Proceedings of to the 9th Scientific Conference of University of Garmian:
Pure science and Technology Applications (SCUG-PSTA-2022).
Kalar (46021) / Sulaymaniyah (26-27 Oct.2022)
(Special issue for Passer journal of basic and applied sciences)
Paper No. 01, 1-16

The Impact of Emotions on the Speed and Score of Computer Games

Hawar Othman Sharif [1] Mazen Ismaeel Ghareb [2] Tara Qadr Kaka Muhamad [3]

[1*] Computer Department, College of Science, University of Sulaimani,Sulaimani, Iraq,46001, 009647701916310

[2] College of Science and Technology, University of Human Development, Kurdistan Region, Iraq,46001, 009647714226262

[3] Computer Department, College of Science, University of Sulaimani, Sulaimani, Iraq,46001, 009647725314591

hawar.sharif@univsul.edu.iq ; mazen.ismaeel@uhd.edu.iq ; tara.qadir@univsul.edu.iq

ABSTRACT

This Research has examined how video game affects the performance of the player. Unity tool has been used to create an interactive game with several ball objects that accrue additional points for each participant. Different methods have been used to strike the balls, using the mouse, keyboard, combination of both, and facial emotion. Image processing techniques have been used to match the facial expression with the EMOGI of the balls the players hit. The performance of the game has been affected by facial expressions. The study demonstrates how widely used, and highly engaging face-emotion techniques are in video games. The usage of visual observation concerning traditional input control and emotion input has been examined, and the differences are demonstrated. Our results show that facial emotions improve the technology for video games; in our game, we tested three types of facial emotions: sad, happy, and angry.

KEYWORDS: computer games; educational games, Face Emotion, Facial Expressions as Game Input, Serious games.

1 INTRODUCTION

Facial Emotion Detection (FED) is recognizing human emotions through facial emotion. Emotions are recognized naturally by the human brain, and software that can identify emotions has recently been developed. This technology is improving all the time. Games have long been recognized as the finest form of entertainment in the world. The game's intriguing feature is that individuals (i.e., players) would willingly complete superfluous trials. When individuals experience unnecessary hurdles in the game, they do not mind being involved in a bad feeling (e.g., irritation, fear, or despair). In games, both positive and negative emotions contribute to the gaming experience. Furthermore, the player's emotions have a significant impact on the experience of the players [1, 2, 3, 4].

When the player interacts with game items (e.g., game environment, mechanics, etc.) via game input, emotional experiences are often established (e.g., keyboard, mouse, joystick, etc.). As a result, boosting the player's experience throughout the game might be accomplished by modifying game elements and/or inputs [5, 6, 7]. Manipulation of game balance is a well-known strategy for increasing players' enjoyment and experiences when playing a game. Game balancing is essential in determining if a game is too difficult, too easy, or balanced for the player. A game that is too difficult would frustrate the player, whereas a game that is too easy would bore the player [8]. During the game, the feelings (such as dissatisfaction, boredom, and so on) are often portrayed willingly through the player's facial expressions. With this nature and the capabilities of an automated Facial Expression Recognition (FER) system, the balancing system might alter game challenges based on the player's reaction to the existing game problems. This technique is growing increasingly accurate. A machine learning system can recognize emotions by studying the meanings behind each facial expression and applying that information to new data. Our understanding of contextual emotion profoundly impacts consequences for society and business. The capacity to identify feelings like shame, worry, and uncertainty in the public sphere may be advantageous to governmental institutions. In order to gauge the audience's emotional reactions, Disney plans to use facial recognition. Because they enable us to understand what others are thinking, facial expressions are essential parts of human communication [9]. One-third of human communication is verbal, and two-thirds is nonverbal, say various surveys, with verbal components making up the difference. One of the most important information channels in interpersonal communication is facial expressions, one of several nonverbal elements that convey emotional meaning. Businesses and organizations may use facial emotion to understand their customers better and create appealing products. This study focuses on how a player's facial expressions may be used to evaluate a game and how this knowledge can help a game developer produce a product that players would like.

