ILKOM Jurnal Ilmiah Vol. 18, No. 1, April 2026, pp. 126-137
Accredited 2nd by KEMDIKTISAINTEK No. 10/C/C3/DT.05.00/2025; E-ISSN 2548-7779 | P-ISSN 2087-1716

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Development of an Intelligent Catch the Stick System for Measuring Human Motor Coordination and Reaction Speed

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Article history: Received August 15, 2025; Revised February 10, 2026; Accepted March 30, 2026; Available online April 20, 2026

Abstract

Conventional clinical methods for assessing sensorimotor coordination, such as the Fugl Meyer Assessment (FMA) and Action Research Arm Test (ARAT), often lack the objectivity and high-resolution sensitivity required to detect subtle micro improvements in motor performance. This study presents the design, development, and validation of an intelligent "Catch the Stick" system aimed at accurately and quantitatively assessing human sensorimotor coordination and reaction speed. The proposed multi-metric system integrates 9 axis inertial measurement units (IMUs), a 60 fps computer vision tracking system, and algorithmic classification to evaluate real-time temporal and spatial responses during random stick-dropping tasks. An experimental study was conducted involving fifteen participants (10 healthy individuals and 5 clinical patients with mild to moderate sensorimotor deficits) tested under varying stimulus loads ranging from 1 to 10 sticks. The system demonstrated strong to excellent test-retest reliability (ICC > 0.75) and high detection precision (±15 ms temporal error, <2 mm spatial error). Experimental results revealed that increased stick quantity directly correlated with prolonged reaction times, thereby objectively quantifying cognitive motor overload. Furthermore, the system exhibited strong concurrent validity with conventional tools, showing significant positive correlations with FMA (r = 0.78) and ARAT (r = 0.74) scores. Notably, the intelligent system proved more sensitive to micro improvements in 72% of participants compared to traditional clinical scales, although ceiling effects were observed in low difficulty tasks among healthy users. Overall, the intelligent Catch the Stick platform offers a robust, scalable, and highly sensitive solution for quantifying sensorimotor performance in clinical settings, laying the foundation for future robotic automation and autonomous training protocols.

Keywords: Reaction Time; Motor Coordination; Intelligent System; Catch the Stick; Microcontroller

Introduction

Sensorimotor measurement systems are critical for evaluating the complex interactions between sensory perception and motor responses. Effective assessment tools must be sensitive to various strategies employed by users, capable of detecting subtle effects of sensory feedback, and designed to avoid ceiling effects where tests become too easy for certain populations yet remain too difficult for others [1]. While conventional clinical methods such as the Fugl-Meyer Assessment (FMA) and Action Research Arm Test (ARAT) are widely used, they often suffer from subjectivity, low resolution, and a lack of sensitivity to micro-improvements in motor performance [2], [3]. Consequently, there is a growing need for quantitative, sensor-based systems that can provide objective, real-time metrics of human motor coordination.

Technological advancements have led to the development of various "Catch the Stick" systems. For instance, Harper et al. utilized inertial sensors on a weighted stick to measure acceleration [6], while Richardson et al. developed the "ReacStick," a rod equipped with accelerometers and LEDs to measure reaction time [7]. However, these existing solutions often focus predominantly on temporal metrics (reaction time) or operate under rigid constraints that limit the assessment of movement quality. They rarely integrate multidimensional analysis combining spatial accuracy, movement smoothness, and adaptive difficulty levels into a single platform. Furthermore, validity comparisons between these sensor-based systems and standard clinical scales (FMA/ARAT) remain limited, leaving a gap in their clinical applicability. To address these limitations, this study introduces an intelligent, multi-metric "Catch the Stick" platform designed to quantify sensorimotor performance with high precision. Unlike traditional setups, this system integrates inertial measurement units (IMUs) with computer vision tracking to capture not only *when* the stick is caught (temporal) but *how* it is caught (spatial accuracy and movement quality). The system employs adaptive stick-dropping protocols (varying from 1 to 10 sticks) to evaluate cognitive-motor overload and coordination under stress.

Effective systems should also provide multiple outcome measures that are sensitive to different sensorimotor strategies. For example, a well-designed system can detect if a user is being overly cautious (reflected in increased search time) or making random guesses (shown as accuracy close to chance with reduced response times). This multi-metric approach provides a more nuanced description of performance than single "good/bad" or completion-time scores. Another critical design principle is the elimination of ceiling effects. Systems should scale in difficulty to accommodate users with different ability levels, avoiding scenarios where tests become too easy for some populations yet remain too challenging for others. Time-based measures can be particularly effective at scaling to different ability levels. [1]. For accurate assessment of sensorimotor skills, systems should operate in real-time and incorporate learning algorithms that can compute temporal parameters during movement execution. For instance, in sports applications, systems can be designed to compute the remaining time before an action is completed (such as stick puck contact in hockey) and trigger appropriate responses, allowing assessment of the user's ability to modify movements online in response to changing conditions [4].

