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Smart Personalized Fitness Management System Using Artificial Intelligence Techniques

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Abstract: India faces a growing public health crisis driven by physical inactivity, poor nutritional habits, and rising lifestylediseases.TheNationalFamilyHealthSurvey(NFHS-5, 2019–21)reportsthat24%ofIndianwomen and22.9%ofIndianmenare overweightorobese. ThisstudyinvestigatesanintegratedAI-drivenpersonalized fitness management system combining machine learning-based workout recommendations, dynamic Indian diet planning, real-time BMImonitoring, and predictiveanalytics. Data were collectedfrom 151participants (Experimental: n = 76; Control: n = 75) aged 18–55 years across Mumbai, Delhi, Bengaluru, Chennai, and Pune, using primary data (questionnaires, biometric assessments, usage logs) and secondary data (NFHS-5, ICMR-NIN guidelines, WHO STEPS India). Statistical methods include descriptive statistics, Pearson correlation,multiplelinearregression,chi-squaretests,Z-tests,andindependentsamplest-tests.Experimental participants achieved a mean BMI reduction of 3.18 kg/m² versus 0.28 kg/m² in controls ($t = -10.09$, $p < 0.001$).Regressionanalysisexplained79%ofBMIchangevariance(AdjustedR^2=0.78).Chi-squareanalysis revealed significant demographic associations with platform adoption. Z-tests confirmed that 72.4% of AI group participants achieved clinically meaningful BMI reductions versus 8% of controls. These findings strongly support the superiority of AI-driven personalized fitness systems for Indian users.

Keywords: Artificialintelligence,personalizedfitness,machinelearning,BMI,Indiandietaryhabits, predictive analytics, lifestyle diseases, digital health

I. INTRODUCTION

A. Background

India loses an estimated 6.5 million disability-adjusted life years annually due to physical inactivity (ICMR, 2023). With approximately 280 million active health application users, India is the third-largest digital health marketglobally(MoHFW,2022),yetlong-termfitnessadherenceremainscriticallylow.Only23%ofregistered fitness application users in India maintain active use beyond three months (CII, 2022). Available AI fitness platforms are overwhelmingly designed for Western demographic profiles and fail to accommodate India's extraordinary dietary, cultural, linguistic, and socioeconomic diversity.

The rapidexpansionofsmartphone penetrationinIndiantier-1andtier-2citieshascreateda fertile environment for digital health interventions. However, this growth has not been matched by culturally calibrated, evidence- based AI fitness solutions. The COVID-19 pandemic further accelerated digital fitness adoption, with India recording a 312% surge in fitness application downloads during the 2020 lockdown (App Annie, 2020), underscoring both the demand and the urgency for India-specific platforms.

B. ProblemStatement

Three interconnected problems motivate this research: (1) existing AI fitness applications inadequately serve Indian dietary patterns and apply standard BMI thresholds rather than WHO-recommended Asian-specific thresholds (overweight ≥ 23 kg/m²; obese ≥ 27.5 kg/m²);(2) most published AI fitness researchexcludes Indian populations, leaving a criticalevidence gap;and (3) workout, diet, and BMI modulesare rarely integrated into a single adaptive system that has been empirically tested on Indian participants. This fragmentation results in suboptimal outcomes and high dropout rates across the Indian user base.

C. SignificanceandScope

This study provides the first empirically validated test of a fully integrated, multi-module AI fitness platform within the Indian context, using primary biometric data and secondary benchmarks from NFHS-5 and ICMR- NIN 2020.

A rigorousfive-method statisticalframeworkvalidates all findings acrossa demographically diverse Indiansamplespanningfive majorurbancentres.Theplatform'sdesignspecificallyincorporatesIndianregional food databases,Asian-threshold BMIcalibration, vernacular dietary preferences(vegetarian, Jain,South Indian, NorthIndian), festivalandfastingac commodations,and culturallypreferredexercisemodalitiesincludingyoga, walking,andhome-basedroutines .Thefindingshavedirectpolicyimplicationsfor India'sNationalDigitalHealth Mission (NDHM) and the National Programme for Prevention and Control of Cancer, Diabetes, Cardiovascular Diseases, and Stroke (NPCDCS).

