follow the Leader" hierarchy generated from the social service selection approach in this experiment, where the top row shows 99 services and the layout shows 100 customers. Leader customers are black in color and independent customers are blue whilst green represents followers.

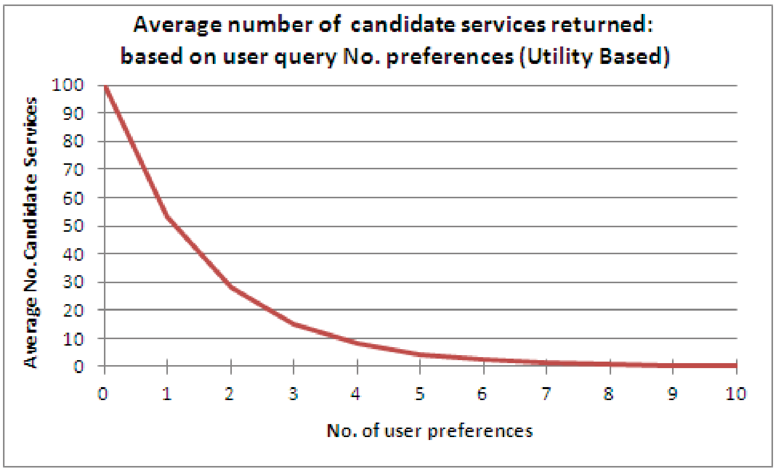

Figure 5.9. Average number of candidate services returned from 99 services match: based on user preferences number (Utility-Based)

5.5.3.2. Utility-based approach results analysis

We analyzed the selection outcomes using the benchmark Utility-based selection approach from five simulations: each with 25 rounds; which represent 125 experiments, as shown in

Figure 5.9. For 99 services in a domain with (10) QoS attributes each, and with 100 users in each round, we note that:

1. If the number of user preferences = 0, then all services that satisfy the functional requirements are considered as candidate services; consequently there is no solution for the best service or top-5 services.
2. If the number of user preferences = 1, then about 55% of the services are considered as candidate services.
3. If the number of user preferences is greater than 60% of QoS attributes of services, then it is not easy to find a match for user preferences.
4. Number of candidate services, for a user with preference number ($PrefNo \geq 6$), can follow an exponential function, and can be expressed as:

$$No.Candidates \approx No.Services * \frac{(QoSNo - PrefNo)}{QoSNo} * e^{-PrefNo/2} \qquad (5.10)$$

I have conducted extra experiments on a varied number of services with a varied number of QoS attributes, using 100 queries each with a varied number of preferences such that ($1 \leq PrefNo \leq QoSNo$). Experimental results show the applicability of Formula 5.10 as shown in the corresponding Figure 5.10.

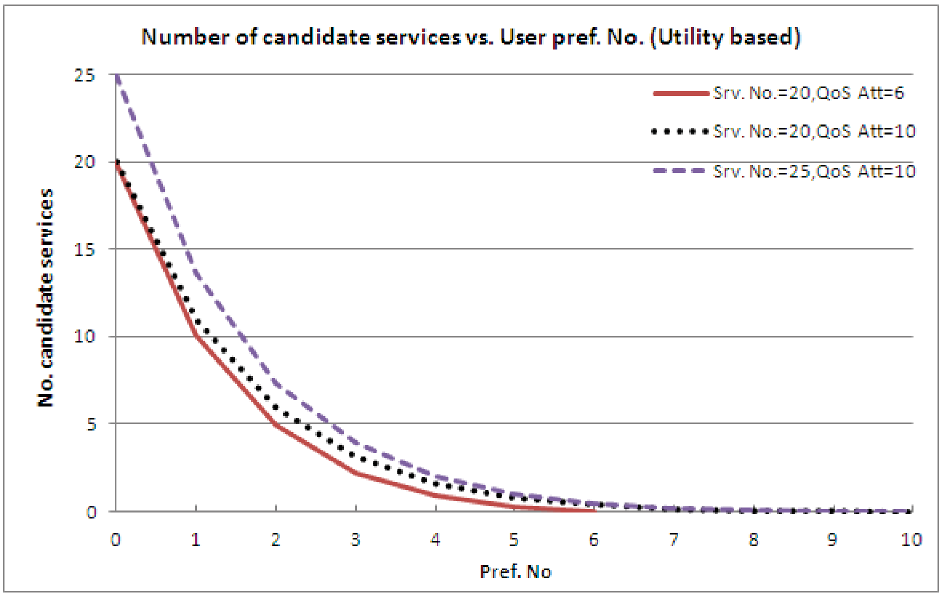

Figure 5.10. Number of candidate services versus varied user pref. number and QoS attributes (Utility-Based)

The following sample query, provided by a leader, supports the argument that the Utility-based approach cannot provide results using home loan services presented in Table 5.1.

The user query is composed of six preferences, which are drawn from the service template using the minimum and maximum values for each attribute; a sample query is presented below.

Sample user query: (1) EstFee <= 2, WT=10 (2) Term >= 26, WT=3 (3) RespTime <= 5, WT=2 (4) MonFees <= 4, WT=4 (5) MaxAmt >= 464, WT=1 (6) RedFee <= 6, WT=5.

In the Utility-based approach, each preference aims to maximize the user utility from that QoS attribute. For example, term number 4 (MonFees <= 4, WT=4), means monthly fees should be <= 4 with preference weight (WT=4 of scale 10). Although the query is feasible from leader's perspective, unfortunately, the Utility-based approach could not provide a solution for 19% of user queries.

5.5.3.3. Performance evaluation

R-precision of the Credibility-based model and the Utility-based model as defined in Section 5.4.3 are computed for six experiments, each with 100 queries, each with a varied number of user preferences, and for varied number of services. For each Rank (Top-M candidate services), the following procedure for each experiment is used:

1. For each rank M, R-precision is computed for each query, and then the average is taken for all queries (100) in that rank.
2. Final average R-Precision is taken over all experiments for that rank.
3. The procedure is repeated for each model, *i.e.*, Credibility-based and Utility-based models.

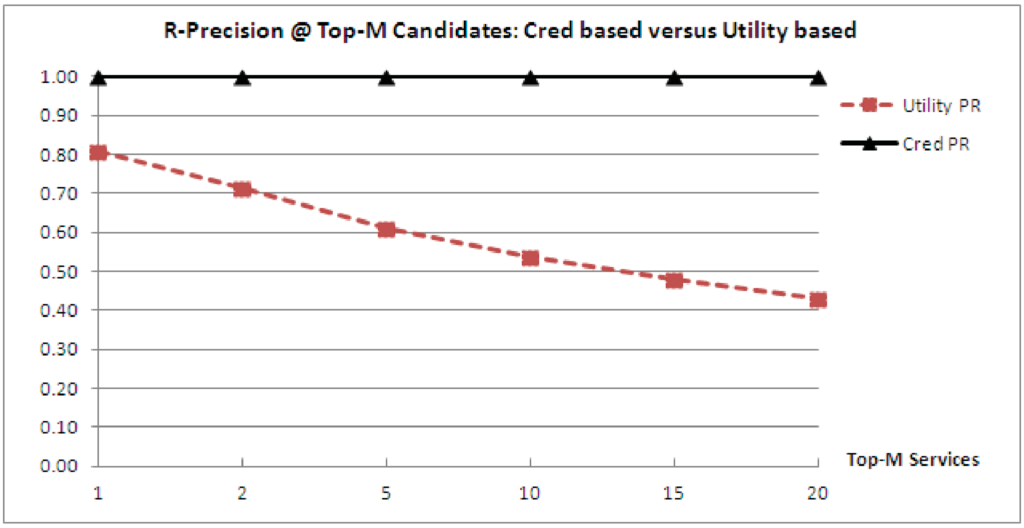

Figure 5.11. R-Precision @ Top-M Candidates: Credibility-based versus Utility-based

Table 5.3: R-Precision for credibility-based and utility-based models

Top-M	Utility PR	Cred PR
1	0.81	1.00
2	0.71	1.00
5	0.61	1.00
10	0.54	1.00
15	0.48	1.00
20	0.43	1.00

Table 5.3 and Figure 5.11 show a comparison between the R-precision average for the Top-M candidate services, where M = (1, 2, 5, 10, 15, 20) for Credibility-based and Utility-based models. Our choice for the 20 as maximum number for Top-M is based on the fact the two experiments used a dataset where the number of services is 20, while two experiments used the loan dataset where the number of services is 25, and the last two experiments each used (99) random services.

As presented in Table 5.3, the average of R-precision for the Credibility-based approach is 1.00. This indicates that the Credibility-based approach provides Top-M services for all users' queries. The Credibility-based approach identifies user to be either leader or follower based on their knowledge of the domain expressed in their queries. Leaders have adequate knowledge to express their queries, while followers do not have the knowledge to express their queries. The Credibility-based approach provides the leaders with the most credible service that match their weighted preferences, and recommends the top credible services used by the leaders to a follower to select from. As a result, all users' queries are replied by the Credibility-based approach. On the other hand, the Utility-based approach provides a maximum R-precision of 0.81 when selecting only one service, then R-precision decreases with increasing the required Top-M candidates. The Utility-based approach could not provide a solution for most of the cases when the number of user preferences is greater than 60% of QoS attributes of services because all user requirements could not be satisfied in the match process of the Utility-based approach as shown in the sample query presented in section 5.5.3.2.

This indicates that the Credibility-based approach provides Top-M services for all users' queries. On the other hand, Utility-based approach provides a maximum R-precision of 0.81 when selecting only one service, then R-precision decreases with increasing the required Top-M candidates.

5.5.3.4. Experiment results and discussion

As we note from previous experiments, social service selection with UDK and credibility outperforms the Utility-based model, in three dimensions:

1. Since the Utility-based model could not provide a solution if the number of user preferences = 0, all available services can be considered as candidate services. In such a situation, the proposed Credibility-based approach considers the customer as a follower, and selects the best service based on the user's best friend or credible leaders in the network.
2. The Utility-based model could not provide a solution for most of the cases when the number of user preferences is greater than 60% of QoS attributes of services. Credibility-based approach considers the customer as a leader, and selects the best service based on the most credible service with user UDK considerations.
3. The Credibility-based model provides ranked Top-M with R-precision = 1.00 for all queries, and for all ranks M, while Utility-based approach provides a maximum R-precision 0.81 when selecting only one service, and its performance decreases when M increases. For example, it provides R-precision of 0.61 for M=5, *i.e.*, Utility-based approach could not meet user requirements in 39% of the cases.

To answer the question: ***Is the returned candidate services' among the highest quality service out of all available services?***

The Credibility-based approach uses the capability measure to determine the initial credibility of the service at the time of bootstrapping for new services; and the capability measure almost similar to Utility-based approach in its computational model, and the credibility of each service changes with time based on its trustworthiness, which is drawn from users' feedback, and its expertise component. Based on the previous justification, we can consider service credibility more feasible than utility to reflect its capability at any point in time, especially after the service is used by customers and proved its credibility. Top-M is considered as a reference point to measure utility-based candidate services.

Experimental results indicate that candidate services from the Utility-based approach represent an average of 11.57% of the Credibility-based approach candidate services for all queries, *i.e.*, Top-M(credibility) ∩ Top-M(utility) = 11.57%. For Top-1, when selecting the best service in each model, the results indicate that only 1.17% of the best service in the Utility-based model match the best service in Credibility-based model. These figures support our claim that service' capability is not static and changes over time.

In conclusion, users experience better utility and better satisfaction with the delivered service when service credibility is considered in their selection decision.

5.5.4. Benchmarking Credibility Based Approach with Trustworthiness Based Approach

The aim of this experiment is to benchmark the Credibility-based approach against the Trustworthiness-based approach presented in Limam and Boutaba [131], and compare the performance of both approaches.

5.5.4.1. Experiment setup

In this experiment, 20 services presented in Limam and Boutaba [131] are used, each with 6 QoS attributes. In each round, 100 users were used, each with a variable number of preferences generated randomly from Table 5.4 within the maximum and minimum constraints. Each user passes their query to the system, and the system follows Algorithm 1 to select the best services with user UDK, credibility of Web service and expected utility considerations, as shown in the flowchart depicted in Figure 5.4.

By the end of each round, leaders provide their feedback to the system about their satisfaction from each QoS attribute in their preference list; this feedback is used to derive a new service' trustworthiness. Service expertise component, which is drawn from its actual performance, is computed based on advertised values and actual delivered values generated randomly. Service credibility is computed from trustworthiness and expertise components with decay factor to be used in the next round.

