Security Nanobot for Industrial Safety and Health in Sports using a Nanobot-Assisted Stochastic Discrete Choice Model

Dr. Abhijeet Madhukar Haval[1], Md Afzal[2]

[1]Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India.
[2]Research Scholar, Department of CS & IT, Kalinga University, Raipur, India.

BACKGROUND Sports injuries restrict participation, impose a significant economic burden and may persist in adverse repercussions for the quality of life linked to health. This paper presents the Nanobot-assisted stochastic discrete choice model (RA-SDCM) for Industrial safety and health in sports. In particular, the mathematical models of behavior by human adversaries depends on two basic human decision-making theory/method: the theory of prospects (PT) and the stochastic models of discrete choices. Besides, proposing an amendment to the standard quantum answer model based on the rank-dependent anticipated utility theory. OBJECTIVES: Then a powerful algorithm to measure the security forces has bene analyzed based on the best response to the various adversary models. Further the comprehensively experiment with human subjects in a web-based game to test the efficacy of the new models, and compare them with the previous models suggested in the literature to deal with the adversary's complete presumption of rationality. RESULTS: Our experimental findings show that the reactions of the subjects more closely follow the proposed new models than the previous assumption of absolute rationality. CONCLUSION: Hence the RA-SDCM demonstrate that our new stochastic discrete choice model generates the defender's strategy to relax the assumption of absolute rationality.

Keywords: Security Nanobot, Industrial safety, and health, Sport, Injury, Nanobot-assisted.

1. Introduction

Sports analysis can be broadly described as data analyzes supporting organizational decision making, talent recognition, recruiting of players, athlete growth, training goals, team selection, game strategy, and injury management [1]. Numerous different dangers related to

Nanobotics in the workplace include: increasing ergonomically with new interactions between people and the machine. New risks like electromagnetic fields, lasers, etc. Susceptibility, accidents can arise because Nanobotic work processes have not understood knowledge or control.

Tests are underway on Nanobots which are the prototype for treating common injuries, such as tennis elbow and back pain, through sports therapy. Researchers hope that the Nanobot will create a high-quality, regular care routine to improve recuperation and to minimize reliance on qualified therapists [2]. Injuries can be avoided and dangers reduced by being aware of a Nanobot's condition. To reduce the risk of injury, safeguards can be implemented. These can include engineering checks such as physical barriers, rails for protection of presence sensing, etc. The Nanobot has several security features that work in tandem with state-of-the-art pressure sensors to ensure patients ' safety and comfort [3]. In the absence of security protocols, industrial Nanobots today may be fatal. This is especially dangerous if employees interact with a Nanobot while programming, maintenance, testing, installing, or adapting it.

In the treatment of diseases or accidents, sports medicine with Nanobot-assisted is increasingly important [4]. A physical therapist may help you with musculoskeletal pain or all kinds of injuries, including arthritis. They are experts in the restoration and reduction of the pain of injured joints. They can, however, work with physical therapists to help patients develop a best functioning treatment program. A major aspect of this relation is the rate at which the injury is handled and rehabilitated [23]. An accident, impact, poor training, incorrect equipment, lack of conditioning, or insufficient warm-up and stretching may result in a sports injury. It's common to develop muscle sprains, strains, tears of tendons or ligaments, split joints, bone fractures, and damage to the head. The spectrum has grown in the field of sports medicine to raise awareness of the dangers of the inactivity of modern society. Providers in sports medicine are mindful of the prevention of illness and injury in professional athletes [6]. In sports for kids and adolescents, they must learn essential time management skills and offer them a range of attractive challenges. Physical activities provide a healthy opportunity for young children to learn and take risks and achieve goals [10]. However, they deal with young people and children involved in sports and with people who work hard. The field experts concentrate on the recovery of the patients ' physical, social and psychological conditions [7]. Playing with a team helps kids build many of their social skills for life. It teaches us to cooperate and to listen to other children less egotistically. It gives a sense of belonging to children too. This helps them to build new friends and their social circle outside of school.

In sport, many injury prevention measures has been estimated and a lack of rigorous behavioral and social science studies have been introduced as contributing to the complexity in achieving and disseminating efficient preventive measures, either in isolation or in conjunction with other approaches [8]. Prevention of injury is an attempt to prevent or reduce the severity of bodily injuries caused by external mechanisms such as accidents.

Causing injury prevention should be an essential part of every physical activity, as it will not help achieve the training objectives and keep safe and healthy [5]. Complex mathematics can harm the brain without adequate preparation and damage the body by carrying out a marathon without proper preparation. While the effectiveness of a wide range of measures or procedures to prevent injuries has increasingly been focused on, the development and research on efficient methods for wider use, disclosure, and delivery of treatments have received far less attention in this context [9].It is crucial that the Nanobotic-assisted model provides resources for going beyond insight into what can be effective or to provide useful data from controlled trials to create and measure strategies involving safety actions in the real world and to sustain them [24] -[11]. The proper use of safety equipment and changes in the play environment can prevent half of all such injuries. Injuries can be prevented if sports rules are followed. The following are the main reasons for sports injuries: Failure to learn about safety precautions and potentially injurious measures. These provide a theoretical and analytical basis for understanding safety behaviors and their determinants and thus provide a systematic way of better understanding the incidents or circumstances that can account for or predict lesions and their relationships [12]. Nanobot-assisted Model considerations within an ecological context are contributory to this by explaining safety behavior's mechanisms [13], including processes for transforming safety behavior [14], as well as the positive and negative effect of both social and physical environments [25] [16]. Figure 1 shows the sports injury prevention model with the Nanobot-assisted system.

