The role of machine learning & motion analysis in enhancing multidisciplinary neurovestibular care: A systematic review

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INTRODUCTION

Falls – often due to balance disorders – have a significant epidemiological burden [1]

Various sensory organs contribute to the incidence of falls including the vestibular system

While various tools (such as computerized dynamic posturography) assessing posture and balance exist, they may be costly, inefficient and have limited availability. Furthermore, few conventional methods have adequate testing parameters to be useful in routine clinical practice [2-4]

Does artificial intelligence or machine learning (ML) enhance these testing parameters?

OBJECTIVE

PICO: For adult patients with **vestibular pathology (P)** undergoing quantitative balance testing requiring **whole-body motion analysis in conjunction with ML algorithms (I)**, what are the **test parameters (C/O)** for the detection and/or diagnosis of disease?

METHODOLOGY

Systematic search: MEDLINE, Cochrane (CENTRAL), Web of Science & Scopus
Manual search: Pubmed, Google Scholar, reference lists, grey literature
Screening: Three independent reviewers using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [5]

Inclusion criteria: Adults patients with vestibular pathology undergoing body motion analysis with ML augmentation
Exclusion criteria: Non-specific balance disorders, case reports, case series (n<10), editorials, perspectives, proof of concept, reviews.

Intervention variables: hardware, data type, ML algorithms + etiology compared
Outcome variables: F1 score, sensitivity, specificity, accuracy, area-under the curve, negative predictive value, positive predictive value

Data: Qualitative summaries including measures of central tendency. No formal meta-analysis conducted given heterogeneity of study designs and data.

