https://doi.org/10.26599/IJCS.2022.9100021 International Journal of Crowd Science

User Experience Adaptation of Complex Game Interface for User Behaviour Modeling Using RNN

Fatima Isiaka[1] ✉, Zainab Adamu[2], and Muhammad A. Adamu[3]

ABSTRACT

In a video game review, the main focus is the narratives, characters, graphics, and mechanics in the gameplay. Some recent research mentions the user interface only when it comes into light as a creative platform for simple interactive narratives from a technical point of view; this narrative is mainly a software tool that requires traditionally modernized inputs from the user. The user needs to interact with the navigational controls or menus in order to start a basic game play. A complex game interface as stimulus is generally considered as having a feeling of immersion that allows for visual tracking of user behavioural patterns and use it to predict the next strategy of the user using robust computational models. A number of users have limited sensory perception in a gameplay and hence rely on complex game stimulus and an adaptive model is paramount when considering behavioural expectations that place the user in a digital environment with more expressive perceptions. We developed a custom based eye tracking and 3D object detection algorithm which was utilised by recruiting users to interact with visual 3D objects and trace their eye movement behaviour to generated data. We then applied the use of recurrent neural network (RNN) for direct tracing of user behavioural activities in a sequential manner to predict their behaviour for interface adaptation. Result indicates that redundant user attributes are flexible and flawless for identifying predicted response of the user in a controlled environment. This would lead to prototypical representation of user behavioural analytics as an embedded platform in the confined digital environment. One of the limitations of the project is its inability to basically specify the 3D gaze point at the inner boundaries of the visual field. Data visualisation is strictly based on combined object flow detection. The originality of the work is its ability to redefine fixation point to a rendered cascaded 3D gaze point and space-defined saccade which is indicated by the distance between one gaze points to the other. The 3D gaze point would be well suited for fixation generalisation on 3D as well as on 2D digital oriented environment.

KEYWORDS

3D object detection; recurrent neural network; user behaviour; embedded platform; eye tracking; complex games' interface; user interphase (UI) design

What comes to mind when considering user interphase (UI) design is the stimulus that can induce user spontaneous response for product optimisation or for enhancing user experience in a broader sense. The three most basic emotions experienced by users when interacting with a particular stimulus within a visual field are illustrated in Eq. (1), which include "stress", "relaxed", and "neutral" mood. The stimuli eliciting paradigm is the object of interest for every usability test. One of the most commonly used stimuli for interface enhancement is the game interface. A complex game interface can stimulate the cortex of the human brain and upsurge visual intelligence quotient (IQ) of the user. Behavioural attributes can be associated with or obtained from the authentic phenomenon relating to human or user interaction based on user emotion because emotion is the motivator to good or negative behavioural tendencies. The behavioural benefits lead to a perceived behavioural control that triggers attitude towards another reaction to user interface. Both subjective and objective views are connected to both perceived and unperceived behavioural benefits of the user. The basic step is to obtain the initial behaviour and intensions of the user, and predictions are made from the preconceived interactions (Fig. 1). A carefully designed user interaction model is needed for obtaining the authentic behaviour patterns of the user; utilising a complex game interface is more appropriate when dealing with such cases[1–3]. This is the reason why game interface is a standard visual stimulus to trace user authentic behavioural patterns.

$$f(x)=\begin{cases}((1-\xi)\times 0)\times(\xi\times s), & \text{if relaxed (positive mood);}\\ ((1-\xi)\times s)+(\xi\times 1), & \text{if stressed (negative mood);}\\ s, & \text{if neutral (neither mood)}\end{cases} \tag{1}$$

where

$$\xi=\begin{cases}0, & \text{if negative behaviour;}\\ 1, & \text{if positive behaviour;}\\ -1, & \text{if neither affects;}\end{cases}$$

$$\text{with}\left\|\begin{matrix} f(s)=\text{user emotion}\\ \xi=\text{users' experience emotion}\end{matrix}\right\|.$$

In a video game review, the focus is mainly on the storytelling, characters, graphics, and mechanics in the gameplay. Most recent research[3–5] mentions the user interface only when it comes into light. A game interface is mainly a creative platform for simple

1 Department of Computer Science, Nasarawa State University, Keffi, PMB 1022, Nigeria
2 Department of Computer Science, Ahmadu Bello University (ABU), Zaria, Nigeria
3 Department of Electrical Electronics, Federal University of Technology, Minna, Nigeria
Address correspondence to Fatima Isiaka, fatima.isiaka@outlook.com