Additionally, incorporating metrics of imitation performance can be valuable for evaluating sensorimotor systems. These metrics should quantify the expert's intentions and the user's ability to accurately replicate these intentions. By analyzing variance across multiple demonstrations of the same sensorimotor skill under different conditions, designers can identify consistent features that remain invariant, which helps in creating more robust measurement systems [5]. Designing an effective Catch the Stick system requires careful consideration of physical components, sensor integration, and spatial arrangement. The core component is a specialized stick, which varies in design across implementations but typically includes sensing capabilities. Harper et al. describe a system using an 80 cm long rigid stick with a weighted rubber disk affixed to one end, equipped with an inertial sensor, specifically Xsens MTw sensors containing 3D accelerometers and gyroscopes to measure acceleration and angular velocities [6]. Similarly, Richardson et al. utilize a "ReacStick" apparatus a lightweight rod attached to a spacer box containing an accelerometer, microprocessor, LEDs, and a display that provides elapsed time measurements between initial acceleration and deceleration, weighing approximately 450g [7].

The system setup typically involves positioning the participant in a standardized posture. Harper et al. describe having participants stand on a force plate with their elbow flexed to approximately 90 degrees, with their hand open and placed near but not touching the stick's weighted portion [6]. The dropping mechanism must ensure consistent release conditions; some systems use a tripod-supported apparatus that maintains the stick in a vertical plane while enabling random-timed releases by an examiner. For enhanced measurement accuracy, motion capture technology can be integrated into the system. Kim et al. developed a computer vision-based 3D motion capture system using two high-resolution, high-frame-rate action cameras to track objects manipulated by hand, employing color-based object detection to estimate the object's 3D location and compute kinematics [8]. This approach enables detailed analysis of fine hand motor skills during the catching task. The stick drop height is a critical parameter that influences task difficulty. Yamakawa et al. conducted experiments using a 16 cm polystyrene stick dropped from heights of either 40 or 70 cm above the catching hand at random timing, noting that the 40 cm height creates a falling time that challenges but remains within human reflex capabilities (approximately 220 ms) [9]. Similarly, Richardson et al. standardized their setup by releasing the ReacStick from desk height (74 cm), which creates a 390-ms interval for participants to respond [7]. Marker placement is another important consideration for tracking movement. Harper et al. positioned infrared reflective markers at the participant's wrist, on the inertial sensor affixed to the weighted rubber disk, and on the tripod support base to enable precise tracking of both the stick and the participant's response movements [6]. Validating a Catch, the Stick system requires comprehensive testing approaches to ensure accurate measurement of sensorimotor responses. One effective validation method involves comparative testing between the proposed system and existing technologies. Yamakawa et al. demonstrated this approach by conducting experiments comparing their high-speed vision-based system (1000 fps) against a standard 30 fps vision system for catching falling objects. Their validation protocol involved twenty trials on each system using a 16 cm polystyrene stick dropped from heights of either 40 or 70 cm above the robot hand at random timing. This comparison allowed them to verify that their system could effectively capture human reflexive responses, which typically occur within approximately 220 ms a timeframe shorter than the stick's 40 cm falling duration [9].

Another important validation approach incorporates real-time performance verification through task-specific challenges. Naour et al. validated their hockey shot assessment system by designing real-time tests that evaluated the system's ability to compute the remaining time before stick-puck contact during slap shot execution. Their validation methodology confirmed that the system was sufficiently accurate to be combined with psychophysical algorithms, allowing the virtual goalkeeper's reactions to be adapted between shots via a staircase procedure. This approach demonstrates how validation can verify both technical accuracy and the system's ability to measure the specific sensorimotor skills being targeted [4]. System validation should also include testing different measurement strategies to determine optimal approaches. Lynch et al. evaluated two distinct grasping strategies in their system: one initiating grasps based on predicted object-gripper contact times and another using alternative timing methods. Their validation methodology employed light gates to provide high-resolution estimation of ball position as it approached the gripper, allowing different grasp timings to be tested in an accurate, repeatable way. This approach maintained lower experimental complexity compared to vision-based tracking systems while still enabling thorough validation of measurement accuracy [10].

For comprehensive validation, testing should also verify the system's performance across different user populations and environmental conditions. This ensures that the system can accurately measure sensorimotor responses regardless of user expertise or testing environment. Additionally, validation protocols should include repeated measures to establish test-retest reliability, ensuring that the system provides consistent measurements over time. Motor coordination is the integration of body movements that combine kinematic (spatial direction) and kinetic (force) parameters to produce purposeful actions [11]. Assessing motor coordination is essential for understanding an individual's ability to respond effectively to their environment, as the speed and accuracy of reactions are critical for adaptation to changing conditions [12]. Quantitative measurements of coordination ability are necessary for comprehensive assessment and typically examine several key aspects of movement control [13]. These aspects include spacing control (spatial parameters), timing control (temporal parameters), grading control (force modulation), and performance speed all of which contribute to overall coordination quality. The most effective approach to evaluating motor coordination involves assessing performance during rapid and alternating movements, with particular attention to both speed and quality of execution. While wearable technology has advanced to provide real-time information about general physical parameters such as speed, acceleration, and physiological feedback, these measures alone do not fully capture the nuanced control of limb movements that characterize human motor skills [14]. A more comprehensive assessment requires examining both temporal and spatial aspects of movement [15].