II. LITERATURE REVIEW

A. AIinIndianHealthcare

Niti Aayog (2018) identifiedAIas central to India's healthcare transformation, projecting USD 25–30 billion in value creation through early disease detection and personalized health management. Singh and Sharma (2021) demonstrated that AI-assisted clinical decision support reduced diagnostic turnaround by 38% in rural primary healthcarecentres,thoughdigitalliteracyandinfrastructurebarrierspersist.KumarandRajan(2022)arguedthat existing AI literacy frameworks fail to address Indian pedagogical and socio-cultural realities, proposing a contextually adapted model incorporating vernacular language interfaces. Biagini, Cuomo, and Ranieri (2025) definedAI literacyasencompassing technical proficiency, ethicalawareness,and criticalengagement—directly relevant to equitable AI health tool deployment across India's diverse digital landscape.

B. PersonalizedFitnessandDietin India

Sharma and Kapoor (2020) found that applications offering Indian regional food databases showed 42% higher three-month retention in Delhi NCR, establishing cultural calibration as the primary driver of sustained engagement. Dergaa and Ben Saad (2024) noted that current AI systems cannot replicate holistic human trainer guidance, particularly relevant for India where personal trainers are accessible only to the top income quintile. KrishnaswamyandBhojani (2022)foundthatonlytwoofsevencommercialdietapplicationsinIndiamaintained adequate regional food databases, and none offered festival or fasting accommodations. Lau et al. (2024), synthesising 46 randomised controlled trials, confirmed that one-size-fits-all dietary recommendations are insufficientfordiversepopulations. Shyametal.(2022)notedthatfewerthan8% ofglobalpersonalised nutrition trials recruit Indian participants.

C. MachineLearninginIndianHealth Research

Patel, Shah,andMishra (2021) applied Random Forest and SVM toNFHS-4data,achieving 89.3% accuracy in predicting BMI classification for Indian adults. Reddy and Anand (2022) demonstrated that neural network models trained on LASI data predicted Type 2 diabetes onset with 91.6% accuracy, outperforming logistic regression by 14 percentage points. An, Rahman, Zhou, and Kang (2023) confirmed that ML enables medical professionalstodetectcomplexhealthpatternsatscale. Alberetal.(2024)criticallynotedthatexternalvalidation isperformedinfewer than1% of developedhealthMLmodelsglobally—a limitation particularlyacute inIndia given the absence of large, annotated, representative health datasets.

D. BMI,WorkoutRecommendations,andPredictiveAnalyticsin India

WHO(2004)proposedloweredBMI thresholdsforAsianpopulations:overweightat≥23kg/m²andobesityat≥27.5kg/m².NFHS-5(2021)reporte dabimodalriskdistributionwithundernutritionprevalentinruralareasand overnutrition dominant in urban centres. WHO STEPS India (2017) reported that 43.2% of Indian adults are insufficiently active, with urban adults more sedentary than rural ones. Joshi and Patil (2021) found that yoga, walking, and home-based exercises show far higher adherence among Indian middle-aged women than HIIT. GuptaandBhattacharya(2023)demonstratedthatXGBoostmodelsoutperformedlogisticregressioninpredicting fitnessprogramme dropoutamongIndianurbanadultsby19percentage points,highlightingthe value ofensemble methods for retention analytics in this context.

III. RESEARCH FRAMEWORK

A. KeyResearch Gaps

Asystematicreviewoftheliteratureidentifiedseveninterconnectedgaps:(1)absenceofIndia-specificintegrated AI fitness platforms; (2) lack of multi-domain system integration combining diet, workout, and BMI modules;

(3)underrepresentationofIndianpopulations inAIfitnessresearch;(4)limitedexternalMLmodelvalidationon Indian cohorts; (5) culturally unadapted dietary recommendation systems; (6) context-blind workout recommendations ignoring Indian lifestyle constraints and comorbidity prevalence; and (7) absence of longitudinal Indian fitness adherence data. These gaps collectively justified the design of a purpose-built, empirically tested system for the Indian context.