RELATED WORK

There are many technology and techniques for developing educational or entertainment games. Some projects used HTML 5 technologies; others used cross-platform javascript and HTML 5 for mobile applications. In this research, the game has been developed using unity as a tool for many other game industries. Video games are part of a broad category of entertainment applications. Only a few video games try to include their players' emotional states in the gameplay, even though they are among the most natural applications of affect. Affective games—or, more precisely, affect-aware games—are what these are called. Unfortunately, throughout the game's creation, this affect awareness is frequently statically included, using the erroneous assumption that the so-called representative player is a model. [10, 11, 12]. In order to begin with, each player differs from the averaged model in some manner. Players' affective states might vary dramatically from session to session, making it very hard to forecast current user feelings throughout the development stage. That is why real-time player impact identification may become vital for the video game business. Only a few affect-aware games have been produced in recent years, mostly as non-commercial research projects. "Feed The Fish" utilizes a player's facial emotions as input and dynamically responds by modifying the game aspects [12]. The proposed system is to leverage human emotions to create a communication channel between the game and the players, making the game more fun to play [13]. Another attempt has been made to provide a common framework for affect-aware games. [14] Proposes a Koko library architecture for abstracting an impact model and sensor handling from other game components like application logic and game engine. As a proof of concept, two example games were created using clear physiological and physical signals like heart rate, skin conductance, or GPS player position. Today's commercial video games focus on evoking powerful emotional responses from players through clever game mechanics and interactions with other players online or in person. The development of affect detection algorithms, novel input devices, and non-intrusive sensors that enable the player to be monitored in many information channels or modalities makes it highly probable that this scenario will alter in the near future. For instance, Valve Software has actively experimented with biometrics by including them in a special build of Left 4 Dead 2. Valve Software sees affect emotion as a crucial component of future games [15]. In the literature review, several methods used for facial expression detection are identified, and the existing systems are contrasted. To recognize the face, extract facial features such the Face Emotions, nose, lips, and so forth, and to determine various moods, several techniques are applied. These systems use a variety of approaches, including machine learning algorithms like Classification and Regression Tree (CART) and Support Vector Machine, to classify facial expressions (SVM). [16] gives access to a Support Vector Machine approach for fully automatic facial emotion identification that can classify eight emotions. Used datasets include the Cohn-Kanade Database (CK) and Extended Cohn-Kanade (CK+). Training and classification portions of the dataset are divided into independent groups. Face detection in OpenCV uses the Haar filter. In real-time, emotions may be recognized using the facial landmarks method. SVM, or Support Vector Machine, is used to categorize facial expressions. Following initial face localization, the Sobel operator and the Hough transform are used in the Haghpanah framework to identify facial landmarks, and Shi Tomasi corner point identification is then carried out. In order to categorize the presented statement using Euclidean distances, the input feature vectors are trained in a Multi-Layer Perception (MLP) neural network. The KDEF database provided the dataset used for this investigation [17]. Raman demonstrates the operation of a speculative method for instantly detecting a person's mood. We extract the matching facial landmarks for each face the camera detects and investigate several traits and techniques for determining human mood [18]. According to experiments, our proposed system has an average accuracy of about 70.65% in recognizing human emotion in real time. Adyapady Based on characteristics obtained through improved principal component analysis, the classifier is random forest (2DPCA). Using improved PCA, or 2DPCA, one may get beyond the limitations of traditional PCA, such as the inability to compute the covariance matrix and the computational difficulty of getting Eigenvectors. In order to measure the parts of the face that best represents a facial expression, a unique extraction method based on the geometric approach is given [19]. This method requires computing six distances. A decision tree is used by two databases (JAFFE and COHN) to develop a facial expression classification system with seven possible classifications; this system uses the six distances (using Euclidian, Manhattan, or Minkowski distance for each face as input) as input [20].

Methods and Materials

2.1 Game Scenario:

Users may earn points by popping variously colored balloons, which is how the game is designed and played. Three alternative kinds of input—mouse, keyboard, and Face Emotions—were used to squish the balloons. The game's primary objective is to assess the effectiveness of different inputs, including the keyboard, mouse, and facial expression. The three types of EMOG images—happy, sad, and angry—that are defined in the balls will all appear at random. When the player adjusts his action, the ball's speed reduces, enabling him to strike as many balls as possible and get more points.