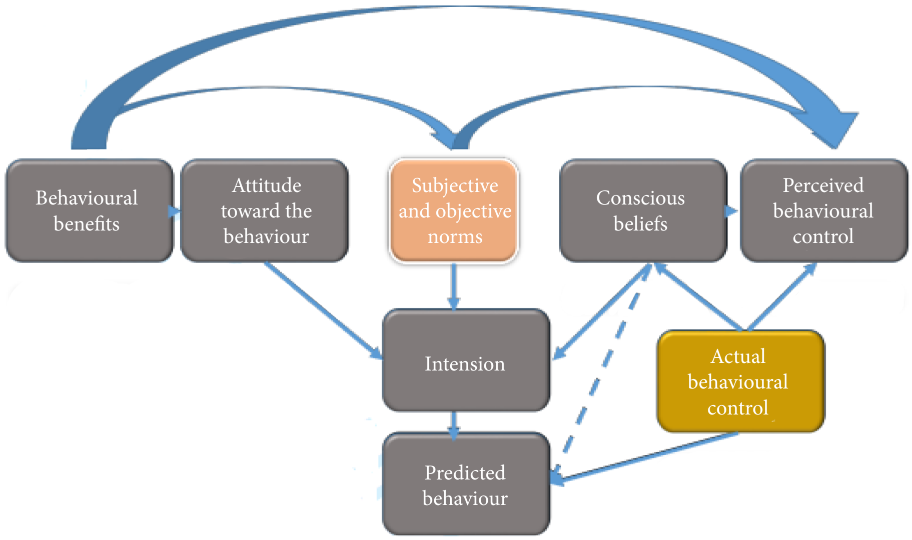


Fig. 1 User behavioural model: The stages to design a user predictive behavioural analytics for user interface configuration.

interactive narratives from a technical point of view; it is mainly a software tool that requires traditionally modernized inputs from the user. The user needs to interact with the navigational controls or menus in order to start a basic game interface. A complex game interface as stimulus is generally considered as having a feeling of immersion that allows for visual tracking of user behaviour patterns and uses it to predict the next strategy of the user using modernised or standard computational model[6–9]. Most users have limited sensory perception in a gameplay and hence relying on complex game is paramount when considering behavioural expectations that place the user in a digital environment. When user experience certain hassles or lacks of progression in a visual field, a user behaviour analytics modelling tool is necessary to avoid guess work[10–12]. This will help modify the user interface. It serves an ace of moral boost to avoid blind spots in UI. The preliminary step is to develop a predictive model which can help predict user behaviour based on redundant attributes; the model will learn the patterns in the complex user behaviour data and fine-tune the output[13–16].

To generate a user refined dataset on user behaviour, an experimental setup that involves the user sitting in front of a game is needed (Fig. 2). The PC that hosts the game console must contain an eye tracking algorithm that monitors the eye movement of the user and records user activities such as mouse click, key press, and console directives[17–21]. These behaviour patterns recoded can contain a thousand instances between one to two seconds of user activities. One of the most adaptable computational methods for user behaviour prediction is the use of recurrent neural network (RNN)[22–25]. The RNN is classical part of artificial neural network (ANN) that connects a group of nodes to form a directed graph along a progressive sequence (Eq. (2)), producing variable length sequence of inputs and exhibiting temporal dynamic behaviour well suited for pattern recognition like behavioural user attributes[26–28],

$$f(t)=\begin{cases} a^t \to b = Wh^{t-1}+Ux^t, \\ h^t \to \tan(h)\,a(t), \\ o^t \to c+Vh(t), \\ \hat{y}^t = \operatorname{softmax}(o(t)), \forall t \in W_i \end{cases} \tag{2}$$

where $x(t)$ is the user attributes measured in time T, W is the given weight, a is the corresponding initial user behaviour, b and c are constants due to environmental constrain, U and V are coefficients of user input, and b is the correlated predicted response behaviour.

Using RNN to recognise user behaviour is a key towards finding how users interact with standard interface. It traces how

Fig. 2 An experimental setup that involves a participant sitting in front of a PC with game interface and a console controlling the game on index page: The mouse and keyboard can be used to direct any quick access to score a higher level.

much time spend on an interactive session and registers what they click on frequently by correlating the time stamp to the point where users' journey bounces off normal track, which will help refine interface widgets. Avoid guess work in user experience design procedures and provide valuable insight to visual interphase contents. The design variations and user attributes have influenced the changes in behaivour patterns that includes placement buttons, characters in video games, and aesthetic modification[25,29,30].

The rationale for using RNN is to give a definite summary of the ultimate goal in user behaviour and adopt a design process that traces reasons why users behave in certain ways. A given interface can be used to identify the triggers that lead to selecting certain strategies that arise at an ultimate position. The main learning pattern for tracing user behaviour includes a deliberate and purposeful action in discovering habitual patterns, mapping sights into users journey through a complex game interface[26], and filtering out user benefits. In a complex game visual field, users love the thought of making their own deliberate choices, have certain strategies, and will not hesitate to take the move; most of the engagement decisions are consciously driven so it is very difficult to get a 100% predictive performance. A residual score (R2) of 0.65 is highly probable regarding human behaviour; the visual perception of things is not that easy and driven by evolutionary causes that predominantly motivate immediate stimuli to remain static in an hostile environment. But recent research has found out that this process is wrapped in a more conscious action. There are several examples that leads to repetitive actions that can be used to change behaviour and direct conscious phenomena towards new measures by ingraining new behaviours.