Modern assessment approaches have evolved to evaluate the quality of movement during goal-directed tasks, as demonstrated by scales like the Reaching Performance Scale that assess compensatory movements in individuals with hemiparesis Motor coordination is the integration of body movements that combine kinematic (spatial direction) and kinetic (force) parameters to produce purposeful actions [11]. Assessing motor coordination is essential for understanding an individual's ability to respond effectively to their environment, as the speed and accuracy of reactions are critical for adaptation to changing conditions [12]. Spatial parameters are essential for evaluating the precision and accuracy of motor coordination. One fundamental spatial measure is endpoint accuracy, which can be quantified through various metrics including absolute error (AE) at endpoint (the Euclidean distance from movement termination to the target location) [16] and final error (fERR) [17]. For sequential finger movements, spatial accuracy is often described using error number (EN) and percentage of correct sequences (%CORR_SEQ), which represent the absolute number of errors and the percentage of correctly performed sequences, respectively [18]. Similarly, path length ratio (PLR) quantifies efficiency by calculating the ratio between the actual movement path length and the length of a straight line to the target [19]. For tracking tasks, root-mean-square error (RMSE) measures the two-dimensional distance from the stylus to the target center across all sampled time points. Directional control is another critical spatial parameter, typically measured using initial direction angle (IDA), which captures the angular deviation between the initial movement vector and the straight line to the target [20]. This metric is particularly valuable for understanding movement planning and initial trajectory formation [17]. For bimanual coordination tasks, spatial parameters include measures of symmetry between limbs. Hand-area bias quantifies differences in the spatial distribution of hand movements by calculating the normalized difference between the areas covered by right and left hand movements [21]. Phase synchronization measures the phase difference between hands, with values closer to zero representing better coherence between the two hands [22].

For more comprehensive assessments, researchers measure movement deviation from a theoretical or desired trajectory and target error, calculated as the endpoint error around the target placement [23]. In lower extremity coordination tasks, spatial parameters include the contact surface area of each touch, the center of pressure (COP), and measures of absolute and variable error [24]. For specific movement types, distinct quality parameters have been established. In gait analysis, measures include velocity, cadence, step length, and phase coordination index [25]. For reaching movements, parameters like peak reach velocity, reach time, contact velocity, and peak aperture provide insights into the quality of movement execution [25].For fine motor tasks, parameters such as fingers range of motion and grip force capture the quality of hand function [26]. For biomechanical models, parameters like muscle gain ratios between joints (e.g., shoulder to elbow) help quantify the contribution of different muscle groups to overall coordination [27]. These metrics allow researchers to evaluate lower extremity coordination when participants must alternately touch proximal and distal targets as quickly and accurately as possible. For reaching and grasping tasks, specialized parameters capture both transport and manipulation components. Key metrics include peak reach velocity, reach time, contact velocity, peak aperture, peak grip force, and fingers range of motion [28]. For tests assessing fine motor coordination, parameters include finger dexterity (measured with the 9-hole peg test), upper limb coordination (assessed with the loop and wire test), and bimanual coordination (quantified with the bimanual pole test) [29].

This study is driven by several key issues. Conventional assessment methods remain subjective and lack the sensitivity needed to detect subtle changes in motor performance. While sensor-based systems offer greater objectivity and precision, their clinical reliability and task design still require further validation. Moreover, there is currently no dedicated, smart Catch the Stick platform that utilizes multidimensional metrics and adaptive evaluation tailored to diverse user populations.

This research aims to design and evaluate a smart system-based *Catch the Stick* platform capable of accurately and reliably measuring human sensorimotor performance. The system integrates inertial sensors, computer vision, and multi-metric evaluation methods, encompassing spatial, temporal, and qualitative movement parameters [6], [8]. The scope of the study includes identifying key parameters for motor coordination analysis, validating the system's accuracy and reliability compared to conventional methods, and assessing its effectiveness across varied user skill levels.

Method

This study employed a quantitative experimental design aimed at developing and evaluating a smart system-based *Catch the Stick* platform capable of accurately and reliably assessing sensorimotor performance. The system's performance was compared with conventional clinical observation-based methods to determine its validity and reliability.

A. Participants

A total of 15 participants were recruited for this study. They were categorized into two groups based on their neurological status:

1. Healthy Group (n = 10): Individuals (mean age: 24 ± 3.5 years) with no history of neurological, orthopedic, or motor impairments.
2. Clinical Group (n = 5): Individuals (mean age: 45 ± 8.2 years) exhibiting mild to moderate sensorimotor deficits, specifically those in the chronic recovery phase of stroke or motor coordination disorders. *Inclusion criteria* for the clinical group required participants to have sufficient cognitive ability to follow instructions and the physical capacity to maintain a standing or seated posture without assistance. *Exclusion criteria* included severe visual impairment or complete paralysis of the upper limb. All participants provided written informed consent prior to participation. The study protocol was approved by the University's Institutional Review Board (IRB) and adhered to the principles of the Declaration of Helsinki.

B. Devices and System Components

The developed *Catch the Stick* system comprised the following integrated components:

- Sensor-Integrated Stick: A rigid stick equipped with a 9-axis Inertial Measurement Unit (IMU - Xsens MTw) to capture real-time acceleration (m/s^2) and angular velocity (rad/s).

