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Predicting the security threats of internet rumors and spread of false information based on sociological principle

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ABSTRACT

With the fast-growing IoT, regular connectivity through a range of heterogeneous intelligent devices across the Social Online Networks (SON) is feasible and effective to analyze sociological principles. Therefore, Increased user contributions, including web posts, videos and reviews slowly impact the lives of people in the recent past, which triggers volatile knowledge dissemination and undermine protection through gossip dissemination, disinformation, and offensive online debate. Based on the early diffusion status, the goal of this research is to forecast the popularity of online content reliably in the future. Though conventional prediction models are focused primarily on the discovery or integration of a network functionality into a changing time mechanism has been considered as unresolved issues and it has been resolved using Predicting The Security Threats of Internet Rumors (PSTIR) and Spread of False Information Based On Sociological (SFIBS) model with sociology concept. In this paper, the proportion of trustworthy Facebook fans who post regularly in early and future popularity has been analyzed linearly using PSTIR and SFIBS methods. Facebook statistics remind us that mainstream fatigue is an important prediction principle and The mainstream fatigue principle, Besides, it shows the effectiveness of the PSTIR and SFIBS based on experimental study.

1. “Internet of things” and “Social networks”

The integration of the “Internet of Things” and the “Social Networks” has been feasible in recent years, and steadily several cool devices are being linked to social networks. There is a growing array of online sites that gathered thousands of users. Presently, Facebook, is one of the world's biggest internet media networks, had about 1 trillion subscribers by 2019, spanning natural scientists, celebrity groups, policy departments and a variety of regular consumer web sites, which also receive public interest through real-time tweets.

Facebook is a social network which has been incredibly significant with big data exchange that enables exposure via intelligent devices in real-time approaches as per the size of its users and its method of contact, Facebook has been used to the Internet as a map of human culture. In [1], through the freedom to upload and accept content, people can openly share their opinions, and all forms of topics have been shared at any given moment, risking the spread of misinformation, misleading facts, and inappropriate online contact. In [2], the advancement of a message is going to burst which has great usefulness in preventing rumors. In [3], the visibility of messages on the famous website will enable people more quickly to catch hot events and make marketers more effective in optimizing their income. In [4], the question of forecasts of popularity is primarily attributed to the unequal phénomene of statistical distribution, which is defined as income distribution, population distribution, and friends distribution via online repositories. In [5] Data shown that most web material does not have a limited proportion gained for significant interest from consumers. The unequal distribution was due to the popular' Pareto theory,' on the Italian economist Vilfredo Pareto, in which 20% of the population compensated for 80% of the collective property. In [6] Over the last couple of years, scientists have worked on enhancing prediction performance.

In [7] the Internet age, written on Nature as a paper has been discovered that most complicated networks such as the Performer Collaboration System, World Wide Web, and Power have been spread according to the Power-Law Index $2 < \infty < 3$. In [8] During the age of

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the online social network, 25% of the maximum popular videos on YouTube caught almost 78% of the users, whereas the other 88% only received 20%. In [9] The key task of the social network success forecasting is to foresee in the future, based on analyses of the initial spread method according to the success of user-created material.

In [10] The key social network popularity forecast is to forecast the success of potential user-produced content based on the initial spreading process. However, a precise answer is quite hard to achieve. In [11] Due to several reasons, including network topology, community behaviors, and material, the diffusion of knowledge has been analyzed. In recent years, scholars have sought to increase the precision of the forecast and In [12] approaches never take into consideration based on sociological analysis, which results in a poor precision of forecasts. In [13]authors, posed the common fatigue hypothesis in this article using the role of estimation of popularity. In [14] expand the SH model (Szabo and Huberman) with the addition of a large fatigue hypothesis, which demonstrates a strong linear Facebook association. In [15] The current approach is called the Mainstream Fatigue Theory (MFL) approach has been used which lists the major contributions based on strong statistical association that occurs between the percentage of operators with regular shares early on and success in the future [15–17]. In [18] This paper offers a stronger way of estimating the frequency of exhaustion. In [19] Facebook studies confirm that the precision of our theoretical model in a long-term success forecast relative to other methods. Researchers made considerable efforts in current studies to the question of estimation and performed an exhaustive study. Most strategies may be classified into three groups depending on the condition of the system, regression and time series. In [20] The group-state approach primarily separates social networks into many states and simulates State transition processes to examine the pattern of popularity evolution. Researchers in [21] used model viral diseases to research the dissemination of Twitter posts, believe that their followers are vulnerable to new nodes in the social network that are tainted the overall amount. In [22] Authors, Improved the conventional twitter message model, the prevalence of blog propagation was calculated to match the power trend and the user's interest showed periodic shifts, and a complex infection risk prediction model was proposed based on a conventional twitter model, considering the impact of topological features on dissemination and proposing Internet rumors. In [23] Regression approaches are typically used to identify key influence factors in the knowledge distribution cycle and to examine the correlation between these factors, popularity and to turn the prediction challenge into the question of classification or regression. In [24] discovering the success of early and future reveals a clear linear association to the logarithm, which forecast late hotness to discover the web video pages, the TV series ' success was related to the historical edition. However, over time, the proportion of random audiences is rising.

