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Research Article

Computational Model of Recommender System Intervention

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A recommender system is an information selection system that offers preferences to users and enhances their decision-making. This system is commonly implemented in human-computer-interaction (HCI) intervention because of its information filtering and personalization. However, its success rate in decision-making intervention is considered low and the rationale for this is associated with users' psychological reactance which is causing unsuccessful recommender system interventions. This paper employs a computational model to depict factors that lead to recommender system rejection by users and how these factors can be enhanced to achieve successful recommender system interventions. The study made use of design science research methodology by executing a computational analysis based on an agent-based simulation approach for the model development and implementation. A total of sixteen model concepts were identified and formalized which were implemented in a Matlab environment using three major case conditions as suggested in previous studies. The result of the study provides an explicit comprehension on interplaying of recommender system that generate psychological reactance which is of great importance to recommender system developers and designers to depict how successful recommender system interventions can be achieved without users experiencing reactance and rejection on the system.

1. Introduction

A recommender system (popularly known as a recommendation system) is an information filtering system that is used for predicting the preference and rating of items that users would select or pick for their personal use [1]. It is a set of techniques and tools used for the main goal of providing preferences and suggestions of products to customers who are inability to make decision based on the number of alternative products available. It is commonly implemented due to its ability to enhance users' decision-making in interventions [2]. It enhances users' decision-making by delivering personalized relevant information to users based on real-time data collection on the products. The adoption and implementation of recommender system is showcased for instance in Amazon (an electronic commerce website) and other classifications of services that are involve in the provision of suggestions which effectively reduce large information spaces intake by users to meet their best preferences and needs on products selection and decision. "Many products are being purchased online, and there is increasing customer demand for a large number of items available on websites to be filtered so that specific items can be more easily founded according to their actual interest." Examples of sites using recommender system include Netflix (Movie recommendation), Amazon, (Book recommendation), Pendura (Music recommendation), Yahoo News (News recommendation) and other information extraction and selection websites based users' preferences and interests on related products or items (for instance most social media platforms like MySpace, LinkedIn and Facebook). Additionally, according to Ojagh et al. [3]; the system has two peculiar features which are location awareness (can trace users' precise location) and ubiquity (can be used anywhere).

However, most recommendation systems information is usually refused, disregarded, and ignored by users [4, 5]. The rationale for this information rejection has been associated with users' psychological reactance which is causing unsuccessful recommendation system interventions [6, 7].

Psychological reactance is stimulated when the recommender system did not acquire necessary factors to limit audiences' threat during the recommendation [8]. The recommender system users feel that their autonomy is threatened by the recommendation of the system which causes them to experience psychological reactance [9]. Psychological reactance trigger irritation, anger, and annoyance that will not allow the autonomy of the system users which then causes deflection towards decision making and the recommendation of the system. Even though previous studies have highlighted models on the effect of psychological reactance such as Reynolds-Tylus et al. [10]; Akhtar et al. [11]; Lowry and Moody [12]; however how users' reactance can be reduced to enhance acceptance of the system recommendation has not been well studied. In addition, none of the previous studies explores computational analysis such as agent-based modelling as a solution to reduce users' reactance which is limiting successful recommendation system interventions. Thus, this study seeks to develop a computational recommendation system for successful intervention.

2. Literature Review

Recommender System (RS) suggests tailored and personalized contents over a pool of collection of products or items to a user. The rationale behind these tailored and personalized contents is to influence the users' decision-making process which is vital to successful intervention. This is achieved when the users find relevant and meaningful information on the suggested products or items. According to Bhaskaran and Marappan [13] there three major classification of RS namely collaborative-filtering RS, content-based RS and hybrid-based RS. Collaborative-filtering RS uses feedback mechanism by exploiting similarities rating among large population of users on an item or product. This is achieved by suggesting similar items that users usually exploit and it is based on user or item behavioral patterns [14]. For example if users usually search for shoes, shirts and wrist watch based on their online behavioral patterns then, shoes and shirts can be recommended to any other user searching for wrist watch.

