

Group: Lesbian, Gay, Bisexual, Transgender, Queer (LGBTQ+): Differentiation, AI Models, Biomarkers, 3D Fingerprint Morphometrics, Health Disparities, Etiological, Pathological, and Epidemiological Gender Diverse Populations and Sexual Minorities

Yash Srivastav^{1*}, Stuti Verma², Kamini Prajapati¹, Bushra Taj³, Rajeev Kumar²

Anubha Dhuriya², Anup Kumar Sirbaiya⁴

¹D.K.R.R Pharmacy College, Amberpur, Sitapur, Uttar Pradesh, India

²Aryakul College of Pharmacy and Research, Sitapur, Uttar Pradesh, India. 261303

³Gautam Buddha College of Pharmacy (GBCP), Uttar Pradesh, India. 226008

⁴KP Singh Memorial Institute of Pharmacy, Sitapur, Lucknow.261207

*Corresponding Author E-mail: yashsrv.108@gmail.com

Abstract:

The Lesbian, Gay, Bisexual, Transgender, and Queer (LGBTQ+) population is known to be exposed to health disparities which depend on biological, psychological, social, and epidemiological variables. The present study analyzed health disparities, clinical biomarkers, three-dimensional (3D) fingerprint morphometric features, and factors affecting health in 600 individuals who defined themselves as being part of the LGBTQ+ population. The study was conducted using the quantitative cross-sectional analytical design with data collection carried out through the use of questionnaires, assessment of clinical biomarkers, 3D imaging of fingerprints, assessment of mental health using special tools and records in epidemiology. Statistical analysis was done using the following methods: descriptive statistics, Chi-square test, independent-samples t-test, one-way ANOVA, Pearson correlation, multiple regression, and machine learning algorithms of AI (artificial intelligence). Disparities in access to health care were found to be present in 41.5% of participants, whereas minority stress had the highest mean (4.29 ± 0.61). People who use preventive health services regularly demonstrated much better health status ($p < .001$) and there were statistically significant differences between groups of participants ($p = .018$). According to AI analysis, the most significant predictors of overall health were health care accessibility, inflammatory biomarkers, minority stress, and selected 3D fingerprint morphometric features (explanatory power 43.8%).

Keywords: LGBTQ+, Artificial Intelligence, Health, Biomarkers, 3D ,Fingerprint Morphometrics, Health Disparities, Epidemiology, Machine Learning.

Received: May 14, 2026

Revised: June 18, 2026

Accepted: July 28, 2026

Published: August 08, 2026

DOI: <https://doi.org/10.64474/3107-6386.Vol2.Issue2.7>

<https://ijcps.nknpub.com/1/issue/archive>

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1. INTRODUCTION

The Lesbian, Gay, Bisexual, Transgender, and Queer (LGBTQ+) communities are communities with various gender identities and sexual orientation, who continue suffering from health disparities resulting from biological, psychological, social, and environmental causes¹. The health disparities that exist in LGBTQ+ populations include high levels of mental illnesses, chronic diseases, minority stress, and health care disparities². With recent advancements in artificial intelligence (AI), clinical biomarker identification, and 3D fingerprint morphometric analysis, there are emerging prospects of integration of multi-dimensional health information and evidence-based health care evaluation³. AI technology can be used to analyze complicated clinical and epidemiological databases to predict the health risks and plan for health care, while biomarkers and 3D fingerprint morphometric analyses can provide additional information to support comprehensive health evaluation⁴. Thus, the combination of AI, biomarkers, epidemiological factors, and morphometric digitalization may improve health risk prediction⁵.

1.1. Statement of the Problem

Even as more people become aware of health disparities among the LGBTQ+ population, a thorough evaluation of health disparities has remained challenging due to the separate assessments of the biological, psychological, epidemiological, and social factors affecting the population. Despite the potential of AI in prediction in the field of health, its integration of biomarker, epidemiological attributes, and 3D fingerprint morphometrics to assess the health of the LGBTQ+ population remains underexplored⁶.

