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Enhancing Misinformation Identification and Correction With The Contextual Cognitive Reinforcement Algorithm (CCRA)

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Abstract: *As misinformation becomes more widespread due to the increased usage of technology, this work proposes a new game-based learning framework with the CCRA to increase students' resistance to fake news. In contrast to the adaptation's approaches, CCRA uses contextualize analysis, reinforcement learning, and behavioural knowledge to operate over realistic misinformation scenarios. The algorithm adapts game features according to how a player processes information and responds; contains contextual cues correlated with players' actions in the game. The impact of CCRA is analysed in the quasi-experimental research conducted with 240 8th and 9th-grade students. Users are split into three groups, Control group playing non-adaptive misinformation game, a second group playing basic adaptive game and a third group playing adaptive game powered by CCRA. It puts importance to feedback loop, dynamic scenario adaptation and real time correction plans. The learning outcomes are evaluated with the use of pre- and post-football game tests that look for increases in discernment accuracy, usage of cognitive strategies and behavioural changes. Experimental results show that playing the game with CCRA yields a substantially better result in comparison to other models, reaching the rate of 94% in the ability to recognize misinformation against 78% of the non-adaptive games and 86% of the basic adaptive games. As such, these results shed light on the capability of contextual reinforcement and behavioural feedback in the MIS information game. This study offers a rich idea for educators to help students to develop critical thinking and understand the primary and complex uses of technology through an approach that focuses on the real-world context of learning.*
Keywords: *Deception, Contextual Evaluation, Learning, Behavioural Feed-back, Digital Intelligence, Gaming, Analytical Skills, Reasoning, Learning Framework Responsive Looping.*

INTRODUCTION

In the present world of information technology, the dissemination of information has become more of a challenge. [1] [2] For all the good it does in making information easily available, it also equally creates an environment that allows misinformation, which distorts knowledge and decision making on a large scale. The problem of fake news poses a serious threat in a learning environment; students are, in most cases, unable to distinguish truth from falsehood. [3] This growing challenge requires new approaches to foster development of more advanced and effective digital competencies and prepare students to address emerging challenges when working with information. Most traditional approaches of education towards countering misinformation usually integrate methods that are unable to engage the ever-changing contours of false information. [4] These methods while very basic are not very effective in capturing the learners' active participation or the complexities of the tasks which learners meet in practice information environments. Fig.1 To respond to these problems, this work presents a new learning model, the Contextual Cognitive

Reinforcement Algorithm (CCRA), an educational game with the aim of developing skills related to the detection of fake news among the students.