1 Tracking User Behaviour Patterns with Eye Movements

User behaviour towards complex interface can be captured through an authentic based eye movement patterns. To encapsulate these behaviour patterns, user attributes were recorded using a custom eye movement behaviour and object detection algorithm which calibrates eye positions and tracks 3D objects using a logical coordinated approach. The algorithm involves three modules. This is an inference engine that automatically detects the pupillary position of the eyes (Algorithm 1) using the camera lens of a PC. This is then used to identify the 3D objects (Algorithm 2) in a virtual field. The gaze points algorithm (Algorithm 3) is used to trace and locate objects at the area of interest (AOI) using the PC's camera lens to calibrate the eye's position.

The object detection (Algorithm 2) detects images or scene in a virtual field given a reference image of the object. Algorithm 2 presents a straight forward step used in detecting specific objects based on finding the point corresponding to reference and target image, and can also detect objects despite changes in the scale and in plane rotation of movement. It is basically robust to small amount of virtual plain rotation. The steps are suitable for most objects in the scene that exhibit non repeating texture patterns, which give rise to unique feature matches. This feature is suited for any object in the scene that moves both in a vertical or horizontal plane in the video game console. Before tracing a particular object, one needs to first detect it, hence the cascaded iris detection algorithm. This detects the location of the object in a video frame. It is configured to detect not only 3D objects but also two dimensional objects as it moves or changes direction. The behaviour of the subject's pupil is also recorded such as "concentration", "intense", "ease", "confusion", "twiddle", "stressed", and "relaxed" mood, which represent the characteristic behaviour of the eyes during attentiveness (Table 1). It would enable designers to identify areas that need basic optimisation. The embedded phase consists of the Java platform used to integrate the eyetracking algorithms as a standalone on the game

Algorithm 1 Subject's iris detection

1. Ready subject's iris
2. **Procedure UpdateItem** (item eye position, current location)
3. Set pupil localisation
4. Trace iris position
5. **if** eyes closed, wait else goto Step 3 **then**
6. Record eye current location
7. **end if**
8. **if** eyes open and no iris detected goto Step 3 **else** Step 4 **then**
9. **end**
10. Update current location
11. **end if**
12. **for** each user **do**
13. Update pupil size
14. Update current location
15. **end for**
16. **End procedure**

Algorithm 2 3D object detection on a 3D video game console

1. **Input:** 3D object, object detector
2. **Output:** Detected object
3. **procedure UpdateItem** (item objects location, frame (j))
4. **for** frame(j) = 1: N frames **do**
5. Initialise Algorithm 1 as a cascade detector object
6. Read in the video frame (VF) and run the detector (Algorithm 1)
7. Read 3D objects from the scene
8. Detect feature points using Algorithm 1
9. Extract feature point descriptors by surrounding the object with 3D gaze cascade
10. Find the putative point matches
11. Locate the object in the scene using Step 8
12. Detect another 3D object
13. **if** video frame VF=0, goto Step 6 **else** goto Step 16 **then**
14. Set to current frame
15. **end if**
16. **end**
17. **end for**
18. **for** each frame **do**
19. Update object position
20. Update frame
21. **end for**
22. **end procedure**

Algorithms 3 Custom eye tracking on a 3D video game console

1. **Input:** Algorithm 1, video game console
2. **Output:** Eye position, update video game
3. **Procedure UpdateItem** (item video frame, eye position)
4. Begin
5. Set calibration for both eyes
6. Locate iris position using Algorithm 1
7. Set point of location as middle of visual field
8. Set scan-path to four corners of visual field
9. Save gaze calibration data
10. Detect 3D object at the virtual centre field
11. Locate eye positions
12. **If** eye position detection fails, goto Step 10 else goto Step 15 **then**
13. Set current eye position
14. **End if**
15. Save eye detection data $T_{c(k)}$
16. Detect other 3D objects
17. Track eye position using iris detection algorithm
18. Verify eye positions using iris detector (Algorithm 1)
19. **If** eye verification is complete, goto Step 22, else goto Step 17 **then**
20. Record eye verification mode
21. **End if**
22. Reset *counter* to update eye position
23. **If** *counter* < $T_{c(1)}$, goto Step 16 else goto Step 10 **then**
24. Set verification mode
25. **End if**
26. **If** gaze off screen, goto Step 11 to reset gaze position else goto Step 16 **then**
27. Set current eye position
28. **End if**
29. Set *counter* +1 counter to $T_{c(1)}$, goto Step 16 else goto Step 10
30. If search for 3-D objects is complete, goto Step 31, else goto Step 16
31. **End**
32. **for** each frame **do**
33. Update eye position
34. Update next object
35. **End for**
36. **End procedure**

console designed with "stuckd". Both engines were sychronised to run on the same platform using the PC camera lens for calibration. Because of the easy steps with algorithm, calibration runs faster with a minimum speed of 0.5 MHz per second. User can interact with the game while their eye movement behaviour is captured alongside the 3D objects in video game.

