Help-Desk Agent Recommendation System Based on Three-Layered User Profile

YongBin Kang[1] and **Arkady Zaslavsky**[2] and **Shonali Krishnaswamy**[3]

Abstract. This paper proposes a novel approach for recommending a help-desk agent that may appropriately handle problems requested by clients. First, we identify a key problem of high tendency to depend on help-desk agent when dealing with a problem. To solve this problem, we present a three-layered user profile with a new concept of role information of users. Then, we emphasize how our new recommendation strategy is working based on the user profile, particularly using the individual/role information in the user profile. We finally demonstrate how our approach works with an example.

1 INTRODUCTION

The main role of help-desk agent (HDAgent) is to behave as a front-line interface to solve a service-call by utilizing accumulated knowledge and learned experience. A key problem of service management in help-desks lies in the high dependency on HDAgent when solving a service-call. The problem may cause two negative situations: *inconsistency* and *unreliability*. More specifically, retrieved solution may be inconsistent according to which a particular HDAgent handled the given service-call. In addition, according to different HDAgents, suggested solutions may be reliable or not. For example, if a novice HDAgent that may not have enough domain knowledge or experience solves a service call, it would not be guaranteed whether the solution from that HDAgent is appropriate or not. In both cases, these problems can be naturally linked to negative effects to the help-desk organization, such as the loss of the confidence and satisfaction of the clients [9].

A practical research area designed to address the issued problem can be found in application using Case-based Reasoning (CBR) approach [5, 15]. A key concern of CBR is how to design a *retrieval function* to generate possible solutions to a given service-call. However, one common weakness of CBR lies in that such function is usually derived by considering only limited two spaces, i.e., service-call and case space. Therefore, that issued problem (i.e., high dependency on HDAgent) still remains unsolved due to the ignorance of the inclusion of the HDAgent knowledge. To address the issue, this paper aims to present a new recommender system that recommends a HDAgent that may adequately handle a given service-call. In particular, we focus on designing a user profile that may represent enough information of users involved in help-desk domains and developing a new hybrid recommendation strategy based on that user profile.

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This paper is organized as follows. In the next section, we discuss the proposed user profile in detail. Section 3 presents the proposed recommendation process and Section 4 shows a demonstration. We review related work in Section 5, followed by the conclusion.

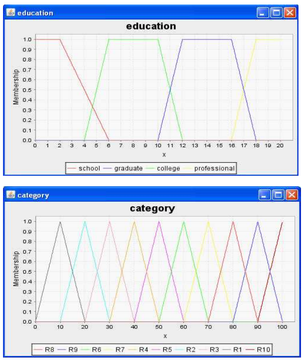
2 THREE-LAYERED USER PROFILE

Our user profile is designed as an uniform profile that may represent enough knowledge of both the client and HDAgent. The basic intuition used here is that personalized information of the client and HDAgent can be uniquely decided on the following combination of three layers, which is motivated by the work [1]: *factual information*, *domain-specific problem features*, and *transactional information* of interactions between the clients and HDAgents. The main differences between the profile proposed in [1] and our profile are that the former model is mainly designed for capturing "purchasing behaviors of individuals" in e-commerce application, while the latter generalizes the former idea into the ITSM domain. In addition, the new concept of *role* is deployed into our user profile.

The first layer represents factual information that consists of four components, such as user identity, company description, role characteristics, and role category (see Table 1). The first two components represent domain-independent user information, which are initially generated by combining explicit user input and stereotypes. The *role characteristics* feature a set of important components of the *roles* (i.e., the task functions or positions of individual or a target group of users [16]) in the client company or help-desk organization. The main reason for defining the role characteristics is to identify the same or similar characteristics of the users, and to set a basis for utilizing both the individual and role information. Thus, it enables that user profiling might be individual or group-based [6]. These characteristics may be differently defined according to different industrial domains using various attributes carefully decided by the domain experts. In this work, some potential characteristics are identified that may address unique roles of the both client and HDAgent. This is consistent with our literature review in [9, 4, 13] as seen in Table 1. The goal of deriving *role category* is to provide better information to both the client and HDAgent when handling the service-call by classifying the role of the user based on the role characteristics. The role category is calculated using fuzzy logic which provides a human-like mechanism to imitate human decision that can be used to reason and aggregate strategy to reach optimal decisions [10]. Fuzzy logic has proved to be quite useful for developing many practical applications which need to enhance the capabilities of industrial automation due to its intelligent ability to formalize and manage inexact and vague information [13]. Having motivated the benefits of using fuzzy logic, the role characteristics are used for generating membership functions in our fuzzy model, and our system assigns pre-defined role categories to users according to corresponding membership values using fuzzy logic. Each characteristic is defined by a membership function which helps to take the crisp input values, and transformed into certain degrees of membership (see also Fig. 1).