By the end of each round, and for each user, the system also implements a trustworthiness-based selection approach presented in Limam and Boutaba [131], as described in Section 5.3.2 and presents to the user Top-M services based on their trustworthiness, identifying the best service to be used.

Table 5.4: User query QoS attributes template

Code	Q1	Q2	Q3	Q4	Q5	Q6
Name	Cost	Uptime	ATTM	TTFF	TBF	TTR
Min	71	97.99	0	0	102	11
Max	100	99.99	92	130	188	48

Since the service Credibility model uses two components: the trustworthiness component and the expertise component, and the Limam and Boutaba's [131] model uses the

Trustworthiness approach for service selection, and the proposed service Credibility model computes service trustworthiness almost similar to Limam and Boutaba's [131] approach in a static service configuration *i.e.*, QoS attributes are not changed during the simulation process; the trustworthiness component from the service Credibility model is considered - to a certain extent - equivalent to the service trustworthiness described in Limam and Boutaba [131]. Moreover, to match the trustworthiness model, in this benchmark all customers are forced to provide feedback about their satisfaction for each delivered QoS attribute against the advertised value.

Extra experiments have been conducted on home loan services and randomly generated services with a varied number of QoS attributes, using 100 queries each with varied number of preferences.

5.5.4.2. Performance evaluation

R-precision is computed for the Credibility-based model and the trustworthiness-based model. Following the same procedure used in the previous benchmark, and for six experiments, each experiment has 100 queries, each query with a varied number of user preferences, and for a varied number of services. The trustworthiness-based model shows high performance as Credibility-based model in providing Top-M candidate services for all queries, with R-precision = 1.

Since the Credibility-based model considers the user to be either a leader or follower based on their UDK, the Credibility-based model provides the leaders with the most credible service, and recommends the top credible services used by leaders to the follower. As a result, all users' queries are replied by the Credibility-based model . On the other hand, the trustworthiness-based model provides all users with the most trustworthy service among all services. Both models reply all queries and identify the same best service for all queries which shows both of the models provide R-precision = 1.

For the Top-M candidates, the trustworthiness-based model provides, on average, 81.2% of overlapped candidates with Credibility model. This means that the common services in Top-M candidates for varied values of M = (1, 2, 5, 10, 15, 20) represent an average of 81.2%, *i.e.*, Top-M(credibility) ∩ Top-M(trustworthiness) = 81.2%. The difference of 18.8% is due to the importance of the expertise component in the credibility model, which is not supported in the trustworthiness model. Since both models use trustworthiness, the difference is justified by the dynamic nature of the expertise component in the credibility model, where some services actual performance differs from users' feedback.

5.5.4.3. Experiment results and discussion

As we note from previous experiments, social service selection with UDK and credibility outperforms the trustworthiness-based model, in the quality of 18.8% of the lowest ranked candidate services, which has been justified previously. The lowest ranked candidate services can receive exceptional privilege, when the highest ranked services fail to make successful execution and the automated system relies on the next ranked service.

One major difference between the two models is the Trustworthiness model, which assumes that all users are capable to provide preferences for all QoS attributes in their query. Different users have varied levels of knowledge in the service' domain, consequently, more than 50% of the users do not have adequate knowledge in the service domain and act as followers for other leaders. The Trustworthiness model captures feedback from all customers, while Credibility-based model captures feedback from leaders only, who are capable of providing more credible feedback.

In conclusion, the expertise component in the Credibility model is an important factor to determine the credibility of the service. The more the expertise is credible, the more users receive better utility and better satisfaction with the delivered service, when service credibility is considered in their selection decision.

5.5.5. Results Summary

We summarize our findings from the previous experiments as follows:

- In a Web-based social network (WBSN), user domain knowledge (UDK) is the determinant of their behavior; different users vary in their level of service domain knowledge and have a varied number of preferences in their queries. Usually customers with a high level UDK act as leaders, while customers with lowest UDK act as followers.
- Web service behavior is a determinant of their credibility in dynamic settings. Different Web services in a specific domain and context vary in their QoS attributes; each service has its unique credibility expressed by trustworthiness and expertise. The trustworthiness component is drawn from its reputation, while its expertise is measured in terms of the number of transactions the service is involved

in, and its conformation to the promised qualities; these metrics represent the extent the service provides what was promised according to the advertised QoS.

- The proposed Web service Credibility model shows its sensitivity to changes in trustworthiness and expertise components. Web service credibility drops significantly when the service behaves maliciously with one or more of its QoS attributes. The service Credibility model can detect malicious behaviors automatically.
- The proposed social Web service selection based on the UDK approach demonstrates its efficiency to propose the best service for all customers' queries. Leaders usually have the knowledge and expertise to express their preferences and select a service from Top-M candidate services that maximize their utilities. Followers do not have adequate knowledge and expertise to express their preferences so they rely on leaders to advise them about the most credible service to use.
- Since leaders have a high level of expertise and knowledge in the service domain, they are the most reliable source for providing feedback. Service Credibility model takes this into consideration and does not rely on followers' feedback to evaluate service trustworthiness.
- New services to the market assigned initial credibility based on their advertised qualities, compared to existing services using the proposed capability measure described in Section 5.2.3. New services can compete in the selection process, where leaders also can select new services to maximize their utilities.
- I showed the scalability and flexibility of the proposed social service selection model using a varied number of services and customers.
- The Credibility service selection model outperforms the Utility-based selection approaches in three dimensions, when the user has no preferences, and when the user has a number of preferences greater than 60% of QoS attributes of services and in the quality of the best service proposed to users.
- The Web service Credibility model is centralized, and based on a statistical approach to compute services credibility; the Credibility model does not require complicated computations, where the computation is performed locally offline, on predefined periods, at a central point that does not need communications overheads. The social service selection approach does not need extra computations

as trust inference approaches to infer cold-start users similarity; it uses leaders as trustworthy experts to provide all followers with the best service based on their previous experience.

5.6. Conclusions

Web service credibility is an indicator of Web service trustworthiness and expertise, which is changing over time. Decision making in service selection has always been a difficult task. Selecting the best service with high credibility that meets user preferences and needs is a challenging issue. More than 50% of the users are cold-start users who have low user domain knowledge (UDK) in service domains and could not express their preferences properly. In a dynamic environment of services' trustworthiness and expertise, and varied users knowledge and expertise; the social service selection is an effective solution to these issues.

I have evaluated the proposed Web service Credibility model, and the social service selection approach using the simulation tool: Social Network Analysis Studio (SNAS) in a specific service domain. I conducted a varied number of experiments that import test data to the simulation tool, or generate test data randomly that simulate services and customers behaviors' in a dynamic environment.

To demonstrate the effectiveness of the Web service Credibility model, first I conducted experiments to validate the applicability of Web service credibility computational model, and then I showed the effectiveness and efficiency of the proposed social service selection, based on user domain knowledge (UDK), and Web service credibility; through benchmarking the social selection approach against other leading Utility-based and Trustworthiness selection approaches.

The results presented in this chapter show that the service Credibility model is an effective approach to identify most credible services, who are the market leaders in the service domain with the highest trustworthiness and expertise among all services.

The empirical results incorporated in this chapter, demonstrate that the social service selection approach is a significantly innovative approach to identifying users based on their behavior and knowledge, making effective and accurate service selection for leaders, and making service recommendations especially for cold-start users (followers) based on "Follow the Leader" strategy.

The Social service selection approach was benchmarked against other Utility-based and Trustworthiness-based selection approaches. The benchmark results demonstrated that the Credibility-based approach outperforms the Utility-based selection approaches in three dimensions. First, when the user has no preferences, as Utility-based approaches do not provide a solution at all; secondly, when the user has a number of preferences greater than 60% of QoS attributes of services, whereas Utility-based approaches do not provide solutions in most cases, the Credibility-based approach provides results for all queries. Finally, the quality of the service selected or recommended to the user is improved when the service credibility is considered in social service selection, because the Utility-based approach does not take service trustworthiness and expertise into consideration.

The Credibility-based approach competes with the Trustworthiness approach in providing similar results in the Top-M ranked services for higher ranked services. While they differ in the lowest order ranks, this difference is due to the expertise component in the Credibility model which is not used in the Trustworthiness model. The expertise component is an essential component for assessing service credibility as shown in the benchmark results.

Chapter 6
Mitigating Risk in Social Service Selection

In Chapter 3, I proposed a Web service Credibility model that uses two credibility components, one based on the trustworthiness of the Web service and the other based on the actual expertise of the Web service. I then showed how this model can be used in social service selection and recommendation.

In the Service Web, a vast number of service providers compete to offer a huge number of services with similar functionalities. Selecting the most trustworthy and credible service is still a significant challenge, especially, when a set of services that fulfill a user's requirements and preferences have been discovered. Determining which service will eventually be invoked by the user is a cognitive challenge and requires the use of an intelligent decision making framework.

Since no Web service is risk free, this chapter aims to mitigate the risk in service selection by using the “Follow the Leader” strategy discussed previously in Section 2.5 of this dissertation, as a new approach for risk-reducing strategy. First, I utilize the user Credibility model presented in Chapter 3, in the context of the “Follow the Leader” strategy in Web-based social networks. Next I show how to evaluate the Web service perceived performance risk based on its credibility. Finally, I present a dynamic social service selection model for selecting the best Web service taking account of the perceived performance risk and customer risk-attitude in service selection and recommendation.

To demonstrate the feasibility and effectiveness of the new “Follow the Leader” - driven approach for alleviating the risk in service selection, I first extended the Social Network

Analysis Studio (SNAS) functionality to analyze the user's behavior from a risk perspective in a social network. SNAS is used to validate the proposed risk mitigation model. The empirical results incorporated in this chapter demonstrate that the proposed approach is a significantly an innovative approach as a risk-reducing strategy in service selection.

6.1. Introduction

Services compete and offer a wide range of similar functionalities in the Service Web [148]. Moreover, some services may collaborate to create new value-added services. In such situations, some services may be new to the service market; other services may act maliciously to be selected; yet other services change their advertised Quality of Service (QoS) without prior notice. A key requirement is to provide a mechanism to assess the associated service performance risk for quality access and retrieval of relevant Web services.

In Web service selection, reputation assessment mechanisms are used to establish trust between consumers and Web service providers. Trust and reputation are used to assess an entity's trustworthiness [223]. In recent research, Kim, Ferrin and Rao [101] show 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 interact with a service provider who has failed to honor their promises; on the other hand, consumers perceive less risk in their interactions with a service provider who has respected their obligations in the past [101]. The Web service selection process involves making a rational decision to select a service from many service providers and service instances [159]. Since QoS changes over time, the associated performance risk is also changes; thus, it is also necessary that the credibility and performance risk calculation takes these changes into account. Moreover, some services are new to the market and need to assess their credibility, as discussed in Section 5.2.3.

As discussed in Section 5.1, selecting the most suitable service instance is a challenging issue. It is restricted by users' willingness and ability to describe their detailed preferences and assign relative weights to such preferences. Consequently, a risk-averse customer who wants to find a Web service often seeks help from their friends, peers, experts, leaders and business partners who have relevant experience. Capturing and specifying user preferences are among the most complex problems in the selection process [202, 252].

Many social service selection approaches based on trust and/or reputation have recently been presented [16, 18, 63, 104, 125, 126, 138, 219]. Nevertheless, few of them consider the impact of performance risk in the social service selection, where it possibly leads to losses such as wasted time and execution resources.

In this chapter, I propose a social service selection approach with service perceived risk and user risk attitude, based on the credibility framework that employs user and Web service credibility. My work is the first to use a formal "Follow the Leader" strategy [70] to mitigate risk in service selection by using the most trustworthy and experienced users in the social network.

This chapter draws its significance from the fact that social service selection has received little attention from researchers, and risk mitigation in service selection has received the least attention. This chapter draws its importance from the following observations:

1. In 2010, the Internet Crime Complaint Center (IC3) in the USA, received the second-highest number of complaints from Internet consumers since its inception [174]. In 2009, IC3 received 336,655 complaints with actual losses of 559.70 Million US Dollars, while in 2010, IC3 received 303,809 complaints with estimated losses of 505 Million Dollars. These figures represent the amount of risk facing Internet consumers in using Web services.
2. Most of the efforts in studying risk [55, 77, 79, 112, 139] concentrate on risk in service composition. Unfortunately, none of these efforts considers the impact of performance risk in the social service selection context.
3. In a recent study used to analyze the power-law degree distribution of social networks, which is due to the effect of preferential attachment, Huang [83] indicated that 20% of the population in a given WBSN holds 80% of the total power of the society, from which we can conclude that 80% of the population can act as followers.

