

Predictive AI Modeling of Biopsychosocial Determinants of Coagulation Risks Post-AstraZeneca Vaccination: A Retrospective Psychosomatic Cohort Study in Tripoli, Libya

Mehdi Haj Ali ^{1*}, Shokri Salah ², Entesar Abukash ³, Ayat Ali ⁴

^{1,2,3,4} Libyan Authority for Scientific Research, Tripoli, Libya

³ Libyan Academy, Tripoli, Libya

⁴ Department of Medical Laboratories, Faculty of Medical Sciences and Technology, Tripoli, Libya

نمذجة الذكاء الاصطناعي التنبؤية للمحددات البيولوجية والنفسية والاجتماعية لمخاطر التخثر
بعد التطعيم بلقاح أسترازينيكا: دراسة أترابية نفسية جسدية استرجاعية في طرابلس، ليبيا

المهدي الحاج علي ^{1*}، شكري صالح ²، انتصار ابوكاش ³، آيات علي ⁴

^{1,2,3,4} الهيئة الليبية للبحث العلمي، طرابلس، ليبيا

³ الأكاديمية الليبية للدراسات العليا، طرابلس، ليبيا

⁴ قسم المختبرات، كلية العلوم الطبية والتقنية، طرابلس، ليبيا

*Corresponding author: m.rheemy@gmail.com

Received: April 28, 2026

Accepted: July 22, 2026

Published: August 08, 2026

Abstract

The ChAdOx1 nCoV-19 (AstraZeneca) vaccine has been globally linked to rare, severe thromboembolic complications like Vaccine-Induced Immune Thrombotic Thrombocytopenia (VITT). While physiological mechanisms are heavily investigated, a substantial research gap exists regarding how post-vaccination psychological distress (e.g., vaccine-related anxiety) interacts with hematological parameters in North African populations. This study bridges this gap using Machine Learning (ML) to process complex biopsychosocial datasets. Methods: A retrospective cohort study was conducted on 100 vaccinated individuals in Tripoli, Libya. Longitudinal laboratory data (D-Dimer, White Blood Cell count [WBC], and Platelet count [PLT]) were paired with psychometric scores evaluating post-vaccination health anxiety. Artificial Intelligence (AI) architectures, specifically Random Forest classifiers, were deployed to discover non-linear correlations and predict sub-clinical clotting risks. Results: Elevated D-Dimer levels (≥ 500 ng/mL) were identified in 6% ($n=6/100$) of the global cohort, showing an incidence rate of 11% among women. An explicit age-dependent escalation in D-Dimer concentration was recorded among the affected female patients. Crucially, all six hypercoagulable individuals presented with completely normal WBC and PLT counts, demonstrating a clear clinical dissociation from typical acute thrombocytopenia. Conclusion: This investigation establishes that AstraZeneca vaccination is associated with a sub-clinical hypercoagulable risk within a 6% subset of the cohort in Tripoli, Libya, driven by clear gender and age factors. Standard complete blood counts are insufficient on their own to rule out localized clotting risks, making quantitative D-Dimer testing a vital independent diagnostic tool.

Keywords: AstraZeneca Vaccine; Artificial Intelligence; Psychological Distress; Coagulation; D-Dimer; Sub-clinical Thrombosis.

الملخص:

ارتبط لقاح ChAdOx1 nCoV-19 (أسترازينيكا) عالميًا بمضاعفات تخثر نادرة وشديدة، مثل نقص الصفائح المناعي التخثري الناجم عن اللقاح (VITT). وبينما تُجرى دراسات مكثفة حول الآليات الفيزيولوجية، لا تزال هناك فجوة بحثية كبيرة فيما يتعلق بكيفية تفاعل الضغط النفسي التالي للتطعيم (مثل القلق المرتبط باللقاح) مع المؤشرات الدموية لدى سكان شمال إفريقيا. تغطي هذه الدراسة الفجوة باستخدام التعلم الآلي لمعالجة مجموعات البيانات البيولوجية والنفسية والاجتماعية المعقدة.

المنهجية: أُجريت دراسة أترابية استرجاعية على 100 شخص مُلقح في طرابلس، ليبيا. وتم ربط البيانات المختبرية الطولية (D-Dimer، وعدد خلايا الدم البيضاء، وعدد الصفائح الدموية) بنتائج القياس النفسي لتقييم القلق الصحي التالي للتطعيم. استُخدمت بنى الذكاء الاصطناعي، وتحديدًا مصنفات الشجرة العشوائية، لاكتشاف الارتباطات غير الخطية والتنبؤ بمخاطر التخثر دون السريرية. النتائج: تم رصد ارتفاع مستويات د-دايمر (≤ 500 نانوغرام/مل) لدى 6% (ن = 6/100) من المجموعة العالمية.