FIGURE 1

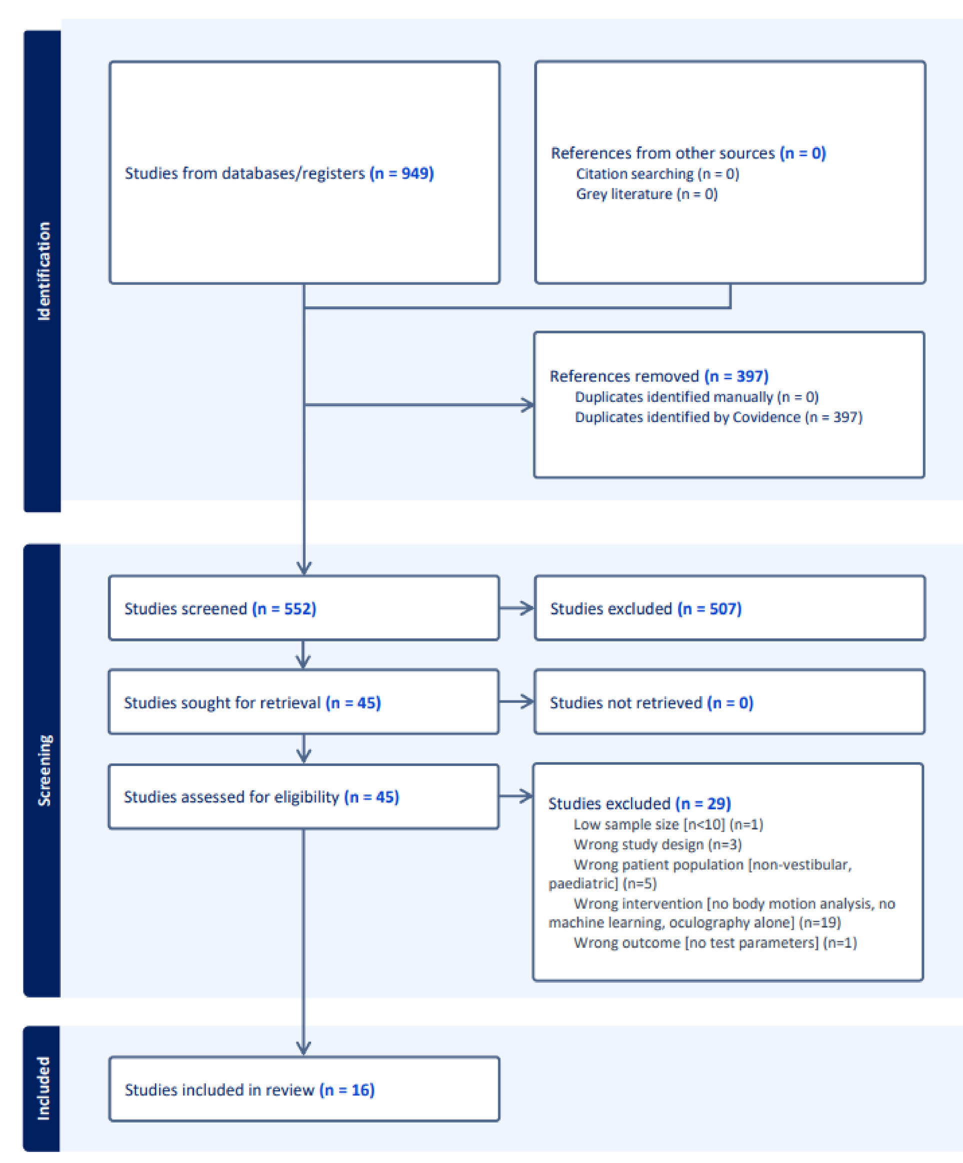


FIGURE 2

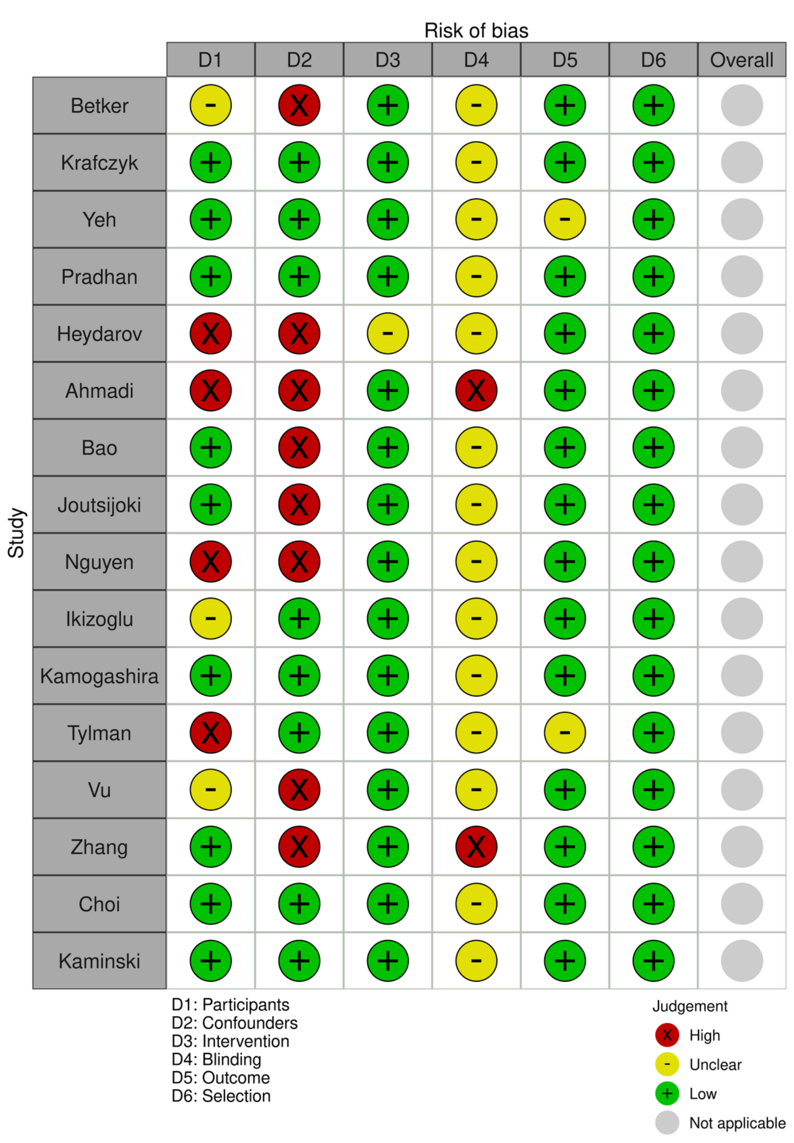


FIGURE 3

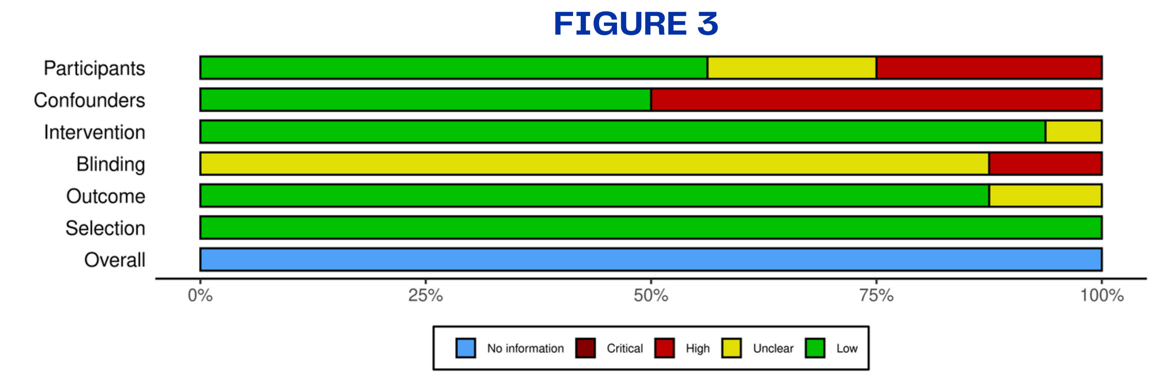


Figure 1. PRISMA flow diagram outlining the screening process
Figures 2 & 3. Risk-of-bias assessment using the Risk of Bias tool for Non-randomized Studies (RoBANS) [6]

RESULTS/FINDINGS

STUDY AND DEMOGRAPHIC VARIABLES

16 STUDIES | 16 QUASI-EXPERIMENTAL | 12 COUNTRIES

2252 INDIVIDUALS

1361 PATIENTS | 891 CONTROLS

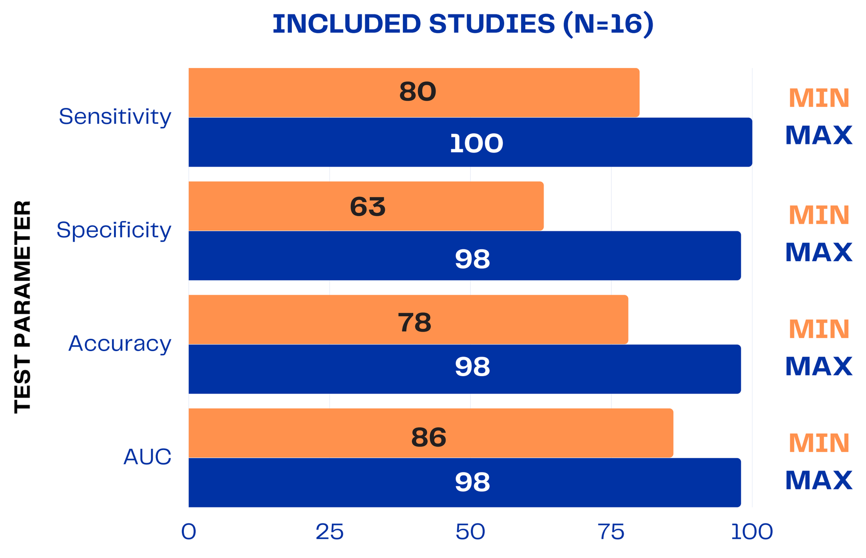
	Patients	Controls
Percent female	21% (RANGE = 8-69%)	15% (RANGE = 7-78%)
Median age	57 years (RANGE = 22-64 YEARS)	48 years (RANGE = 25-71)
Median height	162 cm (RANGE = 162-162CM)	161 cm (RANGE = 161-167CM)

ETIOLOGIES ASSESSED

Phobic postural vertigo
Cerebellar atrophy
Unilateral/bilateral vestibular neuritis
Vestibular hypofunction
Meniere's disease
Benign paroxysmal positional vertigo

INTERVENTION AND OUTCOME VARIABLES

RANGES OF TEST PARAMETERS FOR THE INCLUDED STUDIES (N=16)



*AUC = AREA UNDER THE CURVE

MOST COMMON PROTOCOL
POSTUROGRAPHY
+/- FORCE PLATES

2ND MOST COMMON PROTOCOL
GAIT ANALYSIS
+/- INERTIAL MEASUREMENT UNITS

STRONGEST ML MODEL
SVM CLASSIFIER
+/- Gaussian kernel

CONCLUSION

ML algorithms such as support vector machines (SVMs) in conjunction with motion analysis testing can produce excellent and reliable test parameters for detecting vestibular disease and can subsequently enhance clinical efficiency

ML can not only enhance existing methods (eg. stabilometry), but use newer methods (eg. inertial measurement units) and obtain more efficacious test parameters than conventional methods

Emerging, cost-effective paradigms such as machine vision to quantify body sway and pose should be explored

Limitations include small sample sizes (training/validating ML data considerations), lack of randomization and uncontrolled confounders

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