2 Method

The method adopted here is based on an experimental setup involving sixty participants from different background who are familiar with game interactions. They were given consent form to sign for their agreement to participate in the game session. The complex game interface is embedded in a PC containing a custom eye tracking algorithm (Fig. 2) with easy and fast calibration and a novel 3D gaze points inform of a cascaded object detector (Algorithm 3) that traces their eye movement behaviour and body movement such as clicking and key press. But the major user attributes considered were the embedded user attributes such as "concentration", "intense", "ease", "confusion", "twiddle", "stressed", and "relaxed" which were slot in during the interactive session. These represent different behaviours anticipated on the complex visual field and used as a sequential coordinate (Table 2) for the 3D fixation or gaze point. The original eye movement behaviour was first recorded and the predicted coordinates were displayed on the game interface using the 3D gaze points (bubble gaze point). The recorded data from the study are simulated to two thousand instances of user behaviour data and used as input for the RNN model. 70% and 30% of the data were used as training and test sets, respectively.

Task: The complex game interface consists of four levels where the participants are to build or design their own game from the game's index page. They had to collect some game characters and tools in the first level that would enable them build their game and play the game in the third level. The second level is where they narrate the context behind the game and test it by playing in the third

Table 2 User characteristic behaviour of eye movement detection on 3D game console: Overlapping colors tend to blend to give a unique hue.

User behaviour	Parameter value	Calibration point	Color
Intense	5	0.6	Light
Ease	2	0.4	White
Confused	3	0.8	Light blue
Slack	1	0.7	Blue
Relaxed	4	0.2	Yellow
Stressed	6	0.3	Red

Table 1 Anticipated behaviour attributes to the complex game interface: The colors create rendered cascaded 3D object detector as gaze point for the different users' moods which could be overlapped at some coordinates.

User behaviour	Sequential value	Color mood	Mouse movement	Visual field position
Concentration	4	Red	Right	Centre
Ease	3	Yellow	Left	Right corner
Intense	2	White	Middle	Left corner
Twiddle	5	Blue	Top	Bottom leftC
Stress	1	Light red	Bottom	Top leftC
Relax	7	Light blue	Upper corner	Bottom rightC
Confusion	6	White and yellow	Lower corner	Top rightC

level. Each level takes two seconds to complete. The task given to the participants is to represent the characters they choose to complete every phase of the game. The rationale for choosing a complex game interface is to allow for the experimenter to track every behavioural attributes exhibited by the user. This would require constant mouse click, concentration, and unconscious strategies from the users. These various forms of user movement are recorded by the eye movement software embedded in the system, which is used for analysis with RNN model configuration that computes the response flow and automatically predicts user movements. The section below discusses significant results on two different levels of the game where the users had to build their game and play the game in the next level.

3 Result

The diagram in Fig. 3 shows captured scene of character and user behaviour metaphors on the game interface showing both predicted and initial eye movement behaviour towards the complex game interface. The index pages of the game interface have different characters and tools used to build the game. The second level contains the section where the user needs to narrate the context of the game. The diagram illustrates the actual eye movement behaviour (blue) and predicted user behaviour (bubble gaze point) with the numbers two (2) and five (5) displaying "intensity" and "twiddling" mood of the user on the characters' location (bottom right corner (Bottom rightC) section of the interface). The longer the intensity of the users' look, the larger the bubble.

On the games' narrative page (Fig. 4), the actual eye movement and predicted gaze point of the user shows numbers 2 and 1, indicating stress and intense, respectively.