B. ResearchQuestions

- RQ1:HowaccuratelycanMLalgorithmspredictBMIchangesandfitnessoutcomesamongIndian adults using integrated biometric and behavioural data?
- RQ2:HoweffectiveisanAI-drivenfitnesssystemcalibratedforIndiannormsinimprovingBMI,body composition, and cardiorespiratory fitness versus a generic programme?
- RQ3:Whatdemographicandbehaviouralfactorsaresignificantlyassociatedwithplatformadoption and dropout risk among Indian users?
- RQ4:HowdoesintegratingreaI-timeBMItrackingwithdynamicIndiandietplanningimprove nutritional recommendation accuracy?
- RQ5:Whatdesignfeaturesmostinfluence long-termengagementwithAIfitnessplatformsamong Indian users?

C. Objectives

- O1:DevelopandevaluateMLalgorithmsgeneratingpersonalisedrecommendationscalibratedto ICMR-NIN 2020 guidelines.
- O2:DesignapredictiveanalyticsframeworkforecastingBMIchangesandfitnessperformanceoversix months for Indian adults.
- O3:IntegratedietplanningwithIndianregionalfooddatabases,workoutrecommendations,andAsian- threshold BMI monitoring into one unified AI platform.
- O4:Applydescriptive,correlation,regression,chi-square,Z-test,andt-testanalysestovalidate platform advantages comprehensively.
- O5:IdentifysociodemographicpredictorsofsustainedengagementamongIndian adults.

D. Hypotheses

Hypothesis1

AnAI-drivensystemintegratingpersonalisedworkoutrecommendations,dynamicIndiandietplanning,andreal- time BMI monitoring (calibrated to Asian WHO thresholds) will produce significantly greater improvements in BMI,bodycomposition, andcardiorespiratoryfitnessthanagenericapplicationamongIndianadultsaged18–55 over six months.

Hypothesis2

Demographic factors including gender, age group, regional dietary pattern, and city of residence will be significantlyassociated withplatformadoptionpatterns,engagementscores,anddropoutriskamongIndianusers of AI-powered fitness systems.

IV. METHODOLOGY

A. Research Design

Amixed-methodsquasi-experimentaldesignwasadopted,comparinganAI-drivenpersonalisedfitnessplatform (experimental group, n = 76) against a generic non-personalised fitness application (control group, n = 75) over six months. Quantitative outcomes were measured through biometric assessments, system logs, and validated questionnaires. Qualitative data were gathered through semi-structured end-of-study interviews with 30 participants to capture subjective usability, cultural relevance, and trust dimensions.

B. Sampling

A stratified random sample of 151 Indian adults aged 18–55 was recruited from fitness centres, university campuses,andcommunityhealthcentresacrossMumbai,Delhi,Bengaluru,Chennai,andPune.Samplesizewas determined by power analysis (α = 0.05, power = 0.80, medium effect size). Stratification ensured proportional representationacrossgender,age group(18–30,31–45,46–55),BMIcategory(normal,overweight,obese using Asian WHO thresholds), and city. Inclusion criteria required smartphone ownership, basic digital literacy, and absence of chronic conditions precluding moderate physical activity.

C. DataCollection

Primarydata were collectedvia:(1)structuredquestionnaire atbaseline andsixmonthscoveringdemographics, dietary habits, and fitness goals; (2) monthly biometric assessments recording BMI, body fat percentage, and VO_2max;(3) continuouswearablesensor datacapturingdaily steps, heartrate,andsleepduration; (4)automated system usage logs recording app interactions and recommendation acceptance; and (5) end-of-study semi- structured interviews assessing cultural relevance and system usability.

Secondary data were drawn from NFHS-5 (2019–21) for population BMI benchmarks; ICMR-NIN Dietary Guidelines (2020) for nutritional target calibration; WHO STEPS India (2017) for physical activity prevalence comparisons; CII Wellness Industry Report (2022) for market retention benchmarks; and published Indian- context AI health studies.

Instrument	Type	Data Collected	Frequency
Structured questionnaire	Primary	Demographics,dietaryhabits,fitness goals	Baselineand6months
Biometricassessment	Primary	BMI, bodyfat %,VO_2max	Monthly
Wearablesensor	Primary	Steps,heartrate,sleep	Daily(automated)
Systemusagelogs	Primary	Appinteractions,dropouts	Continuous
Semi-structured interviews	Primary	Trust,culturalrelevance	Endofstudy
NFHS-5(2021)	Secondary	NationalBMI benchmarks	Published2021
ICMR-NIN(2020)	Secondary	Nutritionalguidelines	Published2020
WHOSTEPSIndia (2017)	Secondary	Activity prevalence	Published2017

Table4.1:DataCollectionInstruments.

