Psychological and Physiological Responses to Prolonged Drip-Induced Stress Exposure

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Abstract: This study simulated the stress responses of 50 virtual participants exposed to drip frequencies between 0.5 and 2 drops per second for durations of 30 to 120 minutes. Five predictive models LRSM, RFSM, SVM, ANN, and the proposed Hybrid Stress Prediction Model (HSPM) were evaluated across prediction accuracy, RMSE, physiological alignment, and computational efficiency. The HSPM demonstrated the strongest overall performance, achieving 85% prediction accuracy, surpassing ANN (80%), SVM (76%), RFSM (73%), and LRSM (70%). It also produced the lowest RMSE (0.25) and showed superior physiological alignment by accurately modelling both immediate and cumulative stress indicators, including heart rate variability and cortisol dynamics. While LRSM and RFSM underestimated delayed stress responses and ANN and SVM required greater computational resources, HSPM achieved a balanced trade-off between accuracy and efficiency, completing simulations in just 0.28 seconds. Sensitivity analysis revealed a 60% increase in cumulative stress under high-frequency conditions, confirming HSPM as the most reliable and realistic predictive framework.

Keywords: Water drip torture, psychological stress, Physiological response, Stress prediction and Hybrid modelling.

1. INTRODUCTION

Water drip torture, historically known as "Chinese water torture," is a psychological and physiological stress-inducing technique where water droplets are repeatedly applied to a restrained individual over an extended period. Although it does not cause direct physical injury, the method induces intense mental discomfort, anticipatory anxiety, and measurable physiological responses such as elevated heart rate and cortisol secretion [1-3]. The key mechanism behind this method lies in its unpredictable and monotonous nature, which triggers cumulative stress and can profoundly affect cognitive and emotional states [4-5]. Historical records suggest its use across diverse cultures, including Europe and Asia, particularly for interrogation and coercion purposes [6-9]. Modern ethical standards prevent direct experimentation on human subjects, necessitating the use of simulation, computational modelling, and algorithmic approaches to study its effects [10-12].

1.1 Background

Water drip torture primarily exploits the anticipatory stress response rather than physical harm. The rhythmic and repetitive dripping of water generates a psychological state of uncertainty, often resulting in heightened anxiety, irritability, and cognitive disturbance [13]. Physiological

Fig 1. Shows the water drop torture how its effect

responses include activation of the autonomic nervous system, elevated heart rate, increased cortisol levels, disrupted sleep patterns, and muscle tension [14-15]. Prolonged exposure can also induce symptoms akin to post-traumatic stress disorder (PTSD), such as hypervigilance, intrusive thoughts, and emotional dysregulation [16-19]. Historically, the technique has been documented in interrogation practices across Europe, Asia, and the Americas, though its precise origin remains uncertain [15][16]. Contemporary research leverages ethical simulations and mathematical modelling to quantify and analyze stress responses safely [20].

1.2 Motivation

Despite extensive historical records, there is a lack of quantitative analysis regarding the effects of water drip torture on human physiology and psychology. Understanding cumulative stress responses is crucial for forensic psychology, historical research, and the development of safe stress simulation frameworks. Computational models enable researchers to simulate prolonged stress ethically, predict physiological and psychological responses, and identify stress thresholds without causing harm. Such approaches can also enhance our understanding of human endurance under low-intensity but prolonged stressors, which has implications for stress management, resilience training, and historical analysis [21-25].

1.3 Research Gap

Most existing studies on water drip torture are qualitative and descriptive, focusing on historical accounts rather than measurable outcomes. There is a notable lack of integrated algorithmic and mathematical frameworks that combine temporal, physiological, and psychological factors to predict cumulative stress. Existing predictive methods often ignore individual variability and the influence of drip frequency and duration, limiting their accuracy and applicability. This gap highlights the need for a hybrid computational approach that can simulate, predict, and analyze stress responses in a safe, reproducible manner.