On the other hand, content-based RS uses item or product description representation by comparison to recommendation. This is achieved by mining on the item or product description to make generalization and grouping. For instance, "Star Wars," "Blade Runner" and "Twelve Monkeys" can be classified as Science Fiction movies based on their movie genre information. "Star Wars" and "Blade Runner" movies can also be recommended to users searching for Twelve Monkeys movie or any other Science Fiction movies. The third classification is the hybrid-based RS and it combine both the content-based filtering and collaborative-filtering methods [15]. According to Pachot et al. [16] the hybrid-based RS can be achieved using three different approaches. The first approach is by separately using both content-based and collaborative-based to analysis and predict then integrate the resultant output together. Another approach is to directly integrate both content-based and collaborative-based methods together to obtain the result. This approach uses both methods to analysis and predict to get the result. The third approach is by developing a model out of the two methods of content-based and collaborative-based recommender system. In respect of the hybrid-based RS approach used, the hybrid-based has been identified to be more accurate compare with the other methods (content-based and collaborative-based) because it is found to limitations like accurate, sparsity and cold-start as mentioned by Javed et al. [17] and Reddy et al. [18].

Generally, the implementation and deployment of RS is across various sections and domains like social networks [19–22], news portals [23–25], intelligent assistants [26–28], e-commerce [29–31], search engine [32–34], Internet of Things [35], healthcare management [36–38], smart home [39–41], financial applications [42–44], smart city [45–47], game [48–50], fashion [51–54], tourism [55–58] and other high quality delivery platform which ensure that personalized and tailored information are easily accessible by users.

To improve the efficacy of the RS applications, there have been various evaluation studies such as Alhijawi et al. [59]; Zangerle and Bauer [60]; Verachtert et al. [61] and Fayyaz et al. [62]. In these studies, Fayyaz et al. [62] has identified five major limitations with RS namely Cold-Start (lack of sufficient data availability within the system would cause the RS to be inefficient), Data Sparsity (user–item matrix information would cause the RSs to provide unstable and unreliable recommendations), Scalability (choice among large pool of recommendations to the user), Diversity (selection of the most preferable among large pool of recommendations to the user) and Habituation Effect (presentation manner and platform to the user influence efficient of the RS). Additionally, studies such as Badewi et al. [63]; Sysko-Romańczuk et al. [64]; Li et al. [65]; Aljukhadar and Senecal [7] have argued that RS users' usually experience psychological reactance which lead to refusal, ignore and disregard of recommendations. This argument is further maintained by Ma et al. [6] and Aljukhadar and Senecal [7] that RS recommendation rejection is associated with users' psychological reactance which is the cause of unsuccessful RS interventions. Thus, this paper aims to develop computational models of RS intervention where users' reactance can be reduced to enhance acceptance of the RS recommendations for a successful decision-making interventions.

3. Methodology

In the vast literature, there are many research methods that have been presented to solve any research problems and issues but there is need to identify the most suitable solution for a particular research problem and issue. Hence, taking a critical examination of this study problem as stated in the introduction of this paper which is the development of computational model. The design science research (DSR) method is selected the most suitable due its critical and stepwise approach to model development and its verification. Whereas, other research methods like a case study and experimental design cannot be considered as being appropriate since these research methods did not focus on model design. This is in-line with Kuechler and Vaishnavi [66] submission that DSR is a problem-solving paradigm that has six stages namely identification of problem and objectives, proposed solutions, design of the model, verification, model demonstration, and model communication as summarized in Figure 1.

As reflected in Figure 1 above, the first stage is problem identification which is the reduction of users' psychological reactance on a mobile recommendation system. The second stage is objective identification which is referring to the four stated objectives in the research objective section. The third is the model design and development which will be based on Adegoke et al. [67] and Bosse et al. [68]. Figure 2 shows the activities in this stage based on the procedure used by Bosse et al. [68].

After the formal model development, the model verification is the fourth stage and it is based on Ojeniyi et al. [69] and Ajoge et al. [70]. The fifth and sixth stages will be where the model will be simulated and the simulation traces will be interpreted and reported. The simulation activities is pictured in Figure 3 where the designed formal model is evaluated.

The next subsection, present the model concepts result, the formal model and simulation outputs which represent the simulation traces. The results obtained is discussed in-line with the paper objective and supported with previous studies.

4. Result and Discussion

This study made use of 3 theories (the Theory of Reasoned Action-TRA, the Theory of Planned Behaviour-TPB, and the Self-Efficacy Theory-SET), and 4 conceptual models (the Fogg Behaviour Model-FBM, the Health Belief Model-HBM, the Relapse Prevention Model-RMP and the Trans-Theoretical Model-TM). Based on these 3 theories and 4 conceptual models, sixteen (16) concepts were formulated and presented in Table 1.