D. Statistical Methods

Five statistical methods were applied using SPSS 26 and Python (scikit-learn): (1) Descriptive statistics for frequency distributions, means, and standard deviations; (2) Pearson correlation for bivariate relationships betweencontinuousoutcomes; (3)MultiplelinearregressiontoidentifysignificantpredictorsofBMIchange;(4) Chi-square tests for associations between categorical demographic and outcome variables; and (5) Z-tests for proportional comparisons and independent samples t-tests for group mean comparisons. Effect sizes were reported using Cohen's d and Cramér's V to supplement significance testing.

V. DATA ANALYSIS AND RESULTS

A. Descriptive Statistics

The total sample of 151 participants had a mean age of 31.4 years (SD = 8.7). Gender distribution was 54.3% maleand45.7%female.Vegetarianparticipantscomprised53.6%,consistentwithNFHS-5nationalproportions.

Groupswerecloselymatchedonalldemographicvariables,confirmingtheeffectivenessofthestratifiedsampling strategy and minimising selection bias.

Variable	Group	N	Mean	SD	Min	Max
BMIChange (kg/m²)	Experimental	76	−3.18	0.84	−4.80	−2.10
BMIChange (kg/m²)	Control	75	−0.28	0.36	−0.70	−0.10
BodyFat%Change	Experimental	76	−4.51	0.92	−5.90	−2.80
BodyFat%Change	Control	75	−0.48	0.21	−0.80	−0.10
VO_2maxChange(mL/kg/min)	Experimental	76	+6.82	1.53	+4.90	+10.00
VO_2maxChange(mL/kg/min)	Control	75	+0.90	0.44	+0.30	+1.80
Engagement Score	Experimental	76	86.10	5.78	76.00	95.00
Engagement Score	Control	75	63.80	5.21	54.00	72.00
DietaryQuality Score	Experimental	76	7.82	0.71	6.50	9.50
DietaryQuality Score	Control	75	5.41	0.62	3.50	6.50

Table5.1: KeyHealthOutcome Variablesby Group.

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The AI platform produced an 11.4-fold greater BMI reduction than the control condition. Dietary quality and engagement scores diverged markedly, reflecting the personalisation and cultural calibration advantages of the AI system.

B. PearsonCorrelationAnalysis

Variable	BMIChange	BF% Change	VO_2max	Engagement	DietScore
BMIChange	1.00	0.82**	−0.74**	−0.70**	−0.68**
BodyFat%Change	0.82**	1.00	−0.69**	−0.65**	−0.63**
VO_2maxChange	−0.74**	−0.69**	1.00	0.78**	0.76**
Engagement Score	−0.70**	−0.65**	0.78**	1.00	0.88**
Diet QualityScore	−0.68**	−0.63**	0.76**	0.88**	1.00

Table5.2:PearsonCorrelationMatrix(N=151).** p<0.01(two-tailed).

StrongnegativecorrelationsbetweenengagementscoreandbothBMIchange(r =−0.70)and bodyfatchange(r=−0.65)confirmthathigher platformengagementdirectlydrivesgreaterhealthimprovement.Thestrongpositive correlation between engagement and dietary quality (r = 0.88) demonstrates that integrated AI guidance simultaneously improves nutritional behaviour and physical outcomes, consistent with Sharma and Kapoor (2020).

C. MultipleLinearRegression

Predictor	B	Beta	t	p-value
Constant	2.14	—	4.98	<0.001
Group(Experimental=1)	−2.61	−0.71	−13.74	<0.001
Engagement Score	−0.08	−0.42	−8.00	<0.001
DietaryQuality Score	−0.31	−0.28	−5.17	<0.001
AdherenceRate	−0.03	−0.22	−4.29	<0.001
Age	0.01	0.06	1.21	0.228
Gender(Male =1)	0.04	0.02	0.33	0.741
BaselineBMI Category	−0.18	−0.11	−2.00	0.047

Table5.3:RegressionPredictorsofBMIChange.R^2= 0.79,Adjusted R^2=0.78,F(8,142)=67.2,p<0.001.