2.1.1 Hardware Requirements:

The game has developed on PC with these requirements.

- Intel i7-2600
- 3.6 GHz
- 4 GB of RAM
- 512 GB of storage
- NVID QUARD 600 graphics card.
- To identify the player's face, the computer needs a camera.

2.1.2 Game Design:

The game interface, rules, and examples of how players can interact with one another are shown in the figures below. The last illustration demonstrates how the player receives points by the facial expression tracker interacting with ball movement. If the image from the camera matches the experience on the EMOGI, the speed of the balls will be decreased. If not, the image will be collected and examined. The game was produced using Microsoft Windows 10 64-bit, C# Ultimate 2012, and Unity 18.3. The user interface for the game and how players may pop balloons to earn points are shown in Figure 1. Figure 2 demonstrates how users may slow down the balls' pace and score points by using emotion and the mouse.

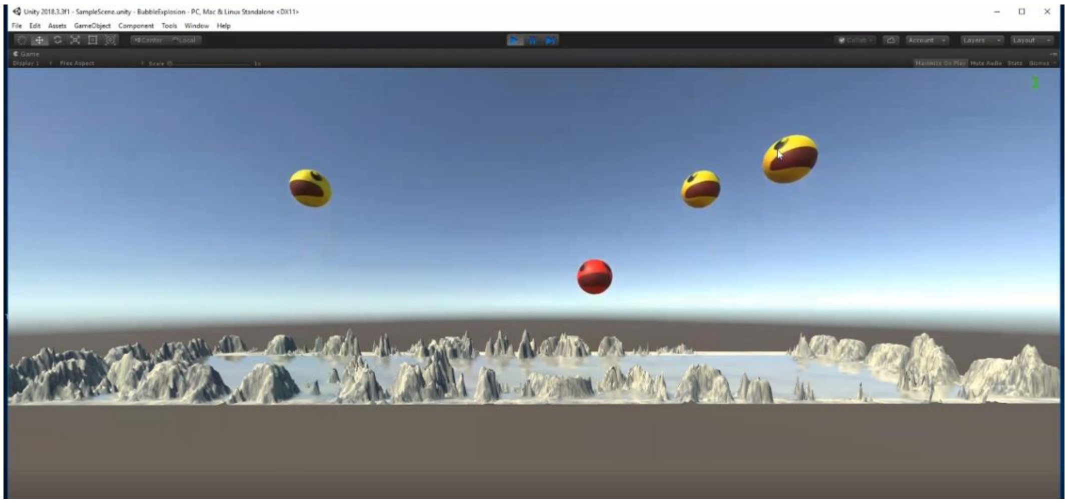

Figure 1 Users Strike Balloons

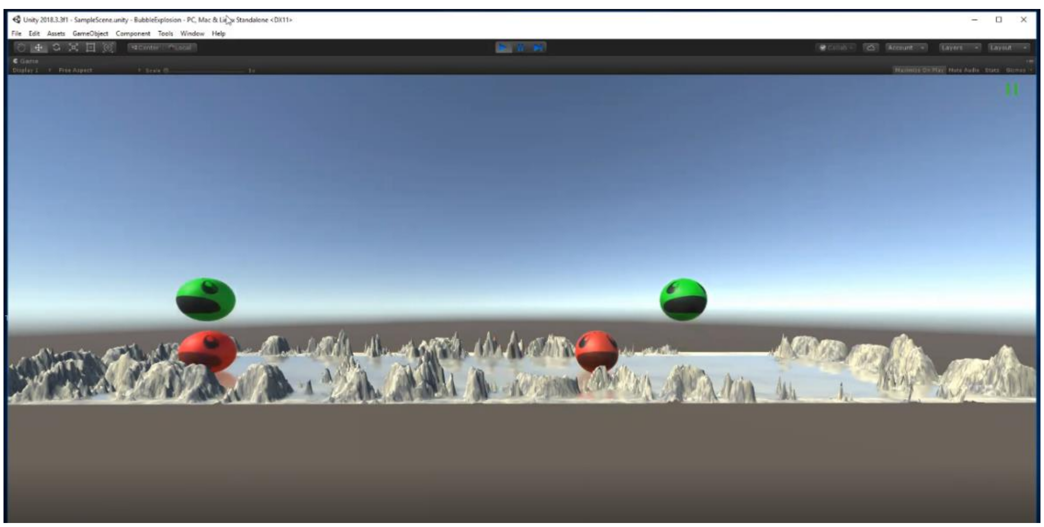

Figure 2 different EMOGI Emotions

The procedure of matching the facial expression from webcams will be as shown in figure 3.