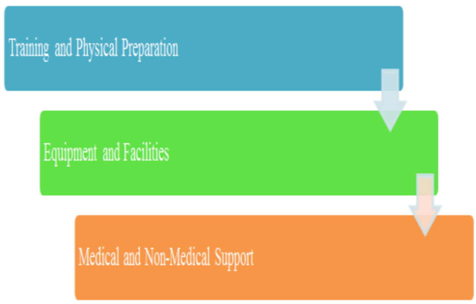

Figure 1: Fields of Injury Prevention

The major contributions of the paper are,

- To proposing the mathematical model of Nanobot-assisted stochastic discrete choice model (RA-SDCM) for Industrial safety and health in sports.
- To developing effective algorithms to determine the defender's optimal strategy in each of the models.
- To extensive experiment to check the effectiveness of the approaches proposed RA-SDCM method.

The remainder of the paper decorated as follows: section 1 and section discussed the background and importance of security Nanobots for Industrial safety and health in sports. In section 3 the mathematical model of Nanobot-assisted stochastic discrete choice model (RA-SDCM) for Industrial safety and health in sports. In section 4 the experimental results has been illustrated. finally, section 5 concludes the research paper.

2. Related Works

Gary B. Wilkerson et al [17] introduced the sensor derived IoT (SD-IoT) data for mitigating sports injury risks. Through combination with research methods, successful use of the Internet of Things (IoT) [18] will improve player safety by recognizing injury risk factors, which can be tackled through the specific risk management exercise [15]. Making the use of IoT tools can make it possible to test the functionality before participation so that the current sports injury prevention model can be greatly promoted [19]. This research provides a framework for the use of SD-IoT data to supplement other data, which is an unreported approach to injury prevention for objective evaluation of the level of injury risk of each soccer college player [20].

Sami Haddadin et al [26] proposed the Physical Human-Nanobot Interaction (PHRI) model for safety and performance in soccer sports. Authors reported scenes from real football games and think about what could have happened if one of the teams was Nanobots instead of men. The most significant result is that elastic joints are required for collision reduction. In the second and third parts, the Nanobot can handle the impact of kicking the ball and how it is capable of achieving the speed required for human football. The key point is once more joint elasticity. In general, the paper discusses a far-away dream. Nevertheless, all of our observations have been focused on concrete tests, studies, sports science findings, forensics, and PHRI results.

Yi Ren et al [21] initialized the active Nanobot-assisted total knee arthroplasty (ARA-TKA) to determine the reliability and efficacy of the mechanical alignment of the knee. They have listed papers from PubMed, Embase, Cochrane Library and Web of Science, including randomized controlled trials and comparative retrospective studies to compare active TKA to the traditional technique. Each study included data extraction and quality evaluation. Revman V. 5.3 has been used to evaluate statistics. The mean difference (MD) and the OR were used to calculate continuous results and dichotomous results. This process allows orthopedists to develop a plan that forecasts postoperative radiological performance. All the studies included in our meta-analysis were using an independent system which means no surgeon was needed during the procedure.

Qiang Song [22] introduced the Dynamic fuzzy Artificial potential field method (DFAPF) for designing mobile Nanobot path planning. A new method is introduced to overcome the limitations of the artificial potential field system to deal with issues using a velocity vector, change possible field force function and use the fuzzy control method to alter in real-time the variables of repulsive potential fields. Simulation experiments are carried out on MATLAB platforms to validate the proposed method and test results show that this proposed method's performance is better than the traditional artificial field potential model. The improved approach has some adaptability and timeliness in a typical position and movement conditions. This algorithm is simple and good route improvement

To overcome these issues, in this paper, the Nanobot-assisted stochastic discrete choice model (RA-SDCM) has been proposed for Industrial safety and health in sports. The first correlation to the Prospect Theory (PT), which allows a concise policy framework under uncertainty which takes into consideration risks as well as variations in the definition by the weighting of probabilities by humans. The other approach adapts principles of discrete choice issues in the literature to game-theoretical contexts, with the fundamental premise that people are more likely to make better decisions, with some noise in decision-making that leads to stochastic choices following a logit distribution.

3. The Nanobot-assisted stochastic discrete choice model (RA-SDCM):

In this paper, the Nanobot-assisted stochastic discrete choice model (RA-SDCM) has been proposed for Industrial safety and health in sports. The mathematical model of the proposed system in a sports environment let's consider the defender has a total of N resources in which the R= $\{ r_j \}$ goals can be covered. The results of the proposed RA-SDCM depend on the success of the attack. If the attacker hits a goal which is protected by the defender, the defender earns a reward for T_j^c, Q_j^c will be punished. improved muscle independence, increased resilience, and decreased risk of falling. The immune system is expanded and is less susceptible to illness. The digestive system developed, and digestion was better regulated. Blood pressure improved, and the chance of heart attack and stroke decreased.

In the former case, the attacker shall receive the penalty Q_j^c and in the latter case, the T_j^b reward. One important feature of the RA-SDCM is the probability of $T_j^c > Q_j^c$ and $T_j^b > Q_j^b, \forall j$ a combination of non-zero games. In other words, it helps the defender to add resources to cover a target and damages the attacker.

