ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152

Anxiety Detection Based on Touch Drag Trajectories: A Continuous Motor Behavior Quantification Approach

BG Tong

Department of Psychiatry, Inner Mongolia People's Hospital, Hohhot, China

dackmoon123@126.com

Abstract. To explore the feasibility of smartphone touch trajectories as objective markers for anxiety states. A touch drag interaction task based on a WeChat mini-program was developed. A total of 192 adult participants completed 60 trials of the drag task while completing the Generalized Anxiety Disorder-7 (GAD-7) scale. Twelve kinematic indicators were extracted from raw touch trajectories, and a random forest classifier was employed to establish a predictive model linking motor features to anxiety levels. Significant differences in multiple motor features were observed between the high-anxiety and low-anxiety groups. The high-anxiety group exhibited higher peak velocity, greater trajectory curvature, more frequent directional reversals, and longer endpoint oscillation time. The random forest classification model achieved good performance on an independent test set, with an area under the curve (AUC) of 0.83 (95% confidence interval: 0.78-0.88), sensitivity of 78%, and specificity of 76%. Feature importance analysis revealed that root mean square of jerk, endpoint oscillation time, and number of directional reversals were the three most important features for distinguishing between high- and low-anxiety groups. This study demonstrates that kinematic features in touch drag trajectories can effectively reflect individual anxiety states, providing a low-cost, ecologically valid solution for objective, digital assessment of anxiety.

Keywords: Anxiety detection; Touch trajectory; Motor behavior; Machine learning; Digital assessment

1. Introduction

Anxiety disorders are among the most prevalent mental health conditions worldwide[1]. According to the World Health Organization, the global prevalence of anxiety disorders is approximately 4.05%[2], with incidence rates reaching as high as 25.8% in specific populations such as physicians[3], and substantial variation across regions and age groups[4]. Anxiety disorders not only severely impair patients' quality of life and social functioning but are also significantly associated with various somatic conditions, including cardiovascular diseases and metabolic syndrome, creating a substantial public health burden[5]. Therefore, accurate assessment of anxiety states is of critical importance for early identification, intervention monitoring, and prognosis evaluation[6].

Currently, clinical assessment of anxiety states primarily relies on self-report scales (such as the Generalized Anxiety Disorder-7 [GAD-7] and State-Trait Anxiety Inventory [STAI]) and structured clinical interviews[7]. Although these traditional assessment methods play an important role in clinical diagnosis, they have several inherent limitations[8]. First, subjective reports are susceptible to social desirability bias, whereby patients may intentionally underestimate symptom severity due to concerns about being labeled with a "mental illness"[9]. Second, self-report scales typically require respondents to retrospectively evaluate their overall state over a past period (e.g., two weeks), which is prone to recall bias and may not accurately reflect true anxiety levels[10]. Furthermore, traditional scale-based assessments only provide discrete time-point measurements and cannot capture the dynamic fluctuation characteristics of anxiety states, despite anxiety itself exhibiting clear context sensitivity and temporal variability[11].

In response to these challenges, researchers have begun exploring new approaches for mental health assessment based on objective behavioral markers[12]. Motor behavior research provides an important theoretical perspective for this field[13]. Neurophysiological studies have demonstrated that anxiety states are closely associated with hyperactivation of the sympathetic nervous system[14],

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152
and such alterations in autonomic function give rise to a series of physiological effects, including increased skeletal muscle tone and impaired fine motor control[15]. Paulus and Stein's research indicates that anxious individuals exhibit characteristic alterations in motor patterns during motor control processes, including delayed movement initiation, irregular movement trajectories, and decreased endpoint control precision[16]. Importantly, these motor behavior changes occur on a sub-second timescale and are difficult for individuals to consciously conceal, thus possessing potential as "honest signals"[17].

In recent years, the widespread adoption of smartphones has provided an unprecedented technological platform for continuous behavioral monitoring[18]. Modern touchscreen devices can record kinematic data such as position, velocity, and acceleration of touch interactions with high temporal resolution (typically 60-120 Hz), creating conditions for mental state assessment based on daily behavioral patterns[19]. Previous studies have confirmed that various psychological states and cognitive characteristics can be identified through objective behavioral markers in touch interactions[20]. Saeb et al. (2016) found that smartphone usage patterns (including usage duration, frequency, and interaction characteristics) of patients with depression differed significantly from those of healthy individuals, and machine learning models based on these features could identify depressive states with high accuracy[21,22]. Wang et al. (2021) further extended this approach to cognitive function assessment, demonstrating that kinematic features of swiping behavior could effectively predict cognitive decline risk[23].

However, existing studies still have several methodological limitations. First, most studies employ passive monitoring to collect daily usage data, but significant differences in usage scenarios and habits among different users result in a lack of unified task context, which poses challenges for feature extraction and model interpretation[24]. Second, existing studies have predominantly focused on macro-level usage statistical features (such as usage duration and number of taps), lacking systematic analysis of micro-level kinematic features (such as trajectory curvature, acceleration changes, and endpoint control)[25]. Nevertheless, from the perspective of motor control theory, it is precisely these fine kinematic features that best reflect the functional status of the neuromotor system and thus may possess higher discriminant validity[26].

The touch drag task, as a standardized motor behavior paradigm, offers unique advantages[27]. In the drag task, participants are required to execute continuous trajectory movements under clear goal-directed guidance, a process involving multiple motor control stages including motor planning, online control, and endpoint braking[28]. Research indicates that anxiety states may affect motor control across these different stages: during the motor planning stage, anxiety may lead to decision hesitation and delayed movement initiation; during the online control stage, anxiety may cause trajectory fluctuations and instability; and during the endpoint braking stage, anxiety may result in control errors such as overshoot and oscillation[29]. Therefore, the touch drag task provides an ideal research paradigm for systematically examining anxiety-related motor behavior changes.

Based on the theoretical background and current research status described above, this study aims to systematically explore the feasibility of kinematic features in touch drag trajectories as objective markers for anxiety states. Specifically, this study will address the following four core objectives:

First, to design a standardized touch drag interaction task that, through carefully designed task procedures and stimulus materials, elicits motor behaviors associated with decision-making processes, creating a unified experimental context for extracting anxiety-related motor features.