Based on the 3 Theories and 4 Models with supporting empirical evidence from the literature, the relationship representations were formed as the conceptual model. The summarized causal relationships that produce the conceptual model of the study is presented in Figure 4.

In the conceptual model, the arrows represent the causal dependencies of the concepts' interplaying relationship as presented in Table 1. The concepts formalization is based on previous studies like Adegoke et al. [67] and Serrano et al. [93]. For instance in equation (1), the formalization of the Severity of the Recommendation (Sr) is dependent on Recommendation task (Rt) and Recommendation reject (Rr) as shown in the Conceptual model in Figure 4. Thus, Sr is considered to be high when both Rt and Rt are high which is evident in previous studies like Sharma et al. [87]. This similar concept is used for other formalization as presented below in equations (1)–(16):

$$\mathrm{Se}(t) = [1 - \mathrm{Nr}(t)]\mathrm{Pb}(t), \tag{1}$$

$$\mathrm{Sr}(t) = [1 - (1 - \mathrm{Rr}(t))]\mathrm{Rt}(t), \tag{2}$$

$$\mathrm{Pb}(t) = (1 - \mathrm{pr}(t))\left[w\mathrm{pb}_1 \cdot \mathrm{Cg}(t) + w\mathrm{pb}_2 \cdot \mathrm{Mr}(t) + w\mathrm{pb}_3 \cdot \mathrm{At}(t)\right], \tag{3}$$

$$\mathrm{Cr}(t) = wc1 \cdot \mathrm{Mr}(t)) + wc2 \cdot \mathrm{Si}(t) + wc3 \cdot \mathrm{Ab}(t), \tag{4}$$

$$\mathrm{Rr}(t) = (1 - \mathrm{Ra}(t)) \cdot [w\mathrm{Rr1} \cdot \mathrm{Pa}(t) + w\mathrm{Rr2} \cdot \mathrm{Tr}(t) + w\mathrm{Rr3} \cdot \mathrm{DFr}(t)], \tag{5}$$

$$\mathrm{Ra}(t) = (1 - \mathrm{Rr}(t)) \cdot [w\mathrm{Ra1} \cdot \mathrm{Se}(t) + w\mathrm{Ra2} \cdot Ic(t) + w\mathrm{Ra3} \cdot \mathrm{Pa}(t)], \tag{6}$$

$$\mathrm{Mr}(t) = (1 - \sigma) \cdot (\mathrm{At}(t)) + \sigma(wm1 \cdot Cr(t) + wm2 \cdot \mathrm{Si}(t) + wm3 \cdot \mathrm{Ab}(t)), \tag{7}$$

where $\sum 1 = 1$, $\sum 1 = 1$, $\sum Wpcj = 1$, $\sum 1$ and $\sum Warj = 1$, $w\mathrm{Pc1}, w\mathrm{Pc2}, w\mathrm{Pc3}, wc1, wc2, wc3, w\mathrm{pb1}, w\mathrm{pb2}, w\mathrm{pb3}, wm1, wm2, wm3, w\mathrm{Ar1}, w\mathrm{Ar2}$ and $w\mathrm{Ar3}$ are the simulation weights factors for the respective equations

$$\mathrm{Pr}(t) = [(1 - \rho) \cdot \mathrm{Pb}(t) + 1 - \rho \cdot \mathrm{Cr}(t)] \cdot \mathrm{Sr}(t), \tag{8}$$

$$\mathrm{Ac}(t) = [1 - \mathrm{Nr}(t)][(1 - \gamma) \cdot \mathrm{Bf}(t) + \gamma \cdot \mathrm{Rk}(t)], \tag{9}$$

$$\mathrm{Ir}(t) = [(1 - \nu) \cdot \mathrm{Rt}(t) + \nu.\mathrm{Se}(t)].\mathrm{Dr}(t), \tag{10}$$