To define a mixed strategy by y, which specifies how the likelihood each target is to be resource-protected and determines such probabilities by y_j. Further, $y = \langle y_j \rangle$ till the end of each goal as the marginal allocation. A mixed strategy for the original conjunctional defender pure strategy in the areas is equal to the marginal probability distribution for the covering of each goal. Furthermore, a method called' comb sampling,' given the marginal coverage of each target, to implement the appropriate combination strategy for the actual resource assignments.

Proposition 1: The (leader) defender initially sticks to a mixed-strategy assuming that, following the strategy of the defender, the attacker (follower) takes a single strategy. In These models the situation in which an assailant monitors the launches on the attack against a single objective to learn about the mixed strategy. The attacker has selected a variables vector $p = \langle p_j \rangle$ for $r_j \in R$ where $p_j \in [0,1]$ is likely to be attacked. Additionally quantify the predicted benefit for the opponent if the goal r_j is attacked by the opponent as

$$V_j^b(y_j) = y_j Q_j^b + (1 - y_j) T_j^b \quad (1)$$

And in this case, the defender's intended utility is,

$$V_j^c(y_j) = y_j T_j^c + (1 - y_j) Q_j^c \quad (2)$$

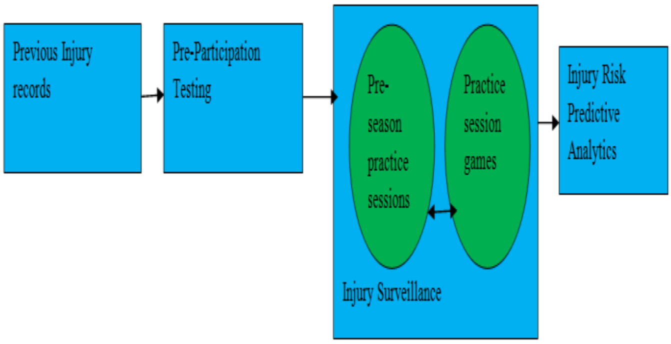

Figure 2: Sequential process for the development of injury prediction model

Figure 2 shows the longitudinal process used to acquire data and develop a prediction model for injuries. The Sports Fitness Index (SFI) study, delivering a score of 0-100 for an athlete's understanding of functional abilities, has been administered for one month before the start of pre-season practice sessions. A higher score on SFI is higher and a lower score is higher due to the effects of the previous injury.

Preposition 2: Prospect Theory

Prospect theory allows a concise model of how people and Nanobot decide between alternatives and risk, a method that maximizes the potential that will soon be identified, rather than the anticipated usefulness. In a more formal sense, the prospect is defined as

$$\sum_k \pi(y_k)\, U(D_k) \quad (3)$$

As shown in equation (3) y_k indicates the receiving probability and D_l as the output. The weighted function $\pi(.)$ explains how the likelihood of y_k is perceived by people. An empirical function form $\pi(.)$,

$$\pi(y) = \frac{y^\delta}{(y^\delta + (1-y)^\delta)^{\frac{1}{\delta}}} \quad (4)$$

The core principles of a function of weighting are that people overestimate higher likelihood and low likelihood.

The value function $U(D_k)$ in equation (4) represents the value of the output D_k. Prospect Theory determines that people are risk-averse regarding gain but risk-seeking corresponds loss, deploying an S-shaped value function. The reference point is the main element in prospect theory. Returns less than the point of reference are called loss and gain.

$$U(D) = \begin{cases} D^\beta & D \geq 0 \\ -\theta(-D)^\alpha, & D < 0 \end{cases} \quad (5)$$

As shown in equation (5) where D is the relative output to the reference point. Let's consider the reference point to be at 0. β, α estimates the extent of non-linearity in the curves.

For the adversary the probability of attacking r_j is determined as

$$\text{prospect}(r_i) = \pi(y_j)U_{\beta,\alpha,\theta}(Q_j^b) + \pi(1-y_j)U_{\beta,\alpha,\theta}(T_j^b) \quad (6)$$

Prospect theory states that subjects shall choose the goal with the greatest prospect. So,

$$p_j = \begin{cases} 1, \text{if prospect}(r_j) \geq \text{prospect}(r_{j'}), \forall r_{j'} \in R \\ 0, \text{otherwise} \end{cases} \quad (7)$$

