Fundamentals for developing an IoT System for monitoring soldiers' nonverbal communication during training and mental preparation for combat

Delia-Teodora CIOBANU[1], Adrian LESENCIUC[2]*, Melinda DAVID[3], Cosmin DUGAN[4], Monica FLORESCU[5,6]

[1] Master's program in Security Systems, Henri Coandă Air Force Academy, Brașov, Romania
delia.ciobanu.std@afahc.ro

[2] Faculty of Air Security Systems, Henri Coandă Air Force Academy, Brașov, Romania
adrian.lesenciuc@yahoo.com, a.lesenciuc@yahoo.fr (*Corresponding author)

[3] University of Bucharest, Romania
melinda.david@s.unibuc.ro

[4] Emergency University Hospital Bucharest, Romania
arw@bueh.ro

[5] Transilvania University of Brașov, Romania
florescum@unitbv.ro

[6] Innomar Group SRL, Brașov, Romania
innomar.group.srl@gmail.com

Abstract: This article aims to contribute as a preliminary research effort, providing a justification framework for the configuration of an Internet of Things (IoT) network designed to monitor the nonverbal communication behaviour of soldiers during training and mental preparation for the battlefield. Based on the results of this research, the network architecture of the IoT system will be configured in order to support the optimization of soldiers' nonverbal communication responses. Accordingly, the study focuses on analysing the role of two nonverbal indicators specific to the training and mental preparation process for the battlefield: physical proximity and paralinguistic aspects, which may reveal important information regarding levels of comfort, stress, concentration, or emotional control. By analysing these parameters, the paper proposes an approach for evaluating the effects of nonverbal communication on training performance and for identifying potential solutions to optimize remote training programs through an IoT network currently under development.

Keywords: Combat mindset; Proxemics, ANOVA, Tukey, IoT-based sensor systems.

Fundamente ale dezvoltării unui sistem IoT pentru monitorizarea comunicării nonverbale a militarilor în timpul instruirii și pregătirii mintale pentru luptă

Rezumat: Acest articol își propune să contribuie ca demers de cercetare preliminară, oferind un cadru justificativ pentru configurarea unei rețele Internet of Things (IoT) concepute pentru monitorizarea comportamentului de comunicare nonverbală al militarilor în timpul procesului de instruire și al pregătirii mintale pentru câmpul de luptă. Pe baza rezultatelor acestei cercetări, arhitectura rețelei sistemului IoT va fi configurată astfel încât să contribuie la optimizarea răspunsurilor de comunicare nonverbală ale militarilor. În acest sens, studiul se concentrează asupra analizei rolului a doi indicatori nonverbali specifici procesului de instruire și pregătire mintală pentru câmpul de luptă: proximitatea fizică și aspectele paralingvistice, care pot evidenția informații relevante privind nivelul de confort, stres, concentrare sau control emoțional. Prin analiza acestor parametri, lucrarea propune o abordare pentru evaluarea efectelor comunicării nonverbale asupra performanței în instruire și pentru identificarea unor soluții de optimizare a programelor de instruire la distanță prin intermediul unei rețele IoT aflate în prezent în stadiu de proiect.

Cuvinte-cheie: mentalitate de luptă, proxemică, ANOVA, Tukey, sisteme de senzori bazate pe IoT.

1. Introduction

The connection of various physical elements equipped with sensors and software into an ensemble called the Internet of Things (IoT), including the human being as both source and terminal, is not new. There are also situations in which humans are subjects of data collection and

https://doi.org/10.33436/v36i1y202604

use through the monitoring of their physiological aspects. The integration of human beings into such networks is often achieved in structures known as the Internet of Bodies (IoB), a concept developed by Matwyshyn (2019). There are several ethical concerns regarding the integration of human beings into such networks, particularly those related to the human being as a functional component of an IoT system, that counterbalance the Kantian principle of human freedom (El-Khoury & Arikan, 2021). Howerver, the reason we propose the possibility of integrating soldiers into IoT systems is grounded in stronger ethical motivations: protecting their physical integrity, maintaining their vital functions and adaptation to the combat environment. With regard to military applications of IoT, including the Network-Centric Warfare (NCW) philosophy of understanding the battlefield as a network, or the integration of the military into IoT systems, our work is distinguished by three essential aspects: (1) the communicational and mathematical foundation of mental preparation for the battlefield based on measurable nonverbal indicators; (2) the subsequent design and construction of the network starting from physiological and communicational aspects conceived to assist the human component; and (3) the dual use of the established network for both military and civilian purposes.

The concept of the soldier as an interconnected element in IoT networks is predominant in studies regarding the use of IoT networks for locating military personnel (Chhabra *et al.*, 2017; Raja & Bagwarim, 2018); for monitoring their health status (Gondalia, *et al.*, 2018; Bandopadhaya et al., 2020; Babu et al., 2023; Sourabh et al., 2025); and for monitoring and extraction operations (Kang et al., 2020; Kavitha & Madhumathy, 2022). In addition, there is also a body of research that highlights various devices capable of equipping soldiers on the battlefield with potential for use within IoT networks (Kandam, Bharathgoud & Balaji, 2020; Sirisha et al., 2025). In parallel with the development of this line of research, another concept relevant to our study has emerged: the Internet of Battlefield Things or Internet of Battle Things (IoBT), with certain variations in naming and application, such as the Military Internet of Things (MIoT) or the Internet of Military Things (IMoT). This concept is focused on Command, Control, Communications, Computers, Intelligence, Surveillance and Reconnaissance (C4ISR) structures and the related doctrine of Network-centric warfare (NCW) (Ray, 2015), integrating into the network Unmanned Aerial Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), smart munitions and various sensors that complete the soldiers' equipment. A number of relevant studies have highlighted IoBT as an applicative particularity of IoT, examining the network infrastructure especially from the perspective of the cognitive and decisional dimensions (Raglin, 2019; Cobb et al., 2021; Kazi, 2025). In addition, the concept developed in the United States as Internet of Battlefield Things Collaborative Alliance (IoBT-CRA) – a collaborative alliance between the defence system, government structures, industry, universities and research institutions – multiplies the effects of the network.