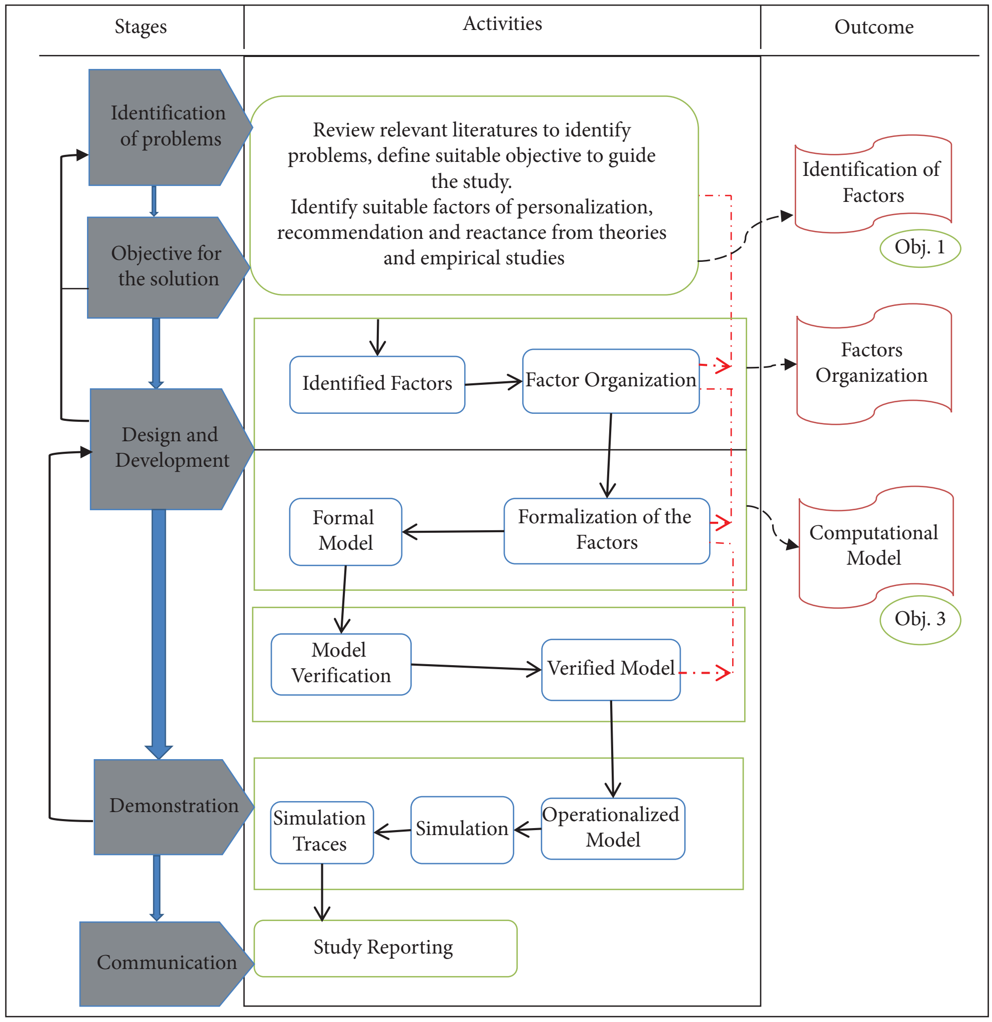

Figure 1: The research framework.

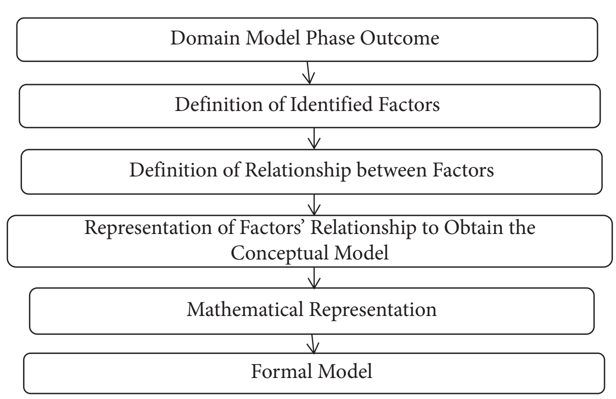

Figure 2: Factor organization activities [68].