TYPES	ROLE CHARACTERISTICS	FUZZY SET
Demographic	Age	young, middle, old
	Education	school, college, graduate, professional
	Task Function	IT_General, IT_Operation, IT_Expert
Knowledge	Domain Knowledge	low, medium, high
	Training	low, medium, high
Experience	Current Experience	novice, medium, senior, expert
	Previous Experience	low, moderate, extensive
Proficiency	IT Speed	low, medium, fast
	Skill	novice, medium, senior, expert
	Attitude	alone, ordinary, positive, cooperative
Evaluation	Performance Satisfaction	poor, average, good

(a)



(b)

Age	Education	Task Function	Domain Knowledge	Training	Current Experience	Previous Experience	IT Speed	Skill	Attitude	Performance Satisfaction	Role Category
Young	School	IT General	Low	Low	Novice	Low	Low	Novice	Alone	Poor	R0
Middle	College	IT Operation	Medium	Medium	Medium	Moderate	Medium	Medium	Ordinary	Average	R1
Old	Graduate	IT Expert	High	High	Senior	Extensive	Fast	High	Positive	Poor	R2
Old	Professional	IT General	Medium	Low	Medium	Extensive	Fast	Low	Cooperative	Good	R3
Young	College	IT Operation	Low	High	Novice	Moderate	Medium	High	Positive	Average	R4

(c)

Figure 1. (a) shows the role types, the role characteristics, and how the role categorization is performed by defining fuzzy set for the role characteristics. Two sample membership functions for input (education) and output (category) using fuzzy logic are shown in (b), and some sample of fuzzy rules are seen in (c).

The second layer of the user profile denotes preferential information which represents the domain-specific feature of the problems (service-calls) encountered, closely related to a particular individual user or his/her role. Namely, this layer particularly reveals the reasons about how/why the user is deeply related to particular types of problems. As seen in Table 1, each problem is composed of problem identity, problem class (either problem taxonomy or troubleshooting option), a composition of attributes which may represent the main characteristics of the problem well enough, relevance weights of these attributes, and relevance weight of each problem indicating its relative importance among all the problems in this layer. The number of components in the second layer corresponds to the number of possible problems that have been encountered. Besides, as the client interacts with HDAgents, the second layer's components are increased, aggregated, and updated with the change of the transactional information in the third layer.

The third layer of the user profile maintains transactional information about how the problems have been handled by certain HDAgents. As seen in Table 1, a single transaction consists of HDAgent identity that solve the given problem, case identity which contains retrieved solutions by this HDAgent, a set of problem identities that are closely related to the solutions in the case identity, and a set of diagnosed problem features, and appropriateness component. The appropriateness component indicates an appropriateness value of the given case for the involved problem identities, which is evaluated by the feedback from the client or HDAgent. Namely, it represents how much the given case is adequate to the related problems. This component is used to update the value of 'performance satisfaction' component in the first layer, and thus also to contribute to updating

Table 1. The proposed three-layered user file structure.

LAYER	TYPE	COMPONENT	
FIRST LAYER	User Identity	Client / HDAgent ID	
		Name	
	Company Description	Affiliation	
		Location	
		Employee Numbers	
		Software in Use	
	Role Characteristics	Demographic	Age
			Education
			Task Function
		Knowledge	Domain Knowledge
			Training
		Experience	Current Experience
			Previous Experience
		Proficiency	IT Speed
			Skill
			(Problem-Solving) Attitude
		Evaluation	Performance Satisfaction
	Role Category	Classified Role	
SECOND LAYER	Problems (≥ 1)	Problem ID	
		Problem Class	
		Attribute ID	Attribute Type(Keyword $\mid$ QA)
			Attribute Name
			Relevance in Problem (%)
		Relevance over Overall Problem (%)	
THIRD LAYER	Case Solved (≥ 1)	Case ID	
		HDAgent ID solved the given problem	
		Problem Identities (≥ 1)	
		Diagnosed-Attributes Sequence	
		Appropriateness(%)	

the 'role category' in that layer according to the increased number of the transactions. Moreover, whenever a new transaction occurs, this new record will be used to update the corresponding instance(s) of related problems in the second layer. Further, once the first layer is created by user explicit input or stereotypes, the whole body of the user profile is automatically built up in an unobtrusive way without extra burdening of both the client and HDAgent by observing the transaction information in the third layer.