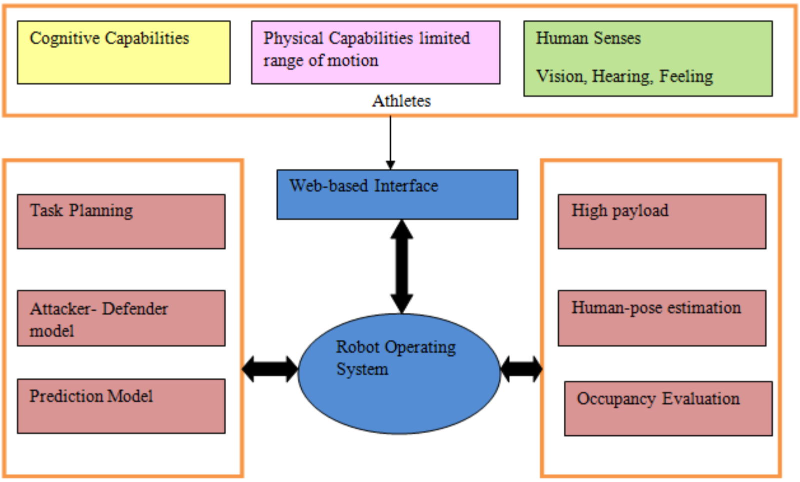

Figure 3: The Proposed System Architecture

Figure 3 shows the program utilizes the cognitive capabilities of the athletes to provide high-level direction and monitoring during the autonomous mission. Sports participation is a way for people to practice and enjoy their free time. Participants must be aware of the dangers due to the risks involved in sport. Most people can enjoy both the fun and the health benefits of exercise with satisfactory caution and care. The autonomous setup depends on the user to make sure the system starts in a suitable state. The individual provides data entry for the fine control to execute the task autonomously. Although the whole task can be accomplished by contacting the mobile manipulator and the Nanobotic, this can be difficult. Such separate functions allow the user to discharge parts of the task which only require the user to control its proper operation, thereby reducing the cognitive load. The purpose of the stand-alone functions is to set the Nanobots so that without further movement the task can be carried out. The system uses the planning system at the task level. The planner generates a right, minimum series of measures to complete the task if necessary. Then a Hierarchical Finite State Machine (HFSM) is generated and executed using the SMACH ROS System. Sportswear means clothes that have been specially designed for sport.

On the other hand, Apparel refers to clothing intended for exercise. Both clothing and activewear have become trends among active people.

Preposition 3:

Quantal Response Equilibrium (QRE) in behavioral game theory is an important solution concept. It is based on a long history of work in the problem of single agents and it leads to a game-theoretical environment. It presumes that in games, individuals respond stochastically:

the ability to choose a non-optimal, rather than strictly optimizing utility. Strategy increases with the decreasing costs of an error. Because the approach profile of all other players is taken into consideration, the player's reaction is modeled as a QR model quantal response.

$$p_j(y) = \frac{e^{\lambda V_j^b(y)}}{\sum_{r_l \in R} e^{\lambda V_l^b(y)}} \quad (8)$$

As shown in equation (8) where $\lambda \in [0, \infty]$ is the variable that captures the rational stage of player q, where $V_j^b(y)$ is the expected utility for choosing a pure strategy j for the attacker.

Combining equation (8) and equation (1) the QR is identical to the better response.

$$p_j(y) = \frac{e^{\lambda T_j^b} e^{-\lambda \left(T_j^b - q_j^b\right) y_j}}{\sum_{r_l \in R} e^{-\lambda \left(T_l^b - q_l^b\right) y_l}} \quad (9)$$

When employing the Quantal Response model to the security game field, When selecting his strategy, the defender utilizes a computer decision support system, so he can determine the optimal strategy. Since the intruder, on the other hand, first takes the defender's tactic for his answer, it can only damage the defender to make her answer rumble as mathematically computed in the algorithm.1.

Algorithm:1 Best Response to Quantal Response

$opt_h \leftarrow -\infty$;

For it← $1, \ldots IterM$ do

$y^{(0)}$ ← randomly produces a feasible starting point

$(opt_k, y^*) \leftarrow find - local - minimum \left(y^{(0)}\right)$

If $opt_h > opt_k$ then

$opt_h \leftarrow opt_k, y^{opt} \leftarrow y^*$

End if

End for

Return opt_h, y^{opt}

As shown in the above algorithm, the Best response to Quantal response has been proposed. In every iteration, the minimum local level with a certain point of start using the Matlab $fminco$ function and the Inner Point Algorithm. If there are several local minima, the algorithm can attain various local minimal with a non zero likelihood by randomly determining the starting point in each iteration. IterN raises its chances of reaching the global minimum by increasing the iteration number. In our experiments, The analysis on empirically put IterN is at 300.

Preposition 4: Rank-related Expected Utility Quantal response

Further the change of model for quantum response because individuals like the least unpredictable and highest rewards are drawn to extreme events. This idea is based on the grade-dependent planned utility model, according to which the utility companies select various alternatives. This concept to safety games, has find such an impact on the goal of the minimum resource. This is the reverse process since he will probably succeed in hitting the goal with the least resources. If this goal with the smallest resources gives the defender great punishment, the Defender could significantly reduce his reward. The conditions and circumstances in which an athletic activity cause or engages in physical activities are Sports Environment. It means that sport environments are all the factors or conditions that foster and encourage sport.

By adding additional weight to the minimum goal, change the QR model. This updated model is called the QRRU model, in which the likelihood of the attacker being attacked is measured as the Rank-relating expected-utility model,

$$p_j(y) = \frac{e^{\lambda_v V_j^b(y_j)} e^{\lambda_w W_j(y)}}{\sum_{r_l \in R} e^{\lambda_v V_j^b(y_l)} e^{\lambda_w W_l(y)}} \quad (10)$$

As shown in equation (10) where $W_j(y) \in \{0,1\}$ denotes whether r_j is covered with the least resources.

$$W_j(y) = \begin{cases} 1, if\ y_j \leq y_j', \forall r_j, \in R \\ 0, otherwise \end{cases} \quad (11)$$

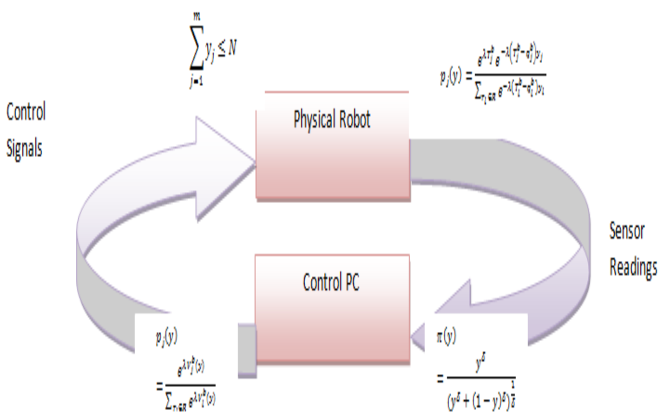

Figure 4: State diagram of Nanobot programming

Figure 4 shows the state diagram of Nanobot programming in occupation safety and health in sports. All Nanobotics have the fundamental challenge: the true state of the environment can not ever be conceived. The Nanobot control software can formulate real-world state only based on its sensor measurements. It can only try to change the real world by producing control signals. The input received by control pc and true state the proposed system generates the output from the sensor readings.