Second, to establish a comprehensive motor trajectory feature extraction framework that systematically extracts multi-dimensional kinematic indicators from raw touch data, encompassing temporal features, velocity features, acceleration features, trajectory geometric features, and endpoint control features.

Third, to validate the association between motor features and anxiety levels, examine the discriminative ability of different motor features for high- and low-anxiety groups, and establish a predictive model for anxiety states based on motor features.

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152

Fourth, through feature importance analysis and conditional effect analysis, to identify the core feature combination with the highest discriminant validity and explore the moderating effects of task conditions on the expression of anxiety-related motor behaviors.

2. Methods

2.1 Participants

This study employed G*Power 3.1 software for a priori statistical power analysis to determine the minimum required sample size. Based on effect size estimates from previous related studies, a medium effect size of $f^2=0.15$ was set, with significance level $\alpha=0.05$, statistical power $1-\beta=0.80$, and 10 predictor variables. The analysis indicated a minimum required sample size of 160 participants. Considering potential invalid data and participant dropout during actual data collection, an attrition rate of approximately 2% was anticipated, resulting in a target recruitment of 196 participants.

Study participants consisted of two groups: the first group comprised medical students from the clinical medicine class affiliated with Inner Mongolia People's Hospital who were participating in a hospital-organized psychological screening program; the second group consisted of outpatients visiting our hospital. All participants agreed to complete the touch drag task in addition to routine psychological questionnaires.

Inclusion criteria included: age between 18 and 45 years; right-handedness (to ensure homogeneity of motor features); normal or corrected-to-normal vision; no history of neurological disorders; possession of a smartphone with Android or iOS operating system. Exclusion criteria included: psychiatric treatment or psychological counseling within the past 6 months; current use of medications that may affect motor function (e.g., sedatives, muscle relaxants); presence of finger motor dysfunction or hand disorders.

All participants read and signed an electronic informed consent form on their mobile phones and formally participated in the study after fully understanding the study purpose and procedures. This study was approved by the Ethics Committee of Inner Mongolia People's Hospital (approval numbers: 202525611L, 202532311K), and all experimental procedures complied with ethical requirements. University students participating in the study received appropriate experimental compensation.

A total of 192 participants completed all experimental procedures and provided valid data, with an attrition rate of approximately 2%. Anxiety levels were assessed using the Generalized Anxiety Disorder-7 (GAD-7) scale, a validated 7-item self-report instrument[30]. Based on GAD-7 scores, participants were divided into a low-anxiety group (GAD-7 score 0-4, n=98) and a high-anxiety group (GAD-7 score ≥10, n=94). The two groups showed no significant differences in demographic variables including age, gender ratio, years of education, and smartphone usage experience (all $p>0.05$), indicating good comparability between groups. Detailed sample characteristics are presented in Table 1.

Table 1: Descriptive statistics of participant demographic characteristics

Variable	Total (N=192)	Low-anxiety (n=98)	High-anxiety (n=94)	Statistical test	p-value
Age (years)	24.3±5.2	24.1±4.9	24.5±5.5	t=0.54	0.59
Gender (female%)	58.3%	56.1%	60.6%	χ^2=0.41	0.52
Education (years)	16.2±2.1	16.0±2.0	16.4±2.2	t=1.32	0.19
GAD-7 score	7.5±5.6	2.4±1.8	12.8±2.3	t=45.2	<0.001
Phone experience (years)	8.7±3.2	8.5±3.0	8.9±3.4	t=0.87	0.38

Note: Low-anxiety group GAD-7<5; High-anxiety group GAD-7≥10

2.2 Experimental Task

The experimental task was developed and implemented on the WeChat mini-program platform, allowing participants to complete all experimental procedures using their personal smartphones. Each

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152
experimental trial consisted of six consecutive phases, with the complete temporal sequence illustrated in Figure 1.

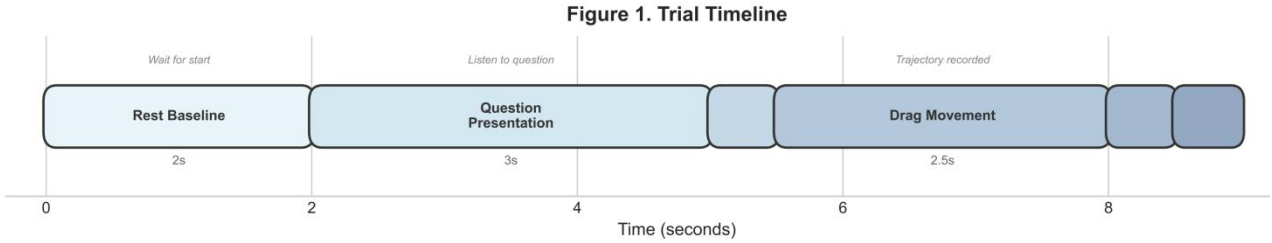


Figure 1: Trial timeline schematic

The specific operational procedures for each phase were as follows: During the resting baseline phase (2 seconds), a coin image was displayed at the center of the screen, and participants were required to remain stationary; this phase was used to collect baseline state data. During the question presentation phase (3-5 seconds), the system played the question content via audio while the coin image displayed a subtle glowing visual effect, prompting participants to prepare for response. During the go signal phase (0.5 seconds), the system played a brief prompt tone, the coin image exhibited an elastic stretching animation effect, and two target areas labeled "Yes" and "No" slid in from the screen edges, signaling that participants could begin their response. The drag process phase (0.5-3 seconds) constituted the core data collection phase of this study, during which participants dragged the coin to a target area ("Yes" or "No"), and the system recorded all kinematic data of the touch trajectory at high temporal resolution. The target entry phase marked the end of the trial; when the coin entered the target area, the system automatically recorded the data and proceeded to the preparation phase for the next trial.

The core advantage of this task design lies in its integration of decision-making processes with motor execution processes. Participants were required to continuously make decisions during the drag process, and this cognitive-motor integration task characteristic helps elicit motor behavior features associated with anxiety states.