In [25, 26] developed the standard regression model based on this result. The SH model improved, taking account of the relation density and depth of the forecast model. In [27] beginning was linked for the finale and introduced a linear regression. He studied hot subjects from a temporary viewpoint on online social networks and introduced an average model for self regression to estimate the number of messages. Next, the principle of diffusion acceleration was implemented and coupled with early success, the multiple regression model to calculate the number of microblogger shares was developed. [28] The time series-based approaches believe that the distribution of knowledge in web material is constant and predicts the potential phenomenon on the quantitative sequence in time points that found throughout history, the time series on YouTube of five million videos have been evaluated and 90% of the videos can be precisely expressed through the Poisson cycle. In [29, 30] took into consideration the importance and popularity in Digg's democratic cycle and introduced a time series model for the final vote counts. It proposed a method of estimation of exogenous images and In [31] authors proposed a system focused on a time series to increase the precision of the short-term estimation of a burst occurrence, splitting the propagative cycle into four stages. In [32-35] Throughout the suggested Poisson improved approach, the decline phase of knowledge transmission was based on the priority relation system. Based on the above discussion and survey, Predicting The Security Threats of Internet Rumors (PSTIR) and Spread of False Information Based On Sociological (SFIBS) model with sociology concept has been discussed as follows,

2. Hyper-Massive online social network such as facebook

The above approaches allowed an effect to forecast success, the predictive precision still needs to be enhanced for the social network on hyper-massive online such as Facebook. The community state approach primarily utilizes the mathematical model to replicate the knowledge diffusion mechanism from a microscopic viewpoint, Here, the node in homage and the likelihood of state transition in the model are too idealized which has been extended to approximate the degree of spread using fixed network topology. Time-series approaches use appropriate features to identify patterns in popularity based on the real-time positive impact related to short-term activities, however, the accumulation may contribute to a gradual decline in accuracy for the long-term forecast. The regression approach attempts to create a future popularity mapping relationship that has been important to derive the features from the acceptance growth, which is ideal predictions.

Hence, this paper has been allowed a detailed study of the Facebook message system and suggest a popularity prediction model based on regression analysis, which incorporates the' bigger exhaustion hypothesis' throughout sociology as a core function of a relation power regression equation and forecasts the ultimate success of the combined messages. The experience indicates, in contrast with other primary models, that this proposed approach can help enhance predictive efficiency.

Popularity in this article refers to the number of shares created on the Facebook homepage below the post. The overall success of web material is expected as shown in Fig. 1 where the most famous Facebook hun-dreds homepage to forecast the importance of messages created by users. Based on evidence from early observations the purpose of the advertising calculation is to obtain a reliable outcome for the web material over some time observation, who posted on every Facebook homepage. According to the material m, describe U_0 for its release date, predict Tref date and reference time. The estimated period differs when the message comes out on U_0 and success is increasing over period and visibility becomes nearly equal as the duration reaches the life span. $U_0 < U_{reference} < U_{Predict}$ should generally describe the moment when the message m receives the response as you do and The diffusion cycle to the $U_{reference}$ can be defined as u_n^l where $l \propto (0,\ o_n)$ allows sharing the message m during the maximum training period (0, $U_{reference}$). Based on the strategies the assumption of problem which has been shown below,

3. Assumption of problem

This Research explores how to forecast the success of Facebook website material, where people will update, support, and post messages. Based on the data from early observations, the goal of the popularity forecast is based on the effective outcome of the online content and The post at the time of the report with every message published on every Facebook homepage.