The dataset was tested on eight different scenarios for the test and training sets. This scenario involved episode where anomalies are considered, such as exclusion and inclusion of outliers to run the test. Another episode is using redundant user attributes such as number of mouse click and key press, and important attributes like fixation coordinates on both X and Y plain, fixation duration, and saccades. Figure 5 shows the performance on dataset for both training and test sets with scores for four different scenarios on the user behaviour data generated during the experimental setup. The performance on test data showed all the dataset with the entire user attributes having a sore of 70% (Fig. 5a), which happens to be the least performance when comparing significance of user

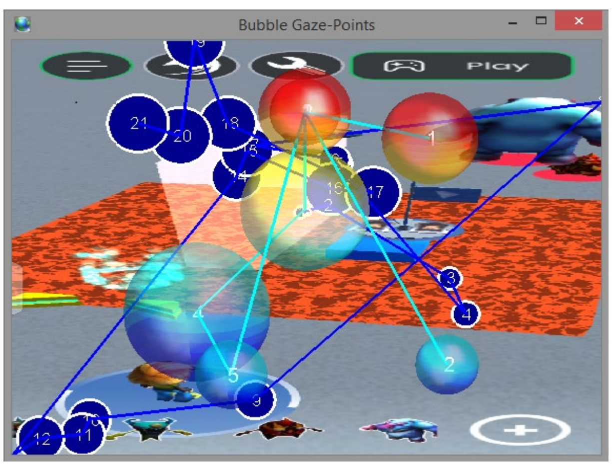


Fig. 3 Initial eye movement behaviour and predicted eye movement displayed on 3D game interface.

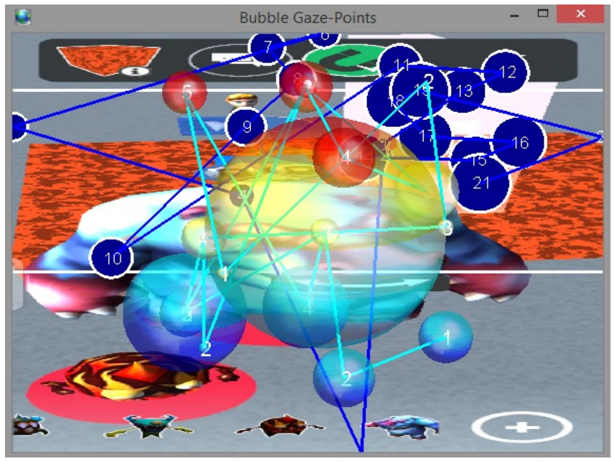
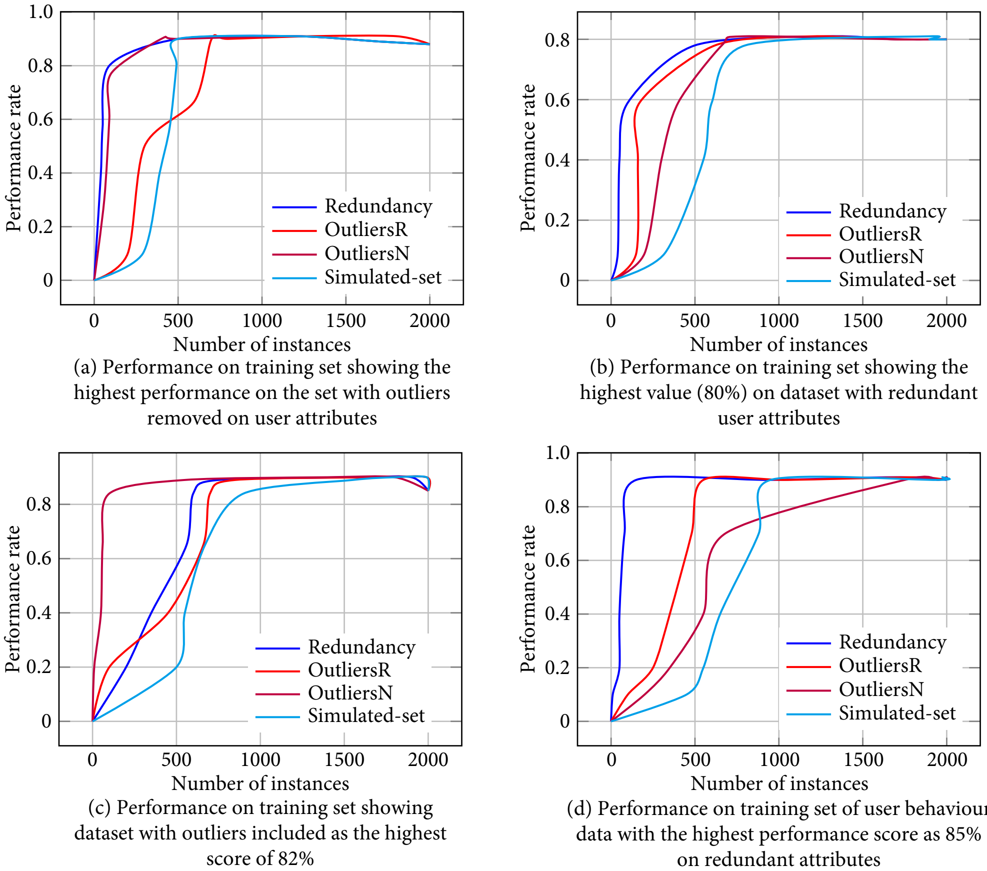


Fig. 4 Game narratives page with intense and stress mood of the user at locations.