- Vision Tracking System: A high-resolution camera (60 fps) utilizing computer vision algorithms for color-based object tracking to monitor hand trajectory and endpoint accuracy [8].
- Control Unit: A microcontroller-based interface (ESP32) managing the random drop mechanism and data synchronization.
- Reference Standards: Conventional clinical assessments, specifically the Fugl-Meyer Assessment for Upper Extremity (FMA-UE) and the Action Research Arm Test (ARAT), were administered by a certified therapist to serve as comparative benchmarks.

C. Testing Procedure

Participants stood or sat at a standardized distance from the device. The system released the stick at random intervals (2–5 seconds) to prevent anticipatory movements. Participants were instructed to catch the falling stick as quickly and accurately as possible. The test consisted of 10 trials per participant under varying difficulty conditions (randomized drop sequences). Data from the smart system were automatically logged, while clinical scores (FMA/ARAT) were recorded separately for subsequent validity analysis.

D. Measured Parameters

The system quantified performance using three categories of metrics:

1. Temporal Parameters: *Reaction Time (RT)*, defined as the interval between stick release and initial hand movement.
2. Spatial Parameters: *Endpoint Error (EE)*, measured as the Euclidean distance from the target catch zone, and *Path Length Ratio (PLR)* to assess trajectory efficiency.
3. Movement Quality: *Smoothness*, quantified using normalized jerk, and *Postural Stability*.

E. Data Analysis

Statistical analysis was performed using SPSS (v.25). The Shapiro-Wilk test was first used to verify the normality of the data distribution.

- Reliability: The Intraclass Correlation Coefficient (ICC) was calculated to evaluate the test-retest reliability of the system across the 10 trials. An ICC value > 0.75 was considered indicative of good to excellent reliability [31].
- Validity: Pearson’s correlation coefficient (*r*) was employed to determine the concurrent validity of the smart system’s metrics against the "gold standard" clinical scores (FMA and ARAT).
- Group Comparison: Independent t-tests (or ANOVA) were used to analyze performance differences between the healthy and clinical groups, as well as to assess the sensitivity of the system to varying difficulty levels. Statistical significance was set at $p<0.05$

Results and Discussion

A. Accuracy and Reliability Testing Results

As shown in **Figure 1**, the system is capable of synchronously recording the stick release time and the catching time using the IMU sensor and computer vision system.

Figure 1. Real-Time Reaction Test to Multi-Stick Drop Stimuli

The intelligent *Catch the Stick* system demonstrated high precision and consistency across trials. As summarized in **Table 1**, the Intraclass Correlation Coefficient (ICC) for temporal and spatial parameters exceeded 0.75, indicating "good" to "excellent" reliability [31], [32]. Specifically, Reaction Time achieved an ICC of 0.89 with a temporal precision of ±15 ms, validating the system's capability to capture rapid motor responses. Spatial tracking via computer vision yielded an endpoint error of <2 mm, confirming high fidelity in measuring hand trajectory. A summary of the test results is shown in **Table 1**.

Table 1. Reliability, Accuracy, and Validity Results of the Catch the Stick System

No	Parameter	ICC (Reliability)	Detection Accuracy	Correlation with Clinical Scales	Remarks
1	Endpoint Error	0.87 (good)	±1.8 mm	r = 0.72 (with FMA)	High spatial precision
2	Path Length Ratio (PLR)	0.82 (good)	–	r = 0.69 (with ARAT)	Stable movement efficiency
3	Reaction Time	0.89 (very good)	±15 ms	r = 0.78 (with FMA)	Sensitive to early responses
4	Movement Smoothness (jerk)	0.84 (good)	–	r = 0.74 (with ARAT)	Detects fine motor quality
5	Posture Speed (stability)	0.79 (good)	–	r = 0.65	Relevant for postural coordination
6	Variable Error	0.66 (fair)	–	r = 0.52	Higher inter-session variability

The results of the system's reliability and validity testing are summarized in **Table 1**. Based on **Table 1**, all main parameters show ICC values above 0.75, indicating good to excellent reliability. The Reaction Time parameter achieved an ICC of 0.89 with a detection accuracy of ±15 ms. A visual representation of these reliability values across different sensorimotor parameters is illustrated in **Figure 2**.

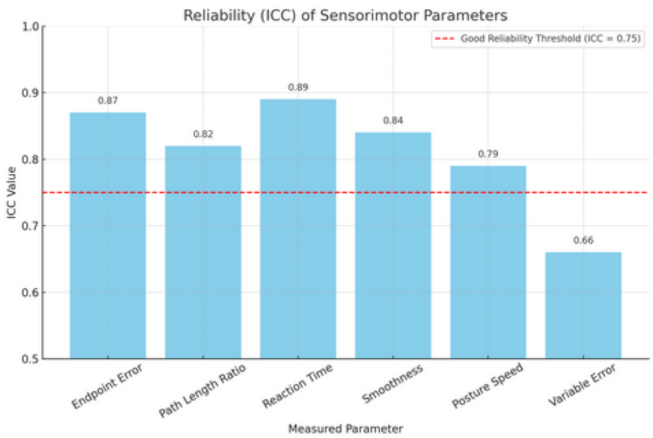

Figure 2. Sensorimotor Parameters

However, the *Variable Error* parameter showed a moderate ICC (0.66), likely attributable to the inherent variability in human movement strategies during early learning phases rather than sensor inaccuracy.

