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Research article

Convergent and discriminative validity of a computer game-based upper extremity evaluation tool (CG-UE) in stroke survivors

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Abstract: *Background:* Accurate, engaging, and objective tools are crucial for assessing upper-limb motor function after stroke. Thus, a computer game-based assessment (CG-UE) system involving interactive manipulation tasks using varied objects with diverse physical and functional demands was designed to quantify the parameters of hand functions. *Objectives:* To determine whether CG-UE metrics correlate with the Wolf Motor Function Test (WMFT) scores (convergent validity) and whether these metrics can differentiate stroke survivors and healthy controls (discriminative validity). *Methods:* A total of 30 stroke survivors and 30 age and gender-matched healthy controls performed game-based tasks using five objects/game scenarios (Joystick, Mug, Mounted-Ball, Bimanual-Ball, Cross-Piece). The metrics included Response Time (RT), Movement Time (MT), Movement Error (ME), Movement Variance (MV), and Success Rate (SR). Spearman's rho evaluated correlations with WMFT Time, Functional domain, and Strength. Mann-Whitney U test and rank biserial correlations assessed between-group differences. *Results:* RT showed moderate positive correlation with WMFT-Time (ρ =

0.448, p = 0.013), whereas Success-Rate correlated negatively with WMFT-Time (ρ = −0.553, p = 0.002) and positively with WMFT-Functional ability grades (ρ = 0.531, p = 0.003). Most metrics, especially RT, ME, MV, and SR, significantly discriminated groups (p < 0.001), with large effect sizes (0.569–0.803). SR showed the strongest discriminative power. *Conclusion:* CG-UE distinguished stroke-related motor deficits from normative performance. A low correlation of most CG-UE measures with WMFT domains, except RT and SR, emphasizes CG-UE's ability to capture objective aspects of hand-arm function in contrast to the subjective and time-based nature of the WMFT. CG-UE shows strong potential for use in objective evaluation and progress monitoring in stroke rehabilitation.

Keywords: stroke; upper-extremity; dexterity; computer game-based evaluation (CG-UE); WMFT

1. Introduction

Stroke burden continues to increase globally and it a major neurologic cause of mortality, morbidity, and residual deficits. Upper limb impairments are known to persist in as much as 60% of stroke survivors and only 5%–20% tend to show complete functional recovery [1]. Difficulties in many gross/fine dexterous activities, including gripping small objects or object manipulation, are well documented to be persisting post-stroke. Thus, rehabilitation focused on functional recovery are largely centered around regaining upper extremity control for dexterity tasks. Opportunities and methods to best evaluate the upper extremity functional ability post stroke have been researched extensively [2,3], and a series of standardized scales, including body function and activity measures like Wolf Motor Function Test (WMFT) [4], Jebsen Taylor Hand Function test (JTHFT) [5], Action Research Arm Test (ARAT) [6], Box and Block test [7], Nine hole Peg Test [8], and Fugl Meyer- Upper extremity assessment (FMT) [9], are among many tests that have been put to clinical and research use.

The Wolf Motor Function Test (WMFT is a popular, widely recognized performance-based assessment in patients post stroke. It evaluates the timed performance of a task, grades movement quality on a 5- point scale, and has a sub-section that evaluates hand grip strength [4].

The traditional tools and measures have shown psychometric properties; however, these conventional instruments primarily use total or average time to summarize performance, providing limited insight into finer aspects of motor control such as reaction/response time (RT) and movement errors (ME). Some measures like FMT and ARAT are ordinal scales and have reported floor and ceiling effects [10]. Additionally, the subjective nature of grading the performances and sensitivity to record smaller changes in the movement quality emphasizes the need for more accurate and refined tools and highlights the need for the use of novel technology to improve the objective assessment of upper limb function after stroke [10]. In addition, the above-mentioned assessments were limited to a narrow range of objects and tasks, such as blocks balls pegs, coins, pen, and cans.

An emerging approach to engaging people in evaluation or therapy is to incorporate computer game aided exercise methods in which a range of well-designed interactive challenges help patients participate in repetitive motor activities and can improve participants' motor skills [11–13]. Based on this need and given the shortcomings, an innovative Computer Game based Upper extremity (CG-UE) evaluation platform was developed that includes a computerized digital game-based assessment subsystem that automatically logs the client's movement response to each game event and computes performance-based metrics such as RT, MT, Movement Variance (MV). Movement Accuracy and Success Rate (SR) [14,15].

CG-UE has been designed to provide instantaneous, objective metrics of task performance during object manipulation using the affected hand while achieving a game objective displayed on the screen [15]. These games often require cognitive processing alongside physical movements for movement strategy and timing. Using objects having a broad range of physical properties with a real-life utility in an engaging game scenario as opposed to mundane repetitive movements makes this approach of evaluation more meaningful for the patients [16,17]. The performance-based metrics are averaged over a number of game events in a stipulated time and are displayed graphically and as numbers.

CG-UE is established as a reliable tool with moderate to high ICC values in measuring hemiparetic hand function using a broad range of standardized computer-guided objects [18]. Further, comparing the outcomes of manipulation tasks by stroke patients using CG-UE interface and the WMFT, a gold standard in upper extremity motor function assessment, is imperative. Additionally, discriminative validity is a critical psychometric property that determines whether CG-UE can distinguish groups with known differences in motor capabilities, and therefore will provide insights into its ability to detect clinically significant differences, a prerequisite for its application in diverse populations [19].