This is the first study to mitigate risk from a social perspective, using "Follow the Leader" as a mitigating strategy in service selection. I believe that followers need more attention than leaders in social service selection, as they cannot express their needs properly because they do not have the adequate knowledge to do so. Furthermore, mitigating service performance risk at the time of selection is an early predictor of successful service composition.

In the rest of this chapter, I refer to customers or users as human users, or software agents that interact in the Web-based social network (WBSN) and are able to perform required interactions. Web service is an atomic service such as a home loan or home insurance service. The proposed approach can be used as a module of a personalized Web services recommender system or a search engine, in which users' behavior can be captured from their interactions in the WBSN.

Decision making in risky, complex situations has always been a difficult task. Service selection is more complicated with the traditional approaches because consumers may not even know with whom they are interacting.

6.2. Motivation and Contributions

To illustrate the challenges involved in social Web service selection, I offer the following example, which illustrates the key difficulties and at the same time motivates my approach.

Recall the home-loan selection scenario presented in Section 1.1. We can consider Bob as a risk-averse person because he is seeking an insurance company to insure his home, and by nature he does not like to spend too much time on analyzing insurance features, so he would rather have the same insurance as his friend Adam. But what if Bob did not know Adam? Could he get reasonable advice from somebody who lives in his area? If not, he would have to embark on the tedious and time consuming process of differentiating between the vast number of home insurance services, all of which may match his request from the functionality perspective, but which may vary in their non-functional properties. Bob may eventually select a cheap service with low performance, leaving him in a vulnerable position.

Using trust in social networks is a promising approach to making recommendations to other users, based on trust propagation in finding a friend, or a friend of a friend, with similar interests. However, some users do not have friends in the social network to infer a trustworthy person who can provide recommendations. Moreover, 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. Furthermore, different users have a range of risk attitudes towards handling the perceived risk in service selection. Consequently, the quality of the selected Web service can be improved by an assessment of its performance risk. The key contribution in this chapter is threefold:

1. A user model with risk-attitude based on the user domain knowledge and its credibility in the “Follow the Leader” context.
2. Web service performance risk metrics that reflect its credibility.
3. A social Web service selection approach based on the service credibility and the “Follow the Leader” strategy to mitigate the performance risk in service selection.

The rest of this chapter is organized as follows: Section 6.3 presents a review of related works. Section 6.4 discusses Web service performance risk and explores perceived risk and risk attitude in Web service selection. In Section 6.5, I propose a user behavior model with risk attitude and an algorithm for service selection with risk attitude and perceived risk considerations, followed by experimental simulations and evaluations. Finally, I conclude the chapter by summarizing experimental findings and discussing the results.

6.3. Related Works

In the following section, I review the literature related to risk in Web service selection. First I review trust and risk in service selection, followed by a review of works used in mitigating risk in Web service selection.

6.3.1. Trust and Risk in Service Selection

Trust between two parties indicates a ‘subjective probability’ that one party, ‘trustee’ will perform favorable actions for the other party, the ‘truster’, or will drive the trustee to behave appropriately with the truster [173]. WBSNs enable users to express their level of trust in other users. Thus, trust provides users with a means to assess other people’s trustworthiness and to discover to what extent users can share or accept others’ generated content [244]. Since most WBSN users are unknown to one another and they have no previous direct interactions with one another, trust inference is used to help them to establish new relationships with other unknown users or to measure trust values between indirectly connected users [137]. The idea here is to search for trustworthy members by utilizing trust propagation over the trust network [155].

Grazioli and Wang [71] define risk as “a consumer’s perceptions of the uncertainty and adverse consequences of engaging in an activity”. Hussain *et al.* [88] define risk as a combination of: 1) The possibility of failure to accomplish the outcom; and 2) The outcome cost as losses incurred from that outcome, which reflects associated risk. Kim, Ferrin and Rao [101] formally define perceived risk as a “consumer's belief about the potential uncertain negative outcomes from the online transaction”. All definitions emphasize that risk is related to *uncertainty*, and that risk has *consequences*; however, risk differs from uncertainty in the consideration of the consequences of risk [82].

In the context of this chapter, risk is considered to be the combination of the uncertainty associated with a Web service's performance (relative to customer expectations) and the associated dissatisfaction that it may cause. In general, the risk of a Web service is identified by two factors: the probability of failure, and the consequence of its failure.

Trust and risk are two tools for making decisions in uncertain environments [95]. When the customer does not have sufficient information about the offered services and their providers in such environments, the customer is forced to accept the risk prior to performance of the service [94], *i.e.*, a customer usually pays for products and services before they are received, which renders the customer vulnerable. For specific problems of risk, therefore, trust acts as a solution; as Gefen *et al.* [65] indicate, trust role is a risk reducer. Trust becomes the essential strategy for dealing with uncertain and uncontrollable future behavior. Trust is mainly applicable in situations of uncertainty where the behaviors of others are unknown, because consumers usually dislike transacting a service with high risk [65].

There are a limited number of computational trust models that take risk explicitly into account. The combination of risk and trust appears in [128] and [95]. In the PErsonalized Trust model (PET), Liang and Shi [128] proposed a personalized trust model to use in building good cooperation in P2P resource sharing. The PET model uses two major modules: reputation calculation and risk evaluation. Liang and Shi [128] conclude that risk is essential in a trust system in addition to reputation rating. Jøsang and Presti [95] differentiate between decision trust and reliability trust and developed a decision trust model utilizing agent reliability, associated utility, and trusting agent risk attitude.

Jøsang [93] described trust as “a positive state of mind caused by the perception that the risk resulting from collaborating with the trusted party is acceptable”. A trust system enables agents to assess the trustworthiness of participating agents; it also provides mechanisms to allow trustworthy entities to be recognized. A trust system allows the most trustworthy agents to collaborate with other agents to prevent untrustworthy and fraudulent agents from interaction, or to encourage agents to behave in a trustworthy way [93].

Trust and risk are essentially related as there is no need for a trust decision unless there is risk involved [56, 169]. Mitchell [167] indicated that perceived risk is a necessary predecessor for active trust, and the outcome from establishing trust is the perceived risk reduction in the relationship or transaction, whereas when a relationship develops and trust builds, risk will decrease as a result. Although the benefits of interaction are often worth the risk, the higher the risk, the less cooperation is likely to occur.

Trust is applicable in situations where a consumer is uncertain about an outcome, with consequences that are out of their control, and they have to enter a risky situation; hence any act of trust and dependency implies some risk [35]. In a recent study, Kim, Ferrin and Rao [101] concluded that when trust increases, consumers perceive risk to be lower; *i.e.*, the consumer's trust level reduces their perceived risk of a Web service transaction.

6.3.2. Mitigating Risk in Social Service Selection

Traditional Web service selection approaches that do not explicitly consider risk preferences can be seen as selection approaches with *risk-neutral* preferences in mind. Moreover, trust-based or reputation-based approaches are considered to be social-based service selection approaches.

In the literature, much effort is used to mitigate risk in Web service selection, and research approaches are varied in their scope. For example, some of these approaches address only one issue of risk, such as risk in payment or risk in security, whereas others include trust and reputation. These approaches are used in trust-building and risk-elimination [11, 110]. Trust can be used to reduce risk despite not acting as a full eliminator of risk in service selection.

Some techniques are used to mitigate risk in payments through the use of trusted third parties; for example, using online debit accounts such as PayPal[23] and its associated online escrow services and Payflow gateway is effective both in trust-building and risk-elimination [11]. Other risk mitigating approaches include entering into Service Level Agreements (SLA) with the supplier, the discovery of alternative services and service performance monitoring [110]. Furthermore, some approaches proposed mitigating risk by detecting malicious attacks [170] and potential fraudsters [36] by addressing service provider reliability.

[23] www.PayPal.com

Applying policies on the reliability of selected services [139] is another approach to mitigate risk in service selection. Other remedy mechanisms, such as money back or insurance [75], are employed to compensate customers.

Mitigating risk explicitly in service selection via reducing online risk through interacting with trustworthy Web sites has also been proposed. Cheshire, Antin and Churchill [40] indicated that when purchasing products, trust is associated with lower risk perception and uncertainty.

Unfortunately, none of these efforts serves to address the perceived risk in social Web service selection explicitly. Mitigating perceived risk in social service selection should address all the dimensions of associated risk in the Web service, and should provide an appropriate mechanism to reduce the risk in the context of the social Web service selection. In the next section, a proposed framework to address these issues is presented.

6.4. 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, I explore the perceived risk of Web service performance and show how customers have different risk attitudes towards handling the perceived risk.

6.4.1. Perceived Performance Risk in Web Service Selection

During Web service selection, consumers often act on incomplete and far from perfect information [101]. Consequently, they are faced with a diverse degree of uncertainty and risk in their selection decisions. Kim, Ferrin and Rao [101] formally define perceived risk as “a consumer's belief about the potential uncertain negative outcomes from the online transaction”. Furthermore, Featherman and Pavlou [58] view perceived risk as “a combination of uncertainty plus seriousness of outcome involved”. Perceived risk refers to the customers feeling uncertainty about loss in a particular transaction [129]; in general, perceived risk is commonly viewed as uncertainty associated with the possibility of negative consequences using a Web service.

In Web service selection, perceived risk has different dimensions such as reliability, availability, response time, security and privacy; I refer to these dimensions as performance risk. When the service provider does not respect the SLA in any of the 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, he/she is aware of the threat of the possibility of credit card fraud, or even disclosure of consumer information to non-authorized people, when security or privacy performance is low or unknown.

In this chapter, I follow Featherman and Wells [59] and define the perceived Performance Risk (PR) in the range [0,1] as a consumer assessment of potential performance problems, malfunction, transaction processing errors, reliability and/or security problems that cause the Web service not to perform as expected.

Risk evaluation involves the consumer assessing the possibility of failure in their interaction with the Web service, and the subsequent possible consequences of their losses involved in that transaction. In general, consumers dislike transacting with a service with high risk. Sitkin and Weingart [205] indicated that when the perceived risk increases, the associated perceived chance of loss increases as well; consequently, the expected utility of the transaction decreases.

Perceived risk is a psychological feeling and subjective understanding on the part of the consumer based on various objective risk dimensions in service selection. Consumers may react against the perceived risk by changing, postponing or canceling the Web service.

6.4.2. Risk Attitude and Perceived Risk

When customers interact with Web services, they develop explicit or implicit attitudes about uncertainties and risks associated with these services [40]. Risk attitude represents the extent of willingness of the customer to take on the perceived risk which is largely dependent on the individual character [42, 82] and their position, *e.g.*, financial position, or their role as a follower or a leader. Different factors affect risk attitude, such as personality type, gender, age, culture, and user's domain knowledge.

Furthermore, 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 a payment then the customer would have varied tradeoffs between perceived risk and associated utility in making their decision.

Hillson and Murray-Webster [82] define risk attitude as a "chosen state of mind with regard to those uncertainties that could have a positive or negative effect on objectives".

This definition indicates that risk attitude is affected by the perception of risk within a specific context.

According to Bauer and Bushe [17], consumer risk attitude determines the possible actions to take. Cautious consumers may avoid risk in their deals and may consequently lose possible opportunities. Since all decisions are associated with an element of uncertainty, ‘all decision-makers are risk takers’ [17]. Decision-makers have different degrees of willingness to take risk that depend on the attitudes of each individual. Furthermore, risk can be accepted, avoided and controlled, and associated risk can be transferred to others.

The risk attitude of the consumer plays a very important role in selecting the most possible choice [17]. In Web service selection, users will have different risk attitudes; customer risk attitude (RA) is given by a number in the range [0, 1]. Zero refers to the most risk-averse customers, while 1 refers to the most risk-seeking customers.

6.5. Customer Risk Attitude and Behavior Model

The conclusion drawn from the previous discussion is that customer risk attitude is impacted by specific factors related to customer personality, character and the context of the decision making. In this section, I model the relationships between these factors in a specific domain or context, as shown in Figure 6.1, which represents customer risk attitude in the context of service selection and “Follow the Leader” strategy.