Let us considered the content "m" as described with release duration as U_0, with the Time estimation and $U_{reference}$ time. Based on the estimated time the U_0 factor represents the Visibility of the message over the moment and described the life cycle awareness about the factor, $U_0 < U_{reference} < U_{Predict}$. Therefore, determine which message n should be exchanged as long as possible and The diffusion cycle up to the $U_{reference}$can be described as u_n^l, $l \propto (0,\ o_n)$, Here nm is the share factor of the message n during the entire period of the training (0, $U_{reference}$).

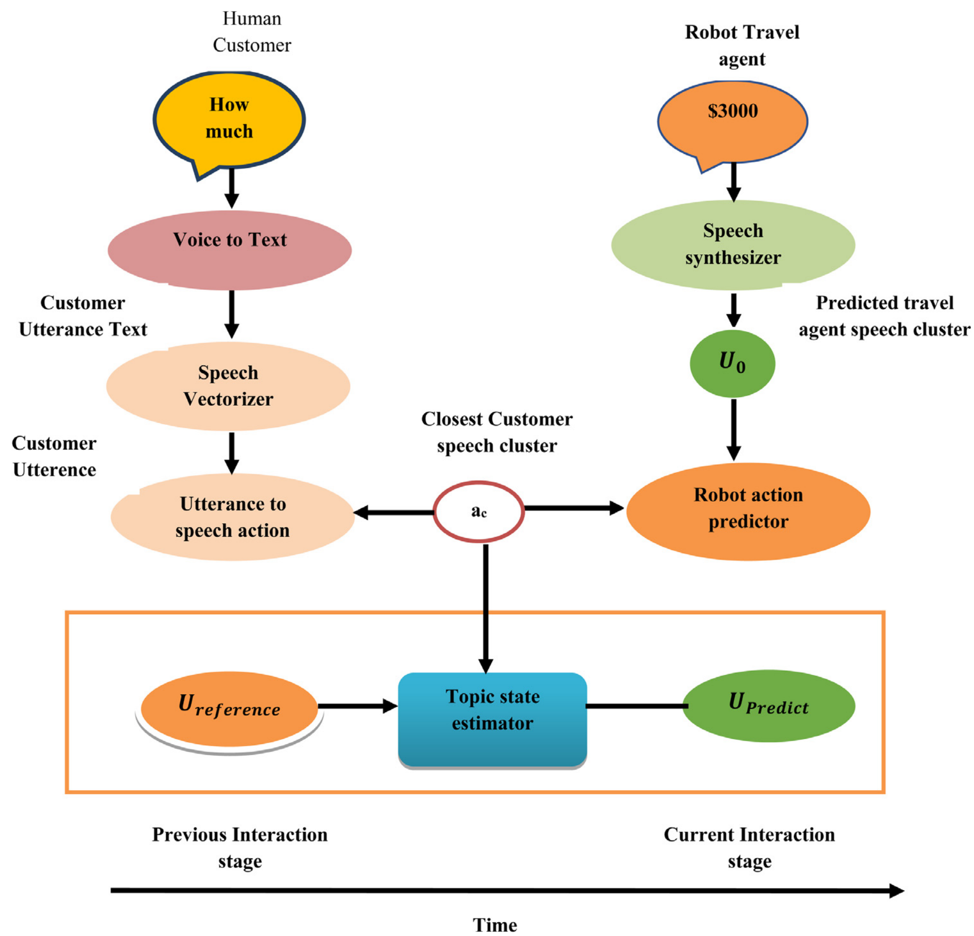

Fig 1. forecast the success of Facebook website material.

4. Facebook life cycle content

Based on the mathematical proof, significant function in this segment contains User interaction that calculates user engagement level for content sharing. Further, The total amount of messages written by the consumer in an hour has less time than the consumer stays. Fig 2 shows the app activity At different times, where the user behavior varies greatly, and throughout the day the operation of the device becomes even greater than at midnight. The survey shows that The highest usage period is around 4 a.m and The lowest consumer frequency is around 12 noon and 3 to 7 p.m. which is the most common period according to consumer preferences and other rules. Therefore, its release date would influence the success of online content and the web material becomes less valuable over time, and success rate becomes gradual over time, Further, a certain amount of time becomes roughly constant, For starters, where the content at Digg spreads quickly to 80% of its overall circulation in just 24 h, whereas videos in YouTube propagate comparatively sluggishly and can only achieve 50 percent of the ultimate share in 7 days.