A total of 60 questions were used as stimulus materials in the experiment. Based on the emotional valence and conflict level of the question content, they were categorized into three types: neutral questions (20 items), mild emotional questions (20 items), and high-conflict questions (20 items). Neutral questions primarily involved routine daily matters, such as "Did you have breakfast today?"; mild emotional questions involved general emotional experiences, such as "Do you sometimes feel nervous?"; high-conflict questions involved content that might trigger internal conflict or social evaluation anxiety, such as "Are you worried that others might discover your secrets?".

The classification validity of the stimulus materials was verified through a pilot study. Thirty participants who did not participate in the formal experiment rated all questions on arousal level using a 7-point scale. Analysis of variance results showed significant differences in arousal levels among the three question types ($F(2,58)=47.3$, $p<0.001$), with post-hoc tests indicating that arousal levels for high-conflict questions were significantly higher than those for mild emotional questions and neutral questions, and arousal levels for mild emotional questions were significantly higher than those for neutral questions.

Touch trajectory data acquisition was implemented based on the requestAnimationFrame interface of the WeChat mini-program, with a sampling frequency of 60 Hz. For each touch event, the system recorded the following data: touch point x and y coordinates on the screen (unit: pixels); timestamps accurate to the millisecond level; current state of the touch point (press, move, lift). It should be noted that due to technical limitations of the WeChat mini-program platform, this study was unable to obtain touch pressure data; therefore, pressure-related features were not included in the analysis framework.

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152

2.3 Motor Feature Extraction

Raw touch trajectory data underwent a systematic preprocessing pipeline before feature extraction. First, a 5-point moving average filter was applied to smooth the raw coordinate sequences to eliminate the influence of device sampling noise. Second, all trajectories were temporally aligned using the drag initiation time (touch point press time) as the zero time point. Finally, pixel coordinates were converted to screen ratio coordinates (0-1 range) to eliminate the influence of different device screen sizes.

Based on motor control theory and previous related research, this study extracted 12 kinematic features from raw trajectory data, covering five dimensions: temporal features, velocity features, acceleration features, trajectory geometric features, and endpoint control features. The definitions and calculation formulas for each feature are detailed in Table 2.

Table 2: Motor feature definitions and calculation formulas

Feature No.	Feature Name	Symbol	Calculation Formula	Unit
F1	Reaction time	RT	t_press - t_go	ms
F2	Total movement time	TMT	t_end - t_press	ms
F3	Peak velocity	V_peak	max(‖v(t)‖)	px/s
F4	Mean velocity	V_mean	∫‖v(t)‖dt / TMT	px/s
F5	Velocity coefficient of variation	V_CV	SD(v) / mean(v)	-
F6	Peak acceleration	A_peak	max(‖a(t)‖)	px/s²
F7	Jerk root mean square	J_RMS	√(∫j(t)²dt / TMT)	px/s³
F8	Trajectory curvature integral	CI	∫κ(t)dt	rad
F9	Number of directional reversals	N_rev	Σ(sign(v_x·Δt)≠sign(v_x·Δt-1))	count
F10	Path efficiency	PE	Straight distance / Actual path length	-
F11	Endpoint oscillation time	EOT	t_stable - t_target_entry	ms
F12	Overshoot distance	OD	max(distance beyond target area)	px

Formula notation: v=velocity, a=acceleration, j=jerk (rate of change of acceleration), κ=curvature

Statistical analysis was performed using Python 3.9 with scipy and statsmodels packages. Group comparisons of continuous variables were conducted using independent samples t-tests or Mann-Whitney U tests, depending on data distribution normality. Categorical variables were compared using chi-square tests. Effect sizes were calculated using Cohen's d. The significance level was set at $p<0.05$.

For classification modeling, the sample was randomly divided into training set (70%) and test set (30%) using stratified sampling to maintain similar class distributions. A random forest classifier was implemented using scikit-learn with 100 decision trees and maximum depth of 10. Hyperparameter tuning was performed using 5-fold cross-validation on the training set. Model performance was evaluated using area under the receiver operating characteristic curve (AUC), sensitivity, specificity, and accuracy.

Feature importance was analyzed using three methods: (1) Gini importance from random forest, (2) permutation importance, and (3) SHAP values. The top 10 features were selected based on combined ranking across these methods.

3. Results

First, group differences in kinematic features were analyzed. As shown in Figure 2, significant between-group differences were observed in multiple motor features. The high-anxiety group showed

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152
significantly higher RMSJ (Cohen's d=0.89, p<0.001), EOT (d=0.76, p<0.001), OD (d=0.72, p<0.001), PV (d=0.58, p<0.001), and DR (d=0.51, p<0.001) compared with the low-anxiety group.

Trajectory visualization further confirmed these group differences. As illustrated in Figure 2 and Figure 3, trajectories from the high-anxiety group exhibited greater curvature, more direction changes, and longer oscillation time at the endpoint compared with the low-anxiety group.