A consequence of the Military Internet of Things (MIoT) is the operationalization of technologies such as digital twins (Warfighter Digital Twin – WDT), considered to be a 'digital replica or virtual copy of the fighter'. These digital twins are built on a set of personalized biomechanical and physiological models, supported by analytical data on the physical, biological characteristics and psychophysiological state of the individual. The military digital twin extends the principle of 'soldier as sensor' to 'soldier as integrated cybernetic system', serving as a bridge between the soldier and the digital ecosystem of the battlefield (Fawkes & Burden, 2025). Human digital twins enable individualized training and equipment designed to optimize performance, health, recovery, safety and career longevity for military personnel. For example, in the case of fighter pilots, the 'e-Pilot' monitors both the health of the human operator and the aircraft's parameters to assist the pilot in situational awareness and provide improved aircraft control options in high-risk situations (Giberna et al., 2025). In other simulations, digital twins can contribute to injury prevention and maintenance of physical fitness by monitoring factors and parameters associated with certain common types of injuries (Lloyd et al., 2023). As an augmented decision support tool, the integration of AI at the digital twin level transforms soldiers from isolated executors into augmented soldiers, contributing to increased decision speed and information advantage on the battlefield.

Human digital twins also offer the possibility of accelerating the training cycle through personalized simulations and continuous real-time feedback. Such an adaptive learning system provides the decision-maker with clear evidence, based on the analysis of extensive datasets, regarding the competencies of each individual. Another capability that can be developed is the enhancement of psychological resilience and mental readiness by exposing soldiers to operational stressors in a controlled virtual environment, as will be demonstrated in this work. Consequently, the digital twin can serve as a tool for continuous psychological assessment, analysing physiological parameters correlated with emotional states to provide an objective measurement of combat stress. As interconnection points between various systems on the battlefield, digital twins contribute to multidomain integration and unified C4ISR by running predictive models and simulations of diverse tactical and logistical scenarios, combining the computational speed of computers with knowledge from the field (Kufakunesu, Myburgh & De Freitas, 2025).

In this context of abundant military applications of IoT, this work aims to integrate the functions of the IoT system. It emphasizes the necessity of interconnectivity between training in a virtual environment under physical stress conditions, with the goal of preventing rather than recovering from PTSD. Accordingly, we propose removing the instructor from the proximity of the trainees, as their presence may influence trainee performance, and delivering the instructor's input through an IoT system during mindset training. Analyzing typical sequences of physical and mental training for the battlefield in the immediate presence of the instructor, we identified nonverbal aspects that contribute to a decrease in focus and, consequently, poorer training results. Based on these findings, the originality of this work consists in the introduction of remote assistance, which is essential to enable soldiers to train under conditions closely approximating the requirements of the battlefield. This 'extraction' of the instructor from the training framework, while still maintaining their role, requires the configuration of an IoT system capable of supporting the process of both physical and mental preparation for the battlefield under optimal conditions.

In this regard, we have included in this article references to preliminary research on mental preparation for the battlefield, data collection and analysis, research methodology, results and discussions, future prospects and conclusions.

2. Materials and methods

2.1. Mental preparation for the battlefield

In mental preparation for the battlefield, the most important aspect is the control of physiological reactions to operational and combat stress, which consists of strong emotional and psychological tension generated by battlefield conditions. Regardless of the performance level of IoT or IoBT systems that integrate the military on the battlefield, self-control or control over human responses is impossible without special training to reduce the effects triggered by the stress mechanism. Under such conditions, the human body exhibits a range of physiological changes and nonverbal reactions, such as tremors, agitation, cold sweat, fatigue, difficulties in thinking, speaking and communicating, immobility of a limb without obvious physical cause, problems with vision, hearing or tactile perception, physical exhaustion, immobility or paralysis to dangerous stimuli, panic, flight, withdrawal, etc. These effects can be mitigated through a mental training program for the battlefield, which is implemented by certain military higher education institutions.

The curriculum of the "Henri Coandă" Air Force Academy in Brașov includes the Combat Mindset (CoMind) training program, developed through an international project financed by EEA funds, entitled "Combat Mindset Training for Romanian Military Students" (2022-2023). This program benefits from specialized laboratories and the experience accumulated by Norwegian partners at the University of South-Eastern Norway (USN) contributing to the implementation of multidisciplinary knowledge, encompassing cognitive approaches, communication sciences, military sciences and martial arts. To maintain control over the participants during the training process, a series of sensors are needed to provide stress-level indicators, which are analyzed in parallel with nonverbal indicators.

The integration of advanced technologies – ranging from facial expression analyzers to machine learning algorithms and biometric sensors – into the military psychological assessment process has opened new perspectives for monitoring mental states and optimizing cognitive performance. However, the application of these technologies in operational or military training settings presents a complex set of challenges, affecting both their practical effectiveness and the ethical foundations of psycho-behavioral data usage. In the military context, where psychological pressure is maximal and constant surveillance can have ambivalent effects, it is essential that these limits are understood, regulated and managed with discernment. Under these conditions, mental preparation becomes an essential element, playing a critical role both in operational success and ensuring survival on the battlefield. Thus, we aimed to highlight the level of mental preparation of soldiers by analyzing specific nonverbal indicators, physical proximity and paralanguage elements, capable of providing relevant data – separately or integrated – regarding the level of comfort or tension in group interactions, as well as stress, concentration or emotional control.

2.2. Data collection and analysis

The data were collected and recorded using the SimRange Lasershot simulator, produced by Shooting Range Technologies, a division of Laser Shot Inc. The simulator was equipped with a short-range projector Vivitech 1080P, an integrated gunshot detection camera (i.e., a laser sensor), remote control, integrated speakers, wireless keyboard, AK-47 assault rifle replicas and Lasershot training software, which allows weapon adjustment, and a virtual polygon. The SimRange simulator is designed to replicate a traditional shooting range with virtual targets, following real-world training standards. For graphical representation and statistical analysis, the OriginPro v2020b software was used.