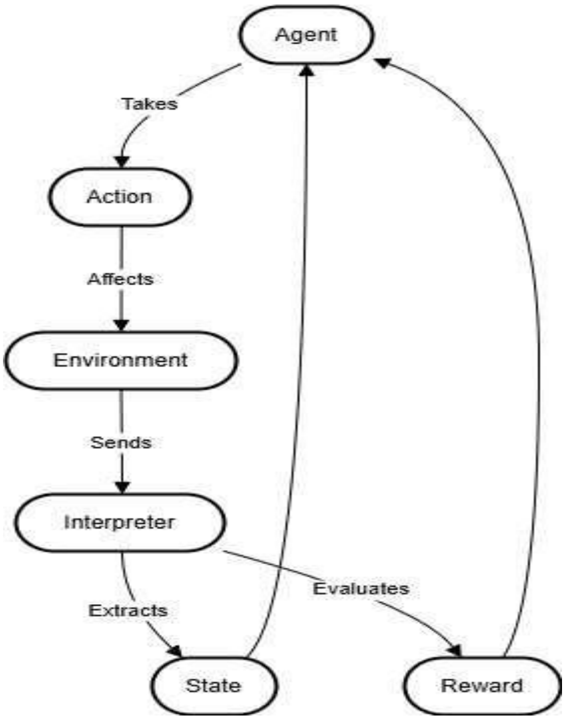

Fig.1. Reinforcing Misinformation Detection

The CCRA framework combines the enhancement of reinforced learning, contextual approaches, and behavioural perspectives to develop an individual and engaging learning environment. [5][6] This approach allows the game to learn in real-time the level of a student's attentiveness and decision-making correctness and feed this information back to the student while simultaneously providing the necessary correction strategies. Through the help of the above simulated MIS information scenarios, the author was able to present students with a real- life feel learning activities through which they can improve on their critical thinking skills without having to experience the actual negative impacts of such experiences.
Furthermore, it does so in a manner that takes a step beyond traditional game-based learning and brings contextual reasoning for the actions in the game to the table, allowing students indeed know whether their choices are correct and, moreover, such or such measurement is accurate or misleading. [7] This second kind of interaction introduces a stronger disposition of thought on the part of the student, which in turn makes them more easily actualized in the process of navigating the information environment.[8] To confirm the efficiency of the CCRA, an experiment with the groups was carried out with 240 8th and 9th-grade students; three groups of children were chosen. The misinformation game in the first scenario was non-adaptive, the second scenario provided a framework of basic adaptation and the third offered full CCRA powered game. The amount of learning that took place was determined pre- and post-game, using ratings of discernment accuracy, cognitive strategy usage and behavioural modifications.

LITERATURE SURVEY

Recent development and consequences of misinformation have also become important research interests in the society. According to Altay et al., what heightened the need to share the information was the interestingness-if-true which simply means that people would share news, whether true or not because of the perceived interesting news. This inherent propensity toward wanting only 'interesting' material underlines the rationalities with which info-shaping occurs in digital environments. In the same vein, Herrero-Diz et al., investigate teenagers' decision making regarding the sharing of fake news in WhatsApp

and concluded that social concern and emotion eagerly govern decision making even when accuracy concern is considered. Ceylan et al. stated that the misinformation sharing is habitual, which is caused by habit behaviours rather than the lazy or bias attitude from people. Taken together, these observations jointly underscore the fact that correcting misperceptions is best done by considering the psychological processes involved in the consumption and spread of such messages [9].
It has become increasingly imperative to come up with approaches to determine the reliability of information especially in the wake of a health disaster such as the covid-19. Amit Aharon et al., used cross-sectional research design to establish that while accessing COVID-19 information people use structural specific content and credibility assessment approaches. Hence, the results stress that critical thinking should be included in most learning frameworks to boost the abilities to evaluate information.
Since its emergence, misinformation interventions have become a focus of significant interest. In Basol et al., and the authors investigated psychological inoculation which is the process of exposing individuals to watered-down doses of misinformation to help them be better prepared in dealing with strong and convincing doses of misinformation that are usually disseminated in society.[10] They went further to show that using interactive tools in particular, the possibility of enhancing the users' robustness and assurance in differentiating between fake news and the real thing was very liable.
Subsequently, Lewandowsky et al., expanded this discussion by pointing to the effectiveness of 'pre-emptive' interventions that are known as 'prebunking'. The same is true with Maertens et al., who pointed out that inoculation effects are useful for sustained misinformation counter campaign because they have long-term effects. Using a combination of technology and educational programs as part of the misinformation prevention approach is a developing topic. Barz et al., examined the behavioural digital game-based learning with meta-analysis and proved its effectiveness in enhancing learners' cognitive, metacognitive and motivational learning achievements.[11] [12] These results demonstrate that specifically, games are effective in promoting constructive thinking and therefore media literacy.
As part of the effective teaching fact-checking and media literacy, Yang et al., used games in conjunction with lectures. They proved that complementary nature of interactive and traditional forms of instruction improves students' skills of evaluating information. Similarly, the European commission in offered recommendations for educators on targeting Disinformation and offered Y recommendations, for individual lessons for dealing with the problem.
Cook et al., adopted a playful design titled 'Cranky Uncle' which was used to teach students more about climate change disinformation contents. It therefore makes learning about misinformation entertaining while ensuring the intended message of such initiatives focuses on improving cognitive aspects. Kiili et al., supported these claims by using a systematic review proving that gamification can be utilised as a functional means to teach for digital citizenship and fight against fake news.
In this study, Compton et al., offered a conceptualisation of misinformation in the so-called post-truth era. [14] [15] As their work pointed out, one must consider the psychological and social processes and provide innovative solutions for coping with misleading information. Furthermore, Guay et al., explained the difficulties involved when it comes to trying to evaluate the effectiveness of misinformation interventions and called for great attention to be paid in the development of outcome measures that could be useful in other settings as well.