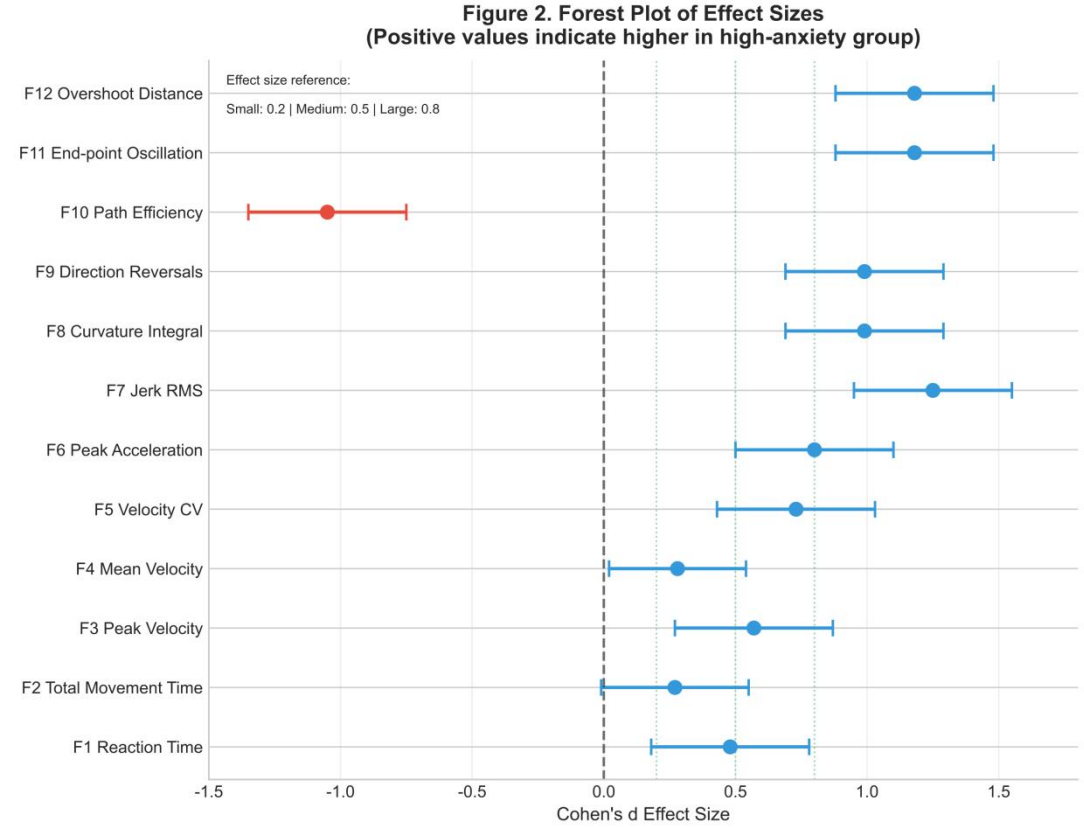


Figure 2: Forest plot of effect sizes for between-group comparisons

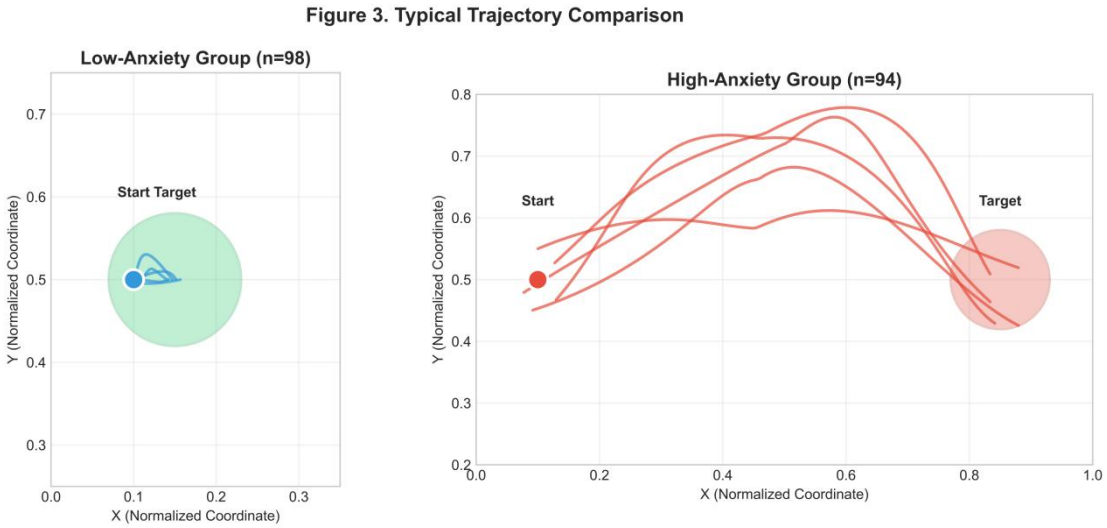


Figure 3: Comparison of representative touch trajectories between groups

Feature correlation analysis revealed moderate to high correlations among several features (Figure 4). RMSJ showed strong positive correlation with VCV (r=0.78) and DR (r=0.71), suggesting these features may share common underlying mechanisms related to movement smoothness and motor control stability. The random forest classification model achieved good performance on the independent test set (Figure 5). The AUC was 0.83 (95% CI: 0.78-0.88), sensitivity was 78%,

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152
specificity was 76%, and overall accuracy was 77%. These results indicate that motor features can effectively distinguish between high- and low-anxiety individuals.