2.3. Research methodology

We designed a pilot experiment to serve as an initial empirical basis for further extensive research, providing an early understanding of the analyzed phenomenon and contributing to the refinement of future hypotheses and methodology. The experiment was conducted using the CPIM shooting simulators at the “Henri Coandă” Air Force Academy with 45 military students, randomly divided into three homogeneous groups of 15 students each, based on training and experience, using the equipment presented in Section 2.2. All participants received the same instructions, with the task of hitting 10 targets. The study was structured around two independent variables: the proximity of the instructor – close (50-60 cm) and distant (over 150 cm) – and the presence or absence of paralanguage, which consisted of noises such as sighs, grunts, laughs, sniffs, lip-smacks, groans, whistles, clicks, moans and munching, produced randomly during shooting. The distances were selected minimize interference with the subject of the experiment, while highlighting the role of nonverbal elements in mental preparation for the battlefield. The close distance corresponds to the close personal zone, characterized by familiarity and, in formal interpersonal relationships, involve feelings of personal space invasion, stress, discomfort, and the need for psychological defence. The distant condition corresponds to the close social zone, typical of formal dialogue, professional relationships and personal negotiations, and does not produce noticeable effects on participants’ behaviour. Paralanguage was used to assess concentration and emotional stability.

The conditions for carrying out the training activity require the mandatory presence of the instructor. The development of the IoT system is therefore also motivated by the need to remotely monitor the cadets during training. The control group (G1), defined as a dependent variable, benefited from the absence of paralanguage and the instructor at a distance (over 150 cm). The second group (G2) benefited from the close proximity of the instructor (50-60 cm), while the third group (G3) benefited from the presence of various sound effects and the distance of the instructor (over 150 cm). Shooting requirements were identical for all participants in the experiment: each trainee performed 10 simulated shots, targeting 10 points per target, for a maximum score of 100 points if all targets were hit. The hypotheses focused on the correlation between the proximity of the instructor and the shooter, as well as the presence of sound elements, in the sense of decreasing shooting performance were formulated.

3. Results and discussions

Over the years, we have identified ways to explore the possibilities of mental preparation for the battlefield by drawing on scientific models of communication which provides explanations for the networking of what has long been considered to be communicational ballast. As introduced in a previous work, it is possible to examine how people mentally prepare for incoming signals – whether highly redundant, predictable or unpredictable – by focusing on the "communicative ballast" (brain activity that readies the mind for the unexpected and filters verbal content) (Lesenciuc & Sauciuc, 2023). There are also other premises, even regarding the need for mental training (Lesenciuc & Sauciuc, 2024) and the need to analyze brain activity (including stress level control) in various contexts (Lesenciuc et al., 2023), i.e., integrated training for the information environment (Lesenciuc, 2024) of the contemporary battlefield, without substantiating to date the need to integrate the military into an IoT system. Herewith, the proposed method is appropriate in situations where direct testing of effects on measurable nonverbal communication behaviour is desired. Through the strict control of variables and replicability of conditions, the method provides a clear picture of how an intentionally produced change influences the outcome.

The choice of distance variables in the experiment was made so as not to interfere significantly with the subject of the experiment. According to Edward T. Hall's proxemic studies (Hall, 1966), there are four types of human interaction zones, with small variations in distance depending on culture. Based on measurements regarding the thresholds for identifying the human voice, Hall distinguished between the intimate zone (0-45 cm), the personal zone (45-125 cm), the social zone (125-360 cm) and the public zone (over 360 cm), each with two subzones – close and far (or distant) – characterizing certain behavioural and communication patterns. The absence or presence of the second variable, paralanguage, had the role of assessing concentration and emotional stability in an environment where such characteristics are essential for military personnel. Paralanguage is one of the nonverbal elements of speech that usually accompanies (and reinforces) verbal behaviour in conversation (Abercrombie, 1968) and serves in numerous studies as an element with a therapeutic or stress-inducing role (Saskovets, Lohachov & Liang, 2025). This use is due to the fact that paralanguage conveys an important part of the speaker's emotional intentions, often having a stronger impact than the verbal content itself (Mehrabian, 1972). In military context, where concentration and emotional stability are essential, such nonverbal signals can be perceived as indications of negative evaluation or disapproval, negatively influencing (self-)efficacy.

Given the three groups, each defined by two variables – distance and paralanguage according to section 2.3 – the calculated means highlight the performance of each group. In order to compare the means of the three groups by analyzing variance, the scores of each group were added into separate columns, and the OneWay Anova statistical analysis was performed in Origin. Table 1 summarizes the descriptive statistics obtained.

Table 1. Descriptive statistics of the scores obtained for each group

	minimum score	maximum score	n_i	$\bar{x}_i$	SD_i
G1 (control)	80	100	15	91.33	7.43
G2 (proximity)	70	90	15	83.33	7.23
G3 (sound)	70	90	15	79.33	7.03

By using the fit statistics based on the overall mean (MG) of all scores, calculated as the weighted average of the group means, we obtained a mean score of 84.66. To determine whether there are statistically significant differences among the scores of the three groups, we will compare the means of scores obtained under different conditions. This comparison will highlight the importance of designing an IoT system to help replace the presence of the instructor in close proximity during training, improving focus and performance. Thus, we will evaluate the effect of nonverbal stressors (proximity and sound and paralanguage) on the performance of military students. By applying variance analysis, the aim is to determine the statistical significance of the observed effects and, if necessary, to identify specific differences between the groups, thus contributing to a deeper and more rigorous understanding of how nonverbal factors may affect performance. Accordingly, we will postulate the alternative hypothesis, following (Diez, Cetinkaya-Rundel & Barr, 2024), stating that the average score varies by group (i.e., the means of one or more groups are different). In order to demonstrate this assumption, the degrees of freedom for three groups is given by:

$$df_G = k - 1 = 2 \tag{1}$$

where k represents the number of groups (k = 3), leaving us with 2 degrees of freedom between groups. Further, the sum of squares between groups (SSG) quantifies the variability or differences among the means of different groups and is calculated as follows:

