

An Experimental Approach to Reputation in E-participation

Igor Serov, Maria Leitner
AIT Austrian Institute of Technology
Digital Safety & Security Department
Vienna, Austria

Email: `firstname.lastname@ait.ac.at`

Abstract—E-participation is about ICT-supported participation of citizens in democratic processes and procedures (e.g., consultation or co-creation). Research has mostly centered on the development of tools to model and deploy ICT-supported democratic processes. So far, the integration and use of reputation has only been rarely considered even though reputation systems provide ratings that could be adapted well to the context of e-participation e.g., evaluating and rating comments and activities of users. Furthermore, reputation in e-participation can increase the trust between users (e.g., new participants) and their activities e.g., commenting or rating. In this paper, we aim to address reputation in e-participation with an overview of state of the art and an experimental reputation model for e-participation. The model measures not only the quality of comments but also the activity of users. Thereby, a certain level of assurance is enabled by users itself; they can mark unqualified posts that can be removed at a certain level. For future work, we aim to perform user acceptance tests in order to identify potential chances and pitfalls and further enhance the proposed solution.

Keywords-authentication; e-participation; reputation systems.

I. INTRODUCTION

Local, regional and national governments are increasingly engaging citizens to contribute their knowledge, expectations, wishes or requirements to public administrations. Recent developments showed that this feedback can be acquired in direct exchange with citizens (e.g., workshops) but also via information and communication technologies (ICT). Often, these electronic participation procedures are defined as electronic participation (e-participation). E-participation is about ICT-supported participation of citizens in democratic processes and procedures (see e.g., [1]). E-participation gives citizens an opportunity not only to communicate with one another and the elected government but also to make and evaluate decisions using ICT [2].

However, recent developments showed that discussions in forums (e.g., bulletin boards, comments at the end of news articles) can also be driven by “trolls” and others leading to negative postings on the Internet (e.g., insults, defamation or malicious gossip). That’s why in particular discussion-based platforms prepare to diminish negative postings and enable equal and fair participation. This signifies providing measures to encourage high-quality postings, enable trust and prevent discrimination. For example, implementing a reputation system is one approach to enable trust between participants.

The system measures users by their activities and quality of comments and thereby increasing the trust and online participation.

Reputation systems are currently widely used in e.g., e-commerce or e-banking (see [3]). Here, users can rate products and services by their experience that can support new customers in the community making decisions (e.g., buying product A or B) [3], [4]. Typical systems use a star schema (e.g., Ebay or Amazon) to display the level of e.g., experienced users or trusted sellers. Scalability, quality and engagement are typical challenges for reputation systems (see e.g., [5]).

In this paper, we describe a reputation system for e-participation. We suggest a system that can discriminate users according to their authentication method and activities in the system. This is in accordance with previous research on how to establish security and privacy in the domain of e-participation (see [6]). The idea is to provide reputation indices for e.g., users, ideas or comments in order to identify qualified from potential unqualified ideas and to increase the trust in the online discussions. As reputation systems have been widely used in various domains such as e-commerce, it is surprising that reputation systems have not been adapted for online participations. For example, reputation systems could be in the context of e-participation such as for evaluating and rating comments and activities of users.

For future work, we plan to integrate the reputation model into an e-participation platform. Furthermore, we will identify potential chances and drawbacks with further evaluation and tests in user studies and acceptance tests.

The rest of the paper is structured as follows: Section II will provide an overview of current state of the art on reputation systems and e-participation. Section III describes the requirements for reputation in e-participation. Section IV specifies the reputation model. The algorithmic implementation is shown in Section V and demonstrated by examples in Section VI. Section VII concludes the paper.

II. BACKGROUND

A. Reputation & Trust

The concepts of reputation and trust are very close despite that they have different meanings. A lot of definitions for trust exist, for example by [7], “Trust is a particular level of the subjective probability with which an agent assesses that

TABLE I
DEFINITIONS OF REPUTATION (SELECTION)

Ref.	Definition
[8]	A reputation is an expectation about an agents behavior based on information about or observations of its past behavior.
[4]	Reputation is that is generally said or believed about a persons or things character or standing.
[9]	Is the opinion of the public toward a person, a group of people, an organization, or a resource.
[5]	Information used to make a value judgment about an object or person.

another agent or group of agents will perform a particular action". The definition of reputation is closely associated to trust and several definitions exist. A set of (related) definitions is shown in Table I.