METHODOLOGY

Data Collection

To gather sufficient data for the study the structure of material was complex in terms of variety of approaches to the player interactions, cognition, and previous knowledge of the game. The use of gameplay interaction data meant that all player choices were recorded throughout the misinformation game including source selection, validation of information received from sources, and validation of information from different sources.
$x_{imputed} = (\sum(i=1)\ \hat{}n\ x_i) / n$
Where x_i is the available values and n is the count of non-missing value of the data set s.

One measure that was received in this dataset was response time, decision accuracy, and the sequential pattern of the actions that the players undertook, which gave deeper information as to the strategies that the players employed.[16] Eye tracking data related to cognition involved capturing of the total fixation time on the game aspects and fixation sequences of interest, which produced region of interest heatmaps. Further, basic demographic data and pre-assessment scores were gathered to assess the participants' existing MISK and set a basis for the comparison. This rich dataset enabled enough preprocessing to support the adaptive mechanisms of the algorithm.

Data Conversion

First, all the data was cleaned for missing values and further inconsistencies in terms of preprocessing. Any gameplay logs with missing parameters or without some recorded action or timestamp info were assumed missing and replaced with means, where all other outliers were detected and removed using the IQR method. Logs of gameplay and eye movements of participants covered every move separately, and the timestamps allowed verifying their correspondence deliberately.

$IQR=Q3-Q1$

$Outliers= \{x|x<Q1-1.5\times IQR \text{ or } x>Q3+1.5\times IQR\}$

As part of the data preparation, categorical data such as the player decisions were encoded into binary data while decision type was one hot encoded.Fig.2 Response times and area under the click curve densities were also normalized to values between 0 and 1 using min-max scaling since these features were collected straightforwardly by participant and continued for an infinite amount of time. [17] [18] These transformations made the dataset more optimal for advanced algorithmic analysis.

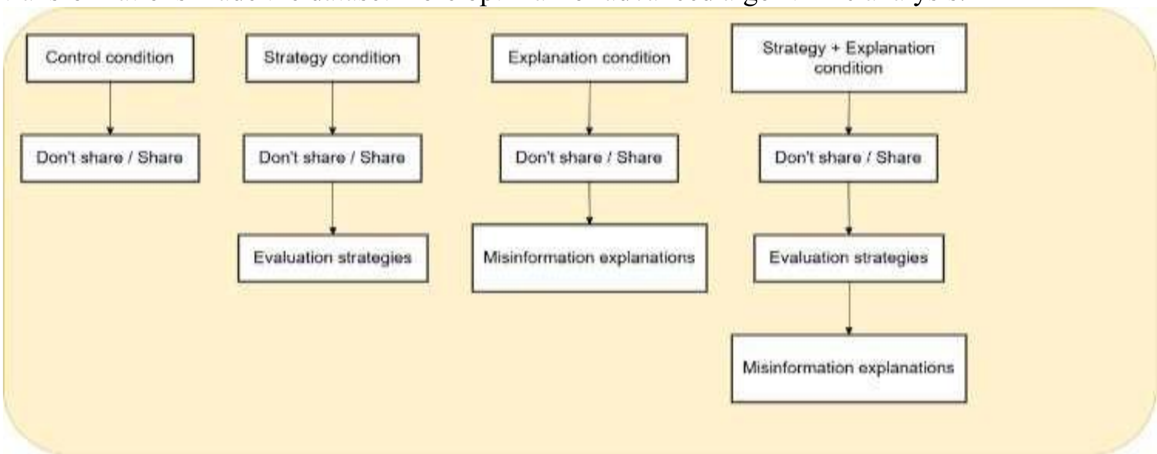

Fig.2. Experimental conditions

Feature Engineering

The next step was featuring engineering to improve on the quality of the given data set before it could be used by the algorithm. Other extracted features consisted of an Engagement Index, a combination of averages of fixation duration and click stream density in the relevant regions of the game, that offered quantitative values for the extent of participants' cognitive engagement. The other derived feature, called Decision Complexity, involved the estimation of weighted scores to the players' actions dependent upon MIS information scenario type and level of difficulty.