3 RECOMMENDATION STRATEGY

This section describes our recommendation strategy that recommends a HDAgent who may appropriately handle a given problem, based on the proposed user profile. This strategy is composed of the following major three steps.

3.1 Weighting Computation Based on Client's Own Experience

Given a problem by a particular client, we calculate the weighting function of relevant HDAgents' role for the client based on their problem-solving experience. More precisely, to compute this weighting, we use the information about the frequencies of the retrieved cases and whose appropriateness values. Such information can be found in the third layer of the user profile. In other words, this weighting indicates how frequently a particular HDAgent have handled the problems given by the client and how appropriate the retrieved solutions suggested by the HDAgent are. The key idea behind this step is to mimic the paradigm of content-based filtering [3]. Namely, we compute the weighting on the basis of the assumption that the more a HDAgent's role is experienced in solving the problems given by the client, the better the HDAgent's role will solve a problem given by the client appropriately in the future.

Formally, let CR and SR be the roles of the entities, clients C and HDAgents S, respectively, and then the weighting function W_1 is conceptually expressed by the correlation between C and SR as: $W_1 : C \times SR \rightarrow Weightings$. The weighting function $W_1(c, s_r)$

of a particular HDAgent's role s_r for a given client c is computed as: $W_1(c, s_r)$ = $\sum$ (*appropriateness values of the cases solved by* s_r *in the given client profile*) / (*total number of such cases*).

3.2 Weighting Computation Based on Similar Client's Experience

In this step, we compute additional weighting function of relevant HDAgents' roles for a given client's role. This weighting function is based on the appropriateness values of the clients having the same role with the given client. The assumption applied in this step is that we would acquire increasingly accurate weighting by taking objective views of similar clients to the given client. The basic idea behind this step is to take advantage of the paradigm of collaborative-based filtering [3]. In other words, we compute the weighting taking into account appropriateness values assessed by those clients who have the same role with the given client.

Formally, the second weighting function W_2 can be represented as: $W_2 : CR \times SR \rightarrow Weightings$. More specifically, The weighting function $W_2(c_r, s_r)$ of the HDAgent's role s_r for a given client's role c_r is computed as $W_2(c_r, s_r)$ = $\sum$ ([*appropriateness values of the cases solved by* s_r *in the client profile having the same role with the given client's role* c_r]/[*total number of such cases*])/(*total number of clients having the same role with the given client*).

3.3 Final Weighting Computation using Linear Combination

As the final step, we combine two separate weightings computed in the previous steps. For this, we adopt linear combination approach due to its generality, simplicity, usefulness, and powerfulness [12]. Our combination formula is defined as, "$W(c, s) : W_1(c, s_r) * (1 - \tau) + W_2(c_r, s_r) * \tau$", where τ denotes a combination coefficient. Here, τ is derived from this formula, $\tau = \left(\frac{N(\hat{CR})}{N(CR)} + \frac{N(\hat{SR})}{N(SR)}\right)/2$, where the $\hat{CR}$ and $\hat{SR}$ are the set of clients and HDAgents that have the same roles with the client c and HDAgent s, respectively. Finally, the HDAgent having the highest weighting is recommended as the most appropriate HDAgent that would solve the problem given by the client.

4 DEMONSTRATION

To evaluate the validation of our recommendation approach, one of the best ways might be to obtain the assessment from real help-desk domains. Remaining that actual evaluation to our future work, we instead illustrate how our recommendation approach is processed with an example to help improve intuitive understanding of it.

Let us consider an example consisting of four clients and five HDAgents profiles, as shown in Fig. 2. Then, we can represent a set of formal definition of that domain as C = {CA, CB, CC, CD}, S = {IA, IB, IC, ID, IE}, CR={CR1, CR2, CR3}, SR = {SR1, SR2, SR3, SR4, SR5}. Now we assume that the client CA presents a new problem with the category ("printing"). To recommend an appropriate HDAgent who would handle the given problem, the following three steps are processed.

First, to compute the first weighting function $W_1(c, s_r)$, we need to know s_r seen in the client profile CA. Given example, note that there exist three HDAgents (i.e., $s \in$ {IA, IB, IC}) and whose three roles (i.e., $s_r \in$ {SR1, SR2, SR3}) that have handle the cases in the client profile CA. In this example, therefore, W_1 is calculated as follows: W_1(CA,SR1) = (0.7+0.25+0.15)/3=0.37, W_1(CA,SR2)=0.6, W_1(CA,SR3) = 0.65.