It can be seen from the definitions in Table I that reputation can be earned or lost through actions (and further related incentives or sanctions) and that reputation can be measured on a scale of trustworthiness. The difference between trust and reputation is that trust can be based on reputation. A person with better reputation can be more trustworthy [4]. Based on these definitions, we aim to address reputation systems in the next section.

B. Reputation systems

The rapid development of ICT enabled the creation of social media platforms that usually emphasize on user-generated content (e.g., ideas or comments). These popularity brings new challenges and complexities not only for users but also for operators. These challenges are defined by [5] as:

- *Problems of scale*: Nowadays more and more people are using the Internet and that is why it is more difficult for website operators to control and manage millions of user contributions.
- *Problems of quality*: How to identify and distinguish between good and bad actions.
- *Problems of engagement*: How to reward the user contributions for increasing users' motivation and encouragement.
- *Problems of moderation*: Because of the huge amount of content, it is difficult to detect bad content fast and efficient and protect good from malicious users only with the support of moderators.

Reputation systems can be used as an approach to tackle these challenges. A reputation system according to [3] is "an electronic system that enables users to rate products, services, sellers, suppliers and people based on their experience". The main goals of reputation systems are to evaluate users activities and to assist to establish trust between unfamiliar users. As reputation systems have been investigated intensively, various reputation models and algorithms appeared that can be used for rating or evaluating users. A selection of approaches for reputation systems is listed in the following:

- **Counting Systems** base on different counters, average score, content reviewing and commenting, user's karma

and abuse scoring. Most known examples are e.g., Ebay, Amazon (see [5], [4]).

- **Flow-based Reputation Models** use Markov chains as the mathematical foundation. Reputation is calculated iteratively and bases on chains. The most known flow-based model is the PageRank algorithm from Google (see [10]).
- **Probabilistic (Binomial Bayesian) Systems** take binary ratings (positive and negative) as input and calculate reputation value based on a beta probability density function (PDF), see e.g. [4].
- **Belief Models** are based on the concept of transitive trust [11]. For example, userA trusts userB, userB trusts userC and by transitivity userA trusts userC.
- **Real-life Rating Algorithms** base on the level of user's expertise and on the level of user friendship and can be adapted to expertise collections. Every resource is ranked by Bayesian weighted rate, which based on Bayesian average, see e.g. [12].

An online reputation system can be manipulated with different types of attacks, such as whitewashing attacks, traitor attacks or self-promoted attacks (see [9], [13]). That is why it is important to develop a confident and reliable system. Recommendations and requirements for developing a correct and secure system are described in e.g., [3] and [14].

III. REPUTATION IN E-PARTICIPATION

As there are huge differences between offline and online environments it is important to find adequate substitutes for online trust and reputation and create an efficient system to support decision making and to improve the quality of online e-participation platforms. Reputation can be used for different tasks such as: identification of abusers from good users, spam filtration, provision more target-oriented advertising campaigns [4].

E-participation platforms enable sometimes the registration of users or require the proof of identity (see [15], [16]). Often, organizers of e-participation procedures want to encourage participants and thereby keeping the authentication methods minimalistic (from no authentication at all to social media). However, a low authentication might not be effective when it comes to other participatory processes such as decision making processes or co-creation where a proof of identity is required. For example, abusers could easily register and try to manipulate the decision making process (push forward harmful initiatives, bother decision making process, spamming and so on).

For preventing these actions, a reputation system can be developed that helps to identify good and malicious users, to further increase quality of comments and to motivate participants. Also reputation systems provide users an opportunity to detect and fight against spam and harmful users themselves. For example, it decreases time for removing bad content [5].

- Reputation in e-participation can be used in various ways
- to identify potential bad from good behavior in order to detect unqualified text (as in typical reputation systems)

- use as a authentication method in order to use a platform (e.g., with social networks: a friendA identifies a friendB)

So far, only in [17], [18], a reputation system is described and visualized for e-participation. In the platform, users can perform different activities e.g., posting, linking, commenting, liking or disliking and rating. The calculation mechanism based on all users' activities and works in a dynamic way. It means that users' total score depends not only their activities but also depends on other users score level. Also there is a game aspect in the platform. Users earn points for the activities to get a new level, which gives users more influence over the system and motivates them to participate more actively.

Based on this overview, we aim to specify the requirements for e-participation in our model.