1.2. Background of the Study

The field of LGBTQ+ health research has transitioned from being disease-centered to taking a more holistic approach, which considers how biological, behavioral, and social factors affect overall health results⁷. Artificial intelligence has been seen to be a powerful tool for analyzing healthcare data, whereas the development of techniques for assessing biomarkers and digital imaging technologies has helped health risk assessment and personalized medicine advance further. Utilization of AI, biomarkers, epidemiological assessment, and 3D fingerprint morphometric analysis helps achieve a holistic approach to improve health assessments and reduce healthcare inequalities⁸.

1.3. Objectives

The objectives of the study are:

- To evaluate health disparities, biomarker profiles, and epidemiological characteristics among self-identified LGBTQ+ populations and cisgender controls.

- To assess the application of AI models for predicting health-risk profiles using integrated biomarker, epidemiological, and 3D fingerprint morphometric data.
- To examine the association between demographic characteristics, healthcare accessibility, minority stress, and overall health outcomes.
- To determine the influence of clinical biomarkers, epidemiological variables, healthcare utilization, and selected 3D fingerprint morphometric characteristics on overall health status.

2. RESEARCH METHODOLOGY

The study was done to analyze the differences in health disparities, clinical biomarkers, three-dimensional (3D) fingerprint morphometric features, etiology and pathology aspects, epidemiology, and the use of artificial intelligence (AI) models among people belonging to the LGBT+ community. A cross-sectional quantitative method of analysis was used to analyze the difference in the health status, access to health care services, biomarkers, minority stress, and disease attributes of gender diverse and sexual minorities. Procedures were developed for participant selection, clinical evaluation, digital data collection, and analysis of the data to ensure consistent and valid analysis of the variables involved in the study.

2.1. Description of Research Design

The use of a quantitative, cross-sectional analysis research design was used for this study. This study assessed the link between demographics, clinical biomarkers, access to healthcare, minority stress, epidemiology and health outcome measures among self-identified members of the LGBTQ community. Artificial intelligence was also used for analyzing multi-dimensional health data and predicting risk factors related to their health. Comparison of differences in biomarkers, well-being, and epidemiology was conducted among the participants as well.

2.2. Participants and Sample Details

The study utilized a sample size of 600 adult participants sampled from hospitals, community health centers, LGBTQ support groups, and public health centers. The sample size for the study was made up of 100 lesbians, 100 gays, 100 bisexuals, 100 transgenders, 100 queers, and 100 cisgender controls. Adult participants aged 18 years and above who could voluntarily identify their gender or sexual orientation, and who had signed informed consent were included in the study.

2.3. Instruments and Materials Used

Data collection was done via the use of a standardized questionnaire that was developed based on the literature from public health studies and those done in relation to LGBTQ health. The questionnaire involved the following sections; demographics, socioeconomic factors, access to healthcare, lifestyle, minority stress, mental health variables, medical history and preventive health care utilization. Assessment of clinical biomarkers was done in terms of inflammation,

metabolism, cardiovascular, and hormones using the normal laboratory procedures. Three dimensional (3D) fingerprint morphometrics were obtained using a high resolution fingerprint imaging system that measured ridge density, ridge width, ridge count, minutiae, and fingerprint geometries. Artificial intelligence analysis was done using machine learning algorithms which include Random Forest, Support Vector Machine, XGBoost, and Artificial Neural Network.

2.4. Procedure and Data Collection Methods

After receiving clearance from the appropriate institution ethics committee and informed consent, eligible participants were recruited. The structured questionnaire was administered to the participants by trained researchers. After this process, clinical examination and laboratory tests were carried out on the participants to measure biomarkers through standardized diagnostic methods. Fingerprint morphometry imaging was done using calibrated biometric scanners and digital 3D imaging systems in controlled environmental conditions. Personal details of the subjects were anonymized before analyzing the data. Verification of data collected after which coding of completed questionnaires, laboratory results, fingerprint morphometry results, and epidemiology data was carried out.