$$SSG = \sum_{i=1}^{k} n_i(\overline{x_i} - M_G) = 1120 \tag{2}$$

where n_i is the number of observations in group i (in this work, the number of members in each group), and x_i is the mean of the n_i observations in group i. Thus, the sum of squares between groups reflects the variability of the group means from the overall mean, where SSG1 = 667.3(3); SSG2 = 26.5(3) and SSG3 = 426.1(3). The mean square between groups (MSG) provides the measurement of the variation among the group means and is calculated using the degrees of freedom and the sum of squares between groups:

$$MSG = \frac{1}{df_G} SSG = 560 \tag{3}$$

Knowing the variation between the groups, the next step is to determine the variation within the groups. The variation within the groups is given by the variation among the residuals (errors). Thus, the degrees of freedom for residuals are calculated as the sum of the degrees of freedom for each group:

$$df_E = n - k = 42 \tag{4}$$

where n represents the total number of observations (45). Further, the sum of squared errors (SSE) quantifies the total squared differences between the actual observed values and the values predicted by fitting the n_i data points of each group. Given the standard deviation, SSE is defined as:

$$SSE = \sum_{i=1}^{k} (n_i - 1) SD_i^2 = 2200 \tag{5}$$

where SSE1 = 774, SSE2 = 733 and SSE3 = 693, highlighting the variability of scores within each group. Similarly, to MSG, given the degrees of freedom for errors and the sum of squared errors, the mean square error can be calculated as:

$$MSE = \frac{1}{df_E} SSE = 52.38 \tag{6}$$

Having comparable measures of variability between the groups (MSG) and within the groups (MSE), the variation among group means, represented by the F-statistic, can be determined. This value indicates the extent to which the group means vary compared to the variation within the groups, and was calculated to be 10.69 using the formula:

$$F = MSG / MSE \tag{7}$$

To determine whether the F value obtained is large enough to consider the differences between groups significant, it can be compared with a critical value from the Percentiles of the F Distribution: F.95(n_1, n_2) Table (Rice, 2007). At a 0.05 level of significance, and given the degrees of freedom between and within the groups, F_{crit} = 3.22. The calculated F value is substantially higher, indicating a significant difference between two of the group means. Thus, the null hypothesis can be rejected and the alternative hypothesis, as postulated at the outset, can be accepted. The group means differ because the observed differences are not due to random fluctuations or variability between subjects (group heterogeneity), making the result statistically significant. In addition, a p-value of 0.00017 was calculated, which is far lower than our level of significance; therefore, the alternative hypothesis is validated, and we can conclude that the group means are significantly different.

To better visualize the variance within the groups, Figure 1. A shows the box plot, graphically illustrating the locality (measured by the mean), spread (variability of scores measured by the standard deviation) and skewness (asymmetry of the distribution) of the scores. For both G1 (control) and G2 (proximity) there are only a few low scores, and most of the data are clustered towards higher scores, while in G3 (sound) most of the data is clustered towards lower scores. These results further highlight the statistically significant differences between the performance means of the three groups, confirming that the nonverbal factors examined (instructor proximity and paralanguage) meaningfully influence the performance of soldiers in simulated shooting. Performance decreases progressively from the control group to the groups in which the stressors are found, indicating a significant effect. This analysis supports the hypothesis that these factors not only affect concentration but also induce an increased level of psychological discomfort, which negatively impacts the results and supports the need to implement an IoT system for mental training.

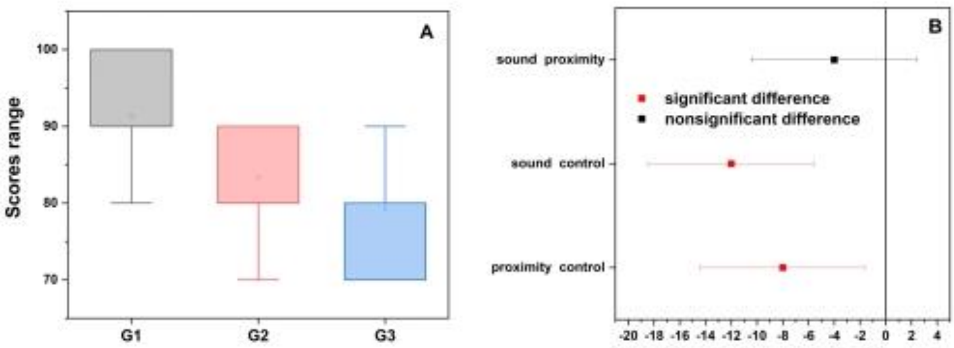


Figure 1. Variance between and within groups, where G1 – control, G2 – proximity and G3 – sound: A. box plot; B. Tukey range test (Author's own research)

Figure 1.B highlights the Tukey's range test (HSD – honestly significant difference), which identifies which of the nonverbal stress factors has the most significant effect on the simulated shooting results. This test is useful for demonstrating the significance of the discovered stand-out difference, when it is already known that there is a significant difference among groups. All possible pairs of means are compared by calculating the differences between means: sound-proximity (G3-G2 = 79.33 - 83.33 = - 4), sound-control (G3-G1 = 79.33 – 91.33 = - 12) and proximity-control (G2-G1 = 83.33 – 91.33 = - 8). The background calculations are based on a computed HSD value, which depends on MSE and the number of means (n) being compared. If any two means differ by more than the HSD value, they are considered significantly different (Laurencelle & Dupuis, 2002):

$$HSD = q \times \sqrt{\frac{MSE}{n}} = 6.42 \tag{8}$$

where q is the critical value from the Q table (Laurencelle, & Dupuis, 2002), determined for three groups with 42 degrees of freedom for errors at a 0.05 level of significance. By comparing the differences between means with the HSD value, we can conclude that the control group differs significantly from both groups exposed to nonverbal stressors, confirming their negative impact on performance in simulated shooting. In contrast, the difference between the proximity-only and paralanguage-exposed groups is not statistically significant, suggesting that both types of stressors affect performance in a similar manner.