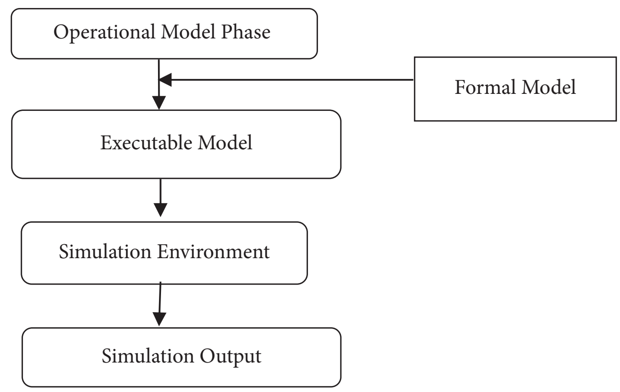

Figure 3: Simulation phase activities [71].

Table 1: The model concept.

No	Concept	Representation	Description	Related theory	Empirical relation
1	Ability to perform the recommendation	Ab	Having sufficient enablement to accept the recommender system	TPB, TRA	Saito and Watanobe [72]
2	Social influence	Si	External opinion on the recommendation		Huo et al. [73]
3	Belief in the recommendation	Bf	A state of the user's trust or confidence placed in the recommender system	FBM	Li et al. [74]
4	Recommendation knowledge	Rk	Knowledge and understanding about the recommender system	TPB, TRA	Rosa et al. [75]
5	Planned action toward the recommendation	Pa	A sequence of steps or activities that must be achieved well, for the recommender system intervention to be successful	TPB, TRA	Workman [76]
6	Recommendation task	Rt	The nature of the recommendation	TPB, TRA	Shishehchi et al. [77]
7	Attitude to the recommendation	At	Mental state	TPB, TRA	Ku and Tai [78]
8	Challenge to the recommendation	Cr	Perceived threat to the recommender system information	HBM, TPB	Mashal et al. [79]
9	Motivation of the recommendation	Mr	Drive to achieve the recommender system information	FBM, TM, HBM	Jain et al. [80]
5	Perceived benefit of the recommendation	Pb	Positive feeling on the recommender	HBM, TPB	Musto et. al [81]
6	Threat to the recommendation	Tr	Perceived risk to perform recommendation	FBM, HBM	Sangeetha et al. [82]
10	Perceived risk of the recommendation	Pr	Negative feeling on the recommender	HBM, TPB	Amirtha et al. [83]
7	Intention to perform the recommendation	Ir	Inclination to achieve the recommender system information	FBM, HBM, RPM	Jiménez-Castillo and Sánchez-Fernández [84]; Amirtha et al. [83]
8	Negative thoughts on the recommendation	Nr	Negative reaction on the recommender	HBM, TPB	Passos et al. [85]
9	Self-efficacy to the recommendation	Se	The self-drive to the achieve the recommender system information	RPM, TPB, SET	Louvigné et al. [86]
10	Severity of the recommendation	Sr	The strictness of the consequences of the recommendation	HBM	Sharma et al. [87]
1	Desire to change for the recommendation	Dr	The emotional feeling toward the recommender system	TM	Andersen et al. [88]
12	Recommendation accept	Ra	A state when the recommendation is accepted	SET	Nilashi et al. [89]
13	Recommendation rejected	Rr	A state when the recommendation is deflected	SET	Lei et al. [90]
14	Dissatisfaction with the recommendation	DFr	Stage of continuous discontent with the recommendation	RPM	Barzegar Nozari et al. [91]
15	Consistency recommendation reject	CRr	Continuous stage of rejecting the recommendation	TRA, RPM	Dewi et al. [92]
16	Consistency recommendation accept	CRa	Continuous stage of accepting the recommendation	TRA, RPM	Dewi et al. [92]