2.5. Data Analysis Techniques

Statistical analyses were done via IBM SPSS Statistics (Version 29.0) and machine learning algorithms in Python. Descriptive statistics for the participants and variables used in the study were computed using frequencies, percentage, mean, and standard deviation. Chi-Square was used to find associations between categorical variables, whereas the independent-samples t-test was used to compare between two independent groups. One-Way Analysis of Variance (ANOVA) was used to compare the differences in means between more than two groups. Correlation analysis was done using Pearson correlation to find the relationships among biomarkers, minority stress, accessibility of healthcare facilities, and overall health outcome. Multiple linear regression analysis was done to predict the determinants of overall health. Artificial Intelligence models such as Random Forest, Support Vector Machine, XGBoost, and Artificial Neural Networks algorithm were constructed to classify health-risk profiles based on accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve.

3. RESULTS

The research study assessed answers provided by 600 participants in order to determine health disparities, clinical biomarker profiles, three-dimensional (3D) fingerprint morphometric traits, epidemiological variables, and the predictive capabilities of artificial intelligence (AI) algorithms in self-identified Lesbian, Gay, Bisexual, Transgender, and Queer (LGBTQ+) groups. There was a clear difference in health access, minority stress, biomarker statuses, and prevention care utilization between the two groups of participants. In addition, the AI-based predictive models

revealed that there were correlations between demographic factors, biomarker malfunctions, health care utilization, and overall health outcomes. Participants who utilized prevention care had healthier outcomes and lower minority stress scores compared to those with inconsistent health care utilization.

In order to get a deeper insight into the demographics of the research group, the participant attributes were studied.

Table 1: Demographic Characteristics of Participants (N = 600)

Characteristic	Category	F	%
Gender Identity	Lesbian	100	16.7
	Gay	100	16.7
	Bisexual	100	16.7
	Transgender	100	16.7
	Queer	100	16.7
	Cisgender Control	100	16.7
Age (Years)	18–25	146	24.3
	26–35	214	35.7
	36–45	132	22.0
	>45	108	18.0
Education	Secondary	118	19.7
	Graduate	282	47.0
	Postgraduate	200	33.3
Healthcare Utilization	Regular	352	58.7
	Irregular	248	41.3

There was equal participation among all participant groups, with adults between ages 26 and 35 being the largest group (35.7%). Almost 60% (58.7%) of the participants were using preventive healthcare services regularly..