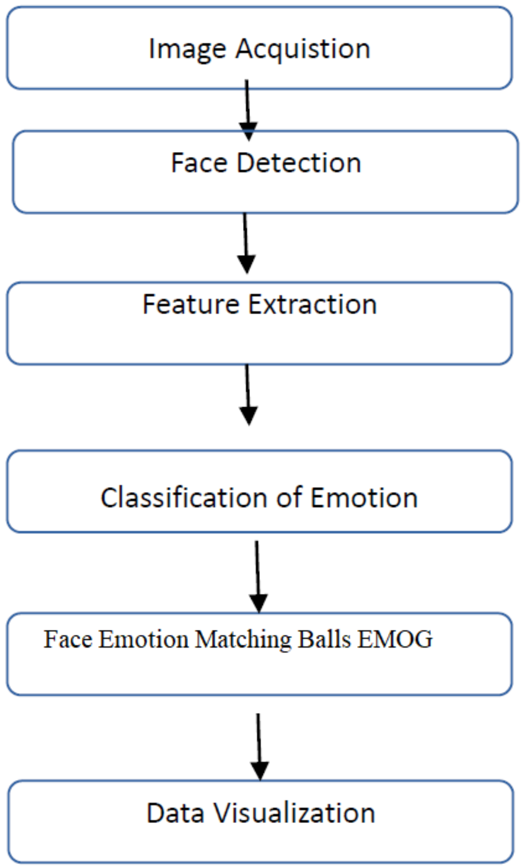

Figure 3 Process of matching face emotion from webcam

2. DATA SET

Data collection on the player was done using 48 users. All of the participants in the game were trained to utilize it and were undergraduate students from the department of computer science. For the purpose of accumulating points, each user used the mouse, Face Emotions, and Face Emotions with Space. The time was measured both with and without recording facial expressions, as shown in table 1 below.

Table 1 Player Score and Time with and without face Emotion

No.	Player Score without face Emotion	Time without face Emotion	Player Score with face Emotion	Time with face Emotion

1	30	46.29	19	141.99
2	45	49.36	47	435.85
3	29	47.02	33	818.27
4	28	35.69	34	743.27
5	38	36.75	35	403.76
6	31	40.79	48	121.67
7	37	47.87	27	103.03
8	25	62.88	18	110.28
9	40	65.52	44	58.47
10	37	42.11	27	42.3
11	35	63.05	20	149.92
12	27	42.81	37	134.44
13	29	39.97	44	138.1
14	43	64.43	45	203.79
15	47	80.71	43	1021.16
16	33	36.42	29	221.11
17	41	47.7	45	48.85
18	37	66.36	10	367.34
19	42	69.42	35	182.35
20	32	49.99	16	158.58
21	17	44.26	27	134.3
22	41	57.42	16	1129.29
23	42	48.06	27	165.73
24	44	76.02	44	151.95
25	37	40.44	32	38.51
26	31	81.27	30	420.144
27	41	32.56	36	143.97
28	29	60.89	39	51.15
29	48	66.81	48	157.88
30	42	68.82	44	183.04
31	36	80.09	22	220.53
32	38	48.12	33	41.95
33	37	30.01	24	44.16

34	22	56.67	32	171.82
35	45	63.83	37	159.96
36	30	71.37	17	137.65
37	38	32.53	30	39.48
38	29	70.75	37	185.42
39	24	84.64	12	181.13
40	44	47.71	25	351.76
41	50	31.31	35	52.12
42	44	35.38	49	157.58
43	46	47.42	41	39.7
44	36	38.87	28	47.04
45	32	53.62	10	159.6
46	29	133.27	42	57.33
47	42	48.19	34	160.39
48	38	64.12	51	136.96