In this paper, a one-dimensional matrix idea of relative action has been proposed, which displays the relative level of operation of users at the time of 24 h. The measurement method can be defined as follows: first, measure the mean n / i for every message in the data set of computing the total $T[j]$ of the jth hour as shown in the Eq (1),

$$T'[j] = \frac{T[j]}{N} \tag{1}$$

As for Facebook's lifecycle as shown in Fig. 1. The theoretical model then uses "day" as a period metric for overall success. To predict the final popularity the prediction factor has accurately set for 10-days estimation. Moreover, in the first 13 h after the message's publication, consumer sharing activity is more intense and $U_{reference}$ is set to 4 h dependent on physical period considerations.

5. Principle of fatigue mainstream

In this method,] a sociological fatigue hypothesis "focused on the traditional "weak relations"' theory. The low connection hypothesis suggested on American sociologist Mark may be a linear mixture of emotional power, confidence, and relationships. Centered on this conventional model, poor ties drive the widespread distribution of knowledge. The topological framework of social networks consisting of pleasant ties which illustrates what the social features are at the macro stage.

It has been found that poor Facebook interaction has a significant effect on data dissemination. Nevertheless, the socially immersive graph demonstrates the distribution of knowledge, the name of the individuals who do not normally exchange material common connect nodes in the contact graph.

As for common news, the dissemination of knowledge often involves multiple non-mainstream nodes. Furthermore, the name of the people who often connect and always exchange faithful fans of contents consisting of specific nodes. Centered on the contact node, a term is introduced that quantifies the frequency of user exchange communications, utilizing the mainstream fatigue parameter g. The meaning is that user k relative exchange frequency on homepage l and the type f is the mainstream fatigue parameters of k.

$$g = \frac{d_{kl}}{\sum_{k-1}^{nl} d_{kl}} \tag{2}$$

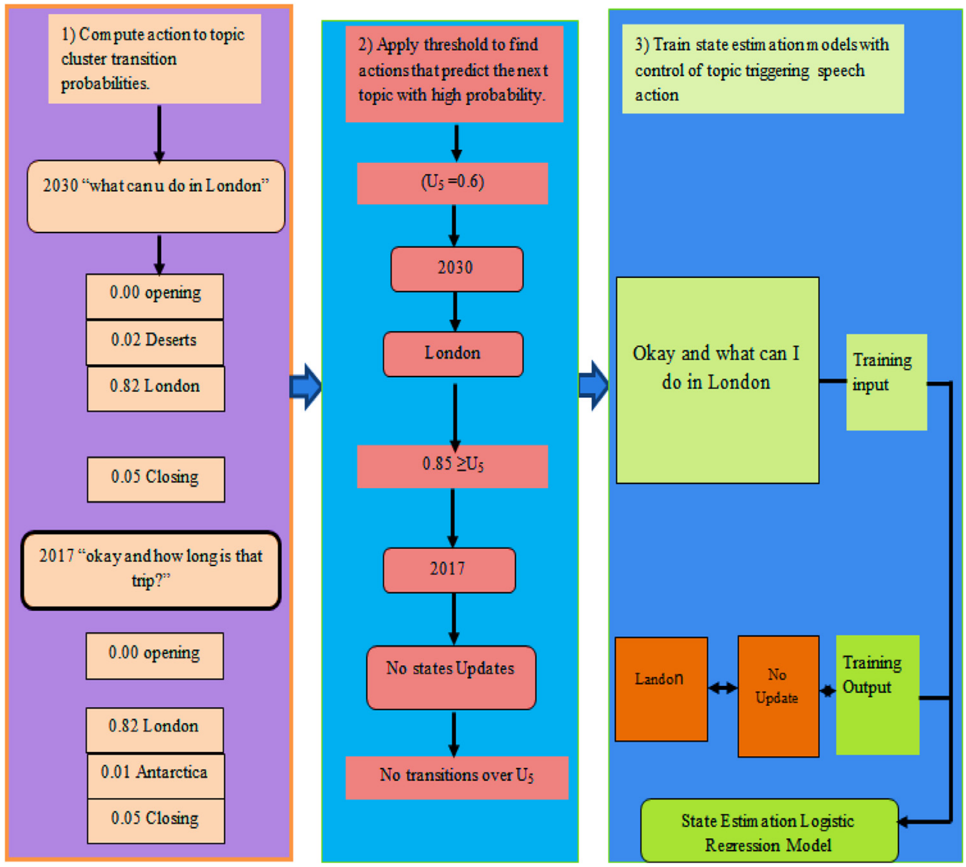

Fig 2. Principle of Fatigue Mainstream.