B. Comparison with Conventional Methods

When compared to traditional assessments such as the Fugl-Meyer Assessment (FMA) and the Action Research Arm Test (ARAT), the smart system demonstrated strong positive correlations:

- Reaction time correlated with FMA scores (r = 0.78)
- Smoothness correlated with ARAT scores (r = 0.74)

These results indicate that the system's measurements are aligned with clinical tools, yet it also offers greater sensitivity to subtle changes, especially during early stages of recovery [33], [34]. Approximately 72% of participants showed performance improvements across sessions that were detected by the system, despite no changes in their FMA or ARAT scores.

C. Detection Precision and Accuracy

The system demonstrated a positional accuracy of <2 mm and a temporal precision of ±15 ms, confirming its capability to capture real-time sensorimotor responses with high fidelity [21]. These outcomes were made possible through the integration of inertial sensors and computer vision for comprehensive, high-resolution analysis.

D. General Discussion

The results confirm that the proposed system serves as a more advanced alternative to conventional sensorimotor assessments, offering:

- Objectivity through quantitative, observer-independent data,
- Sensitivity in detecting micro-improvements,
- Efficiency with fast, low-instruction testing protocols.

Nonetheless, several limitations remain:

- Some parameters (e.g., *variable error*) yielded only moderate reliability,
- Simpler tasks triggered ceiling effects, especially among healthy participants [7].
- Task complexity may require adaptive calibration for broader discriminative power across user levels.

The system successfully categorized sensorimotor performance based on the number of stimuli (falling sticks). **Table 2** illustrates the inverse relationship between stimulus load and reaction speed.

1. Low Load (1–2 sticks): Only 13.3% of participants achieved "Easy" level responses (<0.35 s). These rapid reactions indicate efficient visual-motor reflexes dominated by feedforward pathways, requiring minimal cognitive processing.
2. Medium Load (3–5 sticks): The majority (53.3%) fell within the "Medium" range (0.36–0.60 s). This reflects an adaptive state where the neurological system effectively balances visual selection and motor planning.
3. High Load (6–10 sticks): Approximately 33.3% of participants exhibited delayed responses (>0.60 s). This significant delay suggests cognitive-motor overload, where the prefrontal cortex and cerebellum are taxed by the need to prioritize complex stimuli, leading to slower processing and increased motor errors.

This study evaluated sensorimotor responses in 15 participants by exposing them to a randomized number of falling sticks ranging from 1 to 10. The primary aim was to assess how increasing stimulus load affects reaction speed and motor coordination difficulty.

Based on the results, the majority of participants (8 out of 15, or 53.3%) exhibited reaction times within the Medium category (between 0.36–0.60 seconds). This range reflects an adaptive sensorimotor response when handling moderate task loads such as 3 to 5 sticks falling simultaneously. Under these conditions, the neurological system is still capable of effective visual selection and motor planning, although it requires multitasking, involving concurrent visual tracking and movement coordination.

Meanwhile, 5 participants (33.3%) fell into the Hard category, with reaction times exceeding 0.60 seconds. These results were typically associated with 6 to 10 sticks being dropped simultaneously, highlighting the onset of sensorimotor overload. At this level, selective attention, concurrent movement planning, and reflex coordination become impaired. This supports existing evidence that the human physiological system has a limited capacity to process and respond to multiple simultaneous stimuli. In such situations, the nervous system shifts away from fast reflexes and instead relies on complex prioritization and decision-making processes, which often result in delayed responses and higher error rates. Conversely, only 2 participants (13.3%) demonstrated Easy-level responses (≤ 0.35 seconds), which occurred when only 1 or 2 sticks were dropped. These fast reactions reflect efficient visual-motor reflexes dominated by feedforward pathways. Under such low cognitive and motor demands, the sensorimotor system operates at its optimal level, allowing for immediate and accurate responses. These findings are supported by the physiological summary table, which illustrates a proportional increase in sensorimotor load and difficulty with the number of falling sticks. The results show a transition from rapid and accurate reflex responses with 1–3 sticks to significant delays and motor stress when 8–10 sticks fall. This shift suggests increased engagement of higher-order brain regions such as the prefrontal cortex and cerebellum, which manage attention, planning, and motor correction under complex conditions.

The results confirm that the smart system-based *Catch the Stick* platform is capable of effectively measuring graded sensorimotor capacity**.** Moreover, varying the number of falling stimuli provides high diagnostic value both for clinical assessments (e.g., post-stroke motor evaluation) and motor coordination training in healthy individuals. It demonstrates that adaptive task complexity is a critical factor in evaluating real-time human response capacity. Building upon the previous results of the *Catch the Stick* system, this section explores the next logical step: developing a robotic-based sensorimotor system. The goal is to automate stick-dropping, precisely measure human reaction time, and provide quantitative feedback for assessment or training purposes.