Customer risk attitude is impacted by a number of factors that include user domain knowledge (UDK), user credibility which is drawn from individual trustworthiness and expertise in that domain, other factors related to the context of the decision making, and related personality attributes such as age, gender and culture. In Section 3.5, I defined UDK as the level of expertise exhibited by the user in that domain. UDK in the proposed service selection approach is reflected by two indicators: user credibility and the expressiveness of the user query. The more knowledge the user maintains, the more power the user holds. Schultze [198] indicates that the lesser the customer's domain knowledge, the greater is their perceived risk, and the greater the customer’s dependence on a relationship with the provider.

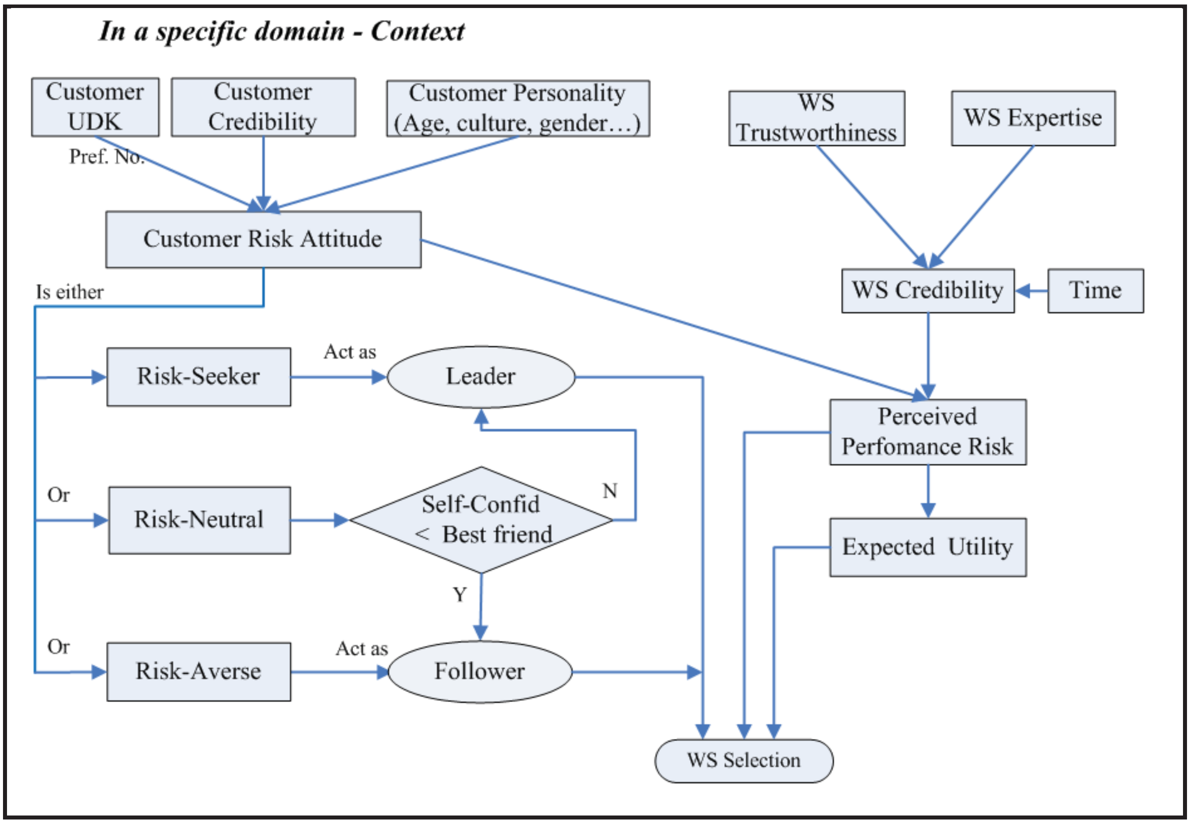

Figure 6.1. User risk attitude and behavior Model

Customer risk attitude is proportional to personal domain knowledge; *i.e.*, when the customer's domain knowledge increases, their risk attitude increases and consequently the level of perceived risk decreases. Moreover, the risk attitude is impacted by other factors such as customer personality (gender and age) and the context of the interaction. I propose the following relationship that satisfies these indicators for customer risk attitude, (RA):

$$RA = P(u) \times UDK \tag{6.1}$$

where $0 < P(u) \leq 1$, and represents the user personality coefficient, capturing the impact of the user's personality which is drawn from their age, gender and culture in a specific domain.

According to Hillson and Murray-Webster [82], as shown in Figure 6.1, a customer in a specific context is risk-averse, risk-neutral or a risk-seeker. A risk-averse customer prefers to select services from a service provider with no risk, or prefers to reduce the risk when it is impossible to eliminate risk completely [44] by following the advice from trusted friends or expert leaders in the domain. On the other hand, a risk-seeking customer prefers to select services with high utilities [42]. In the context of “Follow the Leader”, risk-averse customers usually act as followers while risk-seeking customers act as leaders, and risk-neutral customers base their decisions on the tradeoff between the expected utility and the perceived risk according to their self-confidence about available choices.

6.5.1. Perceived Risk from Risk Attitude Perspective

Risk evaluation involves the consumer determining the failure possibility of their interaction with the Web service, and the subsequent possible consequences for their resources used in that interaction. In general, the higher the perceived risk is, the lower is the likelihood of the consumer using transaction [65]. Kim and Han [40] indicated that higher trustworthiness of Web services correlates with lower levels of uncertainty and associated risk perceptions when interacting with that service.

In Section 3.4, I proposed a dynamic Web service credibility model with two credibility components: a trustworthiness component that is drawn from users’ feedback about their satisfaction with the service aggregated as reputation, and an expertise component that is drawn from the actual performance of the service and its conformance with its promised qualities. The aggregation of these two components represents Web service credibility at any point in time, as shown in Figure 6.1.

Since credibility of the Web service reflects its trustworthiness, and credibility captures different aspects of Web service performance, I argue that credibility, perceived risk and expected utility of the Web service from a risk-aware customer perspective are related according to the following axioms:

1. When Web service credibility drops to zero, the perceived risk increases to the maximum, and consequently the expected utility decreases to the minimum.
2. When Web service credibility increases, the perceived risk decreases and consequently the expected utility increases.
3. When Web service credibility is elevated to one, the perceived risk approaches zero, consequently the expected utility increases to the maximum value depending on the customer risk attitude [0, 1].

To model the relationship between service credibility, perceived risk and risk attitude, I propose the following formula that satisfies the above axioms which represents the perceived risk PR [0, 1] from service S as:

$$PR(s) = e^{-\mu Cr(s)} \tag{6.2}$$

Where $Cr(s)$ is the service credibility as defined in Section 3.4, 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, μ=1; while for a risk-seeker with RA = 1, μ=5. Our choice to set the customer risk attitude coefficient μ in the range [1, 5] based on our intuition that risk-seekers and risk-averse customers each have two categories (low and high) risk attitude, and risk-neutral customers have one category.

Since there is always the possibility that the QoS provided by the service does not match the expectations of the end user, there is an amount of perceived risk (PR) associated with the credibility of the Web service. Perceived risk is reflected by Web service credibility which indicates the probability of failure and the risk attitude of the customer at the same time.

Sitkin and Weingart [205] indicated that when the perceived risk increases, the associated perceived chance of losses increases as well; consequently, the expected utility from the transaction decreases. Service utility is a customer's subjective estimate of the actual value delivered by the service to the user [164]. Since user satisfaction varies with the perceived risk and expected utility, thus I can model the relation between the perceived performance risk (PR) from a Web service (S), and the expected utility EU(s) as:

$$PR(s) + EU(s) = 1 \tag{6.3}$$

Figure 6.2 shows how perceived risk (PR) is related to Web service credibility and how it varies with customer risk attitude (RA) for the following cases: (1) RA = 1 for a risk-seeking customer, (2) RA = 0.5 for a risk-neutral customer, (3) RA= 0 for a risk-averse customer. Since risk-seeking customers perceive less risk than risk-averse customers from the same Web service, we conclude from the above formula that risk-seeking customers have more expected utility than risk-averse customers, as shown in Figure 6.2; consequently risk-averse customers perceive more risk than risk-seeking customers.

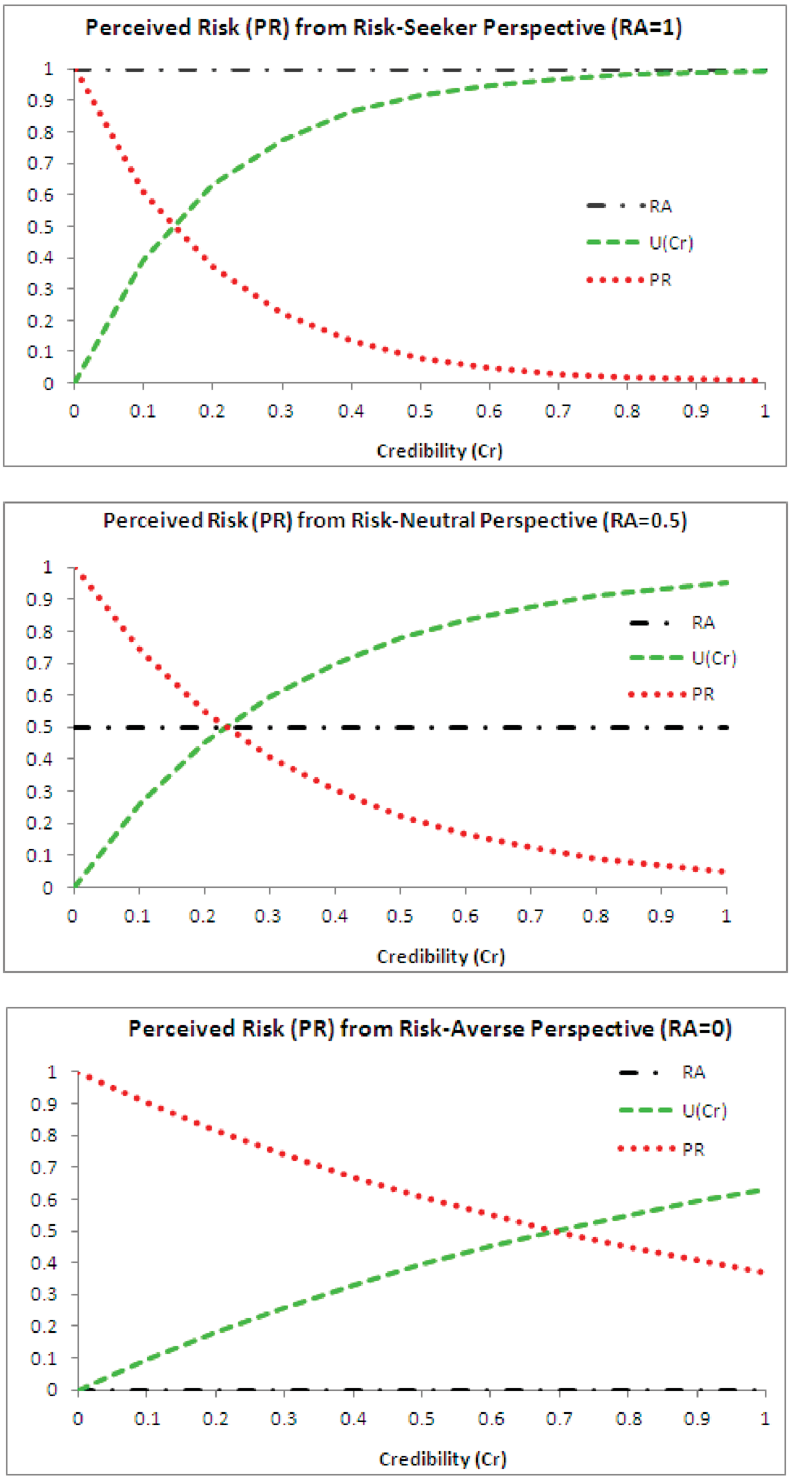

Figure 6.2. Perceived risk variation with different risk attitudes

In summary, the perceived risk from the same service is impacted by its credibility at any point in time, and the risk-attitude of the user who perceives that risk; user risk attitude indicates how much risk the customer is prepared to take, as shown in Figure 6.2. 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 for the same Web service.