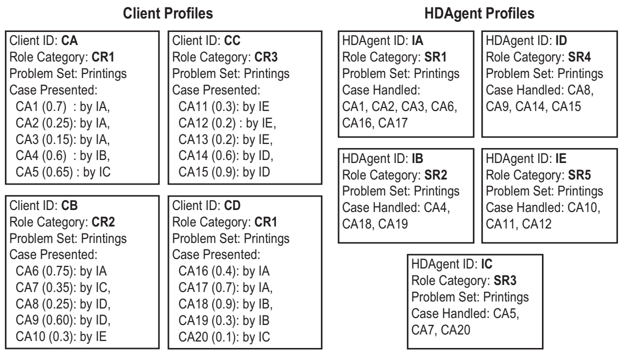


Figure 2. An example of the help-desk domain consisting of four clients and five HDAgents' profiles.

Next, to compute the second weighting function $W_2(c_r, s_r)$, we have to find a set of clients having the same role with the given client's role c_r. In this example, we can observe that there is the only one client CD that has the same role with the client CA's role CR1. Since the client CD has the cases handled by HDAgents IA, IB, and IC, W_2 is computed as: W_2(CR1,SR1) = ((0.4+0.7)/2)/1=0.55, W_2(CR1,SR2) = ((0.9+0.3)/2)/1=0.6, W_2(CR1,SR3) = (0.1/1)/1=0.1.

Lastly, the final weighting function is computed based on the linear combination of W_1 and W_2 as:

Computing the final weighting 'W':
W(CA,IA) = W_1(CA,SR1) x (1-0.35) + W_2(CR1,SR1) x 0.35 =
(0.37x0.65) + (0.55x0.35) = 0.24+0.19 = <u>0.43</u>
(τ = (0.5+0.2)/2 = 0.35)
W(CA,IB) = W_1(CA,SR2) x (1-0.125) + W_2(CR1,SR2) x 0.125 =
(0.6x0.875) + (0.6x0.125) = 0.525+0.075 = <u>0.60</u>
(τ = (0.25+0.2)/2 = 0.125)
W(CA,IC) = W_1(CA,SR3) x (1-0.125) + W_2(CR1,SR3) x 0.125 =
(0.65x0.875) + (0.1x0.125) = 0.22+0.015 = <u>0.24</u>
(τ = (0.25+0.2)/2 = 0.125)

According to that result, we recommend the HDAgent IB who has the role SR2 as the most appropriate HDAgent to handle the given problem in the example.

In order to improve an intuitive impression of the correctness of our approach, the question posed in verification used here is: "Do the recommended agent correctly ensure an appropriate agent ?" Based on this question, we explain how our approach is better than typical content-based and collaborative recommendation methods.

Let us consider a situation where we would apply content-based method with the above example, i.e., only using client CA's past experience. In this case, if the experience is regarded as a normalized summation of the appropriateness values of the cases, the HDAgent IC would be recommended due to the fact that IA=(0.7+0.25+0.15)/3=0.37, IB=0.6, and IC=0.65. But, such outcomes seem to be less confident since these are produced without considering the other client's opinions (i.e., the client CD), even if the client CD has the same role (i.e., similar problem-solving characteristics) with the client CA. Note that if we apply the same method for the client CD, the HDAgent IB will be selected. Thus, we can not guarantee that the IA is more appropriate than IB.

On the other hand, let us assume that we apply collaborative method. Since this method does not have the role information of the clients when trying to recommend, all the experiences (cases) of the clients CB, CC, CD will be taken into account. Because such clients have concerned the same type of problem (i.e., 'printing'). In this case, probably the HDAgent IA could be recommended if we regard the experience as the same notion with the content-based method by means of (IA: $(0.75+0.45+0.7)/3=0.62$, IB: $(0.9+0.3)/2=0.6$, IC: $(0.35+0.1)/2=0.225$, ID: $(0.25+0.60)/2=0.425$, IE: $(0.3+0.3+0.2+0.2)/4=0.225$). However, this outcome also seems to be inadequate since the collaborative method includes the unnecessary or irrelevant experiences of the client CB and CC who have different roles (i.e., problem-solving characteristics) with the client CA. However, in our approach, we overcome those drawbacks by only considering the clients having the same role, i.e., the client CD. Therefore, we believe that our strategy would be intuitively correct compared with those two methods by considering both of the individual/similar group opinions based on the role information of the clients.