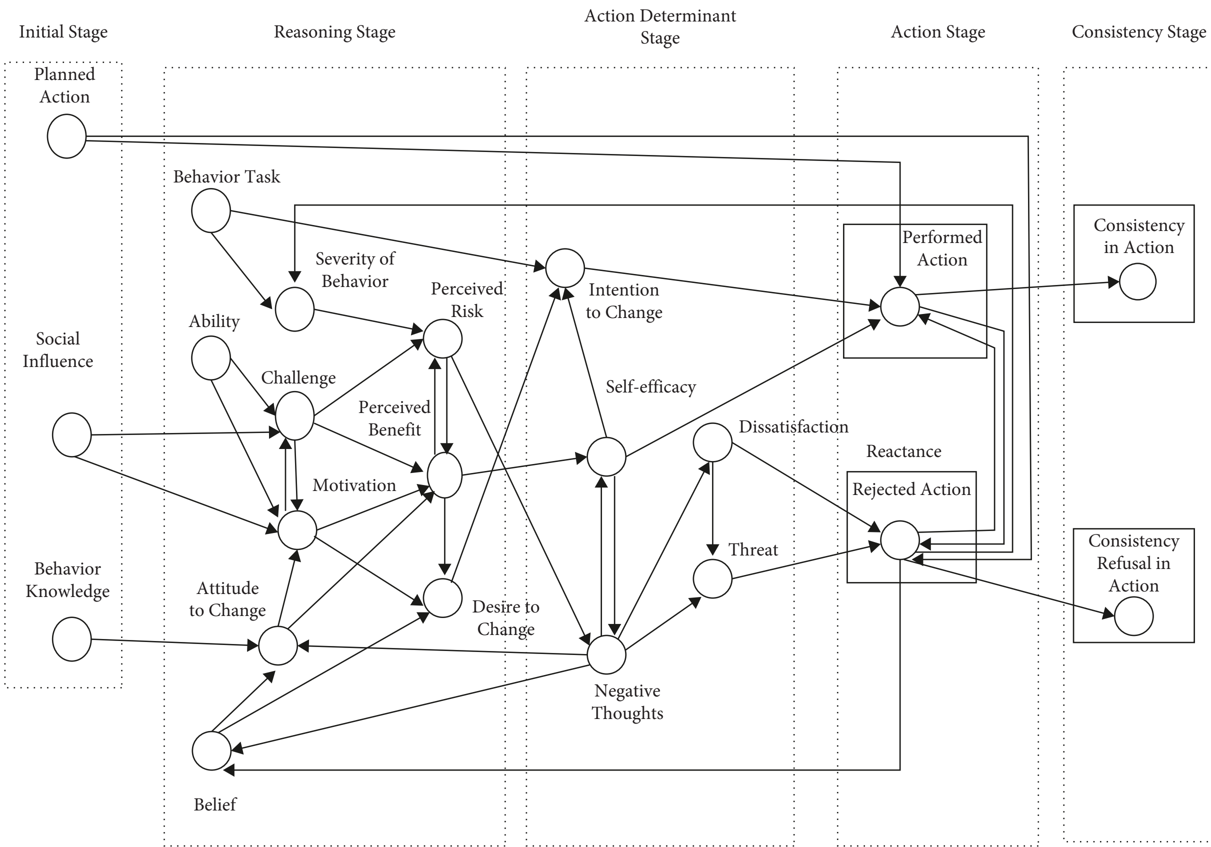

Figure 4: The conceptual model.

$$\mathrm{Dr}(t) = [(1-\eta)\cdot \mathrm{Pb}(t) + \eta.\mathrm{Mr}(t)].\mathrm{Bf}(t), \tag{11}$$

$$\mathrm{Tr}(t) = [(1-\phi)\cdot \mathrm{Nr}(t)] + \phi.\mathrm{DFr}(t), \tag{12}$$

$$\mathrm{Nr}(t) = [(1-\psi)\cdot \mathrm{Se}(t)] + \psi.\mathrm{Pr}(t), \tag{13}$$

$$\mathrm{CRr}(t+\Delta t) = +\varphi\cdot [\mathrm{Rr}(t) - \mathrm{CRr}(t)](1-\mathrm{CRr}(t))(\mathrm{CRr}(t)\cdot\Delta t) + \mathrm{CRr}(t), \tag{14}$$

$$\mathrm{CRa}(t+\Delta t) = +\zeta\cdot [\mathrm{Ra}(t) - \mathrm{CRa}(t)](1-\mathrm{CRa}(t))(\mathrm{CRa}(t)\cdot\Delta t) + \mathrm{CRa}(t), \tag{15}$$

$$\mathrm{DFr}(t+\Delta t) = +\lambda\cdot [\mathrm{Nr}(t) - \mathrm{DFr}(t)](1-\mathrm{DFr}(t))(\mathrm{DFr}(t)\cdot\Delta t) + \mathrm{DFr}(t), \tag{16}$$

Whereas: ζ λ, and φ are the regulating constraints, while Δt refers to the change rate in time (t).