3. Results and Discussions

To determine if there were any appreciable variations between the two entrance techniques, a Pearson correlation analysis for 48 players and a regression analysis of data on overall performance metrics for each sport were carried out. User performance was pleasing to the eye. However, there were no appreciable differences in overall performance for either the keyboard or the mouse. For example, while performing pointing actions, the user typically starts by appearing at the desired outcome and only moves the pointer after selecting a target. Contrarily, when a client uses the Face Emotion pointer, the cursor is brought to the front whenever they click on their Face Emotions. The player's overall number of comments from the game increased as a result, even if they are not aware of it. Users exhibited a clear preference for the Face Emotion component tracker as they continued to play. This is said to be because using Face Emotions reduces the amount of effort needed to move about the persona. The goal required users to move their cursor across the entire screen more than once in order to fulfil it. As soon as the user arrives at the intended goal, they consciously shift the pointer with the mouse. But using the Face Emotion to point in the right direction changed the cursor, thus no hand motions were required to find the intended place. In response to a need, one participant said, "I ought to locate with the view freely and merely clicked on the mouse." Facial Emotion Monitoring permits the expansion of the same visible signs in the digital arena as face emotion movements are used to factor in naturally while chatting with people. The delay that occurred when snapping pictures of a target is said to be the reason for the Face Emotion Tracer's overall worse performance than the mouse throughout the game. The time it takes a shot to reach its target is around one second. Users appeared to have difficulty "guiding" the missiles toward a clean area in front of the cellular target.