attributes. Performance on training set showing the highest value of 80% with redundant user attributes demonstrates the significance of redundancy (trivial user attributes) to behaviour data. The performance on training set showing dataset with outliers included has the highest score of 82% (Fig. 5b). These outlying cases or anomalies could be as a result of environmental constraint that may be due to other distractions such as looking of the screen in a session. Inclusion of outliers has no effect whatsoever on the performance when considering optimisation of behavioural attributes. Performance on training set with the highest score of 85% appeared on the scenario with least redundant user attributes (Fig. 5d). The maximum performance score on test set shows the scenario with the complete user attributes and having a sore of 70% (Fig. 6a), which is also the most considerable. The highest performance on test dataset showing the least score of 86% still indicates redundant attributes and the adaptability of redundancy in user behaviour study which is very significant and should be adopted when considering predictions of user behaviour towards dynamic in interface.

4 Conclusion

The paper seeks to investigate the application of RNN for prediction of user behaviour on a complex game interface. The complexity is not based on the design module of the game but on the expertise of the users towards the game. User behaviour is sometimes difficult and complex to predict due to the fact that they adapt to unconscious response which is an evolutionary and timeless part of human nature or habitual phenomenon. Most user habits are sometimes unconscious and spontaneous therefore rendering the ability for precise likelihood of basic behavioural standards. The rationale for using RNN is based on the fact that it uses sequential patterns, is very robust in dealing with complexity in dataset, and is mostly used for text mining and language processing. As human behaviour is difficult to predict so is the behaviour pattern adopted in the dataset generating from the study which uses custom eye tracking to trace the activity of the user by easy and rapid calibration of their eye positions. The results obtained for RNN runs show that redundant attributes are the most suitable for predicting user behaviour with high accuracy, and the time spent on the session and the distance from one gaze point to the other (saccade). This can forecast the next move of the user or know what the users select for their next line of action, like knowing the kind of product or widgets users prefer in a given interface. In case of game interface, understanding the



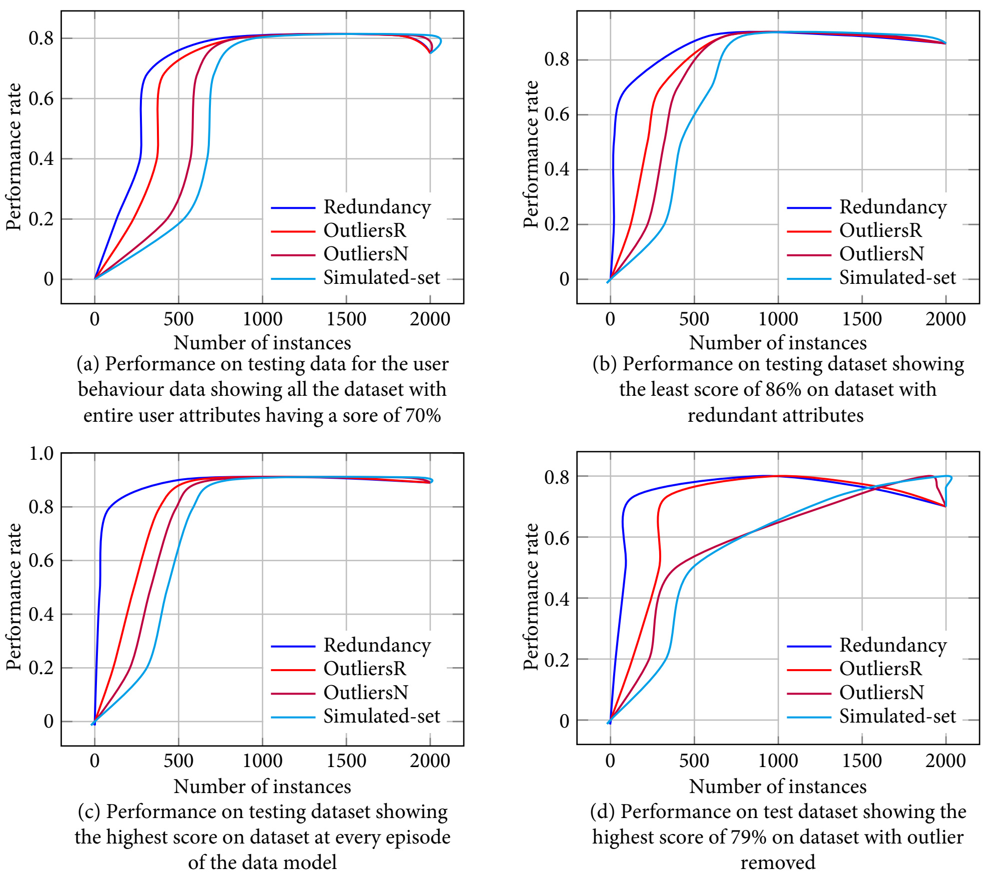
(a) Performance on training set showing the highest performance on the set with outliers removed on user attributes

(b) Performance on training set showing the highest value (80%) on dataset with redundant user attributes

(c) Performance on training set showing dataset with outliers included as the highest score of 82%

(d) Performance on training set of user behaviour data with the highest performance score as 85% on redundant attributes

Fig. 5 Performance on dataset for both training and test sets showing scores for four different scenarios on user behaviour data generated during the experimental setup.