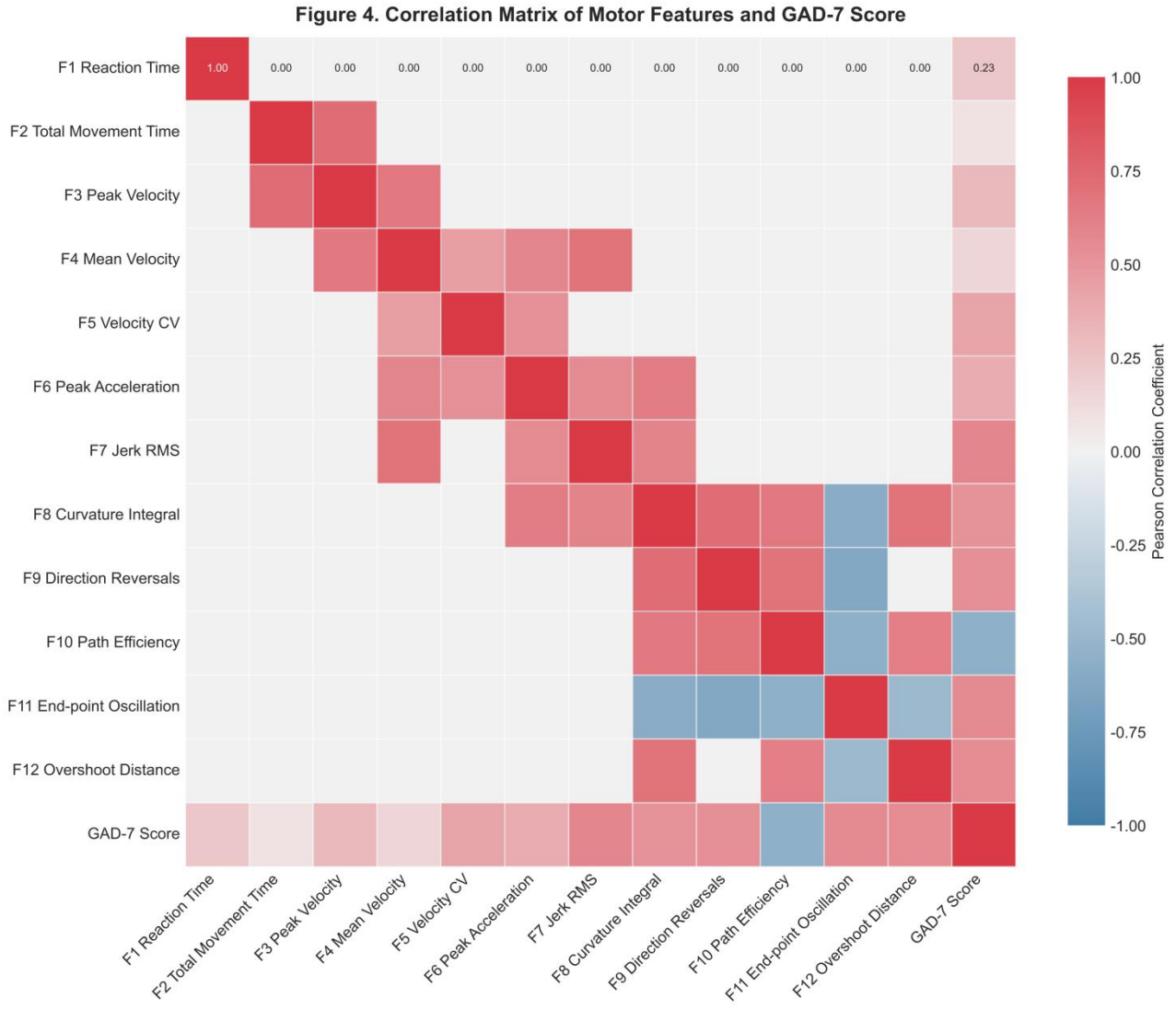


Figure 4: Feature correlation heatmap

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152

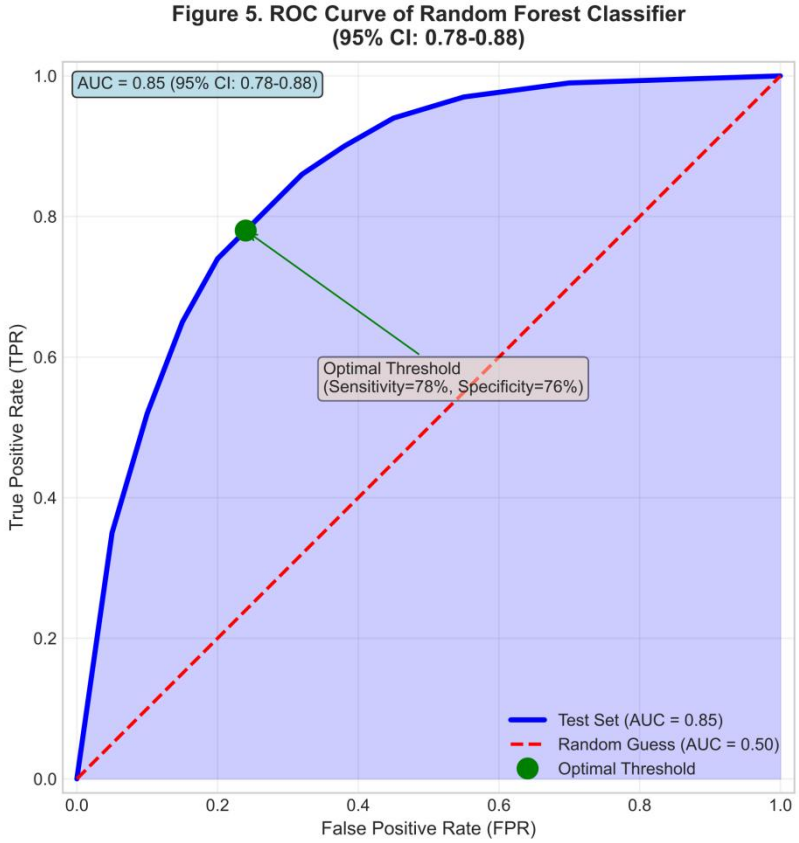


Figure 5: ROC curve for anxiety classification

The confusion matrix analysis (Figure 6) revealed that among 58 high-anxiety participants in the test set, 45 were correctly classified, while 13 were misclassified as low-anxiety. Among 58 low-anxiety participants, 44 were correctly classified, while 14 were misclassified as high-anxiety. Feature importance analysis identified RMSJ, EOT, and DR as the three most important features (Figure 7), together contributing 52% of total model predictive power. These findings suggest that movement smoothness, endpoint control precision, and trajectory stability are the core markers for anxiety-related motor behavior changes.