Given that all groups had only 15 participants, it is important to evaluate the impact of the proximity-only (G2) and paralanguage-exposed (G3) groups on our hypothesis that the physical proximity of the instructor or random sounds can significantly disrupt the participants' ability to concentrate and execute tasks. Assuming that each group has a normal distribution and equal variability, Cohens' *d* value can provide details on the effect size, or magnitude of the stressors, relative to the control group (G1). Determined from equation 9, a Cohens' *d* value larger than 1 suggests that the mean difference is large compared to the variability (d_{G2} = 1.091; d_{G3} = 1.659 – using the data in Table 1). A large Cohen's *d* indicates substantial mean difference relative to the variability. Thus, for both G2 and G3, the impact of stressors on student performance is high, with increased predominance for G3 (Sawilowsky, 2009).

$$d = \frac{\overline{x_1 - G_1} - \overline{x_1 - G_2G_3}}{\sqrt{\frac{(SD^2_{i-G_2G_3} + SD^2_{i-G_1})}{2}}} \tag{9}$$

The observation that a higher percentage of the G2 and G3 populations exceeds the mean of the control can also be correlated to Figure 2B, where students in G2 and G3 exhibit overall lower performance scores. Since the null hypothesis was previously rejected, the effect size can also be expressed using eta squared (η^2), representing the variance ratio explained by the two independent variables (G2 and G3), relative to the control group, G1 ($\eta^2 = SS_{Between\ G2,\ G3\ and\ G1}/SS_{Total}$) (Richardson, 2011). Based on the previously calculated sums of squares, the differentiation ratios are η^2_{G2} = 0.460 and η^2_{G3} = 0.745. In other words, proximity accounts for 46 % of the variance among students in terms of performance (target shooting), while sound accounts for 74 % of the variance. Thus, the presence of stressors – particularly sound – has a large impact on shooting performance.

Another way to illustrate the variance between groups and within the group is shown in Figure 2, where a normalized distribution of the data sets is plotted against the scores obtained for each group.

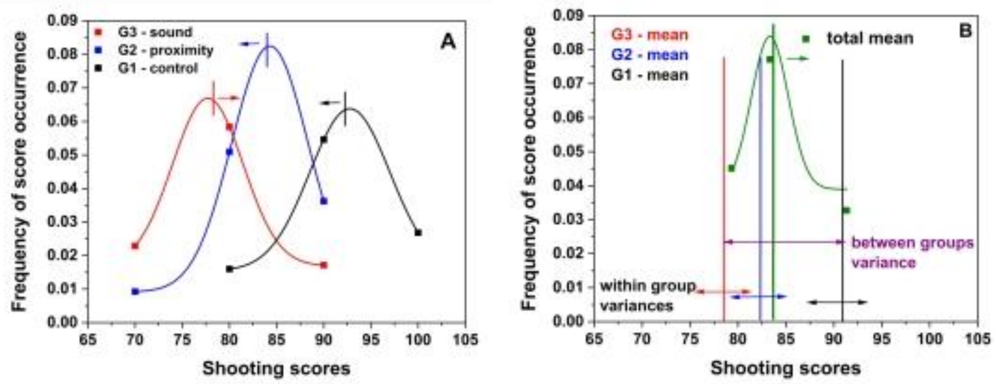


Figure 2. Graphical representation of the analysis of variance (ANOVA) represented as frequency of score occurrence as function of shooting scores, data fitted using the Gaussian fit, highlighted means and group skewness indicated by arrows: A. variance between and within the three groups; B. illustration of significant differences by groups means and total mean (Author's own research)

Data in the first panel (A) was fitted using a Gaussian fit, and the mean obtained from the ANOVA statistics was positioned in the proximity of the peaks for each group. The second panel (B) shows the mean of means, with the long vertical lines representing the mean values, highlighting the rationale behind the analysis of variance between and within groups. The Gaussian fit illustrates the degree of dispersion from the mean and significant deviations. Similarly, to the box plot, the skewness of scores in Figure 2. A shows comparable variation for the control and proximity groups, with a mean shift toward lower scores and a tail extending in that direction, suggesting a data point accumulation at higher scores. In contrast, the tail in G3 shifts toward higher scores, indicating a greater number of lower scores. This reflects a decrease in efficiency in target shooting, likely attributed to the pressure or discomfort caused by random auditory stimuli. Figure 2.B shows that the dispersion of the scores is similar across the three groups (see variances within groups – estimated from the similar SD values), while the distribution between groups (mean of means) is slightly shifted toward higher scores, highlighting a leftward asymmetry with a frequency of scores below the average. Thus, the impact of nonverbal stressors (proximity and paralanguage), indicates a cumulative tendency to reduce performance, reflecting that exposure to stimuli such as the physical proximity of the instructor or random sounds can significantly disrupt the participants' ability to concentrate and execute tasks. The results obtained from the experimental data clearly confirm the primary hypothesis of this study: nonverbal stressors, such as the physical proximity of the instructor and paralanguage elements (specifically randomized sounds), negatively influence the performance of soldiers in simulated shooting exercises. The control group, which was not exposed to any stressor, achieved the highest mean scores (91.33 points), indicating optimal concentration and execution in the absence of disruptive factors. Groups exposed separately to proximity (83.33 points) and paralanguage (79.33 points) recorded significant decreases in performance compared to the control group, supporting the secondary hypotheses that each type of nonverbal stimulus has an individual negative effect on execution capacity. These results are consistent with directions found in specialized literature regarding the influence of nonverbal factors on performance in training and operational contexts with a high degree of psychological demand, such as the military environment.

Therefore, apparently insignificant factors, such as the discreet presence of an instructor at the lower limit of the personal space or simple paralinguistic elements, can produce average variations exceeding 10%. It is worth noting that these nonverbal stressor elements do not manifest themselves similarly in the case of all subjects, as long as there are results (in isolated cases) comparable to those of the control group. This limitation will be addressed in a subsequent phase by setting variables that will not allow for individual differentiation. In general, the absence of extreme deviations or very large dispersions within the experimental groups can be interpreted as evidence of the validity of the testing method and the homogeneity of the sample. At the same time, these observations emphasize the importance of considering individual variables, such as personality traits, coping styles or previous experience, when analysing performance under stressful contexts. Under these conditions, it is necessary to redesign the study to a more advanced level, integrating the soldier into an IoT network in which a remotely located instructor can have control over the general mental training conditions for the battlefield and the individual characteristics of the subjects in the training process.