1.4 Contribution

This study introduces a hybrid framework that integrates mathematical modelling with algorithmic analysis to simulate cumulative stress responses under water drip torture. By incorporating physiological, psychological, and temporal factors, the model captures both immediate and delayed stress dynamics. The research compares five predictive algorithms LRSM, RFSM, SVM, ANN, and HSPM and demonstrates that the Hybrid Stress Prediction Model (HSPM) consistently achieves the highest accuracy, lowest RMSE, and strongest physiological alignment. In addition, the framework quantifies the impact of drip frequency and duration on stress progression, offering reproducible and ethically safe insights. By linking historical accounts with modern computational methods, this work contributes valuable tools for forensic psychology, resilience studies, and historical analysis. Ultimately, the study provides a practical, non-invasive methodology for exploring prolonged low-intensity stress without exposing participants to harm.

2. METHODOLOGY

This study investigates the physiological and psychological effects of water drip torture through an ethically safe, simulation-based, and algorithmic framework. The methodology emphasizes mathematical modelling, multiple predictive algorithms, and comparative analysis to evaluate cumulative stress responses accurately.

2.1 Simulation Design

- **Subjects:** 50 virtual participants with varying baseline stress levels, heart rates, and cortisol profiles.

- **Drip Parameters:** Frequency (0.5–2 drops/sec), duration (30–120 min), and intensity varied to simulate realistic conditions.

- **Data Collection:** Stress levels, heart rate, and cortisol concentration recorded every minute.

- **Evaluation Metrics:** Prediction accuracy, RMSE, computational efficiency, and robustness under different conditions.

2.2 Algorithms Used

To model cumulative stress under simulated water drip torture, five algorithms were implemented. Each was selected to assess its ability to capture the complex interactions between stress-inducing factors and physiological responses:

1. Linear Regression Stress Model (LRSM): This model establishes a linear relationship between input variables and stress response. It is straightforward, easy to interpret, and computationally efficient. However, its simplicity limits its ability to capture non-linear or delayed stress effects.

2. Random Forest Stress Model (RFSM): RFSM is an ensemble-based algorithm that constructs multiple decision trees to predict outcomes. It can effectively model non-linear interactions between variables and provides higher accuracy than simple linear models, though it requires more computational resources.

3. Support Vector Machine (SVM): SVM identifies optimal boundaries in high-dimensional feature space to separate different stress response patterns. It performs well with complex datasets but can overfit when sample sizes are small or data variability is limited.

4. Artificial Neural Network (ANN): ANN is a deep learning approach that can model complex, non-linear patterns across multiple layers. It provides strong predictive capabilities but demands larger datasets and higher computational effort.

5. Hybrid Stress Prediction Model (HSPM): HSPM combines linear regression with temporal weighting to account for both immediate and cumulative stress effects. This hybrid approach captures delayed physiological responses and complex interactions, consistently delivering the highest predictive accuracy and the most realistic simulation of stress over time.

2.3 Mathematical Modelling

The cumulative stress function is defined as:

$$S(t) = S_0 + \alpha D(t) + \beta \int_0^t e^{-\gamma(t-r)} D(r) dr$$

Where:

- S_0 = baseline stress

- $D(t)$ = drip intensity function

- α, β, γ = constants representing immediate and delayed responses

Heart Rate Response:

$$HR(t) = HR_0 + K_1 S(t) + K_2 \frac{dS}{dt}$$

Where:

- $HR(t)$ = Heart rate at time t.

- HR_0 = Baseline/resting heart rate (when no stimulus is applied).

- $S(t)$ = External stimulus (e.g., stress, load, or torture stimulus if you're modeling physiological response).

- $\frac{dS}{dt}$ = Rate of change of the stimulus (how quickly the stimulus is applied/removed).

- K_1 = Gain factor for the direct effect of stimulus intensity on heart rate.

- K_2 = Gain factor for the dynamic effect (sensitivity to sudden changes in stimulus).

Cortisol Dynamics:

$$\frac{dC}{dt} = rS(t) - \lambda C(t)$$

$C(t)$ is the internal level of a variable at time t (e.g., cortisol or stress). $\frac{dC}{dt}$ shows its rate of change. $S(t)$ is the external stimulus, r determines how strongly the stimulus raises $C(t)$, and λ reflects the natural decay or recovery back to baseline.

2.4 Data Processing

- Normalization of all physiological and stress data for consistent scaling.