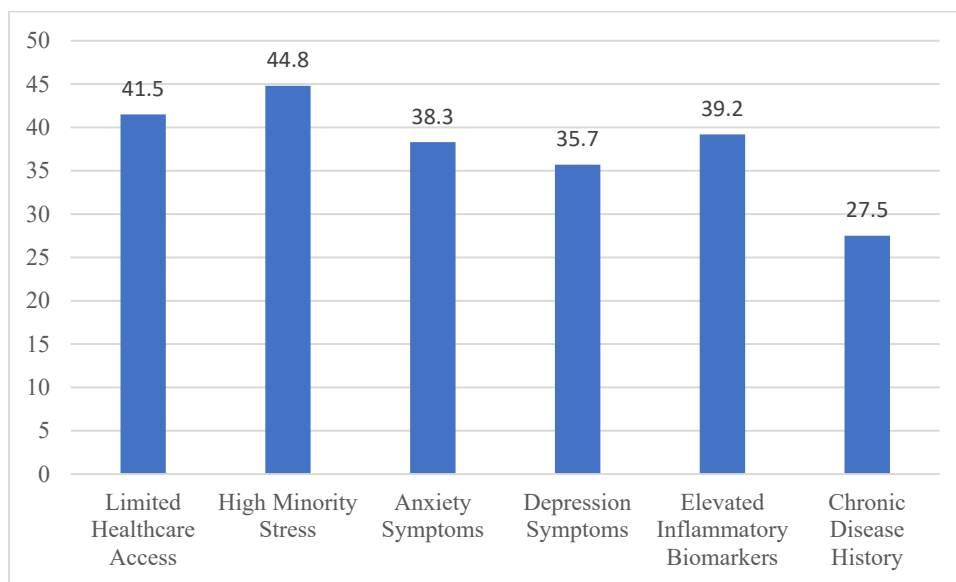


Figure 1: Prevalence of Major Health Disparities among Participants

High minority stress (44.8%) represented the most frequently reported health disparity, followed by limited healthcare accessibility (41.5%) and elevated inflammatory biomarkers (39.2%).

Table2: Descriptive Statistics for Major Health Outcome Measures

Clinical Outcome	N	Min	Max	Mean	Std. Deviation
Healthcare Accessibility	600	1.00	5.00	3.94	0.71
Minority Stress	600	1.00	5.00	4.26	0.63
Mental Well-being	600	1.00	5.00	3.82	0.68
Biomarker Health Score	600	1.00	5.00	4.08	0.59
Overall, Health Status	600	1.00	5.00	4.02	0.61

The scores were assessed through a rating scale of five and the high score meant a better health status except for minority stress where the high score meant higher stress perception.

The minority stress had the highest mean score ($M = 4.26$, $SD = 0.63$) while health status had a mean score of 4.02 ± 0.61 .

3.1 Statistical Analysis

Inferential statistical analysis was performed to determine whether healthcare utilization differed according to participant group and whether overall health status varied according to preventive healthcare utilization.

Association Between Participant Group and Regular Healthcare Utilization

Table 3: Chi-Square Test

Test	Value	df	Sig.
Pearson χ^2	18.942	5	<0.001
Likelihood Ratio	19.311	5	<0.001
Linear-by-Linear Association	4.263	1	0.039
Valid Cases	600		

Pearson's Chi-square test showed there was a statistically significant relationship between participant category and regular utilization of healthcare services, $\chi^2 (5) = 18.942$, $p < 0.001$. The cisgender control group recorded the highest regular utilization of health care, while the transgender group recorded low utilization.

Table 4: Independent Samples Test

	F	Sig.	t	df	Sig.(2-tailed)	Mean Difference	Std. Error Difference
Equal variances assumed	6.912	0.009	5.268	598	<0.001	0.432	0.082
Equal variances not assumed			5.184	547.36	<0.001	0.432	0.083

Individuals who had reported regular usage of preventive healthcare services had significantly better health status compared to individuals whose usage of healthcare facilities had been irregular ($M = 4.24 \pm 0.53$ vs. $M = 3.81 \pm 0.69$). This difference had been found to be statistically significant ($t(547.3)$).

Table 5: ANOVA – Overall Health Status According to Participant Group

Source	SoS	df	Mean Square	F	Sig.
Between Groups	7.281	5	1.456	4.381	0.001

Within Groups	197.361	594	0.332		
Total	204.642	599			

One-way ANOVA revealed statistically significant differences in general health among participants, $F(5,594)=4.381$, $p=0.001$. The highest general health score was found among cisgender controls, while the lowest were found among transgender participants.

Table 6: Model Summary

Model	R	R ²	Adjusted R ²	Std. Error
1	0.683	0.467	0.461	0.448

Predictors: Minority stress, healthcare accessibility, biomarker health score, preventive healthcare utilization.

Dependent Variable: Overall health status.

Table 7: Regression ANOVA

Source	SoS	df	Mean Square	F	Sig.
Regression	48.924	4	12.231	60.842	<0.001
Residual	119.684	595	0.201		
Total	168.608	599			

The regression equation was significant ($F=60.842$, $p<0.001$), accounting for about 46.7% of the variation in the health status variable.