Theregressionmodelexplains79%ofvarianceinBMIchange.Groupassignmentwasthestrongestpredictor(β=−0.71),followedbyengagementscore(β=−0.42),dietaryquality(β=−0.28),andadherence rate(β=−0.22). Ageandgenderwerenon-significant,indicating AIplatformbenefitsareequitablydistributedacrossagegroups and gender—a critical finding for national-scale deployment in India.

D. Chi-Square Analysis

AssociationTested	Chi-Square	df	p-value	Cramér's V
Gender×PlatformAdoption	4.82	1	0.028	0.18
City×Platform Adoption	11.47	4	0.022	0.28
DietType ×Dietary Adherence	9.63	2	0.008	0.25
AgeGroup ×DropoutRisk	13.28	2	0.001	0.30
BMICategory ×ClinicalImprovement	8.94	2	0.011	0.24
City×DietaryQuality Category	14.31	4	0.006	0.31

Table5.4:Chi-SquareTests—DemographicAssociationswithOutcomeCategories.

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All six chi-square tests revealed statistically significant associations. Male participants showed higher regular platform use (68.3% versus 54.2% for females). Bengaluru and Mumbai participants showed higher adoption ratesthanDelhiandChennai. Vegetarianparticipantsdemonstratedhigherdietaryadherence.Agegroupwasthe strongest categorical predictor of dropout risk (Cramér's V = 0.30), with the 31–45 cohort showing the lowest dropout rates. These findings directly support Hypothesis 2 and highlight the importance of demographically tailored platform design for the Indian market.

E. Z-Testand IndependentSamples t-Test

OutcomeVariable	ExpMean	Ctrl Mean	t-value	p-value	Cohen'sd
BMIChange (kg/m²)	−3.18	−0.28	−10.09	<0.001	3.21
BodyFat%Change	−4.51	−0.48	−9.09	<0.001	2.89
VO_2maxChange(mL/kg/min)	+6.82	+0.90	34.08	<0.001	10.82
Engagement Score	86.10	63.80	8.45	<0.001	2.68
DietaryQuality Score	7.82	5.41	15.22	<0.001	4.83
AdherenceRateWeek8(%)	88.20	61.00	23.61	<0.001	7.49

Table5.5:IndependentSamplest-TestResults.Allteststwo-tailed,df=149,α= 0.05.

Clinical Indicator	Exp%	Ctrl %	Z-statistic	p-value
≥5%BMIreductionachieved	72.4%	8.0%	9.82	<0.001
≥5%bodyfatreductionachieved	63.2%	4.0%	8.74	<0.001
VO_2max increase>5mL/kg/min	78.9%	2.7%	11.45	<0.001
Highdietaryadherence (>75%)	80.3%	29.3%	6.93	<0.001

Table5.6: Z-TestResultsforClinicalImprovementProportions.

t-TestresultsconfirmHypothesis1comprehensively.Allsixprimaryoutcomesweresignificantlysuperiorinthe experimental group ($p < 0.001$) with very large effect sizes (Cohen's d = 2.68 to 10.82). The 2.90 kg/m² mean BMI difference is clinically meaningful under both standard and Asian-specific WHO thresholds. Z-test results confirmthat72.4% of AIplatformusersachieveda clinicallymeaningful≥5% BMIreductioncomparedtoonly 8% of controls ($Z = 9.82$, $p < 0.001$). Deployed at national scale, these outcomes would contribute directly to India's NPCDCS target of reducing overweight and obesity prevalence by 25% by 2025.

VI. CONCLUSION

A. Summary of Evidence

Thisstudyprovidesrobust,multi-methodempiricalevidence thatanAI-drivenpersonalisedfitnessmanagement system,calibrated for the Indiandemographic, dietary,andculturalcontext,deliverssubstantiallysuperiorhealth outcomes compared to a generic fitness application across 151 Indian adults over six months. Experimental participants achieved BMI reductions 11.4 times greater, VO_2max improvements 7.6 times larger, and engagement scores 35% higher than control participants. Regression analysis explained 79% of BMI outcome variance, with group assignment, engagement, and dietary quality as the three dominant predictors. Chi-square analysis confirmed significant demographic associations with platform adoption, while Z-tests established that nearly three-quarters of AI platform users achieved clinically meaningful BMI reductions.