As shown in the Eq(2), Where d_{kl} is the user frequency k exchange homepage l, nl is the amount of all users who have broken a homepage l message at least once, and g is user k's connection power on the homepage l. It is observed in numerous studies, that the lesser portion of faithful fans participating early on, would spread, under the assumption of a certain amount of shares use them as a guide, by choosing the number of items viewed on the same web address as shown in Fig 2. There is a strong longitudinal association in dual logarithmic co-ordinate systems (blue solid line) between early and final share popularity. This shows that if the material will be universal, it must not be restricted to a small culture in the early stages, where more foreigners will be interested as non-mainstream nodes in the dissemination of knowledge.

It is tested that the SH model focused on the classic linear return and After the logarithm of early visibility and late prevalence, it is found that there are clear linear connections and an Increased success ratio for the PSTIR and SFIBS paradigm which is optimized for several scenarios.

$$A'_n = b_1 \log C_n + b_2 Log\ (g) + b_3 \tag{3}$$

$$A'_n = \exp[\ \beta_1 \log C_n + \beta_2 Log\ (g) + \beta_3] \tag{4}$$

As inferred From the Eq (3 &(4)), Where A'_n introduces the indicator meaning of material m and where it's possible to know the parameters β_1, β_2 and β_3 from the training results. A'_n is the PSTIR and SFIBS model's success, the users are loyal share among all users over the last 10 months. The time the message is published will affect the true diffusion power and to adjust the forecast outcome which is implemented based on a relative popularity A'_n as represented as follows in the Eq (5 & 6),

$$C'_n = \frac{A_n}{T'(j)} \tag{5}$$

$$A^*_n = \exp[\rho_1 \log C'_n + \rho_2 \log(g) + \rho_3] \tag{6}$$

Since it used to make long-term forecasts, due to several features, the predictive accuracy is poor and a linear link occurs between final success and faithful followers, shows the common trait which is inserted into considered shares. Where, ρ_1,ρ_2,ρ_3 indicates the Global Coefficient and There are three-hour early visibility and final success for growing web material on the Facebook homepage.

5.1. The device of iot node centrality (DINC)

In this parameter to finding the most nodes which is suitable for challenging. Node central has been shown based on the good candidates of the relay. The centrality of the measure has the quantitative of the device of IoT importance, in which the relationship has been a network of the IoT Devices. SI_P-Small Important, AI_P-Average Important,HI_P-High important formularized as represented as follows,

$$T(DINC) = \{(SI_P),\ \ (AI_P),\ (HI_P)\} \tag{7}$$

$$\alpha\ (SI_P) = h(DINC;\ SI_{PO},\ SI_{P1},\ SI_{PXO},\ SI_{PX1}) \tag{8}$$

$$\alpha\ (AI_P) = g(DINC;\ AI_{PO},\ AI_{P1},\ AI_{PXO},\ AI_{PX1}) \tag{9}$$

$$\alpha\ (HI_P) = h(DINC;\ HI_{PO},\ HI_{P1},\ HI_{PXO},\ HI_{PX1}) \tag{10}$$

5.2. False information based on sociological (SFIBS)

Considering the congestion network, some devices of IoT longer wait for some data transmission and The device of IoT has been the longer waiting to have a possibility of high data processing based in the derivative results as represented below,

$$T(SFIBS) = \{(SH_P,\ AH_P,\ HH_P)\} \tag{11}$$

$$\alpha\ (SH_P) = h(SFIBS;\ SH_{PO},\ SH_{P1},\ SH_{PXO},\ SH_{PX1}) \tag{12}$$

$$\alpha\ (AH_P) = g(SFIBS;\ AH_{PO},\ AH_{P1},\ AH_{PXO},\ AH_{PX1}) \tag{13}$$

$$\alpha\ (HH_P) = h(SFIBS;\ HH_{PO},\ HH_{P1},\ HH_{PXO},\ HH_{PX1}) \tag{14}$$

5.3. Predicting the security threats of internet rumors (PSTIR)

The device of IoT will transmit the information on the late tolerant networks until an opportunity communication is accessible. Because of the distinct processing capability of the IoT system, the choice option should take into account the processing ability as shown in the Following Eq (15, 16, 17, & 18)