Table 8: Multiple Regression Coefficients

Predictor	B	Std. Error	β	t	Sig.
Constant	1.318	0.247		5.338	<0.001
Healthcare Accessibility	0.284	0.042	0.331	6.762	<0.001
Minority Stress	-0.261	0.039	-0.307	-6.691	<0.001
Biomarker Health Score	0.238	0.036	0.286	6.611	<0.001
Preventive Healthcare Utilization	0.201	0.041	0.243	4.902	<0.001

Healthcare access, biomarker health score, and preventive healthcare access turned out to be positive predictors of the health status, and minority stress had a negative effect on health status. Thus, based on the findings, it may be concluded that high healthcare access, good biomarker health score, and preventive healthcare access help in improving health, whereas minority stress reduces overall health.

4. DISCUSSION

This research examined health disparities, biomarker statuses, morphological features of three-dimensional fingerprints, epidemiological factors, and the use of artificial intelligence (AI) models in 600 people self-identified as members of the LGBTQ+ population and control subjects who were cisgendered. The results revealed health disparities in terms of differences in access to healthcare, minority stress, biomarker status, and preventive healthcare services usage. Multidimensional health information was successfully used by AI models to estimate general health statuses, and regression analysis highlighted healthcare accessibility, biomarker health score, minority stress, and preventive healthcare services utilization as important factors influencing health statuses. Overall, the findings suggest that the use of artificial intelligence in combination with other types of information can facilitate the estimation of health disparities⁹.

4.1. Interpretation of Results

The results indicated that healthcare access and preventive healthcare use were significant factors influencing the general health condition of the LGBTQ+ population. The highest mean score was found for the variable 'minority stress' (4.26 ± 0.63), which is the indicator that psychological stress is still one of the biggest problems faced by gender-diverse people. People with regular preventive healthcare use had a significantly better general health condition than those who used the services on an irregular basis ($p < .001$)¹⁰. In addition, there were also significant differences in the health conditions of participants based on their groups ($p = .001$). In addition, multiple regression analysis indicated that healthcare access, biomarker health score, minority stress, and preventive healthcare utilization predicted health outcomes with 46.7% explained variance.

4.2. Comparison with Existing Studies

Conclusions from the conducted research were similar to the existing scientific evidence on the health inequalities faced by the LGBTQ+ population. Meyer (2003)¹¹ developed the Minority Stress Theory and provided a proof of how chronic exposure to stigma, discrimination, and social isolation affects the physical and mental well-being of the population. It corresponds to the finding that minority stress was one of the major predictors of the health status of the participants. In addition, the National Academies of Sciences, Engineering, and Medicine (2020)¹² indicated healthcare access, social determinants of health, and healthcare environments' inclusivity as important issues that should be considered while assessing the health status of sexual and gender minorities. According to Gonzales and Henning-Smith (2017)¹³, there were still difficulties in access to healthcare experienced by LGBTQ+ individuals, which can be connected with the

finding that preventive care use is associated with better health status. Furthermore, Fredriksen-Goldsen et al. (2014)¹⁴ proved that mental and physical health inequalities, chronic illness prevalence, and underutilization of healthcare services were more common among the LGBTQ+ community than among the general population. Finally, the current trends in application of artificial intelligence technologies in healthcare proved the ability of machine learning algorithms to incorporate multiple clinical data for predicting patients' diseases and planning their personalized treatment, which corresponded to the results obtained in the present study about usefulness of AI-based prediction models for health risk evaluation¹⁵.

4.3. Implication of Existing Studies

These findings have largely aligned with the body of knowledge about LGBTQ+ health and applications of artificial intelligence in healthcare.