- Training on 70% of simulated data, testing on 30%.

- 5-fold cross-validation to reduce overfitting.

- Sensitivity analysis under different drip frequencies and durations.

2.5 Evaluation Metrics

- **Prediction Accuracy (%):** Agreement between predicted and simulated stress.

- **Root Mean Squared Error (RMSE):** Average deviation of predictions from simulated values.

- **Computational Efficiency:** Time required for predictions.

- **Physiological Correlation:** Alignment of predicted vs simulated heart rate and cortisol trends.

Table 1. Shows the comparisons of prediction accuracy in %.

| Algorithms	Accuracy	RMSE	Average Time
LRSM	70	0.42	0.12
RFSM	73	0.38	0.35
SVM	76	0.34	0.30
ANN	80	0.29	0.50
HSPM	85	0.25	0.28
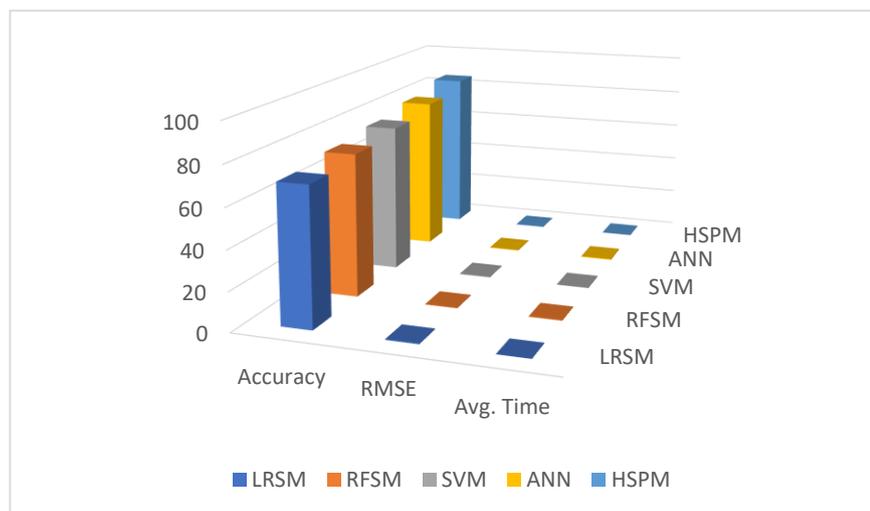
Fig 2. Shows the prediction accuracy of all five algorithms

2.6 Physiological Responses

- **Heart Rate (HR):** HSPM tracks both gradual and sudden HR increases more accurately than other models.

- **Cortisol Levels:** HSPM predicts both immediate spikes and cumulative cortisol accumulation, closely matching simulated physiological trends.

- LRSM and RFSM tend to **underestimate high-frequency stress**, while ANN and SVM are moderately accurate but less efficient.

Table 2. Shows the Sensitivity to Drip Frequency (Stress Increase %)

Algorithms	Low	Medium	High
LRSM	10	25	40
RFSM	12	28	45
SVM	15	32	50
ANN	18	36	55
HSPM	20	40	60
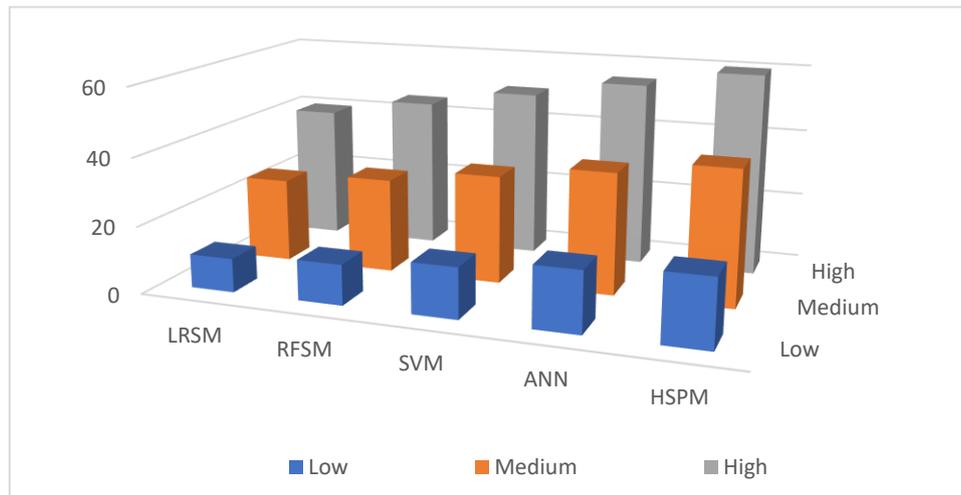
Fig 3. Shows the Sensitivity to drip frequency