6.5.2. Service Selection with Risk Attitude and Perceived Risk

In Section 3.5, I highlighted that top M services should be returned to the consumer; if one service instance from these instances does not match the consumer's needs during run-time, it should be replaced by another similar service [238]. In the Web service Credibility proposed framework, I assign n to the number of QoS attributes of Web services for a specific category in the domain.

In Section 3.5, I also presented three query scenarios that reflect user domain knowledge UDK: expressive query, non-expressive query and partial-expressive query, which reflect user behavior in service selection.

Formula 6.1 relates user risk attitude, RA with UDK and is given by: $RA = P(u) \times UDK$; where $P(u)$ in the range [0, 1], and represents a personality coefficient that captures the impact of user personality, which is drawn from their age, gender and culture in a specific domain.

For simplicity, in the experiments I set $P(u) = 1$, and the user domain knowledge UDK as defined previously in Formula 3.25 and given by:

$$UDK = \frac{Cr(u)}{Cr_{Max}(u)} \times \frac{QoS_P}{n}.$$

where UDK refers to the user knowledge in a category of Web services such as home loan or home insurance services, QoS_P represents the number of user QoS preferences entered in the user query and n refers to the total number of QoS attributes in that service category. $Cr(u)$ represents user credibility in the social network and $Cr_{Max}(u)$ represents the maximum user credibility in the social network as a reference point. Since query expressiveness indicates user knowledge and behavior, and consequently it reflects the customer risk-attitude, we can consider risk attitude RA = UDK for experimentation purposes.

Algorithm 2 as shown in Figure 6.3 presents the proposed social service selection with risk-attitude, perceived risk and expected utility considerations, using the service Credibility model presented previously in Section 3.4. In this algorithm M, refers to the number of candidate services to be returned to the user for selection.

```
Algorithm 2. Social Service selection with RA, PR, Cr & Utility
1.  Capture user query, preferences and weights
2.  Identify functionality of the service, number of QoS attributes stored in the system (n).
3.  Identify expressiveness of the query.
4.  Identify user risk attitude (RA) based on number of entered preferences k
5.  If RA => 0.6 // user act as Leader
6.    MatchList =  given user preferences k, Get M services that match user preferences
7.    For each service in MatchList compute Perceived Risk (PR) & Expected Utility EU(s)
8.    Return Top-M services sorted by highest Utility to select from
9.  Elseif RA <= 0.2 // user act as Follower
10.   Recommend to the user Top-M services used by leaders
11. Else // RA > 0.2 and RA < 0.6
12.   provide user with two options:
13.   (1)  Recommend to user Top-M services used by leaders, and
14.   (2)  Return Top-M services sorted by highest expected Utility to select from, steps (6-8)
15.   If customer self-confidence > confidence in others then
16.       Act as Independent and select a service from option (2)
17.   Else
18.      Act as a Follower and select a service from option (1)
19.   End If
20. End
```

Figure 6.3. Risk-based social service selection: Algorithm-2

Lines (6-8) represent the mechanism used to select services for leaders, based on users' preferences and their risk-attitude. Line 6 obtains M services that match user preferences; for a set of user preferences (k) each with a preference normalized weight (W^j), such that $\sum_{j=1}^{k} W^j = 1$, the ranking score of service S as viewed by that customer, is given by:

$$Score(S) = \frac{\sum_{j=1}^{k} Cr\left(S_t^j\right) * W^j}{Cr_{Max}\left(S_t^j\right)} \tag{6.4}$$

where $Cr_{Max}\left(S_t^j\right)$ represents the maximum credibility of attribute j among all candidate services considered as a reference point.

The MatchList includes the top M services that match user preferences. Line-7, given the user risk-attitude, for each service in the MatchList computes the Perceived Risk (PR) and the Expected Utility, as shown in equations 6.2 and 6.3.

Lines (9-10) represent the mechanism used to select the services for followers, where it recommends the Top-M services used by leaders to the user. In general, followers are risk-averse customers who prefer to mitigate the risk by following other leaders' advice rather than acting themselves.

Customer self-confidence assessment is the final determinant in the selection decision process, as shown in lines (11-19). Customer domain knowledge and consequently customer risk attitude enriches customer confidence; when customer risk attitude increases, customer self-confidence increases, and when customer risk attitude decreases, customer self-confidence decreases. For example, if a customer acquires a recommended service with higher utility (*i.e.*, lower perceived risk) than the one selected, the confidence in others becomes higher than self-confidence; consequently, the customer acts as a follower. On the other hand, if the expected utility from the service that matches their own preferences is higher than the utility of the recommended one, customer self-confidence is higher than their confidence in others, and the customer acts as independent. The following scenarios describe different customers' behavior in service selection:

1. Risk-seeking customers (Leaders): select the service that maximizes their expected utility based on Web service credibility and acceptance of the perceived risk; they usually select the service with the highest credibility score when the perceived risk is within their risk attitude. Risk-seeking customers may adopt new services that have never been used before, or they can use a service where 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 with proven successful performance, even if it is expensive, if it has been used by other trusted friends or expert leaders. Risk-averse customers usually like to avoid risky situations; they prefer to mitigate the risk by following trustworthy advice from leaders or other friends rather than acting themselves.
3. Risk-neutral customers make their decisions based on their risk attitude and the perceived risk from the Web services in hand. They make their decision to follow friends to mitigate a high perceived risk, or they act as independents if they are confident that they can accept the perceived risk from the transaction.

6.6. Experimental Evaluation

Experimental methodology uses simulation to imitate the behaviors and activities of users in a social network environment, where different users have varied risk attitudes in a specific service domain (category), such as home loans. Since there are no services available on the Web for testing purposes, the simulation methodology is used as the best available choice for evaluation.

To demonstrate the feasibility and effectiveness of "Follow the Leader" as a new approach in alleviating the risk in social service selection, I first extended Social Network Analysis Studio (SNAS) using NetLogo platform [171] to handle risk option as selection strategy; it is used to analyze user and Web service behaviors in a social network, based on the simulation tool "4S: Service Selection Simulation Studio" [5] inspired by Goldbaum [70]. The user interface as shown Figure 6.4 is used to evaluate the validity of the proposed risk mitigation approach.

In the following sections, I outline the testing environment; next, the SNAS tool is used to verify the validity of the proposed risk-based social service selection model. The empirical results incorporated in this chapter demonstrate that the proposed approach is a significantly innovative approach as a risk-reducing strategy in service selection.

6.6.1. Simulation Model

To demonstrate the feasibility and effectiveness of the risk-based service selection, I extended the Social Network Analysis Studio (SNAS) presented in Section 5.4.2 to handle social service selection with risk-considerations as shown in Figure 6.4.

The system identifies leaders based on their risk attitude which is drawn from the user domain knowledge UDK that represents the expressiveness of their queries as described in Section 6.5, Formula 6.1. If the customer is qualified as a leader *i.e.*, $RA \geq 0.6$, then the system enables the leader to select the best service from Top-M services returned to the user based on the expected utility EU(s) and the perceived risk PR(s) derived from service credibility. If the customer acts as a follower, *i.e.*, $RA \leq 0.2$, then the system returns to the user the Top-M services used by leaders. When the user risk attitude is in the range $0.2 < RA < 0.6$, then the system provides two lists for the user: List-1, as for leader and List-2 as for follower. Then the user either: (1) follows the best friend with highest credibility from the customer's friends, *i.e.*, when the confidence in that friend is higher than the confidence in himself/herself, or (2) act as independent if the confidence in himself/herself is higher than any of their friends.

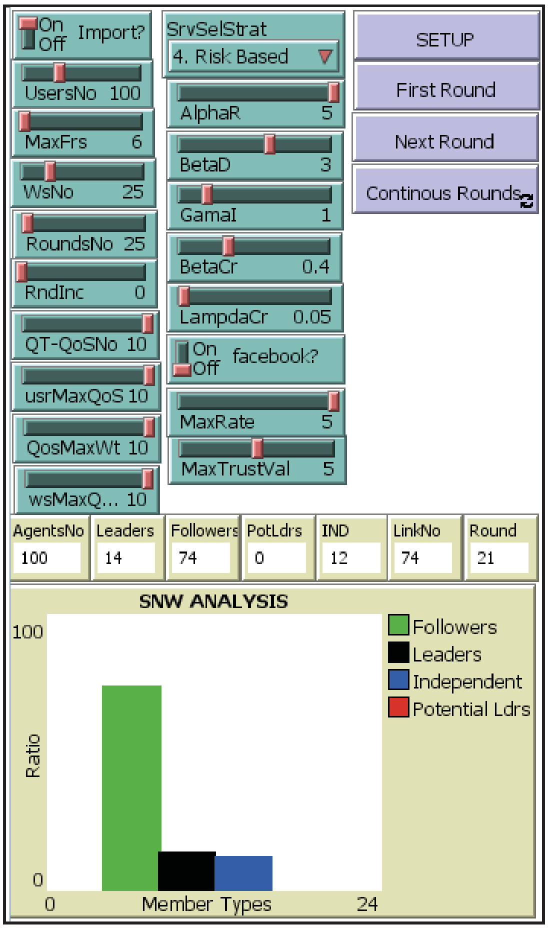

Figure 6.4. SNA Simulation Tool – User Interface

In the following section, I provide a set of experiments to verify the following issues: first, validity of the credibility model to analyze service and customer behaviors, and then I provide the experimental results from the proposed risk-based social service selection.

6.6.2. Validity and Dynamism of Perceived Risk Computation Model

In the following section, I provide the results of two experiments; the first is used to validate the perceived risk computation model, and the second is used to show the dynamism of perceived risk.

6.6.2.1. Validity of perceived risk computation model

This experiment aims to show how different customers with varied risk attitudes perceive varied risk PR from 9 Web services. It shows the expected utility based credibility versus the perceived risk for different customers' risk attitudes: RA = (1, 0.5, 0).

Setup: In this experiment, WS Selection strategy was chosen randomly from all given services (*i.e.*, customers select a Web service randomly from the given services), in order to show the variation in customer perceived risk from each Web service in the last simulation round 25.

Results: Figure 6.5 shows how perceived risk PR varies with each customer risk attitude RA. For 9 services, each with a varied credibility CR computed based on its trustworthiness and expertise.

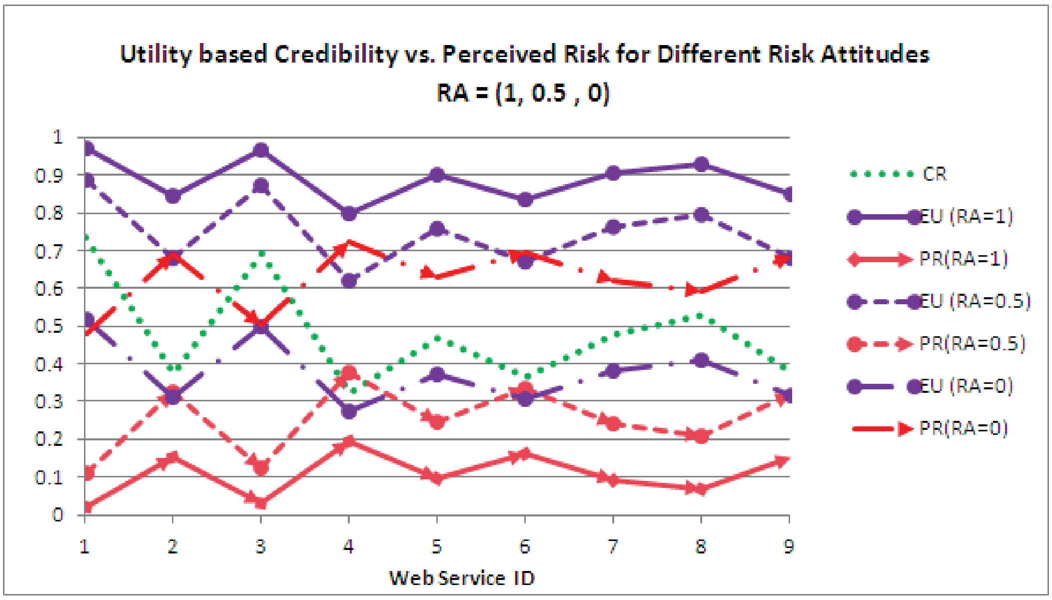

Figure 6.5. Expected utility based credibility vs. perceived risk for different risk attitudes RA = (1, 0.5, 0)

Three different customers with varied risk attitudes were investigated; a risk-seeking customer with RA = 1, a risk neutral customer with RA = 0.5 and a risk-averse customer with RA = 0. User risk-attitude is determined based on the number of preferences expressed in their queries which reflects their personality and their knowledge in the domain UDK, and is reflected by their role in the social network, *i.e.*, either leaders or followers.