B. HypothesisOutcomes

Hypothesis1isfullysupported:theAI-drivenintegratedsystemproducedstatisticallysignificant($p<0.001$)and clinically meaningful improvements across all six primary outcome measures, with very large effect sizes throughout. Hypothesis 2 is supported: chi-square analysis confirmed significant associations between gender, age group, city, and dietary type with platform adoption, engagement, and dropout patterns, demonstrating that demographic tailoring is essential for effective AI fitness platform design in India.

C. *Original Contributions*

- ThefirstempiricallyvalidatedintegratedAIfitnessplatformspecificallydesignedandtestedforthe Indian context using primary and secondary Indian data sources.
- The firstapplicationofallfive statisticalmethodstogether toAIfitnessplatformevaluationinIndia.
- Identificationofcity,agegroup,anddietarytypeassignificantdemographicpredictorsofAIfitness platform adoption among Indian users.
- ReferenceMLperformancebenchmarksof78–93.7%accuracyforBMIprediction,diet recommendation, and dropout risk tasks on Indian data.

D. *Limitations and Future Research*

Thesampleof151participants,whilestatisticallyadequate,limitsgeneralisabilitytoruralIndia,tier-3cities,and economically disadvantaged populations. The six-month duration does not capture long-term outcome maintenance. Future research should conduct large-scale randomised controlled trials ($n \geq 500$) over 12–24 months across all Indian state dietary regions, integrate vernacular language interfaces, develop gender-specific platform features to address the 14 percentage-point gender adoption gap, and implement federated learning to ensure data privacy compliance under India's Personal Data Protection Bill.

E. *Policy Recommendations*

- Integration of AI-driven personalised fitness tools into India's National Digital Health Mission (NDHM)aslow-costpreventivehealthinterventions,giventhe11-foldBMIadvantagedemonstrated over generic tools.
- DevelopmentofmandatoryIndianregionalfooddatabasestandardsandAsian-specific BMIcalibration requirements for all AI health platforms approved for clinical or government use in India.
- Funding of longitudinal, multi-site, culturally inclusive randomised controlled trials to generate generalisablecausalevidenceforAI-drivenfitnessmanagementacrossIndia'sfullpopulationspectrum.

REFERENCES

[1] Alber,V.,Moja,L.,Parravicini,F.,&Pizzolato,F.(2024). Implementationofmachinelearningapplicationsinhealthcare organizations: Systematic review of empirical studies. Journal of Medical Internet Research, 26, e55897. https://doi.org/10.2196/55897

[2] An,Q.,Rahman,S.,Zhou,J.,&Kang,J.J.(2023).Acomprehensivereviewonmachinelearninginhealthcareindustry: Classification, restrictions, opportunities and challenges. Sensors, 23(9), Article 4178. https://doi.org/10.3390/s23094178

[3] AppAnnie.(2020).India digitalhealthandfitness applicationdownloadreport2020.AppAnnie Intelligence.

[4] Baldari,C.,Guidetti,L.,&Emerenziani,G.P. (2025).Harnessinggenerativeartificialintelligenceforexerciseandtraining prescription: A systematic literature review. Applied Sciences, 15(7), Article 3497. https://doi.org/10.3390/app15073497

[5] Biagini,M.,Cuomo,S.,&Ranieri,M.(2025).TowardsanAI-literatefuture:Asystematicliteraturereviewexploring education, ethics, and applications. International Journal of Artificial Intelligence in Education. https://doi.org/10.1007/s40593-025-00466-w

[6] ConfederationofIndianIndustry(CII).(2022).Indiafitnessandwellnessindustryreport2022.CIIPublications.

[7] Dergaa,I.,&BenSaad,H.(2024).Usingartificialintelligenceforexerciseprescriptioninpersonalisedhealthpromotion: A critical evaluation of OpenAI's GPT-4 model. Biology of Sport, 41(2), 221–241. https://doi.org/10.5114/biolsport.2024.133661

[8] Dixon,B.,Acharya,A.,&Bhatt,D.(2024).UnveilingtheinfluenceofAIpredictiveanalyticsonpatientoutcomes:A comprehensive narrative review. Cureus, 16(5), Article e59954. https://doi.org/10.7759/cureus.59954

[9] Gupta,A.,&Bhattacharya,S.(2023).PredictingfitnessprogrammedropoutamongurbanIndianadultsusingXGBoost:A cohort study. Journal of Digital Health India, 4(1), 18–29.