5 RELATED WORK

Help desk systems typically leverage CBR approaches. However, they are limited in many ways as our following discussion shows: Caseadvisor [14] is a representative interactive CBR system that provides solutions for customer's problems effectively in real-time. Its recommendation is usually done interactively by working with the customer through a requirement acquisition and definition process. However, this system tries to search optimal cases using only the given problem and stored cases, ignoring additional useful information such as the knowledge of the clients and help-desk agents.

To extend the limited decision space, knowledge management-centric help desk system is introduced [8]. This system attempts to use diverse knowledge source in the organization including database, files, experts, knowledge bases, and group chat to ensure high utilization and maintenance of knowledge store. Besides, utilizing semantic representation of the decision space [2] is proposed to improve the accuracy of the similarity matching between the problem and cases. Even though, these systems try to extend a decision space by utilizing more amount of knowledge involved in the case and semantical knowledge representation, these do not consider the personalized information about the client and help-desk agent. Moreover, the problem of high dependency on the help-desk agent is not still clearly addressed in these works.

There has been also approaches for reducing the search space for similarity matching and retrieving accurate case retrieval by focusing on the representation of the case. For example, the authors in [11] partition the case into the discrimination part and shared-featured part, and then apply a hybrid reasoning approach by integrating rule-base and case-base techniques. Meanwhile, the research in [7] proposes to use an object-oriented approach to model the domain, in order to overcome very limited knowledge about the structure and semantics of the domain based on attribute-value pairs, textual representation, and question-answer. However, these still rely on the agent's personal expertise to make suitable solutions to the problems.

6 FUTURE WORK AND CONCLUSION

This paper presented a new hybrid design approach for recommending an appropriate help-desk agent to solve the given service-calls based on the user profile. The user profile consists of a three-layered combination of factual, preferential and transaction information, which can richly conceptualize the knowledge of both the client and help-desk agent in an uniform way. The main feature of the user profile is that a new concept of roles of the users was deployed using fuzzy logic based on problem-solving characteristics. Then, we described how our hybrid recommendation strategy using individual/role information of the users is designed.

In the future, we plan to evaluate our approach on real help-desk domains. Moreover, since our approach remains cold-start and sparsity problem unsolved, we will incorporate knowledge of cases into our approach to address such issues.

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Reply Sheet to Reviewers' Comments

Prepared by: YongBin Kang
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Review 1's Comments

- Comment: It is not clear whether the paper is describing a system that has already been built, or whether it presents simply a proposed design..
  - **<u>Response:</u>** The proposed system is research in progress. Some parts of our system have been implemented. This paper presents mostly a design approach.
- Comment: Real Test
  - **<u>Response</u>**: We recognize the value of evaluations on real datasets. Our current evaluations are based on synthetic data that represents real cases/scenarios. The evaluation with real data is part of the future work for this research. **Refer Page 3, Para 4.**
- Comment: The system requires a lot of data about its users (clients and HDAs). It's possible that layer 1 data could be collected for HDAs; it is unlikely it would be collected for clients: they don't want to describe themselves; they want to describe their problem. The paper should discuss whether it is realistic to expect this kind of data to be collected in a help-desk environment.
  - **<u>Response:</u>** Initially, once a user describe his/her domain-independent information using stereotypes, there is no need to describe that information again, and the other information (layer 2 and layer 3) can be unobtrusively aggregated, updated, and increased with the increase of transaction information (layer 3). Furthermore, we note that the information that is collected pertains to the role of the user within an organizational context (e.g. Finance Officer, HR dept. etc.) and typically would not be subject to the privacy concerns raised by the reviewer. **Refer Page 1-2 Para 2.**
- Comment: The layer 2 and layer 3 data is accumulated during use of the system. But this raises the usual problems we find in recommender systems: cold-start problems and sparsity problems. The paper should acknowledge these problems and explain how they will be overcome.
  - **<u>Response:</u>** Clearly the cold-start and data sparsity issues are part and parcel of such research. We acknowledge this in **Page 4, Para 6.** Addressing the issues will be also part of our future work.
- Comment: It is also unclear how the system would fit into an organization. If I phone a help desk to report a problem, then i want the first person I speak to handle the problem. I don't want to have to describe myself & the problem simply to allow the person who answers the phone to use the system to decide who to forward the call to. This irritates customers. (This is the issue that case-based support for HDAs is supposed to alleviate, and this seems to be something you have overlooked/not understood in your review of CBR.)
  - **<u>Response:</u>** We have clarified that the information analysis pertains to what happens at the system level. The user descriptions are obtained through a combination of unobtrusive techniques and well-known domain information. The system would then allocate the task to the right agent. This process is meant to be transparent to the user. We note that the information that is collected pertains to the role of the user within an organizational context (e.g. Finance Officer, HR dept. etc.) and typically would not be subject to the privacy concerns raised by the reviewer. **Refer Page 1, Para 2, Page 2, Para 2.**
  - Comment: proof-reading by a native speaker (**<u>Response</u>**: It's been done)
- The paper cites some useful sources in the research literature. This includes some CBR/help-desk work. But the CBR work is less relevant perhaps than work on expert locators.
  - **<u>Response</u>**: Most recommender systems supporting help-desk management tend to adopt the CBR methodology. But, one of the big issues in using CBR is that they rely main on cases as their main knowledge for making recommendations, and do not exploit personalized information adequately. This is one of the primary motivations for this work. Due to this fact, we believe it is important to describe the relationship between CBR and help-desk research. This point has been clarified in **Page 1, Para 1.**