$$T(PSTIR) = \{(SS_P,\ AS_P,\ HS_P)\} \tag{15}$$

$$\alpha\ (SS_P) = h(PSTIR;\ SS_{PO},\ SS_{P1},\ SS_{PXO},\ SS_{PX1}) \tag{16}$$

$$\alpha\ (AS_P) = g(PSTIR;\ AS_{PO},\ AS_{P1},\ AS_{PXO},\ AS_{PX1}) \tag{17}$$

$$\alpha\ (HS_P) = h(PSTIR;\ HS_{PO},\ HS_{P1},\ HS_{PXO},\ HS_{PX1}) \tag{18}$$

SFIBS and PSTIR have been developed by vagueness management and uncertainty of the process reasoning an intelligent system such as the system-based knowledge, a system expert or a system of logical control which has been discussed in this paper. It consists of the IoT for the main part of the system and it's the elements are basic, where the inference engine, fuzzifier, defuzzifier and Fuzzy rule base (FRB), can use the trapezoidal and triangular of the function of membership for FLC, because they are suitable for the operation of real-time. The $\alpha\ (AS_P)$ in $\alpha\ (HS_P)$ is the center of function triangular $\alpha\ (SS_P)$*in* $\alpha\ (SPL_P)$ which can be left (right) edge function of trapezoidal, and $h(DISD;\ SPVL_{PO})$ can be left (right) width of the function of triangular.

Case: 1; The device of IoT selection Decision (DISD) model has **Selection Possibilities which Is Very Low (SPVL) – where** the device of IoT has shown the probability of very low factors for the selection as shown in the Eq(19),

$$\alpha(SPVL_P) = h(DISD;\ SPVL_{PO},\ SPVL_{P1},\ SPVL_{PXO},\ SPVL_{PX1}) \tag{19}$$

Case: 2, Selection Possibilities is Low (SPL): The device of IoT can be a better job based on the derivative factor which has been shown in the Eq(20),

$$\alpha\ (SPL_P) = h(DISD;\ SPL_{PO},\ SPL_{P1},\ SPL_{PXO},\ SPL_{PX1}) \tag{20}$$

As inferred from the Algorithm.1. The statement, the problem of talent management is one of the main aspects for the right time to hire the people of right. The upper bond to the required process of time of employing "people of right" in each period needs to be analyzed based on the activities for employing her/him desirable as shown in the Algorithm.1.

The bonds of constraint for a specific job are selected at each period and In this portion of process recruitment for the position of job-specific n contains (h) organizing, gathering and documents which are analyzed based on the outcome of the selected candidates. The associated part of times with g and h $A_n' = b_1 \log C_n + b_2 Log\ (g) + b_3$ and $A_n' = \exp[\ \beta_1 \log C_n + \beta_2 Log\ (g) + \beta_3]$ for the position of job n in the period of y, respectively. The addition of two terms in the position of the job shows the overall statistical analysis which has been discussed as follows,

6. RESULT and discussion

To minimize sample noise during pretreatment, pick the ingredient with 10 shares. Root mean Square Error (RMSE) has been calculating the variations between the values expected and the values reported. As shown in the Fig 3 the RMSE decreases slowly with the early-stage development of the major-stream proportion. As $g = 3.852\%$, the RMSE curve hits the trough and Pearson's coefficient of association

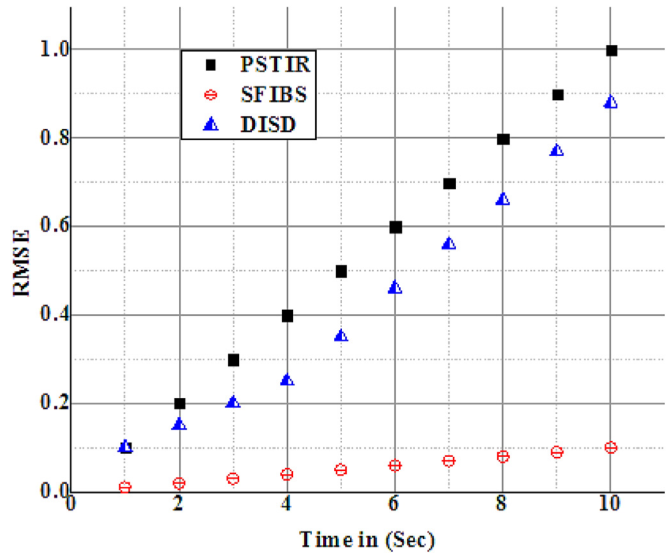

Fig 3. Time Vs RMSE.