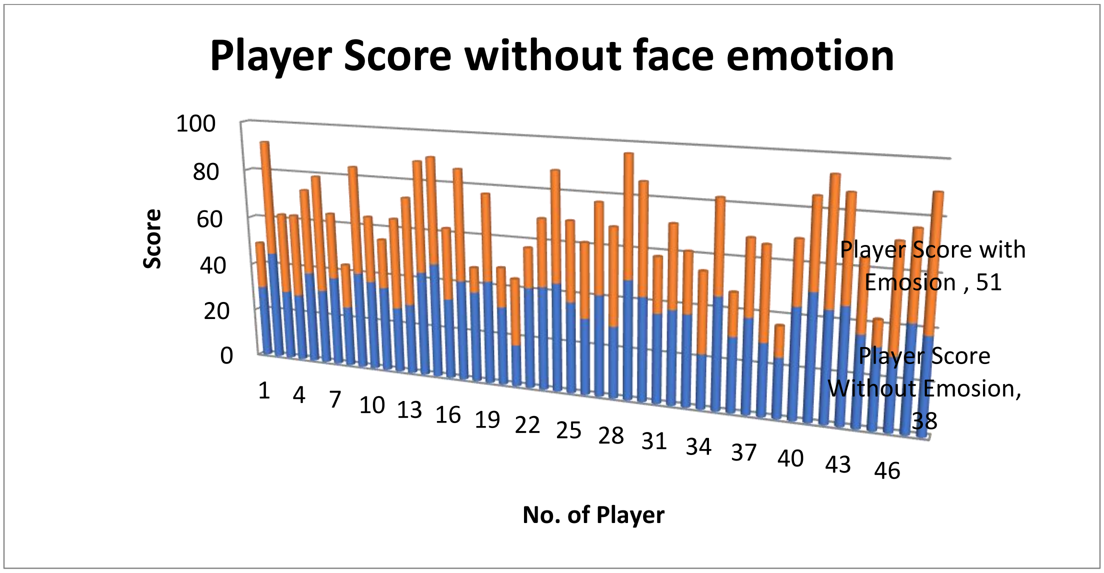

Figure 4 Player Score with and without face Emotion

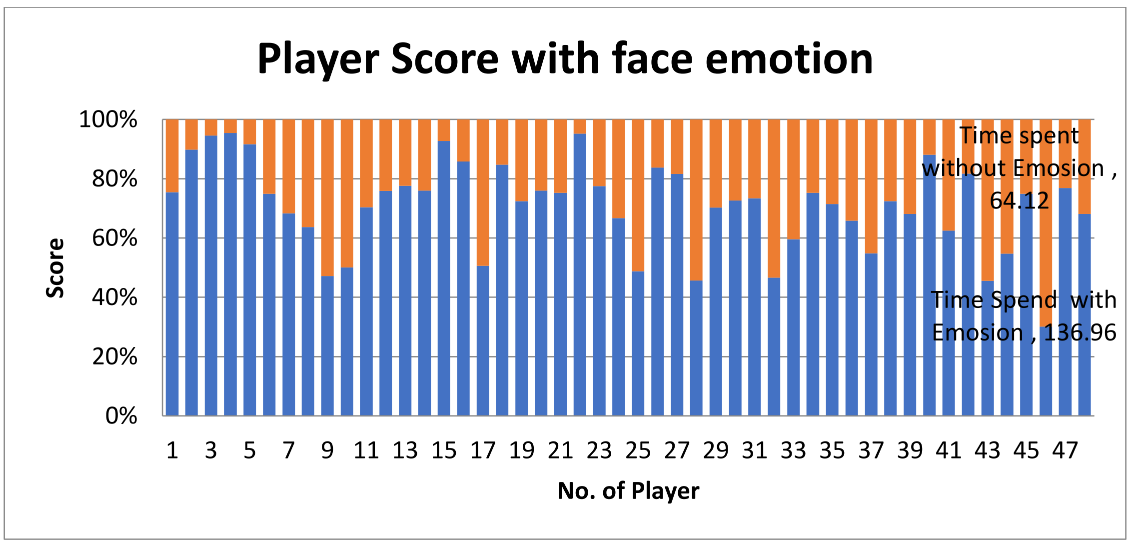

Figure 5 Time spent with or without face Emotion

Figures 4 and 5 depict the little variation in score and time difference. The reason for this is because we did not instruct the players about their emotions when they initially played this new experience. This result demonstrates the influence of emotion on the player's score and time for the first time using this new technique in the game. Certainly, the second time will be more and faster. So the results demonstrate that Face Emotion input performs better than Mouse input by a factor of 45, and Face Emotion input performs better than combined input by a factor of 66. This signifies that the Face Emotion input has values that are appropriate for the players to enter.

This study employed the linear Pearson's correlation. Person Correlation Coefficient (PCC) was utilized to calculate a liner correlation between Time spend for begins the game till end game when playing with and without using the Face Emotion control. The covariance of two variables and the product of standard deviations are computed using the measure. The outcomes range from -1 to 1. Only connections or correlations may be reflected by covariance.

Pearson Correlation Coefficient $= \rho(x,y) = \Sigma[(x_i - \bar{x}) * (y_i - \bar{y})] / (\sigma_x * \sigma_y)$ **[46]**

Table 2 Person Correlation between spending time for scoring with and without face emotion

	Time Spend with Emotion	Time spent without Emotion
Time Spend with Emotion	1	0.088298522
Time spent without Emotion	0.088298522	1

Table 2 above indicate a Strong correlation between the time spending with the game with or without emotion which means the player enjoying of playing with new input as face emotion. And statistically have significant values.

Table 3 Pearson Correlation between Face Emotion and Face Emotion Space input

	Player Score Without Emotion	Player Score with Emotion
Player Score Without Emotion	1	0.38088787
Player Score with Emotion	0.38088787	1

According to Table 3, the Pearson correlation coefficient [46] between with and without using the Face Emotion control is 0.38, indicating that there is less significant correlation between the two variables when the player need to score more points.

Table 4 displays the regression statistics provided by the SPSS statistical tool

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.380888							
R Square	0.145076							
Adjusted R Square	0.12649							
Standard Error	6.943252							
Observations	48							
ANOVA Table 4 Regression Statistics for Face Emotion and Mouse inputs								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	376.3139	376.3139	7.805925	0.007566857			
Residual	46	2217.603	48.20875					
Total	47	2593.917						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	27.89017	3.141394	8.87828	1.55E-11	21.5668767	34.21347205	21.5668767	34.21347205
Player Score with Emotion	0.256272	0.091725	2.793909	0.007567	0.071638599	0.440905213	0.071638599	0.440905213

Table 4 displays the regression statistics provided by the SPSS statistical tool for the difference between Face Emotion scoring and scoring without using Face Emotion. There are strong positive relationships between scoring with emotion and scoring without emotion. R (48) =0.38, p<0.05.