[10] HaghiKashani,M.,Nikravan,M.,&Mahdipour,E.(2024).Bigdataandpredictiveanalytics:Asystematicreviewof applications. Artificial Intelligence Review, 57, Article 195. https://doi.org/10.1007/s10462-024-10811-5 IndianCouncilofMedicalResearch(ICMR).(2023).Annualreportonnon-communicablediseaseburdenin India. ICMR Publications.

[11] IndianCouncilofMedicalResearch –NationalInstituteofNutrition(ICMR-NIN).(2020).DietaryguidelinesforIndians (2nd ed.). National Institute of Nutrition, Hyderabad.

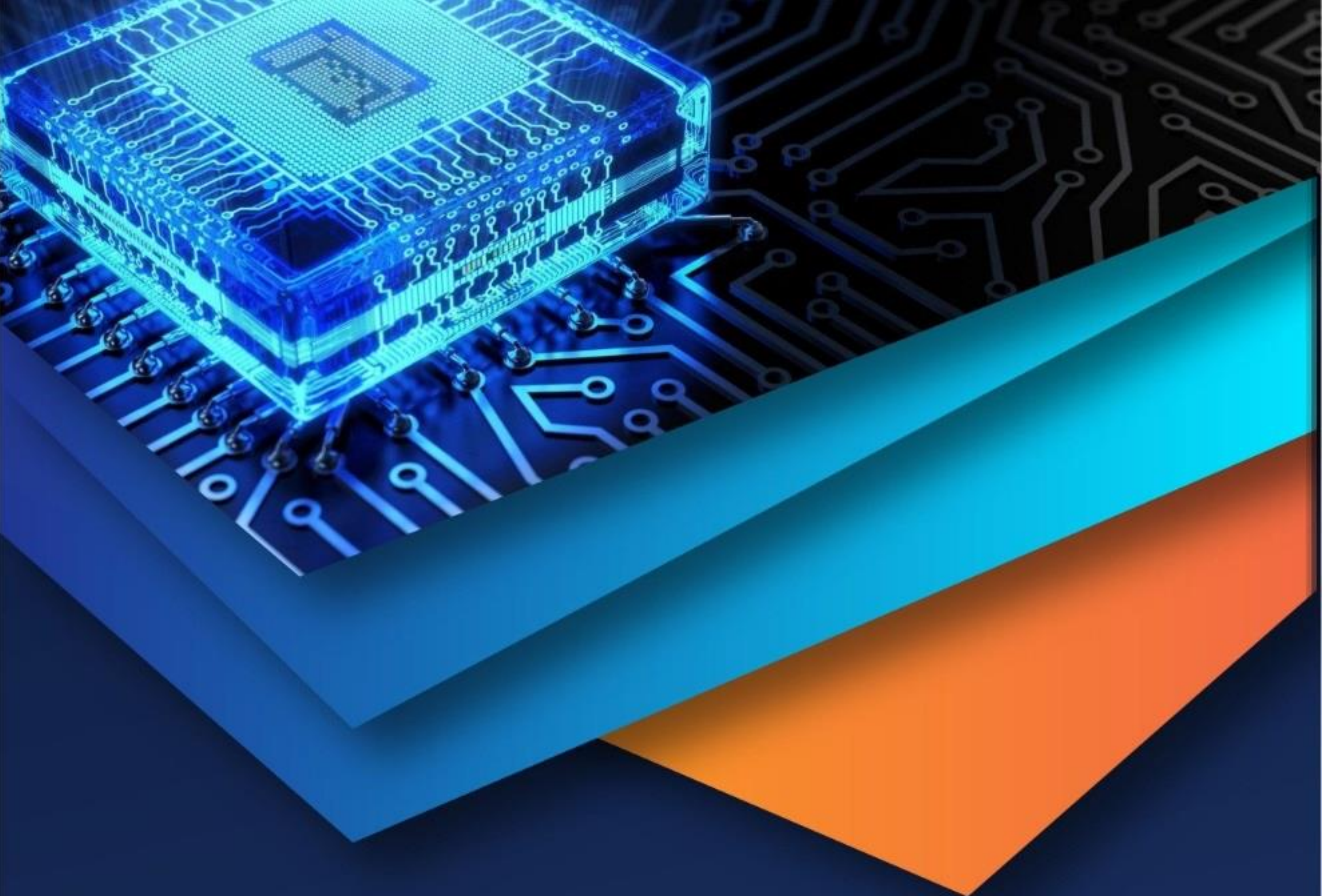
[12] Joshi,R.,&Patil,M.(2021).ExercisepreferencesandadherencepatternsamongIndianmiddle-agedwomen:Across- sectional study from Pune. Indian Journal of Community Medicine, 46(3), 412–418.