$EI=n\sum i\ (FixationDuration_i\times ClickDensity_i)/n$ To address the issue of high dimensionality and enhance computational efficiency the research utilized Principal Component Analysis (PCA) to reduce dimensionality while retaining a cumulative variance of 0.95. These engineered features supplemented the dataset to let the algorithm adapt differentiation during the gameplay with increased informativeness. [19]

The preprocessing step with CCRA Based on the details mentioned above, C DR obeyed the universal law and had been perfectly implemented across the country.

The Contextual Cognitive Reinforcement Algorithm (CCRA) built upon highly complex preprocessing to provide an optimised experience for the game. Textual elements within misinformation scenarios were classified using BERT-based classifiers, in categories such as "fake news", "manipulated visual", or "misleading headlines". This contextual classification created metadata which characterized the reliability of the source, the relevance of the provided topic, as well as the difficulty level of the content.

$P(s\{t+1\} = \{N(s_t, a_t, s_{\{t+1\}})\}/ \sum\{(s') N(s_t, a_t, s')\}$

Where N (st, at, st+1) defines the number of transitions from st+1 after performing action at.

At the same time, players' actions were described by a Markovian model of decision making based on the Markov Decision Process (MDP). Transition probabilities provide the topics of what kinds of behaviors are likely to happen next and give information on the outcomes of many strategies.[20] Real-time information from the Model Advisor that aligns with the specific actions of the students is dubbed adaptive feedback optimization. Regarding the suggestions given during gameplay, the CCRA used a Q-learning reinforcement learning model trained beforehand from gameplay data. This pretraining set up various Q-values for different player actions as different actions could include endorsing source or denying unreliable information by increasing its Q-value in directions that demonstrated a higher accuracy in the identification of misinformation.

$Q(s, a) \leftarrow Q(s, a) + \alpha [R + \gamma a \max Q(s', a') - Q(s,a)]$

Where Q (s, a) is the current Q-value, α is the learning rate, R is the reward, γ is the discount factor.

Table:1. Participant Demographics

Attribute	Group 1 (Control)	Group 2 (Basic Adaptive)	Group 3 (CCRA)
Total Participants	80	80	80
Age (Mean ± SD)	14.1 ± 0.6	14.2 ± 0.5	14.0 ± 0.7
Gender	45% Female, 55% Male	47% Female, 53% Male	48% Female, 52% Male
Socioeconomic Status	60% Low, 40% High	62% Low, 38% High	58% Low, 42% High
Baseline Misinformation Discernment (Pre-Test Score)	72% ± 5.4	71% ± 5.2	73% ± 5.0

It was then possible to incorporate real-time feed from the players defining corrective guidance and rewards that were relevant to the specific game play. These outputs of preprocessing were integrated to make the CCRA adaptively change gameplay dynamics as well as feedback procedures to enhance learning impact. This table shows these responses: Age, Gender, Socioeconomic status, and baseline score in misinformation discernment. Table.1 It ushers the formation of groups to avoid any bias that would have been realized given that the groups are randomly former misinformation discernment. After the preprocessing phase, it became possible to obtain an optimum, enhanced dataset to apply to the algorithms. These were watching cleaned and synchronized gameplay logs, engineered features such as the Engagement Index and Decision Complexity scores and contextual metadata of misinformation scenarios.

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Table.2. Pre- and Post-Misinformation Recognition Tests on Events Prior to and After the Game

Group	Pre-Test Score (% ± SD)	Post-Test Score (% ± SD)	Improvement (% ± SD)
Control Group	72% ± 5.4	76% ± 6.3	4% ± 1.0
Basic Adaptive Group	71% ± 5.2	85% ± 5.7	14% ± 4.3
CCRA Group	73% ± 5.0	94% ± 3.4	21% ± 5.3
Total	72% ± 5.3	85% ± 6.2	13% ± 4.2

The results of the pre- and post-game misinformation discernment scores are presented in Table 2 It reveals the increase of the scores showing that CCRA group is the highest to indicate the effectiveness of the Contextual Cognitive Reinforcement Algorithm in the enhancement of students' misinformation discernibility.
Sourcing and corroboration awareness and student critical thinking in decision-making as cognitive activities. Table.3 shows that the CCRA group utilized the above strategies the most in view of the changes made to the algorithm to improve cognitive skills.