Web service credibility is computed as shown in section 3.4, service credibility is drawn from its trustworthiness represented by users' feedback; and its expertise, represented the degree of the service competency in providing accurate results as promised.

At any point in time, each WS has its unique credibility, and each user views a varied perceived risk PR and a corresponding utility from each service based on their risk-attitude, *i.e.,* for the same service, different users view varied amounts of the risk associated with that service based on their risk-attitude which is drawn from their knowledge.

In this experiment, WS1 shows the highest credibility of 0.73 among all services. From a risk-seeking perspective with RA = 1, the perceived risk PR is the lowest 0.026, with the highest expected utility of 0.974 among all services. While from a risk-averse perspective with RA = 0, the perceived risk PR is 0.481 with expected utility of 0.519. Furthermore, from a risk neutral perspective with RA = 0.5, the perceived risk PR is 0.111 with a corresponding expected utility 0.889.

On the other hand, WS4 shows the lowest credibility of 0.32 among all services. From a risk-seeking perspective with RA = 1, the perceived risk PR is 0.198, *i.e.,* the highest PR from all services, with expected utility of 0.621, *i.e.,* the lowest utility from all services. While from a risk-averse perspective with RA = 0, the perceived risk PR is the highest 0.723 among all services, with the lowest expected utility 0.277.

If we compare WS1 and WS4 perceived risk and the associated utility from different users perspectives, we note that a risk-seeking customer with RA=1 views the amount of risk PR from WS1 as the lowest 0.026 with the highest expected utility 0.974 among all services. While from the same user perspective with RA=1, view the amount of the risk PR from WS4 as 0.198, with corresponding expected utility of 0.621. This indicates that the user can view the service with a higher credibility with less risk than the service with a lower credibility.

This experiment demonstrates that different users with varied risk-attitudes perceive varied amounts of risk from the same service. It demonstrates the validity of the model and shows that relationship between expected utility and perceived risk as EU(s) + PR(s) = 1 is a suitable proposal. It also shows, from any customer perspective when the perceived risk increases the expected utility decreases. From risk-seeking users perspective with RA=1, who are considered as leaders, they perceive a small amount of risk, while for risk-averse users with RA=0, who are considered as followers, they perceive a higher amount of risk from the same service.

6.6.2.2. Dynamism of perceived risk for different users' risk attitudes

This experiment aims to show the dynamism of the expected utility and the perceived risk from the same Web service during a specific period of time, from different users perspectives with varied risk attitudes, RA(1, 0) using the same Web service WS=S05.

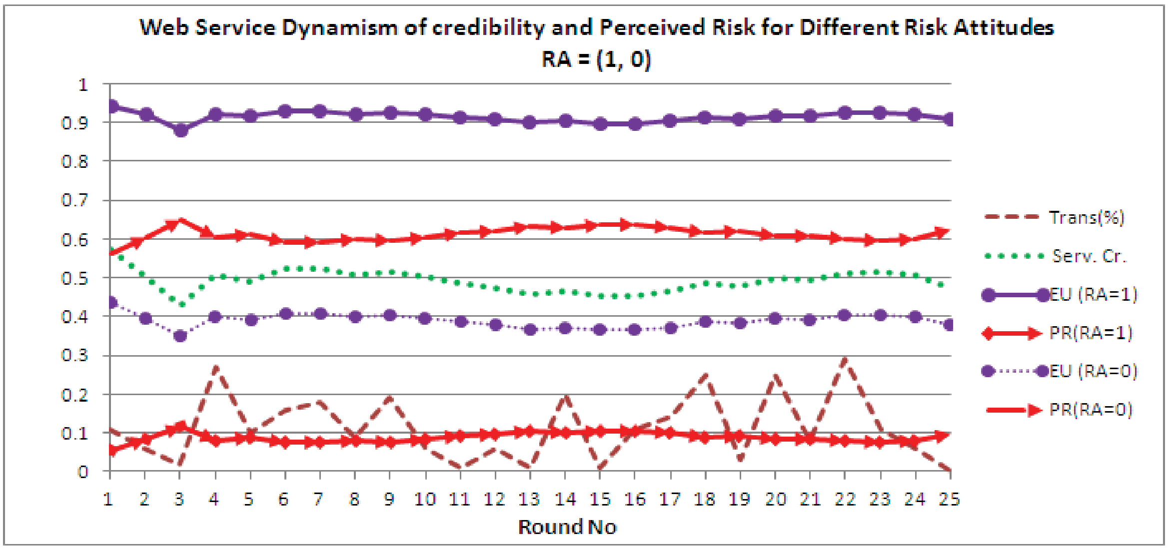

Figure 6.6. Dynamism of expected utility and Perceived Risk for different Risk Attitudes, RA = (1, 0) from (WS=S05)

Setup: In this experiment, WS Selection strategy was set to random from all given services (*i.e.*, customers select Web service randomly from the given services), in order to show the dynamism in the customer perceived risk PR and Web service behavior for a specific Web service WS=S05 over the simulation period 25 rounds.

Results: Figure 6.6 shows how the credibility and the corresponding expected utility of Web service S05 varies with time from customer varied perspective (*i.e.*, with risk attitude RA=1 as risk-seeking customer and risk-averse customer with risk attitude RA=0) with the same model parameters settings.

In round 0, WS credibility is 0.572 represents the highest credibility during the simulation, it attracts 0.11% of the round transactions; it shows for a risk-seeking customer with RA=1, the perceived risk PR = 0.057, with the highest expected utility of 0.943 during the simulation, while from a risk-averse user perspective with RA=0, the perceived risk PR is 0.564, with the highest expected utility of 0.436 during the simulation.

In round 2, WS credibility is 0.428 represents the lowest credibility during the simulation, it attracts 0.02% of the transactions; it shows for a risk-seeking customer with RA=1, the perceived risk PR = 0.117, with the lowest expected utility of 0.883 during the simulation, while from a risk-averse user perspective with RA=0, the perceived risk PR is 0.652, with the lowest expected utility of 0.348 during the simulation.

Then WS credibility enhanced in round 5, WS credibility is 0.524, it attracts 0.16% of the transactions, it shows for a risk-seeking customer with RA=1, the perceived risk PR = 0.073, with expected utility 0.927, while from a risk-averse user with RA=0 perspective, the perceived risk PR is 0.592, with a corresponding expected utility of 0.408.

Finally, in round 15, WS credibility is 0.453, it becomes the second lowest after round 2, it attracts 0.11% of the transactions, it shows for a risk-seeking customer with RA=1, the perceived risk PR = 0.104, with expected utility of 0.896, while from a risk-averse user perspective with RA=0, the perceived risk PR is 0.635, with a corresponding expected utility of 0.364.

Since Web service credibility is changing over time based on its trustworthiness that represents users' feedback satisfaction, and its expertise, we note that any customer experience varied amounts of the perceived risk from the same WS. Risk-seeking customers with RA=1, usually perceive the lowest amount of risk PR, while risk-averse customers with RA=0, usually perceive the highest amount of risk PR, from the same service.

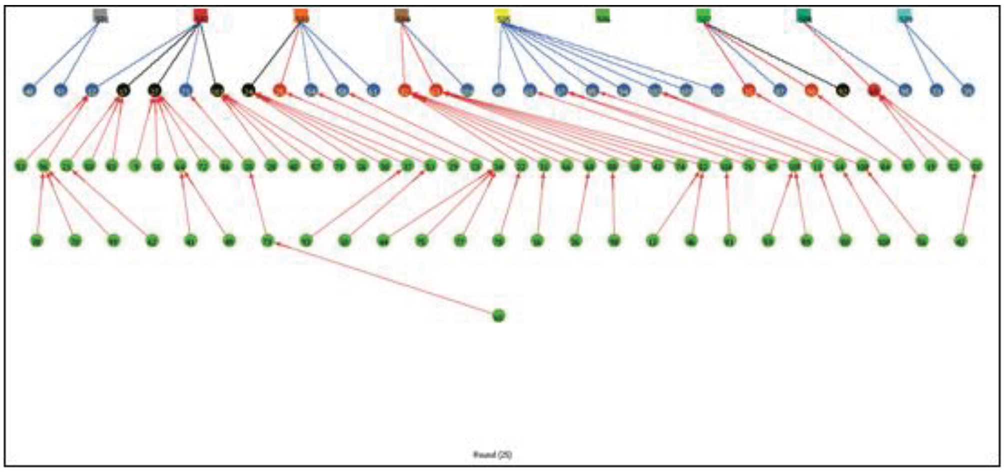

Figure 6.7. Customers select Web service randomly – Follow the leader

Since risk-seeking customers (leaders) can accept the risk, they select the service with the highest credibility as they perceive the lowest PR and the highest utility from the service. While risk-averse customers (followers) view any service with high perceived risk, they make decision to follow their best friends in order to mitigate the risk. Figure 6.7 shows in the first row of the figure how risk-seeking customers (black agents represent leaders and red agents represent potential leaders, with lower credibility than leaders) select a Web service randomly, followed by risk-averse customers (green agents) who follow their best friends. Blue agents represent customers with self-confidence higher than the confidence in any of their friends and elect to take the risk and act as leaders.

Since credibility and expected utility are proportional, we note the variation in the perceived risk and the corresponding expected utility from different customers' risk-attitude perspectives. This experiment demonstrates the dynamism of service credibility over time and the corresponding variations in the perceived risk PR from different customers' perspectives based on their risk attitude. For risk-seeking customers with RA=1, who are considered as leaders, they perceive small amount of risk, while from risk-averse customers perspective with RA=0, who are considered as followers, they perceive a higher amount of risk from the same service.

6.6.3. Risk-Based Social Service Selection

To test the hypothesis that using the "Follow the Leader" approach is an applicable strategy in mitigating the perceived risk in the service selection, the proposed approach using Algorithm 2 is used. Over ten experiments were conducted using either random data generated or predefined services data imported to the simulation tool to evaluate the proposed approach, in this section, I present the results from the home loan services described previously in Section 5.5.2.

In these experiments, 25 predefined home loan services described previously in Section 5.5.2 are used, each with 10 QoS attributes, imported to the simulation system. 100 users are generated randomly by the system, then setting users with their corresponding information. Each round starts with the same set of customers with new random QoS preference values and associated weights and friends. Customers during simulation session build their credibility, which is used by customers to test their self-confidence compared to other friends.

In the risk-based social service selection, the outcome as depicted in Figure 6.8, leaders (Black agents) make their selection choice based on their risk attitude and the available Web services credibility and associated utilities. Since leaders' risk attitude is high and the associated perceived risk is low, they select the service with the highest expected utility which is drawn from its credibility. Whereas for customers with low risk attitude they act as followers (Green agents), they make their decision and follow one of their trustworthy best friends. Finally, other customers with 0.2 < Risk-Attitude < 0.6, they make their decision based on the confidence that one of their friends selected a high expected utility service to follow (Green agent), if their self-confidence is higher than any of their friends in terms of their credibility and risk attitude, then they take the risk and act as independents (Blue agents); consequently they select their best service based on service credibility as leaders.