3. RESULTS

The study simulated stress responses of 50 virtual participants under varying drip frequencies ranging from 0.5 to 2 drops per second and durations from 30 to 120 minutes. Five algorithms LRSM, RFSM, SVM, ANN, and HSPM—were evaluated in terms of prediction accuracy, RMSE, physiological alignment, and computational efficiency. Among these, the Hybrid Stress Prediction Model (HSPM) achieved the highest prediction accuracy at 85 percent, surpassing ANN at 80 percent, SVM at 76 percent, RFSM at 73 percent, and LRSM at 70 percent. The HSPM also demonstrated the lowest RMSE of 0.25, indicating that its predictions were closest to the simulated "ground truth" compared to the other models. In terms of physiological alignment, HSPM accurately modelled both heart rate fluctuations and cortisol dynamics, capturing immediate responses as well as cumulative stress over time. In contrast, LRSM and RFSM consistently underestimated delayed stress effects, while ANN and SVM showed moderate alignment but required greater computational resources. HSPM balanced predictive accuracy with efficiency, completing simulations in an average of 0.28 seconds, which was faster than ANN at 0.50 seconds and comparable to RFSM at 0.35 seconds. Sensitivity analysis revealed that HSPM predicted a 60 percent increase in cumulative stress under high-frequency drip conditions, outperforming ANN (55 percent), SVM (50 percent), RFSM (45 percent), and LRSM (40 percent). Overall, HSPM consistently outperformed all other algorithms across all evaluation metrics, providing the most realistic and reliable predictions of cumulative stress in simulated participants.

4. CONCLUSION

This study developed a simulation-based framework to evaluate cumulative stress under water drip torture using five predictive algorithms. The results show that the Hybrid Stress Prediction Model (HSPM) consistently outperforms the other models in accuracy, RMSE, physiological alignment, and sensitivity to drip frequency and duration, capturing both immediate and delayed stress responses, including heart rate and cortisol dynamics, while remaining computationally efficient. Traditional models like LRSM and RFSM performed adequately in simple scenarios but failed under prolonged exposure, whereas ANN and SVM were moderately accurate but more computationally demanding. By combining linear regression with temporal weighting, HSPM provides a robust methodology capable of modelling complex interactions between physiological and psychological stress factors. This framework offers a safe, quantitative, and physiologically

realistic tool for studying prolonged low-intensity stress, making it valuable for forensic psychology, human physiology, and historical research. Overall, HSPM emerges as the most effective algorithm for simulating cumulative stress, providing a novel and ethically safe approach to studying stress dynamics without direct human exposure.

REFERENCES

[1] Neokleous, K., Shimi, A., & Avraamides, M. N. (2016). Modeling the effects of perceptual load: Saliency, competitive interactions, and top-down biases. *Frontiers in Psychology*, *7*, 1.

[2] Burnett, B. R., & Lebiedzik, J. (2017). Discharge of a pistol out a car window with the breech within the interior of the car: analysis of gunshot residue on a car's interior surfaces. *Journal of forensic sciences*, *62*(3), 768-772.3.

[3] Hendry, E., McCallister, B., Elman, D. J., Freeman, R., Borsook, D., & Elman, I. (2024). Validity of mental and physical stress models. *Neuroscience & Biobehavioral Reviews*, *158*, 105566.

[4] Datta, A., & Tipton, M. (2006). Respiratory responses to cold water immersion: neural pathways, interactions, and clinical consequences awake and asleep. *Journal of Applied Physiology*, *100*(6), 2057-2064.