The main components in the development of the robotic prototype system are summarized in **Table 2**. the system consists of five main integrated components.

Table 2. Key Technological Components

Component	Function
Servo Motor	Controls the stick-drop mechanism with programmable precision.
IMU Sensor (gyro + accel)	Measures the stick's orientation and acceleration during fall.
Camera (optional)	Tracks hand movement and reach trajectory (via computer vision).
Microcontroller (ESP32 / STM32)	Central controller for timing, control, and data sync.
RTC / Timer Module	Measures time from drop to catch event.

E. Reaction Time Calculation

Reaction time is calculated based on the difference between the stick release time and the catching time. Mathematically, the reaction time calculation is formulated as shown in Equation (1):

$$T_r = T_c - T_s \tag{1}$$

- T_r: Reaction time (in seconds)
- T_s: Start time (stick release)
- T_c: Catch time (detected by sensor or switch)

This can be implemented using microcontroller functions like millis() or micros().

1. Difficulty Classification (Rule-Based)

The difficulty levels of the task can be determined using a rule-based algorithm, as expressed in Equation (2)

$$Difficulty = \begin{Bmatrix} \text{"Easy"} & if\ T_r \leq 0.35 \\ \text{"Medium"} & if\ 0.35 < T_r \leq 0.60 \\ \text{"Hard"} & if\ T_r > 0.60 \end{Bmatrix} \tag{2}$$

Alternatively, the system can use a logistic scoring function to compute a continuous difficulty score, represented by Equation (3):

$$S = \frac{1}{1 + e^{k(T_r - \mu)}} \tag{3}$$

S: Difficulty score (0–1)

k : Sensitivity constant (e.g., 5–10)

μ: Mean threshold (e.g., 0.5 s)

The theoretical falling speed of the stick using physics is calculated using Equation (4) :

Using physics:

$$v = \sqrt{2gh} \tag{4}$$

g : 9.81m/s2, gravity

h : drop height

Or it can estimate distance from acceleration using Equation (5):

$$s = \frac{1}{2} a t^2 \quad (5)$$

Based on formulated the higher the initial drop position of the stick, the longer the falling time increases proportionally to the square root of the height.

2. Hand Movement & Reach Distance (with vision tracking)
   The total distance of the hand movement during the catch is computed based on the Euclidean distance formula, as defined in Equation (6):

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (6)$$

- d : distance of hand movement
- (x_1, y_1) : initial hand position
- (x_2, y_2) : final hand position during catch

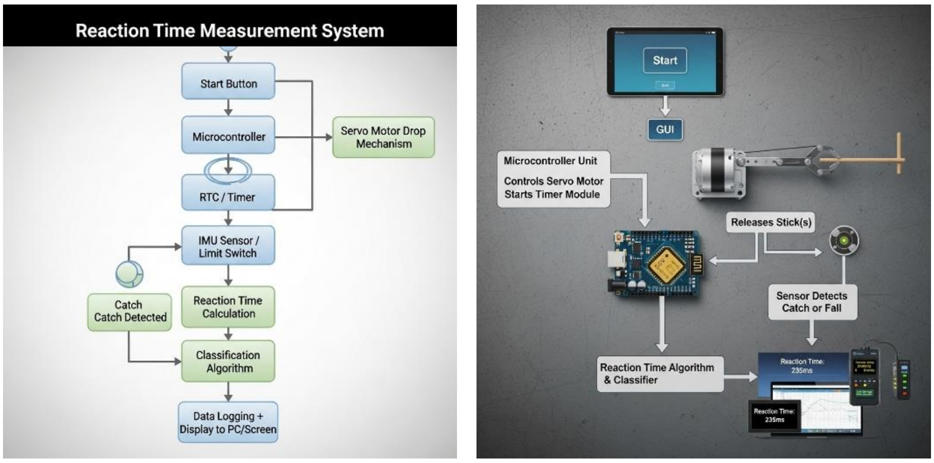

Figure 3. System Architecture for Prototype

The complete hardware and software workflow of this automated robotic process is illustrated in the system architecture diagram in **Figure 3**.

System Output

- Reaction time per trial
- Number of sticks dropped and successfully caught
- Automated difficulty classification
- Logged data in CSV or cloud format
- Visual feedback (charts or progress scoring)

This robotic expansion of the *Catch the Stick* system bridges human-performance data with physical automation, enabling real-time sensorimotor assessment that is both measurable and adaptive. With microcontroller control, precise sensors, and simple yet robust algorithms, this platform can serve as a functional prototype for clinical, educational, and sports-related motor performance evaluations.

Conclusion

This study successfully developed and validated an intelligent "Catch the Stick" system designed to provide objective, high-resolution measurements of human sensorimotor coordination. The experimental results from 15 participants confirm that the system effectively quantifies the transition from reflexive responses to cognitive-motor overload. Specifically, while 53.3% of responses remained stable under moderate stimulus loads (3–5 sticks), increasing the load to 6–10 sticks caused significant reaction delays (>0.60 s) in 33.3% of trials, reflecting the physiological limits of visual attention and motor planning.