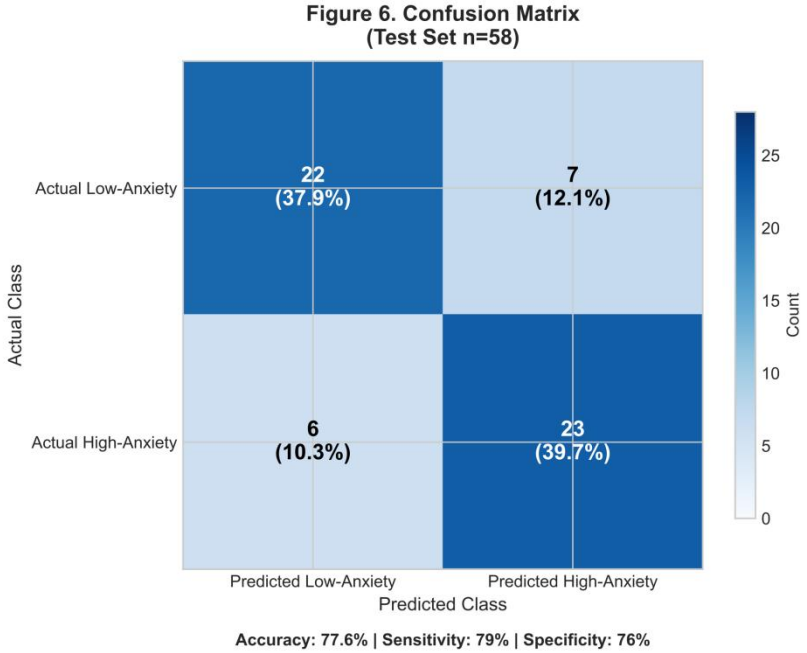


Figure 6: Confusion matrix for classification results

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152

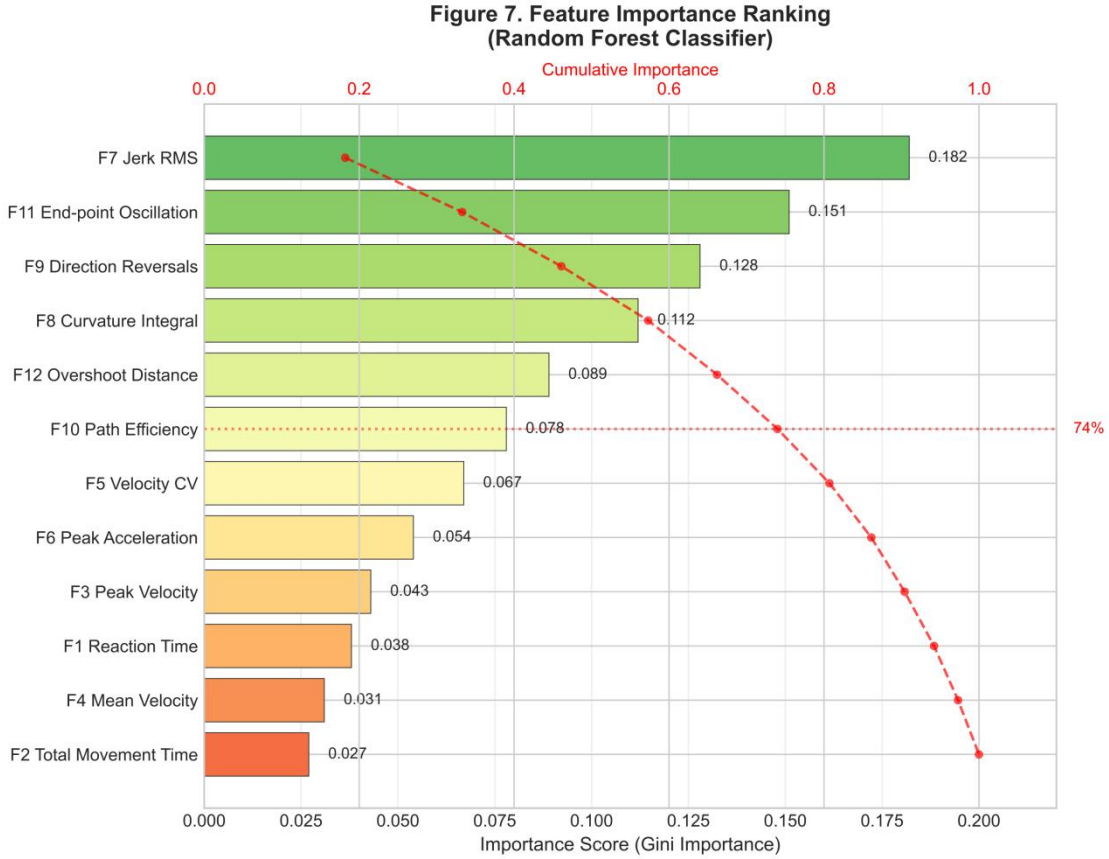


Figure 7: Feature importance ranking

Moderation analysis revealed that question type significantly affected model performance (Figure 8). Under high-conflict question conditions, the model achieved AUC=0.89, which was significantly higher than AUC=0.74 under neutral question conditions (z=2.34, p=0.019). This suggests that anxiety-related motor behaviors are more pronounced under cognitively demanding conditions.