مما يُشير إلى معدل إصابة بنسبة 11% بين النساء. ولوحظ ارتفاع واضح في تركيز د-دايمر مرتبط بالعمر لدى المريضات المصابات. والأهم من ذلك، أن جميع الأفراد الستة المعرضين لفرط التخثر كانت لديهم تعدادات طبيعية تمامًا لخلايا الدم البيضاء والصفائح الدموية، مما يُظهر انفصالًا سريريًا واضحًا عن نقص الصفائح الحاد النموذجي. الخلاصة: تُثبت هذه الدراسة أن التطعيم بلقاح أسترازينيكا يرتبط بخطر فرط التخثر دون السريري لدى 6% من المجموعة في طرابلس، ليبيا، مدفوعًا بعوامل واضحة تتعلق بالجنس والعمر. لا تكفي فحوصات تعداد الدم الكامل القياسية وحدها لاستبعاد مخاطر التخثر الموضوعي، مما يجعل اختبار D-Dimer الكمي أداة تشخيصية مستقلة وحيوية.

الكلمات المفتاحية: لقاح أسترازينيكا؛ الذكاء الاصطناعي؛ الضيق النفسي؛ التخثر؛ D-Dimer؛ التخثر تحت السريري.

Introduction

The emergence of the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in late 2019 precipitated a profound global health crisis, prompting the rapid development and deployment of diverse vaccine platforms. [1][2] Among these platforms, adenoviral vector-based vaccines, such as the ChAdOx1 nCoV-19 vaccine (Oxford-AstraZeneca), played a pivotal role in mitigating severe morbidity and mortality worldwide. [3] Despite its high efficacy in inducing robust humoral and cell-mediated immune responses, post-marketing epidemiological surveillance uncovered a rare but severe prothrombotic phenomenon designated as Vaccine-Induced Immune Thrombotic Thrombocytopenia (VITT).

Mass immunization successfully mitigated pandemic impact, yet public reports of ultra-rare thrombotic events induced widespread vaccine health anxiety. In psychological research, it is well-established that acute distress triggers the Hypothalamic-Pituitary-Adrenal (HPA) axis, initiating a release of cortisol and catecholamines. These neuroendocrine stress mediators alter vascular endothelial integrity, promote platelet hyper-reactivity, and increase blood viscosity. Concurrently, regional healthcare frameworks face constraints in automated surveillance. Here, Artificial Intelligence (AI) offers a paradigm shift. By integrating standard clinical laboratory metrics with behavioral and psychological dimensions, machine learning models can map hidden, multi-dimensional interactions to predict sub-clinical, silent thrombotic risks.[4][5][6][7]

Materials and Methods

Study Design and Setting

A retrospective cohort study was conducted between October and December 2024 to systematically analyze the blood parameters of individuals previously inoculated with the AstraZeneca vaccine within the Tripoli municipal district, Libya. Clinical sample acquisitions and automated laboratory analyses were consolidated and performed at the Tulip Clinic (Tripoli, Libya).[8][9]

Psychometric and Clinical Data Acquisition

The study cohort comprised 100 randomly selected adult Libyan citizens who had received varying dose levels (1, 2, or 3 doses) of the AstraZeneca vaccine. A validated, structured clinical questionnaire was paired with a specialized psychometric scale—the Post-Vaccination Somatization and Anxiety Score (PVSAS)—to quantify psychological distress and health anxiety experienced in the 14 days following inoculation.[10][11]

Hematological and Coagulation Assays

Venous whole blood samples were drawn via standard aseptic venipuncture techniques. For each subject, blood was partitioned into EDTA tubes for complete hematological cellular parsing and buffered sodium citrate tubes (3.2%) for plasma dedicated to automated coagulation kinetics. Plasma D-Dimer concentrations were quantified using the AFIAS-6 Blood Coagulation Device (Boditech Med Inc., South Korea), an advanced automated fluorescence immunoassay platform where values ≥ 500 ng/mL were defined as hypercoagulable. Cellular

parameters—specifically total White Blood Cell (WBC) counts and absolute Platelet (PLT) counts—were parsed using the Mission Automated CBC Hematology Device.[3][4][12][13][14]

Artificial Intelligence Pipeline

To explore potential feature importance and relationships within the biopsychosocial dataset, an exploratory Random Forest (RF) decision-tree analysis was performed. The dataset combined multi-modal parameters: quantitative physiological biomarkers (D-Dimer, PLT, and WBC counts) alongside parameterized psychological variables derived from the Post-Vaccination Somatization and Anxiety Score (PVSAS). Given the small positive cohort size, the decision-tree structure was evaluated as an exploratory descriptive tool to observe feature rankings (such as anxiety scores and baseline parameters) rather than a definitive predictive algorithm.[5][6][15][16][17]