A. Requirements

In our approach, the e-participation platform [19], [20] supports various **(1) participation levels** and **(2) authentication levels**. With (1), the platform enables different levels of participation such as information, consultation, co-operation and co-decision. At the different levels of participation, the platform enables users to perform a wide range of activities such as posting new ideas, commenting, rating content (like or dislike) and voting for ideas. With (2), the platform supports different authentication methods for participants (adequate for the level of participation). The platform provides different authentication methods that are assigned to a level of assurance (LoA). Every supported authentication method was categorized into a certain LoA. For example, no authentication (LoA 0), social IDs (LoA 1) or state-based eIDs (LoA 4).

Based on this foundation, we aim to develop a reputation model that

- provides a start karma for reputation depending on the used authentication method (i.e. LoA)
- measures and evaluates users' activities and identifies good and bad behavior.
- gives users an opportunity to act against spam and trolls.
- separates the reputation scores of (new) ideas and comments (i.e. a reaction of the idea; the discussion).
- motivates participation by providing understandable criteria and transparency
- provides visibility of reputation ratings

In the next section, we will use these requirements as input for the development of the model.

IV. REPUTATION MODEL

From the different reputation systems (see Section II), we've selected to use a modified counting system. The belief models and real-life algorithms use information about friendship relations that is typically not available in e-participation platforms. Probabilistic methods which are based on beta PDF estimate the probability of a success/failure of transactions and are therefore not suitable for e-participation. In the rest of the section, we describe our reputation model for e-participation.

TABLE II
LIST OF ACTIVITY POINTS

Activity	Variable	Values used in Sect. VI
Post an idea	<i>ideaConst</i>	10
Make a comment	<i>comConst</i>	3
Vote	<i>voteConst</i>	5
Like	<i>likeConst</i>	1
Dislike	<i>dislConst</i>	1

TABLE III
START KARMA VALUES

LoA	<i>SK</i>	Start <i>ARK</i>
1	100	10
2	150	20
3	200	30
4	300	40

A. Reputation parameters for users

The reputation model contains different parameters. This section provides a quick overview on all parameters.

- 1) *Start Karma (SK)* specifies a value for the authentication method used and is a start value for the user.
- 2) *Abuse Reporter Karma (ARK)* defines the value of abuse reports a user makes to help against spam and abusive content.
- 3) *Idea Rating (IR)* specifies a rating for ideas; i.e. how users like, dislike or make a comment. These ratings are estimated based on the users' *ACK*. *IR* can be specified within a range from *minComPoint* to *maxComPoint*.
- 4) *Comment Rating (CR)* defines a rating for a comment (including likes, dislikes, and further comments). These ratings are calculated based on the users' *ACK* and *CR* can range between 0 to *maxIdeaPoint*.
- 5) *Average Karma (AK)* is the sum of *AIK* and *ACK*.
- 6) *Average Idea Karma (AIK)* estimates the quality of posted ideas of a user.
- 7) *Average Comment Karma (ACK)* estimates the quality of made comments of a user.
- 8) *Total Idea Rating (TIR)* is the sum of all idea ratings of a user.
- 9) *Total Comment Rating (TCR)* is the sum of all comment ratings of a user.
- 10) *Activity Points (AP)* estimate and specify the number of activities (e.g., posting an idea, making a comment and liking) that a user performs as shown in Table II. A user does not get extra activity points if he/she likes/dislikes his/her own ideas/comments.
- 11) *Total Karma (TK)* is the sum of *SK*, *TCR*, *TIR* and *AP*.

B. Detailed Parameters

1) *Start Karma*: Start karma (*SK*) is estimated based on the users authentication method. In Table III, the start values for *SK* are specified. They are based on the LoA of the authentication method (see Section III-A).

2) *Abuse Reporter Karma*: One of the possible solution against spam and abusive content is to give users an ability to fight against spam content themselves as described in [5]. Users, the abuse reporters, can mark posts that violated the terms of service as “abuse”. In the model, we specify *ARK* as **abuse reporter karma** (ARK). For new users, *ARK* depends on the authentication method like *SK*; its starting values are displayed in Table III.