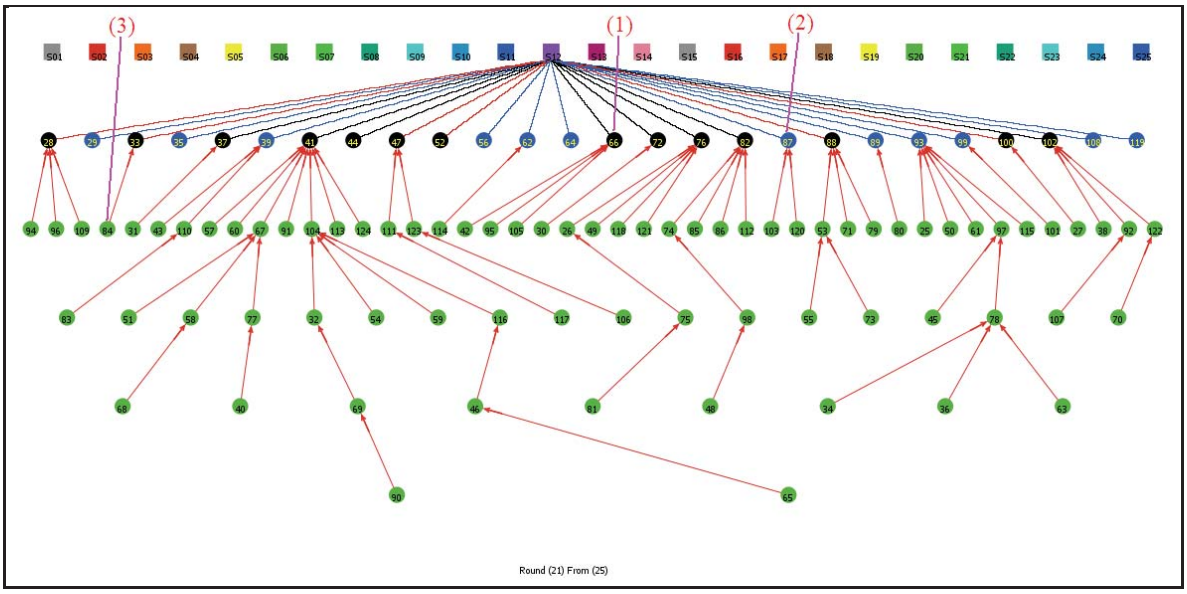

Figure 6.8. Social Service Selection based on customer risk attitude and service credibility –Follow the Leader Model

In Table 6.1, the top-6 services as per their initial credibility are presented. After 20 rounds of simulation while users make a random selection from the top-5 services, apparently S05 was not selected because its initial credibility was not among the top-5 services. Service S12 was selected as the highest credibility by all leaders, as shown in Figure 6.8.

I selected three customers for user behavior analysis; who are marked in Figure 6.8 as: (1) refer to agent id (66) who acts as leader with risk-attitude = 1, (2) refer to agent id (87) who acts as independent with risk-attitude = 0.4 and (3) refer to agent id (84) who acts as a follower with risk-attitude = 0.2.

Since the three customers have varied risk-attitudes, they can perceive varied risks from the best service, S12. Since agent 66 has a high risk-attitude, it acts as a leader and selects the service with the highest utility, *i.e.*, service S12 with expected utility of 0.993. As shown in the perceived risk (PR) columns, there is no service considered as risk free, which supports our previous argument "there is no service risk free".

Table 6.1: Top-5 home loan services perceived risk as viewed from different users

			Agent 66 -Leader(1)		Agent 87 -Ind(2)		Agent 84 -Follower(3)	
Serv-CD	**Init-Cred.**	**Last-Cred**	**66-PR**	**66-EU**	**87-PR**	**87-EU**	**84-PR**	**84-EU**
S12	0.761	1.000	0.007	0.993	0.074	0.926	0.165	0.835
S04	0.647	0.622	0.045	0.955	0.198	0.802	0.326	0.674
S07	0.647	0.539	0.067	0.933	0.246	0.754	0.379	0.621
S24	0.670	0.571	0.057	0.943	0.226	0.774	0.358	0.642
S15	0.658	0.617	0.046	0.954	0.201	0.799	0.329	0.671
S05	0.632	0.000	1.000	0.000	1.000	0.000	1.000	0.000

Agent 84 in this context has a risk-attitude of 0.2, consequently, it follows leader (33) as best friend, who selected service S12 with expected utility 0.993. As we see from Table 6.1, agent 84 could not afford the risk of selecting any of the top-5 services, and rely on others who have better knowledge and expertise in home loans.

Agent 87 has a risk-attitude of 0.4 with user credibility 0.65, also has three friends (42, 55, 81) each with risk-attitude = 0.1, and with corresponding credibility (0.25, 0.18, 0.16). When agent 87 refers to his/her best friend 42, he/she finds that his/her best friend's credibility = 0.25 and he/she has a limited knowledge in the home loan services. Since agent 87 has self-confidence higher than the confidence in any of his/her friends, he/she elected to act as independent and selected service S12 with its perceived risk 0.074 and expected utility 0.926.

Apparently, the number of customers who act as independents in this round is 12, while customers who act as leaders 14, and customers who mitigate the risk in service selection by following other trustworthy friends or leaders in this round is 74, which represent 74% of the population in the network. The results from this experiment agree with the power-law degree distribution of the social network, which is due to the effect of preferential attachment, where Huang [83] indicated that 20% of the population in a given WBSN holds 80% of the total power of the society, from which we conclude that 80% of the population can act as followers.

Furthermore, the average of R-precision for risk-based social service selection approach is computed, all experiments show R-precision = 1.00, this indicates that the risk-based social service selection approach provides the Top-M services for all user queries.

The risk-based social service selection approach identifies a user to be either a leader or a follower based on their risk attitude drawn from their personality and their knowledge in the service domain UDK. Since leaders possess the highest risk attitude RA≈1 among other members in the social network, while followers possess the lowest risk attitude, the risk-based social service selection approach provides the leaders with the most credible service with the lowest perceived risk and the highest utility that matches their preferences, and recommends the top credible services used by leaders to the followers to select from, and thus followers avoid the risk from the service selection. As a result, all users' queries are replied by the risk-based social service selection with R-precision = 1.00 and for all ranks M.

If we consider the Utility-based approach presented in Section 5.5.3 as a risk-neutral approach, we notice that Utility-based approach selects a service to the customer regardless of the customer behavior, *i.e.,* whether they are risk-seeking or risk-averse customers, and ignores customer risk-attitude. Utility-based approach presents to the customer a service regardless its credibility or the perceived risk from that service.

Furthermore, the Utility-based approach provides a maximum R-precision of 0.81, when selecting only one service, and its performance decreases when the number of candidate services M increases, i.e., the Utility-based approach could not meet the customer requirements in 39% of the cases when M=5. Experimental results also indicate that the quality of the candidate services from the Utility-based approach is not guaranteed, it is acceptable as long as it matches customer requirements. For the best service in the Utility-based approach, the results indicate that only 1.17% of the best services in the Utility-based model match the best service in Credibility-based model. As service capability is not static and changes over time, the perceived risk also changes with time based on customer risk attitude.

Moreover, risk-based social service selection approach provides leaders and independent customers with the service with the highest quality among all services, while follower' customers mitigate the perceived risk from the service selection by following expert leaders' advice in the social network.

From the above discussion, we conclude that risk-based social service selection approach is a feasible solution in mitigating the risk in the service selection for all risk-averse customers, and customers experience better utility and better satisfaction with the delivered service when the service credibility and the associated perceived risk is considered in their selection decision.

6.6.4. Results Summary

I summarize the findings from the previous experiments as follows:

- In a Web-based social network (WBSN), customer behavior is the determinant of their credibility; different customers are with varied risk attitudes. In a WBSN credibility of a customer which is drawn from their trustworthiness component and their expertise and knowledge in a specific domain or context is the predictor of their risk attitude. Usually customers with high risk attitude act as leaders, while customers with the lowest risk attitude act as followers.
- Web service behavior is the determinant of its credibility; since different Web services in a specific domain and context have the same functionalities and vary in their advertised QoS attributes, each of these services has its unique credibility expressed by trustworthiness and expertise. The trustworthiness component is drawn from its reputation, while its expertise is measured in terms of the number of transactions involved in, and the extent the service provides what is promising according to the advertised QoS.
- The proposed risk-based social service selection approach is an efficient approach to alleviate the risk in the service selection for customers with low risk attitudes *i.e.*, followers. This approach explores the confidence relation between the follower and their friends which is a function of the customer credibility.
- The proposed risk-based social service selection approach shows its efficiency to propose the best service for all customers' queries. Leaders usually have the knowledge and expertise to express their preferences and select a service from the Top-M candidate services that maximize their utilities. On the other hand, followers do not have the adequate knowledge and the expertise to express their preferences, which decreases their risk attitude and increases their perceived risks; consequently, they rely on leaders to advise them about the most credible service to use.
- Since the proposed Web service Credibility model is centralized and based on statistical approach to compute services credibility, then the Credibility model does not require complicated computations; where the computation performed

offline locally on predefined periods at a central point that does not need communications overheads. Furthermore, social service selection based on risk attitude does not need extra computations as trust inference approaches to infer cold-start users similarity, it uses leaders as trustworthy experts to provide all cold-start users with the best service based on their previous experience.

6.7. Summary and Conclusions

Since no service used is risk free, and decision making in risky complex situations has always been a difficult task, different users with different risk attitudes perceive varied amounts of service performance risk based on the credibility of the Web service. In this chapter, I proposed an approach to mitigate the user perceptions of risk using "Follow the Leader" as a risk-reducing strategy in service selection. I showed how different users with varied risk attitudes make their decisions in the Web service selection process, with the perceived performance risk and expected utility considerations. Furthermore, I showed how the risk-averse customers make their decisions in Web service selection and follow the best trustworthy friend or expert leader in their social network, in order to reduce the perceived risk from the available choices based on "Follow the Leader" strategy.

I have evaluated the proposed framework using the Social Network Analysis Studio (SNAS) in a specific context. The results presented in this chapter show that the proposed service Credibility model is an effective approach to identify most credible services, the service leaders in the context with the highest trustworthiness and expertise among all services.

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

Chapter 7
Conclusion and Future Work

Social Web service selection and recommendation is a challenging problem in theory and practice due to the fact that this is still an emerging field, as evidenced by the lack of automated public service selection and recommendation systems deployed in the commercial world at present. Although there are existing approaches for product selection, services have non-functional properties or QoS attributes that influence their credibility and consumption.

The non-functional properties or QoS attributes of Web services are difficult for the user to determine and control. Users are usually reluctant to spend time describing their complete preferences [33], and are even less willing to assign relative weights to their preferences, especially when the effects and consequences of their inputs are unknown or undetermined. Moreover, users may not even be aware of their implicit preferences. Consequently, a cold-start customer who wants to find a Web service often seeks help from friends, peers, expert leaders and business partners who have relevant experiences. Capturing and specifying user preferences is one of the most complex problems in the Web service selection and recommendation process.

This dissertation proposes a novel approach to automatically selecting and recommending social-based Web services in a dynamic environment. It utilizes Web-Based Social Networks (WBSN) and the “Follow the Leader” strategy in Web service selection and recommendation. It proposes a Credibility-based framework that includes two credibility models; the user Credibility model, which is used to qualify consumers as either leaders or followers based on their credibility, and the service Credibility model, which is used to identify top services that act as market leaders.

The work presented in this dissertation differs from the existing approaches in three major aspects. First, I adopted a social-based service selection approach using Web-based social networks. Second, I used a well established social strategy, "Follow the Leader". Third, the proposed approach is augmented with user behavior analysis and risk considerations.

In the remainder of this chapter, I will provide a summary of the research contributions, and I will conclude with a view of the possibilities for future work.

7.1. Contributions

The main objective of this research is to develop an effective, efficient and flexible social service selection and recommendation model in centralized systems that will facilitate the augmentation of Web-based social networks with semantic Web service selection and recommendation, particularly for cold-start users and risk-averse customers. Moreover, providing an automatic selection and recommendation mechanism of Web services will have a significant impact not only on end users, but also on the integration of Web services from an industrial perspective.

7.1.1. Primary Contribution

The main contributions of this research can be summarized as follows:

1. ***User Credibility model***

   I proposed a novel dynamic user Credibility model in Web-based social networks which uses two credibility components: a trustworthiness credibility component and an expertise credibility component. A new clustering approach is proposed based on the "Follow the Leader" strategy and user credibility to identify the community of leaders in the WBSN. The user Credibility-based approach consists of two steps. In the first step, it makes use of user trustworthiness and expertise to compute user credibility. In the second step, it selects the top ranked credible users as candidate leaders. Leaders in a Social Network are the most credible advisers for the rest of the population in the network.

2. ***Web service Credibility model***

   I proposed an innovative dynamic Web service Credibility model with two credibility components: a trustworthiness component drawn from leaders' feedback about their satisfaction with the service aggregated as reputation, and an expertise component drawn from the actual performance of the service and its conformance with its promised qualities. The aggregation of these two components with decay factor considerations represents Web service credibility at any point in time. The service Credibility model is an effective approach to identifying the most credible services, and who the market leaders are in the service domain that have the highest trustworthiness and expertise among all services.

3. ***Social service selection and recommendation***

   I proposed a new efficient social-based service selection and recommendation algorithm utilizing user credibility, user domain knowledge and Web service credibility in the context of "Follow the Leader" strategy, where users can be identified as leaders or followers based on their credibility and their knowledge in the domain expressed in their queries. Leaders usually select a service that maximizes their utility, while followers rely on expert leaders to select the most credible service from the services recommended by the leaders.