Preposition 5: Optimal defense strategy computing

For new models of adversary behavior, the optimal defender strategy should be determined based on new algorithms, under the assumption that the current algorithms are based on a perfectly rational opponent.

The Best Response to Prospect Theory (BRPT) is a mixed-integer programming approach used to measure the optimal leadership strategy against players with PT-models. Our Brpt in Eqs formula in an abstract version first. Equation (12)–(16), and subsequently presented a more detailed version. Equation (17)-(25) which used the BRPT MILP (Mixed Integer Linear Program) linear approximation in part.

$\max_{y,p,b,c,x} c$ (12)

$s.t \sum_{j=1}^{m} y_j \leq N$ (13)

$\sum_{j=1}^{m} p_j = 1, p_j \in \{0,1\}$ (14)

$0 \leq b - \left(\pi(y_j)U(Q_j^b) + \pi(1-y_j)U(T_j^b)\right) \leq L(1-p_j), \forall j$ (15)

$L(1-p_j) + \left(y_j T_j^c + (1-y_j)q_j^c\right) \geq c, \ \forall j$ (16)

As shown in the above equations the objective is to minimize c, the defender's expected utility. Equation (13) ensures that the constraint on the total resource quantity is reached. The integer variables qi are the pure strategy of the attacker in Equation (14). In BRPT, p_j is constrained to binary since it is clarified and justified in equation [18]. Equation (15) is the key to determining the strategy of the attacker, despite a mixed strategy of the defender, $y = \langle y_j \rangle$. In Equation (16) where L is the enforces that c is only constrained by the goal that is attacked by the adversary.

The major challenge is the non-linear and non-convect functions of the $\pi(\cdot)$ function. In the case of direct implementation, to solve a difficult non-linear and non-convex problem of mixed integrator optimization. Therefore, this problem roughly by describing the non-linear π $(\cdot)$ function as a linear function in a portion. This makes the problem a MILP that appears in Equation [17] –[25].

$\max_{y,p,b,c,x} c$ (17)

$s.t. \sum_{j=1}^{m} \sum_{l=1}^{5} y_{jl} \leq N$ (18)

$\sum_{l=1}^{5} (y_{jl} + \bar{y}_{jl}) = 1, \forall j$ (19)

$0 \leq y_{jl}, \bar{y}_{jl} \leq d_l - d_{l-1}, \forall j, l = 1 \ldots 5$ (20)

$x_{jl} \cdot (d_l - d_{l-1}) \leq y_{jl}, \forall j, l = 1, ..4$ (21)

$\bar{x}_{jl} \cdot (d_l - d_{l-1}) \leq \bar{y}_{jl}, \forall j, l = 1, ..4$ (22)

$y_{j(l+1)} \leq x_{jl}, \forall j, l = 1, \ldots 4$ (23)

$\bar{y}_{j(l+1)} \leq \bar{x}_{jl}, \ \forall k, l = 1, ..4$ (24)

$x_{jl}, \bar{x}_{jl} \in \{0,1\}, \forall j, l = 1, \ldots 4$ (25)

In the equation, (19)–(25) utilize x_{jl} (and x_{jl}) auxiliary integer element. x_{jl}= 0 indicates the segment lth y_j (i.e. y_{jl}) not be used in full, so it is possible to set the corresponding segments to only 0, and vice versa.

Moreover, the updated QR model achieves significantly greater outputs than the base QR model in cases where the minimum resource requirements are subject to significant penalties by the defender. This paper has advanced the state-of-the-art with new models, which better predict human opponents' behavior and new algorithms that calculate strategies that outperform our leading competitor.

4. Experimental Results and Discussion

(i) Reliability Ratio analysis based on Quanlitative reliability analysis

To control the complexity of the framework for specific support activities, the system offers a coarse-to-fine approach to autonomous functions. It performs the "coarse" parts of the task separately, such as shifting the mobile Nanobot base to the appropriate position and setting of the Nanobotic and then provides the user with the power to execute the "perfect" task in detail. During our earlier work on the remote operation of a device without autonomous functions, it is found that the user spent a significant amount of time on each task during order to move the mobile Nanobot and to position the observer close to the task area. The proposed system provides a high-reliability ratio when compared to other existing methods. Figure 5 shows the reliability ratio of the proposed RA-SDCM method.