Result and Discussion

The baseline analytical screen of the 100 vaccinated individuals confirmed that the majority maintained normal coagulation homeostasis. However, distinct hypercoagulable spikes were confirmed: 6% (n=6/100) of the global vaccinated population presented with significantly elevated D-Dimer levels exceeding the standard therapeutic threshold of 500 ng/mL. Stratifying the clinical results by biological sex revealed a profound gender asymmetry, with abnormal hypercoagulable states found exclusively within female participants (11% specific incidence rate among women).[4][18]

Table 1. Hematological and Coagulation Parameter Matrix Comparing Normal and Hypercoagulable Cohort Profiles

Patient Profile Class	Age / Sex	D-Dimer (ng/mL)	WBC (x10^9/L)	PLT (x10^9/L)	AI Smart Classification
Hypercoagulable Female 01	34 / F	506.74	6.80	245	Borderline / Mild Anxiety
Hypercoagulable Female 02	44 / F	706.34	6.9	238	Elevated Stress
Control Participant 01	42/F	310.20	6.40	265	Healthy Reference / Low Risk
Hypercoagulable Female 04	69 / F	829.54	7.40	289	Moderate / Elevated Stress
Hypercoagulable Female 05	73 / F	920.55	9.45	310	Normal Reference
Hypercoagulable Female 06	80 / F	1341.00	8.10	198	Critical Risk Phenotype

When evaluating coagulation biomarkers in older cohorts, standard clinical protocols incorporate age-adjusted D-Dimer cut-offs (Age} \times 10\sim\{ng/mL\} for individuals >50 years). For Patient Female 05 (73/F) and Female 06 (80/F), the age-adjusted upper normal limits are 730\sim\{ng/mL\} and 800\sim\text{ng/mL\}, respectively. While plasma concentrations in these patients (920.55\sim\text{ng/mL\} and 1341.00\sim\text{ng/mL\}) remain elevated above their age-adjusted thresholds, natural physiological vascular aging contributes to higher baselines and must be considered alongside post-vaccination anxiety vectors

A key finding of this study is the clear structural 'disconnect' between elevated coagulation profiles and standard complete blood counts. In classic acute systemic VITT, microvascular thrombosis drives severe, consumptive thrombocytopenia. However, hematological assessment of the hypercoagulable individuals in this cohort revealed that both absolute white blood cell counts and platelet counts remained completely within normal physiological parameters. Exploratory decision-tree feature ranking suggested preliminary associations between D-Dimer elevations, female sex, and advancing age. However, these observational trends remain exploratory due to sample size constraints and require validation in larger cohort studies.[17][19][20][21]

Limitations

This study has several methodological limitations. Primary among them is the extremely small positive sample size (n=6 hypercoagulable cases out of N=100), resulting in a severe class imbalance. Applying machine learning models like Random Forest to a dataset with only 6 positive outcomes introduces a high risk of model overfitting and limits the generalizability of feature-importance rankings. Consequently, all machine learning outputs in this study must be interpreted strictly as preliminary, exploratory analyses rather than validated predictive algorithms. Future prospective studies with larger cohort sizes are necessary to confirm these observations.

Conclusion

This retrospective investigation identifies a sub-clinical hypercoagulable pattern within a 6% subset of the vaccinated cohort in Tripoli, Libya, localized exclusively among female participants. Notably, these elevated D-Dimer levels occurred in individuals presenting with entirely normal leukocyte and platelet counts, indicating that routine complete blood counts alone are insufficient to detect sub-clinical fibrin dynamics. Exploratory decision-tree feature ranking suggests that chronological age, biological sex, and psychosomatic health anxiety warrant further investigation as co-occurring risk factors. Given dataset size constraints and class imbalance, machine learning outputs must be interpreted as preliminary exploratory tools rather than definitive predictive models. Integrating quantitative D-Dimer screening with standardized psychometric evaluations represents a valuable framework for prospective clinical surveillance in larger study cohorts.

Acknowledgement

The authors express their sincere appreciation to the Libyan Authority for Scientific Research and the laboratory personnel at the Tulip Clinic (Tripoli, Libya) for providing the institutional support, technical infrastructure, and resources necessary to successfully execute this multi-disciplinary project.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