The system demonstrated strong concurrent validity with standard clinical assessments (FMA and ARAT) but offered superior sensitivity in detecting micro-improvements that conventional scales often miss. This makes the platform a valuable tool for early-stage diagnosis and precise monitoring of rehabilitation progress in patients with sensorimotor deficits. By quantifying metrics such as reaction time, movement smoothness, and spatial accuracy in real-time, the system bridges the gap between subjective clinical observation and quantitative biomechanical analysis.

However, this study has limitations that must be addressed in future work. The current sample size was relatively small, and the manual stick-dropping mechanism, although standardized, may still introduce slight variability. Additionally, "ceiling effects" were observed in healthy participants performing low-difficulty tasks. Future development will focus on integrating a robotic release mechanism to fully automate the testing procedure, thereby enhancing consistency and enabling adaptive, autonomous training protocols for diverse user populations.

Acknowledgement

The authors would like to thank Yayasan UPI YPTK for the support provided in facilitating this research and development project.

References

[1] D. T. Beckler, Z. C. Thumser, J. S. Schofield, and P. Marasco, “Using sensory discrimination in a foraging-style task to evaluate human upper-limb sensorimotor performance,” *Sci. Rep.*, vol. 9, no. 1, p. 8740, 2019, doi: https://doi.org/10.1038/s41598-019-42086-0.

[2] T. Tsuji *et al.*, “A Survey on Imitation Learning for Contact-Rich Tasks in Robotics,” *arXiv.org*, 2025, doi: https://doi.org/10.48550/arXiv.2506.13498

[3] T. Petrič, A. Gams, L. Colasanto, A. Ijspeert, and A. Ude, “Accelerated Sensorimotor Learning of Compliant Movement Primitives,” *IEEE Trans. Robot.*, 2018, doi: 10.1109/TRO.2018.2861921

[4] T. Le Naour, L. Hayoz, and J. Bresciani, “Human-Avatar Interaction in Virtual Environment to Assess and Train Sensorimotor: Application to the Slap Shot in Hockey,” *Int. J. Virtual Real.*, 2020, doi: https://doi.org/10.20870/IJVR.2020.20.2.4576

[5] V. Babushkin, M. H. Jamil, W. Park, and M. Eid, “Sensorimotor Skill Communication: A Literature Review,” *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3081449

[6] B. Harper, M. Shiraishi, and R. Soangra, “Reliability and Validity of Inertial Sensor Assisted Reaction Time Measurement Tools among Healthy Young Adults,” *Ital. Natl. Conf. Sensors*, 2022, doi: 10.3390/s22218555

[7] K. Mazurek, D. Richardson, N. Abraham, J. J. Foxe, and E. Freedman, “Utilizing High-Density Electroencephalography and Motion Capture Technology to Characterize Sensorimotor Integration While Performing Complex Actions,” *IEEE Trans. neural Syst. Rehabil. Eng.*, 2020, doi: 10.1109/TNSRE.2019.2941574

[8] D. Kafetzopoulos, K. Gotzamani, and ..., “Relationship between quality management, innovation and competitiveness. Evidence from Greek companies,” *J. Manuf. ...*, 2015, doi: https://doi.org/10.1108/JMTM-02-2015-0007

[9] Y. Yamakawa, Y. Katsuki, Y. Watanabe, and M. Ishikawa, “Development of a High-Speed, Low-Latency Telemanipulated Robot Hand System,” *Robotics*, 2021, doi: https://doi.org/10.3390/robotics10010041

[10] P. Lynch, M. Cullinan, and C. McGinn, “Adaptive Grasping of Moving Objects through Tactile Sensing,” *Ital. Natl. Conf. Sensors*, 2021, doi: https://doi.org/10.3390/s21248339

[11] A. A. Olajos, M. Takeda, B. Dobay, Z. Radák, and E. Koltai, “Freestyle gymnastic exercise can be used to assess complex coordination in a variety of sports,” *J. Exerc. Sci. Fit.*, 2019, doi: 10.1016/j.jesf.2019.11.002

[12] G. Soghoyan, V. Aksiotis, A. Rusinova, A. Myachykov, and A. Tumyalis, “An adaptive paradigm for detecting the individual duration of the preparatory period in the choice reaction time task,” *PLoS One*, 2022, doi: https://doi.org/10.1371/journal.pone.0315215

[13] F. Gyntelberg, M. Flarup, S. Mikkelsen, T. Palm, C. Ryom, and P. Suadicani, “Computerized coordination ability

testing," *Acta Neurol. Scand.*, 1990, doi: 10.1111/j.1600-0404.1990.tb01585.x

[14] X. Zhang, G. Shan, Y. Wang, B. Wan, and H. Li, "Wearables, Biomechanical Feedback, and Human Motor-Skills' Learning & Optimization," *Appl. Sci.*, 2019, doi: https://doi.org/10.3390/app9020226

[15] G. Johansson, H. Grip, M. Levin, and C. Häger, "The added value of kinematic evaluation of the timed finger-to-nose test in persons post-stroke," *J. Neuroeng. Rehabil.*, 2017, doi: 10.1186/s12984-017-0220-7