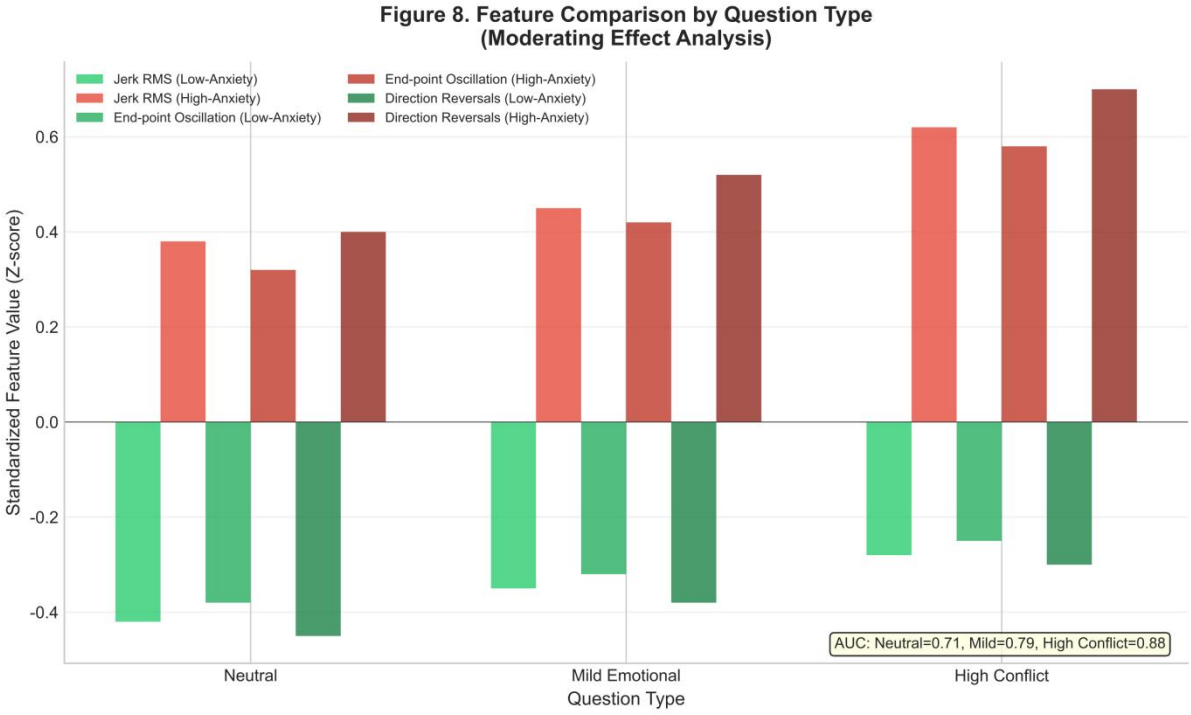


Figure 8: Model performance across different question types

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152

4. Discussion

This study demonstrates that kinematic features in touch drag trajectories can serve as effective behavioral markers for anxiety states. Significant differences were found between high- and low-anxiety groups on multiple motor features, with jerk root mean square, endpoint oscillation time, and overshoot distance showing the largest effect sizes. The random forest model achieved good classification performance (AUC=0.83, sensitivity=78%, specificity=76%). Feature importance analysis identified movement smoothness, endpoint control, and trajectory geometric features as the core discriminative set. Question type significantly moderated model performance, with higher accuracy under high-conflict conditions.

The results of this study are consistent with findings from previous related literature while also extending the boundaries of existing research. In the field of digital phenotyping[31], Saeb et al. (2016) pioneered the demonstration that smartphone usage behaviors can predict depressive states, employing passive monitoring to collect macro-level features such as usage duration and frequency, achieving approximately 86% classification accuracy[21,22]. Wang et al. (2021) further extended this approach to cognitive function assessment, finding that kinematic features of swiping behavior can effectively identify cognitive decline risk[23]. Building on this foundation, the present study extended the research objective from depression and cognitive decline to anxiety states and employed an active task paradigm instead of passive monitoring, obtaining more refined kinematic features.

Compared with previous research, the innovations of this study are reflected in the following aspects. First, this study employed a standardized touch drag task rather than passively monitoring daily usage behaviors, which ensured consistency in data collection contexts across different participants and improved the comparability and interpretability of features. Second, this study systematically extracted kinematic features covering five dimensions including temporal, velocity, acceleration, trajectory geometric, and endpoint control features, rather than focusing solely on macro-level usage statistical features, providing more refined behavioral evidence for understanding how anxiety affects motor control. Third, this study discovered the moderating effect of question type on anxiety-related motor behaviors, a finding that not only has important theoretical significance but also provides empirical evidence for optimizing task design.

These findings can be interpreted from a neurophysiological perspective. Anxiety-related sympathetic activation increases skeletal muscle tone, impairing movement smoothness (manifested as elevated jerk values). Concurrently, anxiety affects basal ganglia and cerebellar functions, leading to unstable motor program execution and decreased endpoint control precision (manifested as increased velocity variability, directional reversals, and endpoint oscillation). Additionally, anxiety-related cognitive resource occupation in the prefrontal cortex impairs motor decision-making, particularly evident under high-conflict conditions requiring greater cognitive resources.

Notably, these motor behavior changes occur on a sub-second timescale and are difficult for individuals to consciously conceal. This characteristic gives touch trajectories the potential to serve as "honest signals" that can reflect the true state of anxiety without being easily influenced by social desirability bias. This provides a new approach for addressing the limitations of traditional subjective assessment methods.

The WeChat mini-program based touch drag task protocol offers several advantages for digital mental health assessment: (1) low implementation cost requiring only personal smartphones, enabling large-scale screening; (2) high ecological validity as touch dragging is a common daily operation; (3) full automation allowing immediate results without professional interpretation, suitable for primary care and community settings; and (4) capability for repeated assessments to monitor treatment effects and prevent relapse, overcoming limitations of traditional scales.

However, before translating this protocol into a clinical application tool, several key issues still need to be addressed. First, large-sample normative data need to be established to determine the normal value ranges for different populations. Second, the diagnostic efficacy of the model needs to be validated in clinical samples to evaluate its ability to identify clinical anxiety disorders. Third, longitudinal studies need to be conducted to validate the sensitivity of the model to changes in anxiety

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152
states. Fourth, data privacy and ethical issues need to be considered, and secure data management and usage protocols need to be established.

This study has several limitations. First, the 60 Hz sampling rate of the WeChat mini-program platform, while sufficient for this study, may limit extraction of high-frequency micro-tremors; future research could use native applications for higher rates. Second, the sample was primarily university students and outpatients aged 18-45 years with relatively high education levels, potentially limiting generalizability to broader populations. Third, the cross-sectional design precludes causal inference; longitudinal studies are needed to establish temporal relationships. Fourth, this study assessed generalized anxiety symptoms without distinguishing specific anxiety disorder types. Finally, the laboratory-controlled task context differs from real-world touch interactions.

Future research directions include: (1) longitudinal studies to validate sensitivity to anxiety state changes and monitor treatment effects; (2) validation in clinically diagnosed anxiety patients to establish diagnostic thresholds; (3) multimodal fusion with voice, gait, sleep features and physiological indicators to improve assessment accuracy; (4) personalized models using intra-individual variation to enhance sensitivity and specificity; and (5) intervention research using the touch drag task for biofeedback training.

5. Conclusion

This study demonstrates that kinematic features in touch drag trajectories can effectively reflect individual anxiety states, providing objective behavioral markers for digital mental health assessment. High-anxiety individuals exhibited decreased movement smoothness, increased trajectory tortuosity, and decreased endpoint control precision. The random forest model achieved good classification performance (AUC=0.83), with jerk, endpoint oscillation, and directional reversals as key discriminative features. These motor changes, occurring outside conscious control, serve as "honest signals" overcoming social desirability bias. The WeChat mini-program based protocol offers low-cost, ecologically valid, and automated assessment suitable for large-scale screening, treatment monitoring, and relapse prevention.