The formal models equation (1)–(16) were implemented using the three cases namely Task Challenging recommendation, the Uninspiring recommendation, and Influential recommendation. The implementation is done in a Matlab using the pseudo-code display in Figure 5.

4.1. Case One: The Uninspiring Recommender. In this case, the recommender is depicted with low Planned action (Pa), Society influence (Si), Ability (Ab), Belief (Bf), and Recommendation knowledge (Rk) while high recommendation task (Rt) as shown in Table 2.

The recommender is characterized by lack of support from others, low ability, inadequate understanding, low belief, and knowledge about the target recommendation in the achieving of the information given by the recommender but the nature of the information is high as illustrated by Tang [97]. The obtained simulation traces after running the codes is presented in Figure 6.

Based on Figure 6, it is observed that DFr leads to both CRr and CRa. Also, there is a very wide range margin between the three. DFr is found tending towards 1 whereas CRa is tending towards 0. This implies that when a recommendation acquires this case condition attribution then its action will be characterized by high dissatisfaction and low consistency recommendation

```
Start
Initialize the numSteps
Initialize the array size
Initialize parameter
Case selection
        Case 1 to Case n
State = Case Selection
end
Initialize equations at t = 1
Do      t = 2: numStep
Compute equations
Until   t = numSteps
End
```

Figure 5: The model simulation pseudo-codes.

Table 2: Values of uninspiring case condition.

Concept	Given value	Reference
Belief (Bf)	0.2	Hagger et al. [94]; Cane et al. [95]; Michie et al. [96]
Society influence (Si)	0.2	
Ability (Ab)	0.2	
Planned action (Pa)	0.2	
Recommendation knowledge (Rk)	0.2	
Recommendation task (Rt)	0.9	

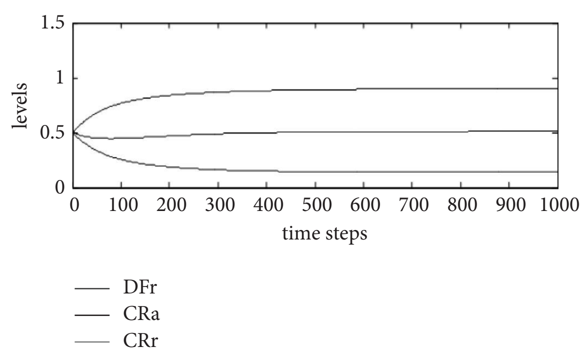

Figure 6: The uninspiring case simulation.

acceptance which indicates that the recommendation system will not be able to consistently perform the target intervention due to its extremely susceptibility to high dissatisfaction [98].

4.2. Case Two: The Task Challenging Recommender. The task challenging recommender is depicted with high Social influence (Si), Recommendation knowledge (Rk), Belief (Bf) and Recommendation task (Rt) whereas low Planned action (Pa) and Ability (Ab) as shown in Table 3.

This recommender possesses low initiative and the capability to achieve a difficult task. The simulation traces obtained after running the simulation code is presented in Figure 7.

The simulation traces in Figure 7 show that DFr leads to both CRr and CRa whereas CRr leads to CRa with a close margin. This suggests that recommender with this characteristic will display dissatisfaction which will make it unable to achieve the task due to reactance [101, 102].

4.3. Case Three: The Influential Recommendation. The case condition presented recommender with characteristics with high recommendation knowledge (Rk), Ability (Ab), Belief (Bf), Society influence (Si), and Planned action (Pa) whereas only recommendation task (Rt) is low as shown in Table 4.

The case is characterized by a recommender with high capabilities and influence to achieve the task. The simulation traces obtained after running the code are presented in Figure 8.

The simulation traces presented in Figure 8 shows that CRa leads to both DFr and CRr. Also, a wide margin lag is observed between DFr and CRr but a close margin lead is observed between CRa and DFr. In other words, when a recommender acquires this case characteristic then it will possess high CRa, reduced DFr and extremely low CRr. This is because of the influence that the system possesses which able it to achieve its task. A similar result was pointed out by Fogg [104] that systems that provide enabling support and influence are mostly to achieve their target tasks. The

Table 3: Values of task challenging case condition.