4. Future prospects

The results obtained in this study highlight the need for remote monitoring of nonverbal and physiological indicators during the process of preparing the military personnel for the battlefield. Effective mental preparation, which involves training reactions to simulated stimuli through specialized laboratories or simulators, requires – at least in the initial phase – an adequate control of other stressor factors that are absent on the battlefield. In our experiment, these factors are included the presence of the instructor within the personal space (45-75 cm), (Hall, 1966) and the expression of presence through sounds emitted from the close subzone of the social zone (124-220 cm). By inducing stressors through nonverbal elements that create subtle differentiation and observing the noticeably altered shooting results for groups G2 and G3 compared to G1, the need becomes clear to configure a training environment that removes the presence of the instructor from the proximity of the trainee and incorporates an IoT network to guide the training. Research in military psychology (Stokes & Kite, 1994; Flood & Keegan, 2022; Lokyan, Baghdasaryan & Hovhannisyian, 2025) demonstrates a direct relationship between success in tactical activities and combat simulations and the quality of the training.

To continue the experiment under conditions that also highlight the individual characteristics of the subjects, it is necessary to configure a network architecture that includes the instructor as the terminal decision-maker (Figure 3). This network, configured in accordance with IoT principles, involves the inclusion of interconnected devices and sensors capable of providing the necessary data for collection and analysis regarding the level of mental preparation for the battlefield. Such an IoT-based sensor system structure requires the inclusion of a mobile electroencephalographic (EEG) headset, which provides real-time data on the subjects' brain activity, including engagement, excitement, frustration, interest, relaxation and stress levels. Research using the EMOTIV + EPOC EEG device and associated software for transforming EEG frequencies into information of interest in the field of mental training for the battlefield (e.g., Emotiv BCI), has been conducted in previous experiments (Lesenciuc & Sauciuc, 2023). In addition, other sensors should be incorporated that collect other physiological parameters such cardiac activity, lung activity, perspiration levels and environmental conditions.

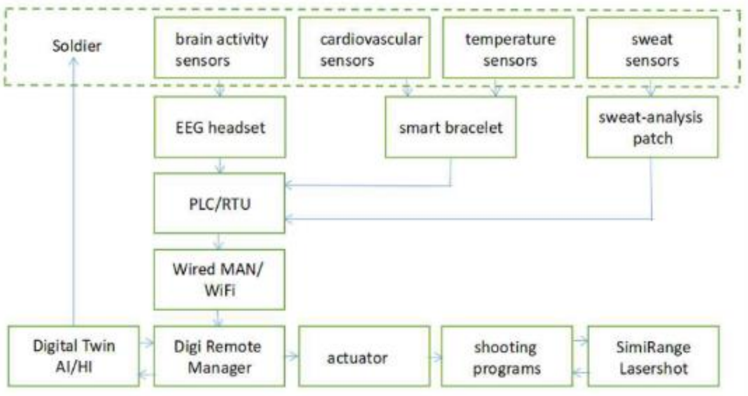


Figure 3. Proposal of the IoT architecture (Author's own research)

Therefore, the next step in our research is to repeat the experiment under remotely assisted firing conditions, incorporating additional stressors present on the battlefield, through an IoT-based sensor system. This will include network configuration, taking into account the establishment of the main tasks on the network nodes, creation of the system block diagram and signal analysis, while providing results with a high degree of accuracy by combining environmental parameters with individual parameters. The proposed IoT system architecture is based on research in progress.

5. Conclusions

This work highlights the necessity of replacing the instructor with an IoT system during mindset training, as their presence may influence the trainee’s performance. The analysis of statistical parameters provides a justification for designing an IoT based sensor system as a necessary tool for mental preparation for the battlefield. The results demonstrate that apparently insignificant factors, such as proximity or simple paralinguistic elements, can produce significant average variations compared to the control group. According to the analysis of variance (ANOVA, complemented by Tukey’s test), the impact of these nonverbal stressors shows a cumulative tendency to reduce performance. Furthermore, graphical representation of variances between and within groups illustrate the locality, spread and skewness of the scores, highlighting the significance of observed differences.

Author contributions

Conceptualization: A.L.; Methodology: A.L., M.F.; Validation: M.D; Formal Analysis: D.T.C. and C.D.; Investigation: D.T.C.; Resources: A.L; Data Curation: C.D.; Writing – Original Draft Preparation, D.T.C, M.D. and C.D.; Writing – Review & Editing, A.L., and M.F.; Visualization, M.D.; Supervision, M.F.

Submission: 15 February 2026; Revised: 16 February 2026; Accepted: 26 February 2026; Published: 31 March 2026.

REFERENCES

Abercrombie, D. (1968) Paralanguage. *British Journal of Disorders of Communication*. 3(1), 55-59. https://doi.org/10.3109/13682826809011441.

Babu, S. K. S., Kumar, G. R. & Begum, R. (2023) Soldier Healthcare Parameters Monitoring System Using IoT. *Int. J. Sci. Res. Engineering and Technology*. 10(1), 384-391. https://doi.org/10.1051/e3sconf/202561903003.

Bandopadhaya, S., Dey, R. & Suhag, A. (2020) Integrated healthcare monitoring solutions for soldier using the internet of things with distributed computing. *SUSCOM*. 26, 10037. https://doi.org/10.1016/j.suscom.2020.100378.

Chhabra, J. S., Chajed, A., Pandita, S. & Wagh, S. (2017) GPS and UoT Based Soldier Tracking & Health Indication System. *Int. res. j. eng. Tech.* 4(6), 1228-1232.

Cobb, A. D., Jalaian, B. A., Bastian, N. D. & Russell, S. (2021) Robust Decision-Making in the Internet of Battlefield Things Using Bayesian Neural Networks. In *2021 Winter Simulation Conference (WSC), Phoenix, AZ, USA*. IEEE, pp. 1-12. https://doi.org/10.1109/WSC52266.2021.9715532.