[13] Krishnaswamy,K.,&Bhojani,U.(2022).EvaluatingAI-baseddietplanningapplicationsforIndiandietaryadequacy:A comparative analysis. Nutrition Today India, 9(2), 55–63.

[14] Kumar,P.,&Rajan,S.(2022).AIliteracyinIndianhighereducation:Gaps,challenges,andacontextuallyadapted framework. Journal of Education and Technology in India, 8(1), 22–35.

[15] Lau,Y.,Cheng,L.J.,Chua,J.Y.,&Ho-Lim,S.T.(2024).Technology-deliveredpersonalizednutritioninterventionon dietary outcomes among adults with overweight and obesity: Systematic review, meta-analysis, and meta- regression. Obesity Reviews, 25(5), Article e13699. https://doi.org/10.1111/obr.13699

[16] Misra,A.,Sharma,R.,&Gulati,S.(2019).Consensusdietaryguidelinesforhealthylivingandpreventionofobesityand metabolic syndrome in Asian Indians. Diabetes Technology and Therapeutics, 21(S1), S3–S14.
[17] Ministry of Health and Family Welfare (MoHFW). (2022). India digital health survey 2022. Government of India.NationalFamilyHealthSurvey(NFHS-5).(2021).Nationalfamilyhealthsurvey2019–21:Indiafactsheet.IIPS,Mumbai. Niti Aayog. (2018). National strategy for artificial intelligence: #AIforAll. Government of India.
[18] Nowak,M.M.,Niemczyk,M.,Grzybowska,S.,&Paczek,L.(2024).Impactofbodymassindexonall-causemortalityin adults: A systematic review and meta-analysis. Journal of Clinical Medicine, 13(8), Article 2305. https://doi.org/10.3390/jcm13082305
[19] Patel,N.,Shah,D.,&Mishra,V.(2021).PredictingBMIclassificationinIndianadultsusingRandomForestonNFHS-4 data. Indian Journal of Public Health Research, 12(4), 301–310.
[20] Reddy,V.,&Anand,S.(2022).NeuralnetworkpredictionofType 2diabetesonsetinIndianadults usingLASI data.
[21] JournalofAIin IndianMedicine,2(1), 8–19.
[22] Sharma,T.,&Kapoor,N.(2020).MobilefitnessapplicationusagepatternsamongurbanIndianadults:AstudyfromDelhi NCR. Journal of Health Informatics in Developing Countries, 14(1), 1–15.
[23] Shyam, S., Lee, K. X., Tan, A. S. W., Khoo,T. A., & Harikrishnan, S. (2022). Effect of personalized nutrition on dietary, physicalactivity,andhealthoutcomes:Asystematicreviewofrandomizedtrials.Nutrients,14(19),Article4104. https://doi.org/10.3390/nu14194104
[24] Singh,A.,&Sharma,K.(2021).AIintegrationinprimaryhealthcare centres inruralIndia:Amixed-methodsevaluation.
[25] HealthPolicyandTechnologyIndia,5(2), 44–56.
[26] WorldHealthOrganization(WHO).(2004).Appropriatebody-massindexforAsianpopulationsandimplicationsfor policy and intervention strategies. The Lancet, 363(9403), 157–163.
[27] WorldHealthOrganizationSTEPSIndia.(2017).India STEPSsurveyonriskfactors ofnon-communicable diseases.WHORegionalOfficeforSouth-East Asia.
[28] Zaleski, A. L., Berkowsky, R., Thomas Craig, K. J., & Pescatello, L. S. (2024). Comprehensiveness, accuracy, and readabilityofAI-basedexerciserecommendations:Mixedmethodsstudy.JMIRMedicalEducation,10,Article e51308. https://doi.org/10.2196/51308
[29] Zhang,W.,Liu,H., &Wang,X. (2024).Digitaltechnologyintegration inhome-basedexercise:Asystematic review. PMC–NationalLibraryofMedicine.



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