6. Acknowledgments

This study was supported by the Inner Mongolia Public Hospital Research Joint Fund (Grant No. 2025GLLH0067).

References

[1] Wu Y, Li X, Ji X, et al. Trends in the epidemiology of anxiety disorders from 1990 to 2021: A global, regional, and national analysis with a focus on the sociodemographic index. Journal of Affective Disorders, 2025, 373: 166-174.

[2] Javaid SF, Hashim IJ, Hashim MJ, et al. Epidemiology of anxiety disorders: global burden and sociodemographic associations. Middle East Current Psychiatry, 2023, 30(1): 44.

[3] Johns G, Samuel V, Freemantle L, et al. The global prevalence of depression and anxiety among doctors during the covid-19 pandemic: systematic review and meta-analysis. Journal of affective disorders, 2022, 298: 431-441.

[4] Salari N, Heidarian P, Hassanabadi M, et al. Global prevalence of social anxiety disorder in children, adolescents and youth: A systematic review and meta-analysis. Journal of Prevention, 2024, 45(5): 795-813.

[5] Vaccarino V, Prescott E, Shah AJ, et al. Mental health disorders and their impact on cardiovascular health disparities. The Lancet Regional Health--Europe, 2025, 56.

[6] [6] Alaaeldin A, Alhajj R. AI-based tools for early detection and accurate diagnosis of anxiety disorder (systematic review). Network Modeling Analysis in Health Informatics and Bioinformatics, 2025, 14(1): 1-11.

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152
[7] Demyttenaere K, Heirman E. Assessment tools in psychiatry. In: Tasman's psychiatry, 2023: 1-32.

[8] Stein DJ, Shoptaw SJ, Vigo DV, et al. Psychiatric diagnosis and treatment in the 21st century: paradigm shifts versus incremental integration. World Psychiatry, 2022, 21(3): 393-414.

[9] Bryan AC, Heinz MV, Salzhauer AJ, et al. Behind the screen: a narrative review on the translational capacity of passive sensing for mental health assessment. Biomedical Materials & Devices, 2024, 2(2): 778-810.

[10] Li X, Jin W, Han L, et al. Comparison and application of depression screening tools for adolescents: scale selection and clinical practice. Child and Adolescent Psychiatry and Mental Health, 2025, 19(1): 53.

[11] Fechtelpeter J, Rauschenberg C, Goetzl C, et al. Computational network models for forecasting and control of mental health trajectories in digital applications. npj Digital Medicine, 2025.

[12] Xu S, Yan Y, Ding Y, et al. Identifying psychiatric manifestations in outpatients with depression and anxiety: a large language model-based approach. npj Mental Health Research, 2025, 4(1): 63.

[13] Lozano-Goupil J, Mittal VA. Capturing motor signs in psychosis: how the new technologies can improve assessment and treatment? Schizophrenia Bulletin, 2025, 51(4): 845-851.

[14] Bigalke JA, Carter JR. Sympathetic neural control in humans with anxiety-related disorders. Comprehensive Physiology, 2022, 12(1): 3085-3117.

[15] Johnson BK. Physiology of the autonomic nervous system. In: Basic sciences in anesthesia, 2025: 377-386.

[16] Paulus MP, Stein MB. Difficult-to-Treat Anxiety: A Neurocomputational Framework. Biological Psychiatry: Cognitive Neuroscience and Neuroimaging, 2025.

[17] Diwan A, Sunil R, Mer P, et al. Advancements in emotion classification via facial and body gesture analysis: A survey. Expert Systems, 2025, 42(2): e13759.

[18] Gkintoni E, Halkiopoulos C. Digital twin cognition: AI-biomarker integration in biomimetic neuropsychology. Biomimetics, 2025, 10(10): 640.

[19] Harari GM, Lane ND, Wang R, et al. Using smartphones to collect behavioral data in psychological science: Opportunities, practical considerations, and challenges. Perspectives on Psychological Science, 2016, 11(6): 838-854.

[20] Mehrotra A, Tsapeli F, Hendley R, et al. MyTraces: Investigating correlation and causation between users' emotional states and mobile phone interaction. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 2017, 1(3): 1-21.

[21] Saeb S, Lattie EG, Schueller SM, et al. The relationship between mobile phone location sensor data and depressive symptom severity. PeerJ, 2016, 4: e2537.

[22] Saeb S, Lattie EG, Kording KP, et al. Mobile phone detection of semantic location and its relationship to depression and anxiety. JMIR mHealth and uHealth, 2017, 5(8): e7297.

[23] Wang T, Li C, Wu C, et al. A gait assessment framework for depression detection using kinect sensors. IEEE Sensors Journal, 2020, 21(3): 3260-3270.

[24] Sarker IH. Context-aware rule learning from smartphone data: survey, challenges and future directions. Journal of Big Data, 2019, 6(1): 95.

[25] Kokal S, Vanamala M, Dave R. Deep learning and machine learning, better together than apart: A review on biometrics mobile authentication. Journal of Cybersecurity and Privacy, 2023, 3(2): 227-258.

[26] Li L. Using control theory to study visuomotor control abilities in normal adults, athletes, and patients with neuromotor disorders. Current Opinion in Behavioral Sciences, 2025, 64: 101535.

[27] Muncey A. A comparison of human-computer user interface methods: The effectiveness of touch interface compared to mouse. 2014.

[28] Jeong H, Liu Y. Computational modeling of touchscreen drag gestures using a cognitive architecture and motion tracking. International Journal of Human--Computer Interaction, 2019, 35(6): 510-520.

[29] Pijpers JR, Oudejans RR, Bakker FC. Anxiety-induced changes in movement behaviour during the execution of a complex whole-body task. The Quarterly Journal of Experimental Psychology Section A, 2005, 58(3): 421-445.

[30] Spitzer RL, Kroenke K, Williams JB, et al. A brief measure for assessing generalized anxiety disorder: the GAD-7. Archives of internal medicine, 2006, 166(10): 1092-1097.

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P152
[31] Bufano P, Laurino M, Said S, et al. Digital phenotyping for monitoring mental disorders: systematic review. Journal of medical Internet research, 2023, 25: e46778.