Diez, D., Cetinkaya-Rundel, M. & Barr, C. (2024) ANOVA Calculations. In: D. Diez, M. Cetinkaya-Rundel, M., Barr. *OpenIntro Statistics.* Chapter 7. I*nference for Numerical Data.* Forth Edition. OpenIntro. https://openintro.org/go/?id=stat_ better_understand_anova&referrer=/book/os/index.php [Accessed: 07 August 2025].

El-Khoury, M. & Arikan, C. L. (2021) From the internet of things toward the internet of bodies: Ethical and legal considerations. *Strategic Change*. 30, 307–314. https://doi.org/10.1002/jsc.2411.

Fawkes, A. & Burden, D. (2025) Digital human twins and the military metaverse: opportunities and challenges. *AI & Society.* 1-13. https://doi.org/10.1007/s00146-025-02508-2.

Flood, A. & Keegan, R. J. (2022) Cognitive Resilience to Psychological Stress in Military Personnel. *Front. Psychol*. 13, 809003. https://doi.org/10.3389/fpsyg.2022.809003.

Giberna, M., Voos, H., Tavares, P. et al. (2025) On Digital Twins in Defence: Overview and Applications. To be published in *Cryptography and Security*. [Preprint] https://doi.org/10.48550/ arXiv.2508.05717 [Accessed: 07 August 2025].

Gondalia, A., Dixit, D., Parashar, S. et al. (2018) IoT-based Healthcare Monitoring System for War Soldiers using Machine Learning. *Procedia Comput. Sci.* 133, 1005–1013. https://doi.org/10.1016/j.procs.2018.07.075.

Hall, E. T. (1966) *The Hidden Dimension.* New York: Anchor Books/ Doubleday.

Kandam, S., Bharathgoud, N. & Balaji, R. (2020) A review on smart wearable devices for soldier safety during battlefield using WSN technology. *Mater. Today: Proc.* 33(7), 4578-4585.

Kang, J. J., Yang, W., Dermody, G. et al. (2020) No Soldier Left Behind: An IoT-Based Low-Power Military Mobile Health System Design. *IEEE Access*. 8, 201498-201515. https://doi.org/10.1109/ACCESS.2020.3035812.

Kavitha, N. & Madhumathy, P. (2022) IoT-Based Health and Tracking System for Soldiers. In *Advance Healthcare Systems: Empowering Physicians with IoT-Enabled Technologies*, Rohit Tanwar, S. Balamurugan, Rakesh Kumar Saini, Vishal Bharti, Premkumar Chithaluru Eds.; Wiley, New York. 115-136. https://doi.org/10.1002/9781119769293.ch9.

Kazi, K. S. L. (2025) A Study on AI-Driven Internet of Battlefield Things (IoBT)-Based Decision making: KSK Approach in IoBT. In *Merging Artificial Intelligence with the Internet of Things*. IGI Global Scientific Publishing. 203-238. https://doi.org/10.4018/979-8-3693-8547-0.ch007.

Kufakunesu, R., Myburgh, H. & De Freitas, A. (2025) The internet of battle things: a survey on communication challenges and recent solutions. *Discover Internet Things.* 5, 3. https://doi.org/10.1007/s43926-025-00093-w.

Laurencelle, L. & Dupuis, F.-A. (2002) *Statistical tables, explained and applied*. Singapore, World Scientific Publishing Company. https://doi.org/10.1142/4935.

Lesenciuc, A. & Sauciuc, I. G. (2023) Combat Mindset as a Communication Process: Task Awarenes, Preparation and Execution. *Redefining Community in Intercultural Context.* 11(1), 15-25.

Lesenciuc, A. & Sauciuc, I. G. (2024) Conștiință și identitate a militarului în executarea mișcărilor de front. De la protoself la conștiință extinsă. In: A. Hrițuleac, I. A. Măgureanu, C. M. Tofan (eds.). *Paradigma conștiinței - abordări multi și interdisciplinare. Limbajele conștiinței.* Iași: A.I. Cuza University Publishing House.

Lesenciuc, A., Șerbeszki, M. & Andronic, R.-L., Warner-Søderholm, G., Boe, O., Marineanu, V.D., Țăranu, I. (2023) Combat Mindset. The millisecond that could save your life. *Redefining Community in Intercultural Context.* 11(1), 7-9.

Lloyd, D. G., Saxby, D. J., Pizzolato, C. et al. (2023) Maintaining soldier musculoskeletal health using personalised digital humans, wearables and/or computer vision. *Journal of Science and Medicine in Sport*. 2023 Jun; 26 Suppl. 1:S30-S39. https://doi.org/10.1016/j.jsams.2023.04.001. Epub. 2023 Apr 16. PMID: 37149408.

Lokyan, A., Baghdasaryan, S. & Hovhannisyian, H. (2025) Enhancing psychological training in military personnel: Modern approaches, systemic assessment and hands-on recommendations. *Asian Journal of Psychiatry*. 106, 104442. https://doi.org/10.1016/j.ajp.2025.104442.

Matwyshyn, A. M. (2019) The Internet of Bodies. *Wm. & Mary L. Rev.* 61(1), 77-167.

Mehrabian, A. (1972) Some Subtleties of Communication. *Language, Speech, and Hearing Services in Schools.* 3(4), 62-67. https://doi.org/10.1044/0161-1461.0304.62.

Raja, P. & Bagwarim S. (2018) IoT Based Military Assistance and Surveillance. In *2018 International Conference on Intelligent Circuits and Systems (ICICS), Phagwara, India, 19-20 April 2018*. IEEE, pp. 340-344. https://doi.org/10.1109/ICICS.2018.00076.

Raglin, A. (2019) Presentation of Information Uncertainty from the IoBT for Military Decision Making. In *Distributed, Ambient and Pervasive Interactions*. HCII 2019, Streitz, N., Konomi, S. Eds.; Springer, pp. 39–47. https://doi.org/10.1007/978-3-030-21935-2_4.