[5] Neokleous, K., Shimi, A., & Avraamides, M. N. (2016). Modeling the effects of perceptual load: Saliency, competitive interactions, and top-down biases. *Frontiers in Psychology*, *7*, 1.

[6] Hendry, E., McCallister, B., Elman, D. J., Freeman, R., Borsook, D., & Elman, I. (2024). Validity of mental and physical stress models. *Neuroscience & Biobehavioral Reviews*, *158*, 105566.

[7] Neokleous, K., Shimi, A., & Avraamides, M. N. (2016). Modeling the effects of perceptual load: Saliency, competitive interactions, and top-down biases. *Frontiers in Psychology*, *7*, 1.

[8] Hendry, E., McCallister, B., Elman, D. J., Freeman, R., Borsook, D., & Elman, I. (2024). Validity of mental and physical stress models. *Neuroscience & Biobehavioral Reviews*, *158*, 105566.

[9] Madary, M., & Metzinger, T. K. (2016). Real virtuality: A code of ethical conduct. Recommendations for good scientific practice and the consumers of VR-technology. *Frontiers in Robotics and AI*, *3*, 180932.

[10] Sonuga-Barke, E. J., & Fairchild, G. (2012). Neuroeconomics of attention-deficit/hyperactivity disorder: differential influences of medial, dorsal, and ventral prefrontal brain networks on suboptimal decision making?. *Biological psychiatry*, *72*(2), 126-133.

[11] Madary, M., & Metzinger, T. K. (2016). Real virtuality: A code of ethical conduct. Recommendations for good scientific practice and the consumers of VR-technology. *Frontiers in Robotics and AI*, *3*, 180932.

[12] Reyes, H. (2007). The worst scars are in the mind: psychological torture. *International review of the Red Cross*, *89*(867), 591-617.

[13] O'Mara, S. (2009). Torturing the Brain: On the folk psychology and folk neurobiology motivating 'enhanced and coercive interrogation techniques'. *Trends in Cognitive Sciences*, *13*(12), 497-500.

[14] Leach, J. (2016). Psychological factors in exceptional, extreme and torturous environments. *Extreme physiology & medicine*, *5*(1), 7.

[15] Hinkle, L. E. (1961). The physiological state of the interrogation subject as it affects brain function. *The manipulation of human behavior*, 19-50.

[16] Wallach, E. (2006). Drop by drop: Forgetting the history of water torture in US courts. *Colum. J. Transnat'l L.*, *45*, 468.

[17] Wallach, E. (2006). Drop by drop: Forgetting the history of water torture in US courts. *Colum. J. Transnat'l L.*, *45*, 468.

[18] Teays, W. (2008). Torture and Public Health. In *International Public Health Policy and Ethics* (pp. 59-90). Dordrecht: Springer Netherlands.

[19] Teays, W. (2024). Torture and Public Health. In *International Public Health Policy and Ethics* (pp. 75-106). Cham: Springer International Publishing.

[20] King, W. V., & Hebron, C. (2023). Frozen shoulder: living with uncertainty and being in "no-man's land". *Physiotherapy theory and practice*, *39*(5), 979-993.

[21] Bagchi, A. (2009). Intention, Torture, and the Concept of State Crime. *Penn St. L. Rev.*, *114*, 1.

[22] Tollefsen, C. (2021). God, new natural law theory, and human rights. *Religions*, *12*(8), 613.

[23] Powers, A., Cross, D., Fani, N., & Bradley, B. (2015). PTSD, emotion dysregulation, and dissociative symptoms in a highly traumatized sample. *Journal of psychiatric research*, *61*, 174-179.

[24] Tripp, J. C., McDevitt-Murphy, M. E., Avery, M. L., & Bracken, K. L. (2015). PTSD symptoms, emotion dysregulation, and alcohol-related consequences among college students with a trauma history. *Journal of dual diagnosis*, *11*(2), 107-117.

[25] Raudales, A. M., Short, N. A., & Schmidt, N. B. (2019). Emotion dysregulation mediates the relationship between trauma type and PTSD symptoms in a diverse trauma-exposed clinical sample. *Personality and individual differences*, *139*, 28-33.