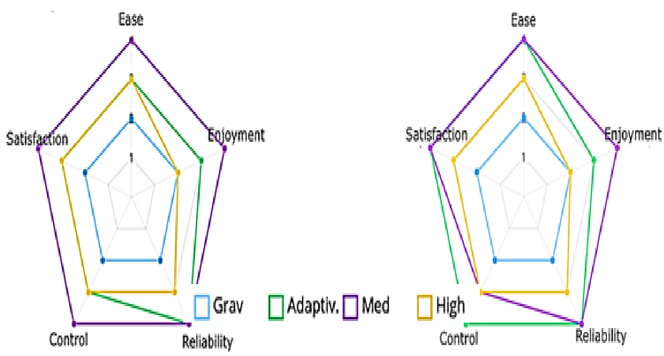

Figure 5: Reliability Ratio analysis

Table 1 shows the performance analysis of the proposed RA-SDCM method. The conduct of a comprehensive empirical analysis using the crowdsourcing platform to analyze the performance of various adversary models. To simulate a security scenario, first designed an online game called "The Guard and Treasure." Then develop classification techniques to select payout structures for experiments to separate the model well from one another and to represent the gaming space in the payoff structures. Some student-athletes may experience severe psychological problems like depression, fear, disordering eating, drug consumption, or abuse due to the psychological response to injury.

Table 1: Performance analysis

Total Number of Datasets	SD-IoT	PHRI	ARA-TKA	DFAPF	RA-SDCM
10	34.1	35.3	36.7	37.9	38.4
20	46.2	47.4	48.2	50.1	60.8
30	67.1	68.6	70.7	72.8	75.9
40	78.3	79.5	80.7	83.0	84.3
50	87.2	88.2	89.6	90.2	95.9

(ii) Average Game Time

As the number of players increases, the average game time is increasing. Because more players find it more challenging to agree on which target to capture. The clear advantage of all game settings indicates that the lead-following diagram is useful for interment and optimization. This shows an example of Nanobot action in the game. The maximum time limit is 1000 time steps for all of our experiments. This will use simulated human agents as human agents for convenience. Figure 6 shows the average game time of the proposed RA-SDCM method.

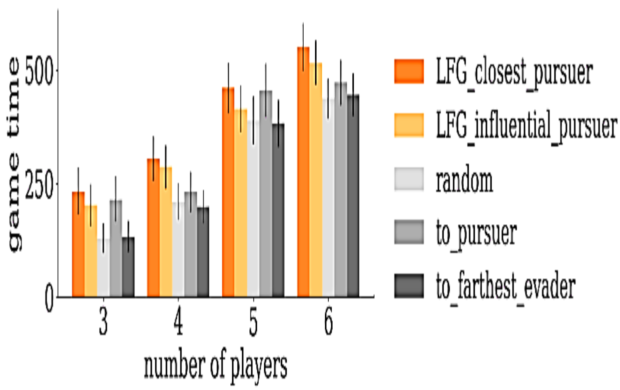

Figure 6: Average Game Time

(iii) Probability ratio determination

The Nanobot can then choose acts that increase the risk of the Nanobot becoming the leading leader and reduce the likelihood of the most powerful leader to fulfill the group objective. In that agents can change their leaders at all times the leadership-following graph is complex. In a leading follower graph, assume that if an agent j follows agent i, it could implicitly follow the ultimate goal of the agent. Over time the likelihood of the Nanobot being the leader of the human agent s_{jl} increases to 73%, which is multiplied by the orange-striped rows. Our method is good compared with the average random baseline of 26%, defined by the gray striped line. Figure 7 shows the probability of the proposed RA-SDCM method. Ensure that the sports environment is safe by ensuring: no breakdown of the equipment, no uneven area, and no sharp waste are available. The child is playing sports that match their size, age, and skill. In the cold or hot sun they do not stay too long. They wear environmentally friendly clothes.

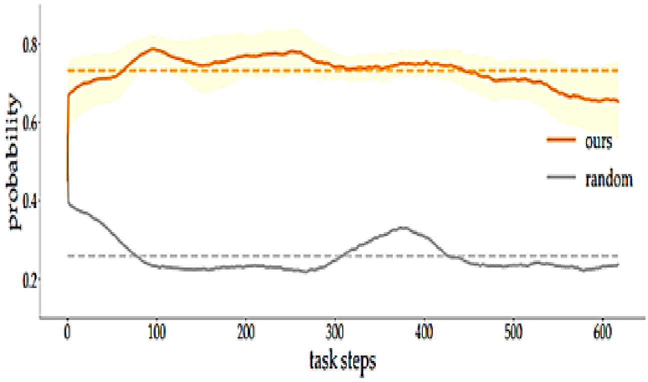

Figure 7: Probability Ratio determination

(iv) Accuracy Validation

For the different leader approaches, define the parameter settings first. Send our experimental results and examine them. Further, compare the quality of the various advocate strategies against the people involved and the exactness of the various enemy models in the sense that they follow this model. Then analyze the prediction of actual human response from each model using three different metrics mean square deviation (MSD), inaccuracy proportion (POI) and euclidean distance (ED). Figure 8 shows the accuracy of the proposed RA-SDCM method when compared to other existing methods proposed method achieves high accuracy in predicting the injury of the sportsperson.

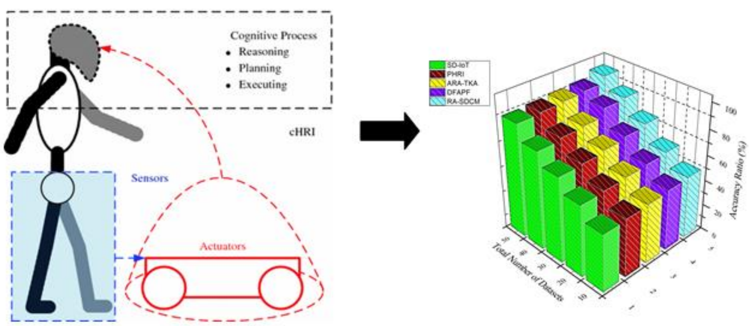

Figure 8: Accuracy Validation

Table 2 shows the accuracy analysis of the proposed RA-SDCM method. The analyzed online games "The Guard and the Treasure" the results of defender tactics as well as the accuracy of various adversary models with human subjects. Further, it has been carried out two assessments: the first involves the same 7 reward constructs as in the experimental outcomes; the second centered on contrasting the QR model with the QRRU model.