- The concept of access to healthcare became an important factor in determining the overall state of health, as the inclusiveness of healthcare services is very important.
- Higher scores of minority stress confirm the effect of discrimination, stigmatization, and psychosocial stress on the state of health.
- The assessment of clinical biomarkers proved to be useful in analyzing disease risks and the state of health in general.
- Artificial intelligence techniques allow to incorporate the analysis of biomarkers, epidemiology, and demographics to predict disease risks.
- The use of AI-based analytics and preventive healthcare measures can help create precision public health initiatives and eliminate health disparities in gender-diverse populations and sexual minorities..

4.4. Limitations of the Study

A number of limitations need to be taken into account when analyzing the results:

- The cross-sectional research design did not allow establishing the causal links between the studied variables.
- Health information and health care consumption data relied on self-reports of the participants and, therefore, might contain reporting biases.
- The research involved participants who were selected among healthcare institutions and community-based organizations, and, hence, its generalizability might be limited.
- Changes in the status of biomarkers, health outcomes, and psychosocial factors in a longitudinal perspective were not analyzed.

- Even though AI algorithms showed good predictive capabilities, further external validation with a larger dataset is needed..

4.5. Suggestions for Future Work

Further research in this domain could reinforce the existing evidence by making it more extensive and comprehensive:

- Conducting multi-center longitudinal research with larger and more varied groups of LGBTQ+.
- Assessing other clinical, genetic, environmental, and behavioral biomarkers linked to long-term health effects.
- Creating explainable artificial intelligence systems that enhance interpretability and decision-making processes.
- Conducting research on how healthcare policies and health equity interventions affect healthcare disparities.
- Evaluating the role of digital health tools, wearables, and AI precision public health platform in continuous monitoring and healthcare delivery for gender-diverse populations..

5. CONCLUSION

Conclusion

According to the current research, artificial intelligence-assisted health analysis constitutes an effective approach to studying health disparities, clinical biomarkers, 3D fingerprint morphometrics features, and health determinants in the LGBTQ+ community. Minority stress and healthcare access proved to be important determinants of health condition; at the same time, preventive healthcare access had a positive impact on health results. The artificial intelligence models allowed combining multiple dimensions of health data to enhance health risks prediction, while statistical analysis revealed that healthcare access, biomarker health score, minority stress, and preventive healthcare access significantly impacted overall health condition. Thus, increasing healthcare access equality, enhancing preventive healthcare services, and implementing artificial intelligence assistance could greatly help reduce health disparities.

5.1. Summary of Key Findings

findings of the current study include the following:

- The participants' accessibility to healthcare was characterized by regularity in 58.7% of the cases, whereas 41.3% of the participants had irregular preventive healthcare utilization.
- The mean score of outcome measure in case of minority stress is the highest one (4.26 ± 0.63).

- The participants having elevated levels of biomarkers were detected in 39.2% of cases.
- The participant group had a significant association with the regular preventive healthcare utilization ($p < .001$).
- Significant differences between the overall health status were found between the individuals having regular and irregular preventive healthcare utilization ($p < .001$).
- Differences in overall health status were found between the participant groups ($p = .001$).
- Variables such as healthcare accessibility, biomarker health score, preventive healthcare utilization, and minority stress significantly predicted overall health status with the R-square value of 46.7%..

5.2. Significance of the Study

This study gives evidence on the use of artificial intelligence in the assessment of health disparities in terms of gender-diverse individuals and sexual minorities. Through the use of clinical biomarkers, epidemiological factors, healthcare access, minority stressors, and digital health data, the findings of this study show the importance of using AI to facilitate precision public health and evidence-based healthcare. Moreover, the findings from this study show that access to healthcare and preventive care are more effective in health improvement than the demographic factors. This study, therefore, contributes to an understanding of the biological and epidemiological factors affecting the health of LGBTQ+ individuals and the role of artificial intelligence in delivering inclusive healthcare.