which is clearly shown below,

It is attributed to the assumption that since the application parameters for common applications become strict, fewer samples are included in the model. If further tests are used, the effects of the prediction are increased. However, the relationship coefficient has been decreased and the RMSE rises if g is greater than the maximum. Eventually, if $g = 1$ our process degenerates into the PSTIR and SFIBS construct.

In the 'Fox News' homepage of Facebook equate the estimation exactness of the proposed (DISD) system with the online Facebook market popularity forecast dependent on the PSTIR and SFIBS model as shown in the Fig. 4. display the Fox News homepage scatter map.

Based on the Facebook user lifecycle that appears in the Fig. 5, comparison period to 242 to ensure the aggregation of all exchange knowledge. Accuracy (ACC) is determined as the quantity of every right forecast partitioned by the absolute number of the dataset. Accuracy of best is 1.0, while the most noticeably not good is 0.0. It can likewise be determined by 1 – PSTIR.

$$Accuracy\ =\ TN\ +\ TP/TN\ +TP\ +\ FN\ +\ FP \tag{21}$$

However exclude the samples that have less share in the first three

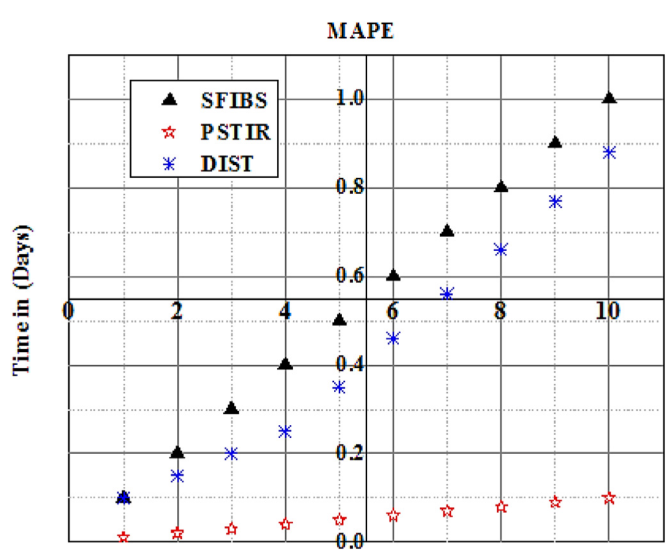

Fig 4. Time Vs MAPE.

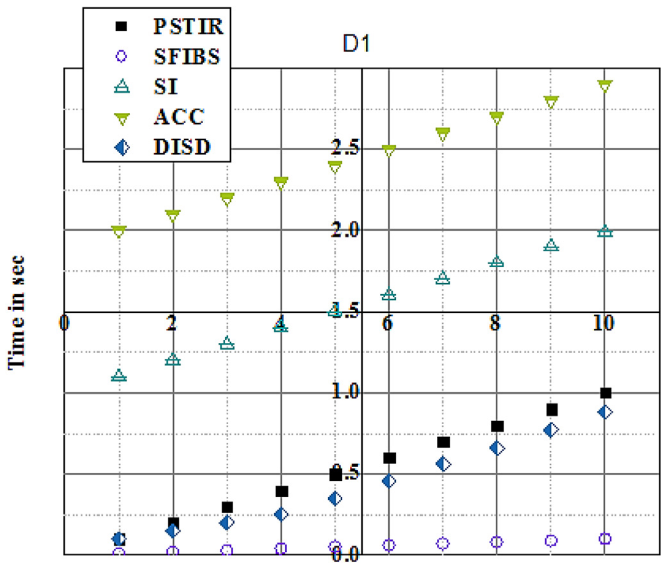

Fig 5. Facebook time Vs Accuracy (D1).

Table 1
Data Set of DISD and PSTIR.