Concept	Given value	Reference
Belief (Bf)	0.9	Zhang et al. [99] and Zheng et al. [100]
Recommender knowledge (Rk)	0.9	
Recommender task (Rt)	0.9	
Society influence (Si)	0.9	
Ability (Ab)	0.2	
Planned action (Pa)	0.2	

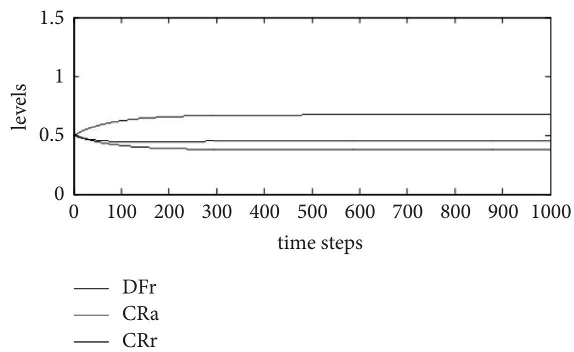

Figure 7: The task challenging case simulation.

Table 4: Values of the influential case.

Concept	Given value	Reference
Belief (Bf),	0.9	Zhou et al. [103]
Planned action (Pa)	0.9	
Recommender knowledge (Bk)	0.9	
Society influence (Si)	0.9	
Ability (Ab)	0.9	
Recommender task (Ba)	0.2	

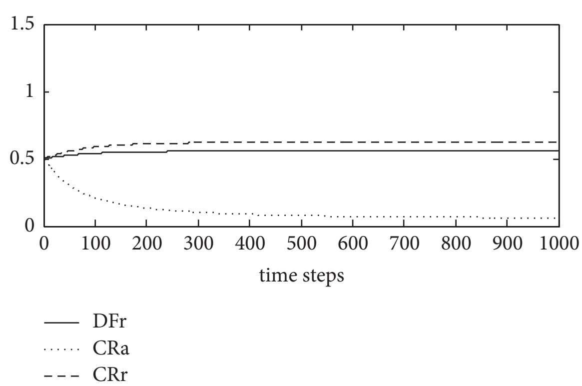

Figure 8: The influential case simulation.

recommender will be able to consistently achieve its tasks while there will be a slight level of dissatisfaction due to low recommender tasks (this is because recommender tasks should be moderately challenging for users). The summary of the result is presented in Table 5 depicting the three selected cases.

Therefore, the only influential recommendation case is found to experience no psychological reactance which is the reason for it to achieve the task. Also, the task challenging and the uninspiring recommenders acquired possess features that lead to reactance which made them unable to achieve their tasks Hence, this has explicitly depicted the rationale behind recommender system failure during decision-making intervention as caused by psychological reactance. The finding will be of great importance to recommender system developers and designers to depict how successful recommender system interventions can be achieved.

Table 5: Summary of the three Selected Model Case.

Case	Psychological reactance	Consistency recommendation reject	Dissatisfaction	Consistency recommendation accept	Outcome
Uninspiring recommendation	High	Average	High	Low	Task not achievable
Task challenging recommendation	High	Low	High	Very low	Task not achievable
Influential recommendation	Low	Very low	Average	High	Task achievable

5. Conclusion

The three simulated cases depict that recommender system design with a low task (Rt) and high Planned action (Pa), Ability (Ab), Belief (Bf), Society influence (Si), and recommendation knowledge (Rk) tends to limit users' reactance during decision-making intervention. Although other possibilities can be further investigated to comprehend the relationship between user's reactance and successful recommender system intervention, however, this study argues based on the finding that the rightful implementation of these identified factors and concepts will enhance successful intervention of the recommender system. This can assist designers and developers of recommender systems to pay attention to the implementation of these concepts for successful interventions. 'Practically, the study proposed personalized support agent simulator which depict the influence of each factor in the reduction of psychological reactance and successful system intervention. The personalized support recommender system simulator is based on the support personalized model. In addition, it further broadens the understanding of how the mobile recommendation system employs the act of personalization and recommendation attributes which serve as core components in scientific reasoning for system intervention. The formal model of the personalized support agent enable designers to make predictions and scientific reasoning for futuristic scenarios on users' decision-making'. This paper covers personalization and recommendation attributes of mobile recommender system while future studies can explore or redefine these factors and concepts used in this study for an improved model. This can be implemented in an electronic commerce website to further validate the model.

Data Availability

No data has been generated during the study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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