After the abuse report, the post c increases its index (ind_c) by the *ARK* of the abuse reporter. The idea is that not only one single mark automatically leads to the deletion of the post but several reports. As the user’s *ARK* can be within the range of $[10; 100]$, how fast content c is deleted depends on the *ARK* value of the reporter. Equation 1 specifies that if the index is more than 100, it will be deleted.

$$ind_c = \sum_{0 < i <= n} ARK_{user_i} > 100 \text{ then delete content } c \quad (1)$$

For reporting a unqualified post, the *ARK* will be increased by 10 as shown in Formula 2.

$$ARK_{user_i} = ARK_{user_i} + 10 : i = 1, \dots, n \quad (2)$$

As a result of the removal of content, the author of the content is penalized. In Equation 3, the authors *IR* and *CR* is decreased.

$$\begin{cases} IR_c = -2 * maxIdeaPoint, \text{ if } c \text{ is an idea} \\ CR_c = -2 * maxComPoint, \text{ if } c \text{ is a comment} \end{cases} \quad (3)$$

Note that if the author disagree, he/she can write the administrator/ moderator to check the removed content. This is not included in the model but within the e-participation platform.

3) *Idea Rating*: Idea rating specifies a value to measure the quality of the idea. Posting a new idea gives the user *ideaConst* points and he/she can get extra points from positive and negative ratings: such as commenting, liking and disliking. The quality of each idea depends on these ratings as shown in Equation 4. A user can get between $[0; maxIdeaPoint]$ points for posting an idea.

$$IR_i = irc_1 * \sum_{j=1}^{N1} ACK_j[Comment_i] + irc_2 * \sum_{j=1}^{N2} AK_j[Like_i] - irc_3 * \sum_{j=1}^{N3} AK_j[Disl_i] \quad (4)$$

The irc_1, irc_2, irc_3 are weights. Every constant has a different weight, their sum equals 2. In our later examples, irc_1 has much more weight than irc_2 and irc_3 as it takes more to comment a post than to just “like” them. The *IR* for an idea i is the sum of *ACK* from users $[1; N1]$ that made comments, the sum of users’ average karma (*AK*) from users $[1; N2]$ that like the idea i , and the sum of users’ *AK* from users $[1; N3]$ that dislike the idea i . If a user deletes the idea, all points for the idea (*ideaConst* points for creation and all extra points) will be removed.

4) *Comment Rating*: Comment rating specifies a value to measure the quality of a comment. While an idea is always the root element of a thread that consists of multiple comments. A comment cannot be the root in our model. In our model, making a new comment gives the user *comConst* points and the user can get extra points from positive and negative ratings. The quality of each comment depends on positive and negative ratings (ie. likes and dislikes).

$$CR_i = crc_1 * \sum_{j=1}^{N1} AK_j[Like_i] - crc_2 * \sum_{j=1}^{N2} AK_j[Disl_i] \quad (5)$$

The crc_1, crc_2 are weights and their sum equals 2. The user can get $[minComPoint; maxComPoint]$ points for each comment and is very similar to the *IR*.

5) *Average Karma*: Average karma (*AK*) depends on user’s quality of contribution. It takes a different value ranging from 0 to 3 and can be calculated as sum of Average Idea Karma (*AIK*) and Average Comment Karma (*ACK*):

$$AK = AIK + ACK \quad (6)$$

Average idea karma (*AIK*) measures the average idea quality and has a value ranging from 0 to 2 (see Equation 7).

$$AIK = \begin{cases} \frac{\sum_{i=1}^N (IR_i)}{0.5 * maxIdeaPoint * (N+1)} + 0.7 * \frac{1}{N+1}, \text{ for } \sum_{i=1}^N (IR_i) > 0 \\ 0.7 * \frac{1}{N+1}, \text{ for } \sum_{i=1}^N (IR_i) = < 0 \end{cases} \quad (7)$$

Where N is total amount of user’s ideas. If a user posts only few ideas (in this case about one) the value of *AIK* will approach the default value (0.7).

Average comment karma (*ACK*) measures the comment quality and its value is ranging from 0 to 1 and is specified as follows:

$$ACK = \begin{cases} \frac{\sum_{i=1}^N (CR_i)}{maxComPoint * (N+3)} + 0.5 * \frac{3}{N+3}, \text{ for } \sum_{i=1}^N (CR_i) > 0 \\ 0.5 * \frac{3}{N+3}, \text{ for } \sum_{i=1}^N (CR_i) = < 0 \end{cases} \quad (8)$$

Where N is total amount of user’s comments. If an user has few comments, *ACK* value will approach the default value (0.5). If the sum of all user’s *CR* less then 0, *ACK* will converge to zero.