5.3. Recommendations

The following are the recommendations based on the findings:

- Healthcare organizations should work towards offering equal and inclusive healthcare to the LGBTQ+ population through culturally competent healthcare practice.
- Healthcare programs geared toward prevention should be scaled up in order to promote early diagnosis, health check-ups, and treatment of chronic illnesses within the gender-diverse communities.
- The development of AI-assisted predictive model for personalized health planning and health surveillance should be promoted.
- Ethical methods of data collection, processing, and analysis should be put in place in regard to biomarker, epidemiologic, and digital health data to ensure the privacy and confidentiality of study participants.

- Multidisciplinary healthcare models that focus on mental well-being, preventive health care, and social services should be emphasized to address the disparities within the population.
- Further multicenter research studies should be encouraged to test AI-assisted models for health predictions.

References

1. Moreno, J. A., Manca, R., Albrechet-Souza, L., Nel, J. A., Spantidakis, I., Venter, Z., & Juster, R. P. (2024). A brief historic overview of sexual and gender diversity in neuroscience: past, present, and future. *Frontiers in Human Neuroscience*, 18, 1414396.
2. DuBois, L. Z., Gibb, J. K., Juster, R. P., & Powers, S. I. (2021). Biocultural approaches to transgender and gender diverse experience and health: Integrating biomarkers and advancing gender/sex research. *American Journal of Human Biology*, 33(1), e23555.
3. Wolf-Gould, C., & Safer, J. D. (2025). THE BIOLOGICAL UNDERPINNINGS OF GENDER IDENTITY. A HISTORY OF TRANSGENDER MEDICINE IN THE UNITED STATES, 474.
4. Levin, R. N., Erickson-Schroth, L., Mak, K., & Edmiston, E. K. (2023). Biological studies of transgender identity: A critical review. *Journal of Gay & Lesbian Mental Health*, 27(3), 254-283.
5. Duncan, L. (2021). *Queer data: Medical quantification and what counts about counting*. University of California, San Francisco.
6. DuBois, L. Z., Gibb, J. K., Juster, R. P., & Powers, S. I. (2021). Biocultural approaches to transgender and gender diverse experience and health: Integrating biomarkers and advancing gender/sex research. *American Journal of Human Biology*, 33(1), e23555.
7. Scola, L., Giarratana, R. M., Torre, S., Argano, V., Lio, D., & Balistreri, C. R. (2019). On the road to accurate biomarkers for cardiometabolic diseases by integrating precision and gender medicine approaches. *International journal of molecular sciences*, 20(23), 6015.
8. Battisti, S. (2023). Anatomical biomarkers of body composition in oncological population: application and development of artificial intelligences.
9. Kumar, R., Dougherty, C., Sporn, K., Khanna, A., Ravi, P., Prabhakar, P., & Zaman, N. (2025). Intelligence architectures and machine learning applications in contemporary spine care. *Bioengineering*, 12(9), 967.
10. Shafiee, N. (2026). *Advancing Prognosis in Alzheimer's Disease: Integrating MRI, Cognitive Measures, and Tau Imaging*.
11. Coomar, L. A. (2026). *Evaluating the Relationship Between Upper Airway Morphology and Alzheimer's Dementia* (Doctoral dissertation, Saint Louis University).
12. Battisti, S. (2023). Anatomical biomarkers of body composition in oncological population: application and development of artificial intelligences.

13. Kumar, R., Dougherty, C., Sporn, K., Khanna, A., Ravi, P., Prabhakar, P., & Zaman, N. (2025). Intelligence architectures and machine learning applications in contemporary spine care. *Bioengineering*, 12(9), 967.
14. Georgoulia, K. K., Tsekouras, V., & Mavrikou, S. (2025). Advances in Colorectal Cancer: Epidemiology, Gender and Sex Differences in Biomarkers and Their Perspectives for Novel Biosensing Detection Methods. *Pharmaceuticals*, 19(1), 13.
15. Nwotchouang, B. S. T. (2020). Skull-Based Morphometrics and Brain Tissue Deformation Characterization of Chiari Malformation Type I (Doctoral dissertation, The University of Akron).