Table 2: Accuracy validation

Total Number of Datasets	SD-IoT	PHRI	ARA-TKA	DFAPF	RA-SDCM
10	45.2	46.4	47.8	48.9	50.2
20	56.2	57.5	60.7	67.2	70.1
30	72.3	75.1	77.2	80.9	83.1
40	79.3	80.4	83.5	85.2	86.9
50	89.2	90.4	91.9	93.6	97.4

(v) Error rate analysis

The three QR models have the most advantage under the ED score, which is the error of the model in estimating the distribution of subject matter choices. The three QR models have significantly lower ED values than the other models. By presenting the problem as an optimization problem in the present paper, To get theoretical insight into that situation and another essential stability condition. This is primarily the three models that has been significantly better suited than the other models. The optimized aid algorithm for Nanobot assistance uses a compounding factor, less than the human factor to forget. The proposed RA-SDCM method has less error rate when compared to other existing methods. Figure 9 shows the error rate of the proposed method.

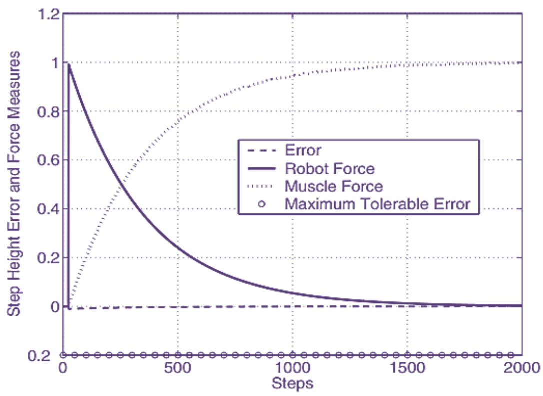

Figure 9: Error rate analysis

The present game model, however, abstracts the security situation in the real world. To reflect more scenarios, the model could be refined further. The current game, for instance, assumes that each target is covered by a single unit of resources and is protected by the resources (i.e. protected / unprotected). The effect of having multiple units of capital to safeguard a goal is an important path for future work. Simultaneously, another significant path in future work is to expand the current game model to include domains in which the defender and the attacker communicate constantly online.

5. Conclusion

The methodology used in this study produced findings with possible applications for other populations, which undoubtedly have consequences for the promotion of the health and well being of athletes. For instance, the high incidence of musculoskeletal injuries in many workplaces can be tackled with our approach. Athletes with a high risk of injury can easily be detected by examining diverse data, including those obtained using the RA-SDCM method. The provided evidence using several methodological approaches to support the use of the binary risk assessment model to prevent injuries based on game experience, chronic self-reported effects and the efficient evaluation of postural stability. More types of screening tests are carried out and data accumulate for subsequent assessments over time, which will better serve the individual athletes who will most probably benefit from preventive interventions.

“Acknowledgement” This work was supported by Anhui Social Science Foundation: Anhui Province "1 + 1 + 1" Sports and Medicine Fusion pattern and effect evaluation"（AHSKY2020D78）;Open Fund Project of Hubei Leisure Sports Development Research Center:Research on the mechanism and path of sports and medical integration under the healthy China strategy（2020Y016）

Conflict of interest

None to report.

References

1. Appathurai, A., Manogaran, G., & Chilamkurti, N. (2019). Trusted FPGA-based transport traffic inject, impersonate (I 2) attacks beaconing in the Internet of Vehicles. IET Networks, 8(3), 169-178.
2. Timpka T, Ekstrand J, Svanström L. From sports injury prevention to safety promotion in sports.Sports Medicine. 2006 Sep 1;36(9):733-45.
3. Gao, J., Wang, H., & Shen, H. (2020). Task failure prediction in cloud data centers using deep learning. IEEE Transactions on Services Computing.
4. Nguyen, V. C., & Kostarakis, P. (2018). The impact of green systems and signals on the health of green residences' habitants. Annals of General Psychiatry, 17(1), A12.
5. S. Neelima, Manoj Govindaraj, Dr.K. Subramani, Ahmed ALkhayyat, & Dr. Chippy Mohan. (2024). Factors Influencing Data Utilization and Performance of Health Management Information Systems: A Case Study. Indian Journal of Information Sources and Services, 14(2), 146–152. https://doi.org/10.51983/ijiss-2024.14.2.21
6. Yang, P., Yang, Y., Wang, Y., Gao, J., Sui, N., Chi, X., ... & Zhang, H. Z. (2016). Spontaneous emission of semiconductor quantum dots in inverse opal SiO2 photonic crystals at different temperatures. Luminescence, 31(1), 4-7.
7. Shahriar, M. R., Al Sunny, S. N., Liu, X., Leu, M. C., Hu, L., & Nguyen, N. T. (2018, June). MTComm based virtualization and integration of physical machine operations with digital-twins in cyber-physical manufacturing cloud. In 2018 5th IEEE International Conference on Cyber Security and Cloud Computing (CSCloud)/2018 4th IEEE International Conference on Edge Computing and Scalable Cloud (EdgeCom) (pp. 46-51). IEEE.
8. Smith MD. Violence and sport. Violence and sport.. 1983.
9. Manogaran, G., Varatharajan, R., Lopez, D., Kumar, P. M., Sundarasekar, R., & Thota, C. (2018). A new architecture of Internet of Things and big data ecosystem for secured smart healthcare monitoring and alerting system. Future Generation Computer Systems, 82, 375-387.
10. Rahmawan, S., Tandiyo, R., Sugiharto & Heny, S. (2023). Software Development Tools with Android Base for Skills Data Collection in Physical Education. Journal of Internet Services and

Information Security, 13(1), 22-33.