(a) Performance on testing data for the user behaviour data showing all the dataset with entire user attributes having a sore of 70%

(b) Performance on testing dataset showing the least score of 86% on dataset with redundant attributes

(c) Performance on testing dataset showing the highest score on dataset at every episode of the data model

(d) Performance on test dataset showing the highest score of 79% on dataset with outlier removed

Fig. 6 Performance on dataset for both training and test sets showing scores for four different test sets.

user behaviour will enable the designer come up with strategies that would easily lead them to achieve their goal with minimal stress and also reduce the easiness of a game level by increasing the number of obstacles. Future perceptive will be to address other standard models of ANN and machine learning algorithms to compare with custom models. If the rate in performance is increased, the next level of decision would be to develop a smart and robust AI oriented analytical tool for accurate prediction of user behaviour towards dynamic interface with less complexity.

Acknowledgment

We wish to acknowledge Nasarawa State University for their contribution to this paper.

Dates

Received: 7 November 2021; Revised: 14 May 2022; Accepted: 19 May 2022

References

[1] M. Cavallari, Information systems security and end-user consciousness—A strategic matter, in *Management of the Interconnected World*, A. D'Atri, M. D. Marco, A. M. Braccini, and F. Cabiddu, eds. Heidelberg, Germany: Physica-Verlag, 2010, pp. 251–258.

[2] M. D. M. G. -D. L. Salmones, A. Herrero, and P. Martnez, Determinants of electronic word-of-mouth on social networking sites about negative news on CSR, *Journal of Business Ethics*, vol. 171, no. 3, pp. 583–597, 2021.

[3] N. S. Safa, M. Sookhak, R. V. Solms, S. Furnell, N. A. Ghani, and T. Herawan, Information security conscious care behaviour formation in organizations, *Computers and Security*, vol. 53, pp. 65–78, 2015.

[4] G. Krug, K. Drasch, and M. Jungbauer-Gans, The social stigma of unemployment: Consequences of stigma consciousness on job search attitudes, behaviour and success, *Journal for Labour Market Research*, vol. 53, no. 1, pp. 1–27, 2019.

[5] P. Wang, W. B. Hawk, and C. Tenopir, Users' interaction with world wide web resources: An exploratory study using a holistic approach, *Information Processing and Management*, vol. 36, no. 2, pp. 229–251, 2000.

[6] F. H. Huang, Y. L. Lee, and S. L. Hwang, E-shopping behavior and user-web interaction for developing a useful green website, in *Proc. 13th International Conference on Human-Computer Interaction*, San Diego, CA, USA, 2009, pp. 446–454.

[7] J. Brank, N. M. Frayling, A. Frayling, and G. Smyth, Predictive algorithms for browser support of habitual user activities on the web, in *Proc. 2005 IEEE/WIC/ACM International Conference on Web Intelligence* (*WI'05*), Compiegne, France, 2005, pp. 629–635.

[8] E. Papatheocharous, M. Belk, P. Germanakos, and G. Samaras, Towards implicit user modeling based on artificial intelligence, cognitive styles and web interaction data, *International Journal on Artificial Intelligence Tools*, vol. 23, no. 2, p. 1440009, 2014.

[9] Y. Lee and S. Cho, Abnormal usage sequence detection for identification of user needs via recurrent neural network semantic variational autoencoder, *International Journal of Human—Computer Interaction*, vol. 36, no. 7, pp. 631–640, 2020.

[10] K. Lee, S. Lee, and J. Lee, Interactive character animation by learning multi-objective control, *ACM Transactions on Graphics*, vol. 37, no. 6, pp. 1–10, 2018.

[11] T. Man, R. D. Yoshinov, V. Osipov, N. Zhukova, M. Schukina, and E. Evnevich, Problems of human secure interaction with the internet space, *Problems of Engineering Cybernetics and Robotics*, vol. 75, pp. 15–34, 2021.

[12] L. Zhang, P. Liu, and J. A. Gulla, A neural time series forecasting model for user interests prediction on Twitter, in *Proc. 25th Conference on User Modeling, Adaptation and Personalization*, Bratislava, Slovakia, 2017, pp. 397–398.