6) *Total Karma*: **Total idea rating** (*TIR*) is the sum of all idea ratings of a user $TIR = \sum_i IR_i$. **Total comment rating** (*TCR*) is sum of all comment ratings of a user $TCR = \sum_i CR_i$. In addition to the total ratings, **Activity Points** (*AP*) are provided to measure the behavior of users and to provide incentives for activity and participation. Therefore, *AP* is a sum of all user’s activities but includes a cooling factor for inactive phases. In Equation 9: C is cooling rate and D is number of days since an activity was made.

$$AP = ideaConst * \sum_i Idea_i * e^{-C * D_i} + comConst * \sum_i Com_i * e^{-C * D_i} + likeConst * \sum_i Like_i * e^{-C * D_i} + voteConst * \sum_i Vote_i * e^{-C * D_i} + dislConst * \sum_i Disl_i * e^{-C * D_i} \quad (9)$$

Finally, the **Total karma** (TK) combines measurements for quality of ideas and comments including likes and dislikes (TIR, TCR), for the used authentication method of the user (SK) and the activity behavior of the user (AP). TK is the sum of SK, TIR, TCR and AP . The value of TK is limited to the interval $[0,1000]$.

$$TK = SK + TIR + TCR + AP \quad (10)$$

V. ALGORITHMS

This section provides two example algorithms for the reputation model. Please note that due to page limitations we can only describe several functions. Algorithm 1 specifies the estimation of the IR (see Section IV-B3). Idea Rating is calculated as the sum of production of the users' AK and ACK (their values is saved in array $getAllRatings$ as $ExtPoints$) and the constants irc_1, irc_2 and irc_3 . The algorithm for CR will be similar to the algorithm of IR .

Algorithm 1: Calculation of Idea Rating

```

Input: An Idea idea
Output: value of the Idea Rating rating
1 rating  $\leftarrow$  0;
2 foreach elem idea.getAllRatings() do
3   switch elem type do
4     case is type of Comment do
5       rating  $\leftarrow$  rating + irc1 * elem.ExtPoints();
6       break;
7     case is type of Like do
8       rating  $\leftarrow$  rating + irc2 * elem.ExtPoints();
9       break;
10    end
11    case is type of Dislike do
12      rating  $\leftarrow$  rating - irc3 * elem.ExtPoints();
13      break;
14    end
15  end
16 end
17 return rating

```

Algorithm 2 estimates the AP per user by summarizing the activities a user performs on a platform (see Section IV-B6). In addition, the intensity of the activities AP will be reduced by introducing a cooling factor ($coolingFact$). The factor is estimated on a cooling rate C and the number of days since the activity was performed ($numOfDays$). The AP will therefore decrease if users are not active on a regular basis.

VI. DEMONSTRATION

In this section, we display two examples to demonstrate our proposed model. The scores used for the example are shown in Table II. In the examples, the value of $maxIdeaPoint$ is 20, $minComPoint$ is -10 , $maxComPoint$ is 10, irc_1 is 1.3, irc_2 is 0.4, irc_3 is 0.3, crc_1 is 1.4 and crc_2 is 0.6.

a) **Example 1: User authentication and several user activities:** In the first example, $User\ T$ is authenticated with a Facebook account (LoA 1) as shown in Section III-A. The start values are: $SK = 100$; $ARK=10$; $ACK = 0.5$; $AIK = 0.7$; $AK = 1.2$; $TCR = 0$; $TIR = 0$; $AP = 0$

Algorithm 2: Calculation of Activity Points per User

```

Input: An User user
Output: sum of all activity points sum
1 sum  $\leftarrow$  0;
2 foreach act in user.getAllActivities() do
3   coolingFact  $\leftarrow$   $e^{-C*act.numOfDays()}$ ;
4   switch activity type do
5     case is type of Comment do
6       sum  $\leftarrow$  sum + comConst * coolingFact;
7       break;
8     case is type of Like do
9       sum  $\leftarrow$  sum + likeConst * coolingFact;
10      break;
11    end
12    case is type of Dislike do
13      sum  $\leftarrow$  sum + dislConst * coolingFact;
14      break;
15    end
16    case is type of Idea do
17      sum  $\leftarrow$  sum + ideaConst * coolingFact;
18      break;
19    end
20    case is type of Vote do
21      sum  $\leftarrow$  sum + voteConst * coolingFact;
22      break;
23    end
24  end
25 end
26 return sum