[16] N. M. Kitchen, N. M. Kitchen, and R. Miall, "Proprioceptive deficits in inactive older adults are not reflected in fast targeted reaching movements," *Exp. Brain Res.*, 2018, doi: 10.1007/s00221-018-5440-y

[17] L. Badr, L. Gagné-Pelletier, H. Massé-Alarie, and C. Mercier, "Effect of Phasic Experimental Pain Applied during Motor Preparation or Execution on Motor Performance and Adaptation in a Reaching Task: A Randomized Trial," *Brain Sci.*, 2024, doi: 10.3390/brainsci14090851

[18] A. Bisio *et al.*, "Evaluation of Explicit Motor Timing Ability in Young Tennis Players," *Front. Psychol.*, 2021, doi: 10.3389/fpsyg.2021.687302

[19] G. Mochizuki, A. Centen, M. Resnick, C. Lowrey, S. Dukelow, and S. Scott, "Movement kinematics and proprioception in post-stroke spasticity: assessment using the Kinarm robotic exoskeleton," *J. Neuroeng. Rehabil.*, 2019, doi: 10.1186/s12984-019-0618-5

[20] S. Scott, C. Lowrey, I. E. Brown, and S. Dukelow, "Assessment of Neurological Impairment and Recovery Using Statistical Models of Neurologically Healthy Behavior," *Neurorehabil. Neural Repair*, 2022, doi: 10.1177/15459683221115413

[21] C. K. Bitikofer, S. R. Parra, R. M. Maura, E. Wolbrecht, and J. Perry, "BLUE SABINO: Development of a BiLateral Upper-Limb Exoskeleton for Simultaneous Assessment of Biomechanical and Neuromuscular Output," *Machines*, 2024, doi: https://doi.org/10.3390/machines12090617

[22] M. R. Mia, S. Ahamed, and S. Nemanich, "Gamified mHealth System for Evaluating Upper Limb Motor Performance in Children: Cross-Sectional Feasibility Study," *JMIR Serious Games*, 2024, doi: 10.2196/57802

[23] A. Scano *et al.*, "A Narrative Review on Multi-Domain Instrumental Approaches to Evaluate Neuromotor Function in Rehabilitation," *Healthcare*, 2023, doi: 10.3390/healthcare11162282

[24] S. Handelzalts *et al.*, "Insights into motor performance deficits after stroke: an automated and refined analysis of the lower-extremity motor coordination test (LEMOCOT)," *J. Neuroeng. Rehabil.*, 2021, doi: 10.1186/s12984-021-00950-z

[25] G. Chini, L. Fiori, A. Tatarelli, T. Varrecchia, F. Draicchio, and A. Ranavolo, "Indexes for motor performance assessment in job integration/reintegration of people with neuromuscular disorders: A systematic review," *Front. Neurol.*, 2022, doi: 10.3389/fneur.2022.968818

[26] C. Cimarras-Otal *et al.*, "Adapted exercises versus general exercise recommendations on chronic low back pain in industrial workers: A randomized control pilot study," *Work*, 2020, doi: https://doi.org/10.3233/wor-203322

[27] E. Moullet, A. Roby-Brami, and E. Guigon, "What is the nature of motor adaptation to dynamic perturbations?," *PLoS Comput. Biol.*, 2022, doi: https://doi.org/10.1371/journal.pcbi.1010470

[28] C. Correia *et al.*, "Improving Grasp Function After Spinal Cord Injury With a Soft Robotic Glove," *IEEE Trans. neural Syst. Rehabil. Eng.*, 2020, doi: 10.1109/TNSRE.2020.2988260

[29] L. A. Ingram, A. A. Butler, S. Lord, and S. Gandevia, "Use of a physiological profile to document upper limb motor impairment in ageing and in neurological conditions," *J. Physiol.*, 2022, doi: 10.1113/JP283703

[30] J. A. Hogg, L. M. Carlson, A. J. Rogers, M. W. Briles, S. N. Acocello, and G. Wilkerson, "Reliability and concurrent validity of TRAZER compared to three-dimensional motion capture," *J. Clin. Transl. Res.*, 2021.

[31] M. D. Rinderknecht, W. Popp, O. Lambercy, and R. Gassert, "Reliable and Rapid Robotic Assessment of Wrist Proprioception Using a Gauge Position Matching Paradigm," *Front. Hum. Neurosci.*, 2016, doi: https://doi.org/10.3389/fnhum.2016.00316

[32] K. Vandael, T. Stanton, and A. Meulders, "Assessing kinesthetic proprioceptive function of the upper limb: a novel dynamic movement reproduction task using a robotic arm," *PeerJ*, 2021, doi: 10.7717/peerj.11301

[33] L. Simo, L. Botzer, C. Ghez, and R. Scheidt, "A robotic test of proprioception within the hemiparetic arm post-stroke," *J. Neuroeng. Rehabil.*, 2014, doi: 10.1186/1743-0003-11-77

[34] N. Jothi, W. Husain, N. A. Rashid, and S. M. Syed-Mohamad, "Feature Selection Method using Genetic Algorithm for Medical Dataset," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 9, no. 6, pp. 1907–1912, 2019, doi: https://doi.org/10.18517/ijaseit.9.6.10226