[13] P. Chakraborty, S. Ahmed, M. A. Yousuf, A. Azad, S. A. Alyami, and M. A. Moni, A human-robot interaction system calculating visual focus of human's attention level, *IEEE Access*, vol. 9, pp. 93409–93421, 2021.

[14] L. Gong, M. Yu, S. Jiang, V. Cutsuridis, and S. Pearson, Deep learning based prediction on greenhouse crop yield combined TCN and RNN, *Sensors*, vol. 21, no. 13, p. 4537, 2021.

[15] M. Xia, H. Shao, X. Ma, and C. W. D. Silva, A stacked GRU-RNN-based approach for predicting renewable energy and electricity load for smart grid operation, *IEEE Transactions on Industrial Informatics*, vol. 17, no. 10, pp. 7050–7059, 2021.

[16] K. Vivekanandan and N. Praveena, Hybrid convolutional neural network (CNN) and long-short term memory (LSTM) based deep learning model for detecting shilling attack in the social-aware network, *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, pp. 1197–1210, 2021.

[17] P. K. Jain, V. Saravanan, and R. Pamula, A hybrid CNN-LSTM: A deep learning approach for consumer sentiment analysis using qualitative user-generated contents, *Transactions on Asian and Low-Resource Language Information Processing*, vol. 20, no. 5, pp. 1–15, 2021.

[18] I. E. Livieris, S. Stavroyiannis, E. Pintelas, T. Kotsilieris, and P. Pintelas, A dropout weight-constrained recurrent neural network model for forecasting the price of major cryptocurrencies and CCi30 index, *Evolving Systems*, vol. 13, pp. 85–100, 2022.

[19] J. Chung, S. Hong, S. Kang, and C. Kim, Sequential UI behaviour prediction system based on long short-term memory networks, *Behaviour and Information Technology*, vol. 41, no. 6, pp. 1258–1269, 2022.

[20] T. Tancogne-Dejean, M. B. Gorji, J. Zhu, and D. Mohr, Recurrent neural network modeling of the large deformation of lithium-ion battery cells, *International Journal of Plasticity*, vol. 146, p. 103072, 2021.

[21] S. E. Lundsaunet, Effects of different map interfaces on cognitive map development, Master dissertation, Norwegian University of Science and Technology, Trondheim, Norway, 2021.

[22] S. Laato, S. Rauti, A. Laato, T. H. Laine, E. Sutinen, and E. Lehtinen, Learning history with location-based applications: An architecture for points of interest in multiple layers, *Sensors*, vol. 21, no. 1, p. 129, 2021.

[23] I. BlečIć, S. Cuccu, F. A. Fanni, V. Frau, R. Macis, V. Saiu, M. Senis, L. D. Spano, and A. Tola, First-person cinematographic videogames: Game model, authoring environment, and potential for creating affection for places, *Journal on Computing and Cultural Heritage*, vol. 14, no. 2, pp. 1–29, 2021.

[24] O. Bendel, Love dolls and sex robots in unproven and unexplored fields of application, *Paladyn, Journal of Behavioral Robotics*, vol. 12, no. 1, pp. 1–12, 2021.

[25] A. Farmaki, H. Olya, and B. Taheri, Unpacking the complex interactions among customers in online fan pages, *Journal of Business Research*, vol. 125, pp. 164–176, 2021.

[26] M. A. Friehs, M. Dechant, S. Vedress, C. Frings, and R. L. Mandryk, Shocking advantage! Improving digital game performance using non-invasive brain stimulation, *International Journal of Human-Computer Studies*, vol. 148, p. 102582, 2021.

[27] L. Steenbergen, M. J. Maraver, R. Actis-Grosso, P. Ricciardelli, and L. S. Colzato, Recognizing emotions in bodies: Vagus nerve

stimulation enhances recognition of anger while impairing sadness, *Cognitive, Affective, and Behavioral Neuroscience*, vol. 21, pp. 1246–1261, 2021.

[28] Z. Esmaeilpour, G. Kronberg, D. Reato, L. C. Parra, and M. Bikson, Temporal stimulation targets deep brain regions by modulating neural oscillations, *Brain Stimulation*, vol. 14, no. 1, pp. 55–65, 2021.

[29] J. A. Villacorta-Atienza, C. C. Tapia, S. Díez-Hermano, A. Sánchez-Jiménez, S. Lobov, N. Krilova, A. Murciano, G. E. López-Tolsa, R. Pellón, and V. A. Makarov, Static internal representation of dynamic situations reveals time compaction in human cognition, *Journal of Advanced Research*, vol. 28, pp. 111–125, 2021.

[30] M. Schoemann, D. O'Hora, R. Dale, and S. Scherbaum, Using mouse cursor tracking to investigate online cognition: Preserving methodological ingenuity while moving toward reproducible science, *Psychonomic Bulletin and Review*, vol. 28, no. 3, pp. 766–787, 2021.