Review 2's Comments

- Comment: While a recommendation task, the use-case of recommending help desk agents is quite unique and I do not clearly see how the approach may be generalized to more general use-cases (and, hence, be of use for recommender systems research as a whole). Anyhow, hybrid recommendation techniques are already quite well-investigated for recommendations in general and even though applying such a technique to the help desk domain may be new, the idea as such is not very innovative.

- Our focus is to extend the ideas to proposed in the paper with a novel context-aware, personalized recommendation process. We believe this to be both innovative and generalized – which will also have a particularly novel impact in the area of Help Desk Management. Due to the page scope, we do not remark about it in the paper.

- Comment: The authors claim to "design a new three-layered user profile" in this paper, but the model was already introduced in their references. Instead of being wholly new, the model is only adapted to the specialized domain. The adaptations should be made clearer to enable a better judgement of this paper's original contribution.
    - **Response**: Originally, the user profile model referenced in this paper is mainly designed for “capturing dynamically changing user needs” in an e-commerce application. Based on that user profile, we have newly added the dimension of a role with role characteristics and role category information. This is clarified in **Refer Page 1, Para 1**.
- Comment: Real Test
    - **Response**: We recognize the value of evaluations on real datasets. Our current evaluations are based on synthetic data that represents real cases/scenarios. The evaluation with real data is part of the future work for this research. **Refer Page 3, Para 4.**
- Comment: Some technical notes:
    - do not use "X". Use "\times" in LaTeX (**Response**: It’s been corrected)
    - There is a subsection 3.1 but no 3.2 (**Response**: This problem has been corrected)
    - proof-reading by a native speaker (**Response**: It’s been done)
    - Formula (2) seems overly complicated for what it does intuitively. I do not think that serious harm would be done if it was simply left out (**Response**: According to the comment, it is left out)
- Comment: Formatting of references:
    - Please correct references [3,5] to make author naming consistent with the others (i.e. full first names, no "by", no "1" in name) (**Response**: [3] has been left out due to page limitation and misspelling words have been corrected in terms [5])
    - [1,17] have the same main author and should be next to each other (**Response**: one of them are left out due to the page limitation)
    - Reference [19] seems to have an illegal character "&#263" (**Response**: one of them are left out due to the page limitation)

Review 3’s Comments

- Comment: Real Test
    - **Response**: We recognize the value of evaluations on real datasets. Our current evaluations are based on synthetic data that represents real cases/scenarios. The evaluation with real data is part of the future work for this research. **Refer Page 3, Para 4.**
- Comment: it is not clear why first layer (in particular features like age and education) are really necessary
    - **Response**: In fact, role characteristics should be carefully determined with the help of domain experts. Of course, age and education are not essential factors as role characteristics. However, based on our survey work in terms of help-desk management, we have found that some demographics factors (e.g., age and education, financial status, time with company, etc.) have significant effects on classifying customer groups. The main merit of our user profile is that regardless of which factors are used as role characteristics, we can successfully derive the unique roles of the clients and help-desk agents.
- Comment: In section 4 Demonstration the sentences "Since the client CD has the cases handled by the clients IA, IB" should be corrected. It seems that instead of clients IA, IB Helpdesk Agent are meant.
    - **Response**: This mistake has been corrected.