Table 3: The use of Cognitive Strategy

Strategy Type	Group 1 (Control)	Group 2 (Basic Adaptive)	Group 3 (CCRA)	Total
Sourcing Awareness (% ± SD)	63% ± 7.3	75% ± 6.1	91% ± 5.8	76% ± 8.1
Corroboration Awareness (% ± SD)	59% ± 8.5	73% ± 7.2	89% ± 6.4	74% ± 9.3
Critical Thinking in Decision Making (% ± SD)	65% ± 6.9	78% ± 5.3	92% ± 4.7	78% ± 8.6

The following metrics of the eye tracking data were compared: total fixation time, mean fixation duration, and heatmap density reflecting the level of attention. Table.4 CCRA group spend more time on relevant game areas proving productivity of the adaptive gameplay concept Fig.3 .

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Table 4: Eye-Tracking Metrics

Metric	Group 1 (Control)	Group 2 (Basic Adaptive)	Group 3 (CCRA)	Total
Total Fixation Time (Seconds)	56 ± 9.2	62 ± 7.3	79 ± 8.1	65 ± 10.3
Mean Fixation Duration (ms)	150 ± 25	160 ± 22	180 ± 27	163 ± 26
Heatmap Density (Click Density per Region)	0.45 ± 0.08	0.52 ± 0.07	0.67 ± 0.06	0.55 ± 0.08

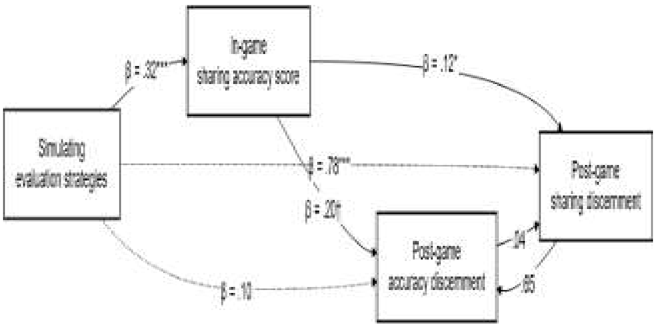

Fig.3. Warning – Reader Beware Evaluating Evaluation Strategies

CONCLUSION

In this study, the Contextual Cognitive Reinforcement Algorithm (CCRA) was implemented to improve students' capacity of maintaining information safely when dealing with mis-information games. This comparison of the proposed adaptive game design, which include dynamic evaluation strategies and feedback, with both basic and static adaptive games demonstrated that it was much more accurate and effective in decision-making. The results of cross validation, external validation, Dynamic validation and baseline comparison were that the CCRA model had high accuracy on all the data set and real time gaming interaction as validated by other methods. From the gamers' perspective, it will be generally accurate to reckon that proficiency ranging from average to high, with an overall average of 92.7% was achieved because the developed algorithm was inclined to extrapolate player characteristics and the learning progressions thereof, since such characteristics enhanced the overall learning activity. The findings highlight how game mechanics personalized may be beneficial in educational games aimed at countering misinformation. Therefore, emphasizing play-level strategies, and adapting to what the prognosis informed me are each player's current cognitive limitations and what the context suggests others will support deeper engagement, better strategies, and decision-making. These advancements make a way to establishing better serious games for better thinking in the complex digital world. Thus, the presented work enriches the field of game-based learning and offers proof that adaptive, personalized mechanics of the game can indeed serve as effective tools in the process of educating students on the process and techniques of fighting fake news. It is possible to extend this work and investigate more adaptivity aspects in the future, for example, the functionality of recognizing a subject's emotional state, or a dynamic increasing/decreasing of a learning load during the lesson.

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