Table 5 Regression Statistics Time Spent for player using face emotion or not

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.088298522							
R Square	0.007796629							
Adjusted R Square	-0.01377301							
Standard Error	243.3617574							
Observations	48							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	21407.63371	21407.63	0.361463	0.550646193			
Residual	46	2724347.469	59224.94					
Total	47	2745755.102						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	156.6904862	109.8588333	1.426289	0.160537	-64.44387231	377.8248	-64.4439	377.8248447
Time spent without Emotion	1.133734148	1.885728775	0.601218	0.550646	-2.662040945	4.929509	-2.66204	4.929509242

The regression data of the difference between time spent for player to use Face Emotion or not input are shown in Table 5. These figures were obtained using the SPSS statistical software. There is weak positive relationships between time spending with the player for using face emotion or not using it, R (48) =0007, p>0.05.

Table 6 Descriptive statistics for player Score with and without face emotion

Player Score Without Emotion		Player Score with Emotion	
Mean	36.20833333	Mean	32.45833333
Standard Error	1.072280633	Standard Error	1.59369278
Median	37	Median	33.5
Mode	29	Mode	27
Standard Deviation	7.428978147	Standard Deviation	11.04142747
Sample Variance	55.18971631	Sample Variance	121.9131206
Kurtosis	-0.383659483	Kurtosis	-0.733891762
Skewness	-0.357261642	Skewness	-0.318178186
Range	33	Range	41
Minimum	17	Minimum	10
Maximum	50	Maximum	51
Sum	1738	Sum	1558
Count	48	Count	48

Table **7** Descriptive statistics for player time spent in the game with and without face emotion

Time Spend with Emotion		Time spent without Emotion	
Mean	219.272375	Mean	55.19979167
Standard Error	34.88681739	Standard Error	2.717087078
Median	154.765	Median	48.775
Standard Deviation	241.7029609	Standard Deviation	18.82453147
Sample Variance	58420.32133	Sample Variance	354.3629851
Kurtosis	6.15407736	Kurtosis	4.834647656
Skewness	2.4941962	Skewness	1.584002492
Range	1090.78	Range	103.26
Minimum	38.51	Minimum	30.01
Maximum	1129.29	Maximum	133.27
Sum	10525.074	Sum	2649.59
Count	48	Count	48
Largest(1)	1129.29	Largest(1)	133.27
Smallest(1)	38.51	Smallest(1)	30.01
Confidence Level (95.0%)	70.18322277	Confidence Level (95.0%)	5.466074063

Table 6 and 7 describes the descriptive statistics for the three games supplied for Mean, Standard Error, Median, Standard Deviation, Sample Variance, and Confidence Level. The results explain superior outcomes for Face Emotion Tracker in several statistical parameters while Time spent for player has not shown strong relationship between time spent in game using face emotion or not. These findings suggest that players may utilize Face Emotion techniques has been a significant effect on the player mood and interactions with the games.

.

4. Conclusion

This paper focused on the introduction of novel video game input. Face Emotion movement is a crucial component in video games since it encourages player participation and increases the game's difficulty and challenge. 48 participants (undergraduate BSc students) participated in the case study to test the game utilizing a variety of inputs, including face movement, the mouse, the keyboard, the mouse, and the keyboard, as well as other inputs like the keyboard and the keyboard. The results show that using Face Emotion input approaches to score points significantly impact gameplay. This encourages player participation and allows for greater input. The game will slow down, though, depending on the conditions. Finally, the results show a strong link between all of the inputs (Face, Emotion, Mouse, and Keyboard).

Authors contribution

Tara Qadr Kaka Muhamad and Hawar Othman Sharif came up with the idea for the study, collected the data, and coded it. Mazen Ismaeel Ghareb wrote the research strategy and went over every piece of information.

Acknowledgements

We would like to express our gratitude to the University of Human Development for its ongoing support, the head of the computer science department at the University of Sulaimani, and all of the department's students who took part in the game.