References

- [1] See, I., Lale, A., Marquez, P., Streiff, M. B., Wheeler, A. P., Tepper, N. K., ... and Shay, D. K. (2022). Case series of thrombosis with thrombocytopenia syndrome after COVID-19 vaccination-United States, December 2020 to August 2021. *Annals of Internal Medicine*, 175(4): 513–522.
- [2] Buoninfante, A., Andeweg, A., Baker, A. T., Borad, M., Crawford, N., Dogné, J. M., ... and Cavaleri, M. (2022). Understanding thrombosis with thrombocytopenia syndrome after COVID-19 vaccination. *npj Vaccines*, 7(1): 141.
- [3] Tang, J., Amin, M. A., & Campian, J. L. (2025). Past, present, and future of viral vector vaccine platforms: a comprehensive review. *Vaccines*, 13(5), 524.
- [4] Saha, A., Ghosh Roy, S., Dwivedi, R., Tripathi, P., Kumar, K., Nambiar, S. M., & Pathak, R. (2025). Beyond the pandemic era: recent advances and efficacy of SARS-CoV-2 vaccines against emerging variants of concern. *Vaccines*, 13(4), 424.
- [5] Steidl, M., Felderer, M., & Ramler, R. (2023). The pipeline for the continuous development of artificial intelligence models—Current state of research and practice. *Journal of Systems and Software*, 199, 111615.
- [6] Rider, N. L., Coffey, M., Kurian, A., Quinn, J., Orange, J. S., Modell, V., & Modell, F. (2023). A validated artificial intelligence-based pipeline for population-wide primary immunodeficiency screening. *Journal of Allergy and Clinical Immunology*, 151(1), 272-279.
- [7] Perrault, A., Fang, F., Sinha, A., & Tambe, M. (2020). Artificial intelligence for social impact: Learning and planning in the data-to-deployment pipeline. *Ai Magazine*, 41(4), 3-16.
- [8] Sohn, J. H., Chillakuru, Y. R., Lee, S., Lee, A. Y., Kelil, T., Hess, C. P., ... & Joe, B. N. (2020). An open-source, vendor agnostic hardware and software pipeline for integration of artificial intelligence in radiology workflow. *Journal of digital imaging*, 33(4), 1041-1046.
- [9] Lu, H., & Cheng, Y. F. (2025). Artificial intelligence in energy pipelines: opportunities and risks. *Engineering*.
- [10] Bernardi, F. F., Mascolo, A., Sarno, M., Capoluongo, N., Trama, U., Ruggiero, R., ... and Perrella, A. (2023). Thromboembolic events after COVID-19 vaccination: an Italian retrospective real-world safety study. *Vaccines*, 11(10): 1575.
- [11] Al-Rousan, N. and Al-Najjar, H. (2024). Evaluation of the effects of MERCK, MODERNA, PFIZER/BioNTech, and JANSSEN COVID-19 vaccines on vaccinated people: A metadata analysis. *Informatics in Medicine Unlocked*, 49: 101564.
- [12] Ibrahim, M. A. A. A., Nafady, A. A. H. and Sayed, R. F. (2024). Assessment of Coagulation Profile in Adults Vaccinated Against SARS-CoV-2. *Clinical and Applied Thrombosis/Hemostasis*, 30: 1–12.
- [13] Greinacher, A., Thiele, T., Warkentin, T. E., Weisser, K., Kyrle, P. A., and Eichinger, S. (2021). Thrombotic thrombocytopenia after ChAdOx1 nCoV-19 vaccination. *New England Journal of Medicine*, 384(22): 2092–2101.
- [14] Kumar, S., Akhtar, Z., Satsangi, H., Sehrawat, S., Arora, N., & Bamal, K. (2024). Depression Prediction Using Machine Learning Techniques. In *Artificial Intelligence in Healthcare* (pp. 241-265). CRC Press.
- [15] Zhao, Q., Zhang, C., Zhang, W., Zhang, S., Liu, Q., & Guo, Y. (2025). Applications and challenges of biomarker-based predictive models in proactive health management. *Frontiers in public health*, 13, 1633487.

- [16] Vispute, D., & Pawar, U. B. (2025, July). Exploring deep learning and machine learning approaches for mental health status prediction: A review. In *AIP Conference Proceedings* (Vol. 3327, No. 1, p. 020018). AIP Publishing LLC.
- [17] Sawalha, J. (2023). Learning effective machine learning models for clinical applications in psychiatry.
- [18] Jiménez-Grande, D. (2024). *Machine learning-based identification of key electromyography and kinematic features for chronic neck pain classification* (Doctoral dissertation, University of Birmingham).
- [19] Bhatt, R. R. (2024). *Decoding the Neurological and Genetic Underpinnings of Chronic Pain*. University of Southern California.
- [20] Osmanoglu, Ö., Gupta, S. K., Almasi, A., Yagci, S., Srivastava, M., Araujo, G. H., ... & Dandekar, T. (2023). Signaling network analysis reveals fostamatinib as a potential drug to control platelet hyperactivation during SARS-CoV-2 infection. *Frontiers in Immunology*, 14, 1285345.
- [21] Zhang, Y. (2026). *Integrative Computational Approaches to Structural and Molecular Remodeling in Diseased Vasculature* (Doctoral dissertation, Boston University).

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of **AJAPAS** and/or the editor(s). **AJAPAS** and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.