4. ***Mitigating risk in service selection***

   I proposed a new efficient approach to mitigate the user perceptions of risk using "Follow the Leader" as a risk-reducing strategy in service selection. Different users with a variety of risk attitudes make their decisions in the Web service selection process according to the perceived performance risk and expected utility considerations. Risk-averse customers usually make their decisions in Web service selection and follow the most trustworthy expert leaders in their social network to reduce the perceived risk from the available choices based on the "Follow the Leader" strategy.

The integration of the proposed credibility models with "Follow the Leader" strategy creates a flexible unified framework to enable efficient and effective social service selection and recommendation. In a Web-based social network (WBSN), user domain knowledge (UDK) is the determinant of their behavior; leaders usually have the knowledge and expertise to express their preferences and select a service that maximizes their utilities. On the other hand, followers do not have adequate knowledge and expertise to express their preferences; consequently they rely on leaders to advise them about the most credible service to use.

The proposed social service selection and recommendation model meets the challenges addressed in Section 2.4. First, the social service selection and recommendation approach handles cold-start users who represent more than 50% of the population in the network. Since followers cannot express their preferences, expert leaders can provide them with practical advice about the deemed service. Consequently, this approach eliminates the problems associated with cold-start users, sparsity and capturing user preferences. The recommender system does not rely on followers to capture their similarity and preferences and consequently followers' information is not used in recommendations, which leads to preserved privacy for followers.

Second, since the leaders are the most trustworthy customers in the network, leaders are able to express their needs and preferences, and the recommender system relies on leaders only to provide feedback about services. Leaders by nature like to exhibit their preferences and their expertise to others. This approach eliminates the capturing user feedback and privacy issues which collaborative-based filtering and trust-aware recommender systems suffer from.

Finally, since the proposed Web service Credibility model is centralized and based on a statistical approach to compute services credibility, the Credibility model does not require complicated computations in which the computation is performed locally offline on predefined periods at a central point and therefore does not have communications overhead. Furthermore, the social service selection approach does not need extra computations to infer cold-start users' similarity, as trust inference approaches do. Rather, it uses leaders' trustworthiness and expertise as a valuable source to provide all followers with the best service based on their previous experience. Furthermore, the Credibility-based framework is scalable, efficient and effective in identifying expert leaders and market leaders in a social network.

7.1.2. Secondary Contributions

While my primary objective is to propose a social service selection and recommendation approach, below is a set of secondary contributions that are presented in this dissertation and are considered to be of independent value:

1. ***Bridging the gap between theory and practice***

One aim of this dissertation is to help bridge the gap between theoretical and practice-based efforts by evaluating the applicability of the proposed social service selection and recommendation approach.

For a solution to be successfully utilized by the industry, it needs to be simple, easy to understand, develop and maintain, If we analyze product recommendation applications such eBay, Amazon and EPINIONS, we note that these applications avoid complexity in their design and implementation.

Since the proposed social service selection and recommendation is credibility-based; it is easy to understand and to implement. Furthermore, the flexibility, scalability and robustness of the model support its capability for automated service selection and recommendation from the industry perspective.

2. ***User behavior model with user risk-attitude***

I proposed a user model with risk-attitude based on the user domain knowledge and its credibility utilizing the “Follow the Leader” strategy. Different users have varied risk attitudes in different contexts and perceive varied amounts of risk from the same service. Risk-averse customers usually act as followers while risk-seeking customers act as leaders, and risk-neutral customers base their decisions on the tradeoff between the expected utility and the perceived risk and their self-confidence about available choices.

3. ***Social Network Analysis Studio (SNAS)***

I developed a new and significant tool Social Network Analysis Studio (SNAS) utilizing the NetLogo [171] platform. Although NetLogo is used as a simulation tool, it has the facility to capture real data. This facility is used to analyze and evaluate the validity of the proposed service selection and recommendation. Moreover, SNAS can be utilized to visualize social networks and can be used as a social network analysis tool.

One of the interesting issues in building the “Follow the Leader” model is the cyclic trust relationship. This phenomenon appears when members trust one another in a cycle mode. To build the “Follow the Leader” hierarchal models, it is necessary to avoid such cycles; hence, I used the confidence relation [185] to resolve this issue, where for each cycle, the member with the highest credibility is identified, then we break the link from that member to the member with lower credibility in that cycle.

4. ***A new clustering approach***

I proposed a new efficient clustering approach based on the "Follow the Leader" strategy and user credibility to identify the leaders' community in the WBSN. The proposed approach consists of two steps. The first step makes use of user trustworthiness and expertise components to compute user credibility, and then selects the top ranked credible users within a credibility threshold as candidate leaders.

I used degree centrality as a metric to measure the effectiveness of the proposed clustering approach based on the credibility of the members in the social network. Leaders in the social network are identified based on their credibility, which is drawn from their trustworthiness and expertise. Since leaders possess the highest average in-degree and highest average out-degree, which in both cases is more than followers' and more than the average member in the network, they are the most prominent and *influential* members in the network. This effect is drawn from their trustworthiness and expertise; leaders possess high average rated items in the network.

Furthermore, I showed that leaders' community exhibits Interest Similarity with other users more than the 1st level friends' community, which proves that leaders are more credible advisers than 1st level friends.

5. ***Web service credibility bootstrapping***

When a new service enters the market, setting its initial credibility is a challenge. I proposed a new service *capability measure*, as a relative capability measure of the new service with respect to other available services in the domain.

6. ***Performance metrics***

For cold-start users without a ratings history or with a small number of ratings, I proposed MAE2 to measure the prediction accuracy for a specific item with respect to the average of the item rating by all users who rated that item, which reflects the population opinion about the item and reflects leader's reliability in providing ratings.

I also introduced R-precision, sometimes called Top-K precision, to measure the quality of the returned services to the user from the social service selection and recommendation algorithm.

7.1.3. Scalability, Flexibility and Robustness

Using the user Credibility-based approach on different sizes of three large datasets shows the scalability of the model. The model can be applied to small networks and huge networks at the same time. The model can support networks with ratings only or with trust statements only or with both ratings and trust statements. This leads to the conclusion that credibility-based clustering is scalable for small datasets as well as for large datasets. The model can provide recommendations for cold-start users as well as for experienced users.

Since some networks do not have ratings, or the ratings are not important in the domain of the application; the user Credibility model is capable of identifying leaders with trust relations only, simply by ignoring the expertise component in the model; *i.e.*, set the system tuning parameter that represents the importance of expertise component ($\alpha = 0$).

On the other hand, in some networks, explicit trust statements are not always available or are not important in the domain of the application. The user Credibility model is capable of identifying expert leaders with items ratings only, simply by ignoring the trustworthiness component in the model; *i.e.*, by setting the system tuning parameters that represent the importance of trustworthiness components to zero, *i.e.*, ($\beta = 0$ and $\gamma = 0$). In such scenarios, leaders are considered as experts among the entire population. Since the proposed Credibility model relies on the number of items rated and on the quality of rating in qualifying expert leaders, the proposed user Credibility-based approach is more efficient and reliable than other approaches that use the number of ratings only to qualify experts. Moreover, extracting implicit trust using users' similarity in their rating [243] is an alternative to establishing trust in the model.

The social service selection approach does not need extra computations such as trust inference approaches to infer cold-start users similarity, because it uses leaders as trustworthy experts to provide all followers with the best service based on their previous experience. I proved experimentally that the Credibility-based prediction algorithm is more efficient than the Trust-based prediction algorithm even in prediction response time.

7.1.4. Applications and Possible Commercialization

The Credibility-based framework and social-based service selection and recommendation can be applied in application systems where users have varied preferences, interests and judgment criteria. Although the proposed framework in this dissertation focuses on financial domain services, the Credibility-based framework can be applied in other service domains, such as health care, and in centralized systems, such as e-commerce websites. Furthermore, the proposed Credibility framework can be applied in decentralized systems that utilize resources selection such as file sharing systems and other resources selections on the cloud, or networked fashion resources such as sensor networks.

Possible commercialization opportunities include:

- User Credibility model coupled with Social Network Analysis Studio (SNAS) can be utilized as a tool to identify other leaders in a social network, such as political leaders and terrorist leaders which is a difficult and an important issue. Identifying information and command paths and visualizing these paths among members in a social network is very important and useful in a wide range of security applications.
- Since search engines are the gateways to knowledge over the Internet, and search engines cannot guarantee the trustworthiness of the content in the search results, the Credibility-based framework can be used as a module in such search engines. It can be utilized in two dimensions: first, by identifying users with limited knowledge in the search domain and utilizing leaders to provide recommendations to those users. Second, since a casual observer might not be able to differentiate between trustworthy and untrustworthy content, the proposed service credibility can be extended to assess content credibility and provide the consumer with the most trustworthy content, and at the same time, mitigating perceived consumer risk.
- The Web service Credibility model can be used to mitigate risk in e-commerce applications for various aspects of risks such as security, privacy and financial concerns, beside the global credibility metric that reflects the product/service’s trustworthiness and expertise at the same time. The proposed Credibility framework can be used to assess Web services’ credibility and to identify associated risks and consequently reduce Internet theft.
- The Credibility-based framework can be used to build a Social-based Web service selection and recommender system. The user Credibility model can be used to

identify expert leaders in a variety of service domains. Leaders can provide expressive queries and provide assessment and evaluations for varied Web services. The Web service Credibility model can also be used to identify market leaders in these service domains.

7.2. Future Research Directions

This section introduces future developments that can be pursued on the basis of this dissertation. A number of areas of interest came to my attention which I was not able to further develop or study due to time constraints. I therefore summarize the areas which I consider to be worthy of future research and outline a possible path for the future development of the recommender system discussed in this dissertation. These include:

1. Exploring the impact of distrust or negative trust relationships on the trustworthiness component of the user Credibility model. To what extent can we consider the enemy of my enemy to be my friend in building trustworthiness in a user Credibility model?
2. Exploring other flexibility issues of a user Credibility model, such as implicit trust extraction, where the proposed model shows that trust indicates interest similarity. On the other hand, does similarity infer trust and to what extent?
3. Exploring the areas that we consider to be the boundaries to our work (presented in Section 1.2.1). For example, how the proposed Credibility-based framework can be employed in Web service composition, and how the perceived risk in Web service composition can be mitigated. In other words, to study Web service collaboration and cooperation towards service composition with credibility and risk considerations.
4. Utilize the user Credibility model and Social Network Analysis Studio (SNAS) in social network analysis for other social networks such as Twitter and Facebook, to identify the leaders in those contexts and analyze the strength of relationships among members, identifying influential and power members in the social network. Also, to utilize SNAS to visualize and analyze the links between social network members.
5. The proposed Credibility-based framework is designed with centralized management and control in mind. However, the proposed social service selection can be extended to operate in decentralized or distributed environments, in which a

number of social networks each operate in centralized settings. How can these social networks cooperate to exchange expertise and advice? For example, how could leaders' communities from two or more social networks cooperate to provide advice on a specific issue?

6. This dissertation studied leaders' influence and power from two perspectives: degree centrality measures (in-degree and out-degree) and interest similarity measures. The social network influence analysis issue is an interesting and new research area in social network mining. There are many potential future directions in this area.

7.3. Concluding Remarks

This dissertation addresses challenge issues in Web service selection and recommendation from theory and practice perspectives; these challenges include cold-start users who represent more than 50% of the social network population, capturing users' preferences, risk mitigation in service selection, privacy and scalability. I provide an innovative approach to address these issues based on the Credibility-based framework and the "Follow the Leader" strategy. The significance of the proposed approach is justified by the following arguments:

1. Social-based service recommendation using the "Follow the Leader" strategy is significantly more computationally efficient than traditional collaborative filtering (CF) and trust-aware approaches, and can be implemented in WBSN communities and utilized in large-scale recommender systems.
2. The sound predictive power of social leaders indicates social influence on other users that explains the feasibility of the proposed approach.

Experimental evaluation results demonstrate that the social network service selection and recommendation utilizing the Credibility based framework and "Follow the Leader" strategy offer an efficient, effective and scalable solution to provide consumers with credible services, especially for cold-start users. The research results are a further step towards developing a social-based automated and dynamically adaptive Web service selection and recommendation system in the future.

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