References

[1] Lazzaro, N., 2009. Why we play: affect and the fun of games. Human-computer interaction: Designing for diverse users and domains, 155, pp.679-700.

[2] Chowanda, A., 2018. Towards emotional and socially realistic game companions with personality (Doctoral dissertation, University of Nottingham).

[3] Yannakakis, G.N. and Paiva, A., 2014. Emotion in games. Handbook on affective computing, 2014, pp.459-471.

[4] Chowanda, Andry, et al. "Computational models of emotion, personality, and social relationships for interactions in games." The 2016 International Conference on Autonomous Agents & Multiagent Systems. 1930.

[5] Prasetio, Y.L., Wijaya, R., Sjah, M.P., Christian, M.R. and Chowanda, A., 2017. Location-based game to enhance player's experience in survival horror game. Procedia computer science, 116, pp.206-213.

[6] Jennett, C., Cox, A.L., Cairns, P., Dhoparee, S., Epps, A., Tijs, T. and Walton, A., 2008. Measuring and defining the experience of immersion in games. International journal of human-computer studies, 66(9), pp.641-661.

[7] Brockmyer, J.H., Fox, C.M., Curtiss, K.A., McBroom, E., Burkhart, K.M. and Pidruzny, J.N., 2009. The development of the Game Engagement Questionnaire: A measure of engagement in video game-playing. Journal of experimental social psychology, 45(4), pp.624-634.

[8] Moniaga, J.V., Chowanda, A., Prima, A. and Rizqi, M.D.T., 2018. Facial expression recognition as dynamic game balancing system. Procedia Computer Science, 135, pp.361-368.

[9] Muhammad, T.Q.K., Sharifi, H.O. and Ghareb, M.I., 2022. Eye Tracking Technique for Controlling Computer Game Objects. UHD Journal of Science and Technology, 6(1), pp.43-51.

[10] A. M. Darwesh, M. I. Ghareb. and S. Karimi. "Towards a serious game for kurdish language learning." Journal of University of Human Development, vol. 1, no. 3, pp. 376-384, 2015.

[11] M. I. Ghareb. HTML5, future to solve cross-platform issue in serious game development. Journal of University of Human Development, vol. 2, no. 4, pp. 443-450, 2016.

[12] A. Ahmed and M. Ghareb. Design a mobile learning framework for students in higher education. Journal of University of Human Development, vol. 3, no. 1, p. 288, 2017.

[13] Obaid, M., Han, C. and Billinghurst, M., 2008, December. " Feed the Fish" an affect-aware

game. In Proceedings of the 5th Australasian Conference on Interactive Entertainment (pp. 1-6).

[14] Szwoch, M. and Szwoch, W., 2015. Emotion recognition for affect aware video games. In Image Processing & Communications Challenges 6 (pp. 227-236). Springer, Cham.

[15] Izountar, Yousra, Samir Benbelkacem, Samir Otmane, Abdallah Khababa, Mostefa Masmoudi, and Nadia Zenati. "VR-PEER: A Personalized Exer-Game Platform Based on Emotion Recognition." Electronics 11, no. 3 (2022): 455.

[16]Baby, B. and Jojy, C., 2022. Live Video Emotion Detection Using Convolutional Neural Network.

[17] Haghpanah, M.A., Saeedizade, E., Masouleh, M.T. and Kalhor, A., 2022, February. Real-Time Facial Expression Recognition using Facial Landmarks and Neural Networks. In 2022 International Conference on Machine Vision and Image Processing (MVIP) (pp. 1-7). IEEE.

[18] Raman, S., Patel, S., Yadav, S. and Singh, V., 2022. Emotion and Gesture detection. International Journal for Research in Applied Science and Engineering Technology, 10, pp.3731-3734.

[19] Adyapady, R.R. and Annappa, B., 2022. A comprehensive review of facial expression recognition techniques. Multimedia Systems, pp.1-31.

20] Canal, F.Z., Müller, T.R., Matias, J.C., Scotton, G.G., de Sa Junior, A.R., Pozzebon, E. and Sobieranski, A.C., 2022. A survey on facial emotion recognition techniques: A state-of-the-art literature review. Information Sciences, 582, pp.593-617