Ray, P. P. (2015) Towards an Internet of Things based architectural framework for defence. *2015 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT)* Kumaracoil, December, IEEE, pp. 411-416, https://doi.org/ 10.1109/ICCICCT.2015.7475314.

Rice, J.A. (2007) *Mathematical Statistics and Data Analysis*. (3rd edition) Belmont, CA: Duxbury.

Saskovets, M., Lohachov, M. & Liang, Z. (2025) Paralanguage as a tool for shaping stress response in Listeners: Multimodal physiological sensing study. *Comprehensive Psychoneuroendocrinology*. 23, 100309. https://doi.org/10.1016/j.cpnec.2025.100309.

Sawilowsky, S. S. (2009) New Effect Size Rules of Thumb. *Journal of Modern Applied Statistical Methods*. 8(2), 26. https://doi.org/10.22237/jmasm/1257035100.

Sirisha, N., Revanhi, V., Albawi, A. et al. (2025) AI-Driven Predictive Health Monitoring and Early Warning Systems for Enhancing Soldier Safety in IoT-Enabled Wearable Devices. In *Smart Electronics for Sustainable Solutions, Proceedings of the 3rd International Conference on Sustainable Green Energy Technologies, Barcelona, Spain, November 20-22*. EDP Sciences. 619, 03003. http://doi.org/10.1051/e3conf/202661903003.

Sourabh, S. H., Rakshita, B.R., Bharath, R. & Chavan, S. C. P. (2025) A Comprehensive IoT and ML Solution for Soldier Health and Situational Awareness System. In *Data Science and Big Data Analytics, Proceedings of the International Conference on Data Science and Big Data Analysis, 2024, Indore, India*. Durgesh Mishra, Xin-She Yang, Aynur Unal, Dharm Singh Jat, Eds. Springer, Singapore, vol 43.

Stokes, A. F. & Kite, K. (1994) *Flight Stress. Stress, Fatigue, and Performance in Aviation*. 1st ed.; Publisher: Routledge, London. https://doi.org/10.4324/9781315255200.

Delia-Teodora CIOBANU is a graduate of the „Henri Coandă” Air Force Academy (AFAHC) in Brașov, where she defended her bachelor’s thesis entitled "Nonverbal Indicators of Mental Preparation for the Battlefield." She is currently a master’s student in the Security System at the „Henri Coandă” Air Force Academy (AFAHC).

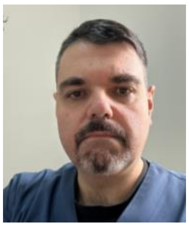
Delia-Teodora CIOBANU este absolventă a Academiei Forțelor Aeriene „Henri Coandă” (AFAHC) din Brașov, unde și-a susținut lucrarea de licență cu titlul „Indicatori nonverbali ai pregătirii mintale pentru câmpul de luptă”. În prezent, este studentă la programul de masterat Sisteme de securitate, Academia Forțelor Aeriene „Henri Coandă” (AFAHC).

Adrian LESENCIUC is a tenured university professor with a multidisciplinary background: a bachelor’s degree in anti-aircraft artillery and missiles, a master’s degree in communication and two doctoral programs, one in military sciences and intelligence at the National Defense University (UNAp) and another in communication sciences at the National University of Political Studies and Public Administration (SNSPA).

Adrian LESENCIUC este profesor universitar abilitat, cu pregătire multidiciplinară: studii de licență în domeniul artileriei și rachetelor antiaeriene, masterat în comunicare și două programe de studii doctorale, unul în științe militare și informații la Universitatea Națională de Apărare (UNAp) și altul în științele comunicării la Școala Națională de Studii Politice și Administrative (SNSPA).

Melinda DAVID, currently a Ph.D. student in Chemisty at the University of Bucharest, obtained in 2017 her Ph.D. in the field of physics. Her research interest include the development and characterization of sensors and biosensors. She has over 20 publications and more than 400 citations, with H-index of 11 (WOS: ABB-4738-2020).

Melinda DAVID, actualmente student doctorand în chimie la Universitatea din București, și-a finalizat doctoratul în 2017, în domeniul fizicii. Domeniile sale de interes pentru cercetare includ dezvoltarea și caracterizarea senzorilor și biosenzorilor. Are peste 20 de publicații și mai mult de 400 de citări, cu un indice H de 11 (WOS: ABB-4738-2020).



Cosmin DUGAN is a senior physician/ consultant in geriatrics and internal medicine at the Emergency University Hospital in Bucharest, with postgraduate studies in security, sociology, and medical engineering. He holds a Ph.D. in National Security and Intelligence .

Cosmin DUGAN este medic primar/consultant în geriatrie și medicină internă la Spitalul Universitar de Urgență din București, cu studii postuniversitare în securitate, sociologie și inginerie medicală. Deține titlul de doctor (Ph.D.) în Informații și Securitate Națională.

Monica FLORESCU is a full professor of physics and biophysics at Transilvania University of Brașov and administrative organizer at Innomar Group SRL. She completed her bachelor's and master's in physics at the University of Bucharest (1988–1993), obtained a Ph.D. in physics in 2007 at the University of Bucharest, and later earned a second Ph.D. in medicine in 2019 at Transilvania University of Brasov. Following postgraduate research (including in the United States), she returned to Brașov in 1998 where she has continued her teaching and research activities. Her research focuses on biological physics and the design of innovative biosensors.

Monica FLORESCU este profesor titular în fizică și biofizică la Universitatea Transilvania din Brașov și administrator al Innomar Group SRL. A absolvit studii de licență și masterat în fizică la Universitatea din București (1988-1993), a obținut titlul de doctor în fizică în 2007 la Universitatea din București și, ulterior, în medicină în 2019 la Universitatea Transilvania din Brașov. După cercetări postuniversitare (inclusiv în Statele Unite ale Americii), s-a întors în Brașov în 1998, unde și-a continuat activitatea didactică și de cercetare. Cercetările sale se concentrează pe studiul fizicii biologice și pe proiectarea de biosenzori inovatori.