11. Kato N, Kamimura S, editors. Bio-mechanisms of swimming and flying: fluid dynamics, biomimetic Nanobots, and sports science. Springer Science & Business Media; 2008 Jan 8.
12. Marchal-Crespo L, Reinkensmeyer DJ. Review of control strategies for Nanobotic movement training after neurologic injury. Journal of neuroengineering and rehabilitation. 2009 Dec;6(1):20.
13. Emken JL, Bobrow JE, Reinkensmeyer DJ. Nanobotic movement training as an optimization problem: designing a controller that assists only as needed. In9th International Conference on Rehabilitation Nanobotics, 2005.ICORR 2005. 2005 Jun 28 (pp. 307-312). IEEE.
14. Emken JL, Benitez R, Reinkensmeyer DJ. Human-Nanobot cooperative movement training: learning a novel sensory-motor transformation during walking with Nanobotic assistance-as-needed. Journal of neuroengineering and rehabilitation. 2007 Dec;4(1):8.
15. Saadawi, Enas Magdi, Abdelaziz Said Abohamama, and Mohammed Fathi Alrahmawy. "IoT-based Optimal Energy Management in Smart Homes using Harmony Search Optimization Technique." (2022).
16. Mohamed, K.N.R., Nijaguna, G.S., Pushpa, Dayanand, L.N., Naga, R.M., & Zameer, AA. (2024). A Comprehensive Approach to a Hybrid Blockchain Framework for Multimedia Data Processing and Analysis in IoT-Healthcare. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), 15(2), 94-108. https://doi.org/10.58346/JOWUA.2024.I2.007
17. Reinkensmeyer D, Lum P, Winters J. Emerging technologies for improving access to movement therapy following neurologic injury. Emerging and Accessible Telecommunications, Information and Healthcare Technologies. 2002 Jun:136-50.
18. Reinkensmeyer DJ, Wolbrecht E, Bobrow J. A computational model of human-Nanobot load sharing during Nanobot-assisted arm movement training after stroke. In2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2007 Aug 22 (pp. 4019-4023). IEEE.
19. Secoli R, Milot MH, Rosati G, Reinkensmeyer DJ. Effect of visual distraction and auditory feedback on patient effort during Nanobot-assisted movement training after stroke.Journal of neuroengineering and rehabilitation. 2011 Dec;8(1):21.
20. Wilkerson GB, Gupta A, Colston MA. Mitigating sports injury risks using the internet of things and analytics approaches. Risk analysis. 2018 Jul;38(7):1348-60.
21. Bobir, A.O., Askariy, M., Otabek, Y.Y., Nodir, R.K., Rakhima, A., Zukhra, Z.Y., Sherzod, A.A. (2024). Utilizing Deep Learning and the Internet of Things to Monitor the Health of Aquatic Ecosystems to Conserve Biodiversity. Natural and Engineering Sciences, 9(1), 72-83.
22. Ren Y, Cao S, Wu J, Weng X, Feng B. Efficacy and reliability of active Nanobotic-assisted total knee arthroplasty compared with conventional total knee arthroplasty: a systematic review and meta-analysis. Postgraduate medical journal. 2019 Mar 1;95(1121):125-33.
23. Song Q, Liu L. Mobile Nanobot path planning based on dynamic fuzzy artificial potential field method. International Journal of Hybrid Information Technology. 2012 Oct;5(4):85-94.
24. Weinstein JN, Lurie JD, Tosteson TD, Zhao W, Blood EA, Tosteson AN, Birkmeyer N, Herkowitz H, Longley M, Lenke L, Emery S. Surgical compared with nonoperative treatment for lumbar degenerative spondylolisthesis: four-year results in the Spine Patient Outcomes Research Trial (SPORT) randomized and observational cohorts. The Journal of Bone and Joint Surgery. American volume. 2009 Jun 1;91(6):1295.
25. Baskar, S., Dhulipala, V. S., Shakeel, P. M., Sridhar, K. P., & Kumar, R. (2019). Hybrid fuzzy based spearman rank correlation for cranial nerve palsy detection in MIoT environment. Health and Technology, 1-12.https://doi.org/10.1007/s12553-019-00294-8
26. Aoyagi D, Ichinose WE, Harkema SJ, Reinkensmeyer DJ, Bobrow JE. A Nanobot and control algorithm that can synchronously assist in naturalistic motion during body-weight-supported gait

training following neurologic injury.IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2007 Sep 17;15(3):387-400.

27. Haddadin S, Laue T, Frese U, Wolf S, Albu-Schäffer A, Hirzinger G. Kick it with elasticity: Safety and performance in human-Nanobot soccer. Nanobotics and Autonomous Systems. 2009 Jul 31;57(8):761-75.