```

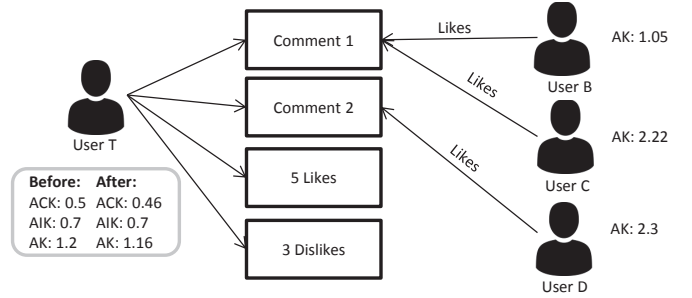


Fig. 1. Example 1: Authentication and user activities

and $TK = 100$. In this example, $User\ T$ makes 2 comments, 5 likes and 3 dislikes on various ideas on the first day of registration. This activities are shown in Figure 1. $Comment\ 1$ receives immediately two likes from users B ($AK = 1.05$) and C ($AK = 2.22$) and one like for $Comment\ 2$ from user D ($AK = 2.3$).

After the comments and likes by the other users, the parameters of the $User\ T$ are recalculated. $User\ T$ receives for $Comment\ 1$ $CR_1 = 4.58$ and for $Comment\ 2$ $CR_2 = 3.22$ new comment rating values. The ACK is reestimated to be $ACK = 0.46$ and $user\ T$ gets activity points: $AP = 14$. In Table IV, it is shown how AP and TK of $user\ T$ change over time with a cooling factor $c = 0.05$. The idea is that AP measures the level of activity. However, if a user is not active, AP decreases over time. You can see that the AP is decreasing, converging to zero and in 186 days it is approximately 0.

b) **Example 2: New user posts an idea:** In the second example, a new user posts an idea. We will show how

TABLE IV
EXAMPLE 1: TK AND AP VALUES OVER TIME

Time	AP Value	TK Value
On the first day	14.00	121.80
After 7 days	9.87	117.67
After 31 days	2.97	110.77
After 186 days	0.001	107.801
After 365 days	0.00	107.80

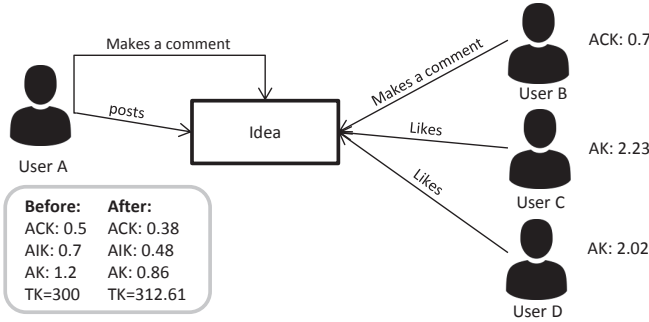


Fig. 2. Example 2: User A posts an idea

parameters change by a single activity. This is important as studies show that users often only perform a few single actions rather than a lot of actions. It can be seen that model prevents self-promoting attacks: a user does not get extra points for liking or disliking or commenting his own ideas or comments.

In Figure 2, user A is authenticated by a method with LoA 4 ($SK = 300$) and posts a new idea. User B and A comments the idea, user C and D like the post. User A gets activity points ($AP = 10$) and points for the idea ($IR = 2.61$). But User A does not get activity points for the comment and his comment has no influence on idea rating. CR for the comment of user A is equal to 0. AIK , ACK and AK will be recalculated: $AIK = 0.48$, $ACK = 0.38$ and $AK = ACK + AIK = 0.48 + 0.38 = 0.86$. TK of user A will be recalculated: $TK = 312.61$.

VII. CONCLUSION AND OUTLOOK

While reputation systems are widely adopted in e.g., e-commerce, they are rarely used in e-participation. This paper proposed a reputation model for e-participation. With this model, we aim to define reputation for users based on their activities (e.g., presenting an idea or making a comment) and authentication method. For example, the user's karma (i.e. total karma) depends on user's activity and the reaction/feedback of other users' activities e.g., commenting, suggesting an idea, (dis-)liking or voting. With this model, we aim to establish reputation of users and in the long run increase trust between participants. The reputation model will be integrated into our e-participation platform. For future work, we will identify potential chances and drawbacks with further evaluation and tests in user studies and acceptance tests.

ACKNOWLEDGMENTS

This work is part of the project eParticipation (845507) and is funded by the Austrian security research programme KIRAS and the Federal Ministry for Transport, Innovation and Technology (bmvit).

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