DATASET GROUP	DISD		PSTIR	
	TRAINING	TESTING	TRAINING	TESTING
1	96.0	95.0	98	98
2	97.0	95.0	98	98
3	84.0	77.0	89	83
4	92.0	86.0	97	94

hours because very little share will affect the accuracy of the forecast, so it is virtually difficult to obtain high visibility unexpectedly in one week with such material that exceeds the threshold as shown in Table 1. Moreover, in the estimates, the red dots represent 82% of the data collected as a training sample from the homepage data and the black dots represent the other 32 percent as a study collection.

The blue solid line indicates the training outcomes for the least quadratic form. The result of the (DISD) model is better than the PSTIR and SFIBS model as shown in Table 2. Specificity (SP) is determined as the quantity of right negative forecasts partitioned by the all-out number of negatives as shown in Fig 6. It is likewise called a true negative rate (TNR). The specificity of best is 1.0, though the most noticeably not good is 0.0.

A few popular Facebook pages, including "National Geographic" and "The Simpsons", for greater analysis of the PSTIR and SFIBS model. For reference, picked the test sets from the data collection, To calculate the prediction performance, the RMSE and Pearson correlation coefficient is added. The Pearson (DISD) correlation coefficient which is around 0,8, showing that our proposed model has a very linear correlation. Therefore, RMSE is still under 2.3 and fairly stable for this popular Facebook homepage. In comparison, 32 percent greater than the PSTIR and SFIBS model in total is obtained with the new system (DISD).

Table 2
Data set of DISD and PSTIR.

DATASET	DISD	PSTIR
1	0.91	0.97
2	0.91	0.93
3	0.85	0.89
4	0.93	0.95

Algorithm 1. SFIBS and PSTIR.

Input is *FLC* = 3 *input;*
For IoT device node (n = 3)
T(PSTIR) = {(SS_P,AS_P,HS_P)}}
Train (T) – generate the model triangle or trapezoidal(j);
For each input h do;
Calculate the class T(SFIBS) using the model of (n);
To get the output of FLC (O) to T;
Else;
End if,
End for,
End for.

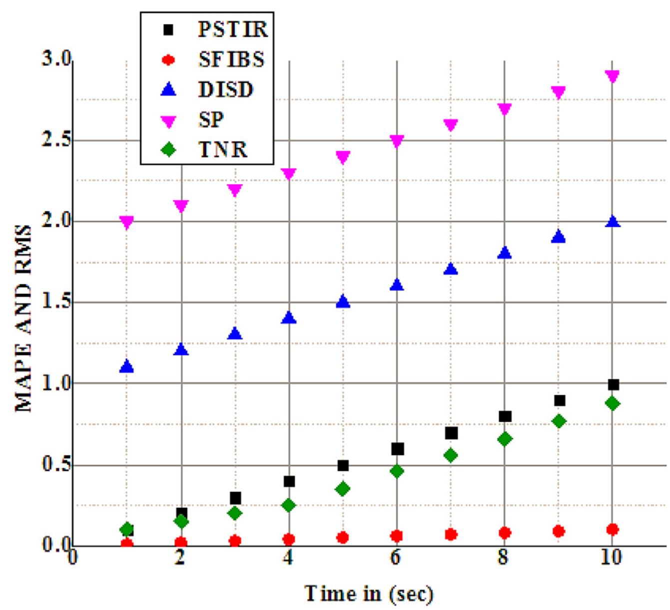

Fig 6. Time Vs MAPE and RMS.

7. Conclusion

This paper focused on sociological theory to address the question that existing approaches are not predictively reliable enough. It considers that the proportion of loyal fans on Facebook's site with regular early and potential popularities is extremely dimensional. The experimental findings on Facebook show a clear position in the estimation of the principle of social physics. Besides, laboratory experiments demonstrate that the proposed approach is successful. The findings indicate that the model suggested may yield better results than the other models due to the importation of the conventional tiredness theory which validates the efficacy of our model in the projection of popularity.

Author statement

We are submitting a manuscript entitled **"Predicting the Security Threats of Internet Rumors and Spread of False Information based on Sociological Principle"** for the special issue section titled **"Natural Language Processing for Digital Library Management"** in the **Computer Standards & Interfaces** Journal. This is an original submission which have not been published before.

Declaration of Competing Interest

We, the authors, solemnly declare that we do not have any conflicts

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.csi.2020.103454.

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