Thus, we investigate the convergent validity of CG-UE evaluation interface with WMFT and examine its discriminative validity with an aim to contribute to the growing body of evidence supporting the integration of technology-driven tools into rehabilitation. The findings are expected to have significant implications for establishing assessment precision, report patient outcomes, and promote the adoption of CG-UE systems in neurorehabilitation settings.

In this study, we evaluate the convergent validity of the CG-UE interface with WMFT and examine its discriminative validity, while evaluating the hand functions among stroke survivors and healthy controls.

2. Materials and methods

2.1. Sampling and criteria for inclusion

Purposive sampling technique was employed to recruit stroke survivors with upper limb paresis/deficits who were referred to neuro physiotherapy OPD by qualified medical practitioners. This study was conducted on 60 participants (30 stroke patients and 30 healthy adults) who were age and gender matched and were recruited as per the priori power calculation ($\alpha = 0.05$, power 0.80) on the G power software. This established a requirement of 29 stroke individuals to detect a correlation ($r = 0.50$) and 30 per group to detect a large effect size ($d = 0.80$) for between group discriminative validity. Participants were evaluated for performance parameters on CG-UE and WMFT tests for upper extremity functions.

First time stroke survivors between the age- group of 40–70 years with intact sensory function on the affected upper extremity, cognitive function on MoCA scale (defined as score >19/30) [20] upper extremity spasticity less than or equal to 1+ on Modified Ashworth scale [21], and Brunnstrom hand recovery stages of 4, 5 for shoulder and elbow recovery stages of 4, 5 [22] were considered criteria for inclusion. Additionally, patients needed to demonstrate an ability to independently maintain sitting posture and perform/initiate little finger extension and/or shoulder abduction [23–26] to be included in the study.

Patients with visual, auditory deficits, having any other co-existing neurological conditions/deficits, any associated or pre-existing musculoskeletal/neurological conditions impairing the hand functions and patients unwilling/unable to participate were excluded.

2.2. Ethics approval of research

The study was approved by the IEC, SDM Medical College and Hospital (SDMIEC:88:2020). Written informed consent was obtained from each participant before evaluation.

2.3. Evaluation protocol

The CG-UE evaluation tool uses a low-cost inertial-based (IB) motion mouse (Scoop Pointer 87 Remote Model: RXR1000–0302E, Hillcrest lab). It is miniature, wireless, plug-n-play computer interface device. The mouse contains a multi- axis gyroscope and firmware that detects instantaneous angular motion, which causes the movement of a computer cursor or game paddle, enabling continuous recording of motion signals from any instrumented object and makes it function as a standard mouse [17]. The miniature motion mouse can be easily attached to many objects with Velcro, and this flexibility makes it a versatile evaluation tool. These "mouse-equipped" objects were then used to perform the gross or fine motor skills.

Participants were comfortably seated before a computer monitor positioned at eye level, which displayed the game tasks. Participants were provided with a demonstration and were given practice trials using their unaffected arm to familiarize with the game task. The software displayed a target object appearing at random locations at the top of the display and moving to the bottom within two seconds to disappear. One 'game event' was defined as the time between the appearance of a target and its disappearance. The patient was required to move the mouse mounted objects to move the game paddle and catch the moving target. After one practice trial, each task was evaluated for 30 seconds, which produced 15 movement cycles. The upper limb movements of every 'game event' were displayed as graphical outputs on the screen (Figure 1).

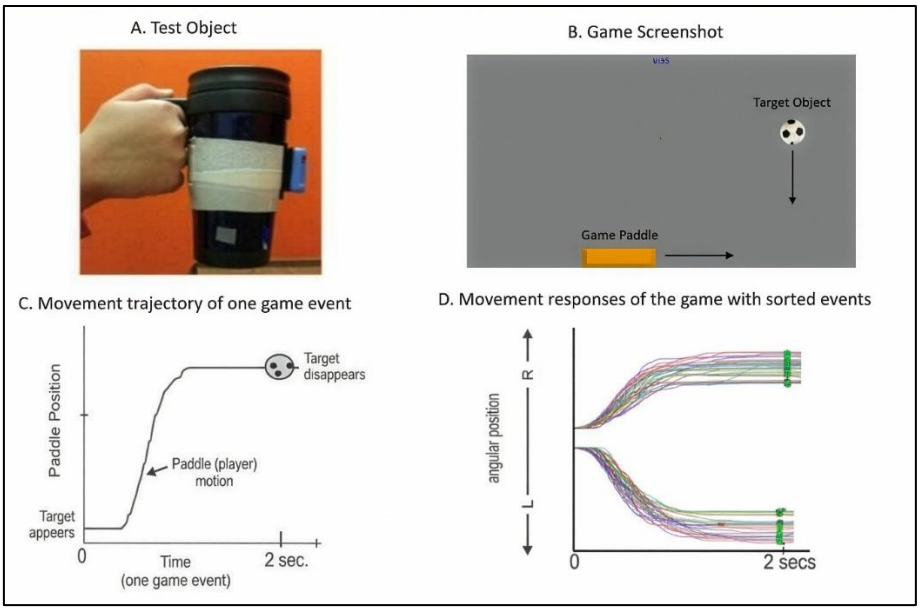


Figure 1. CG-UE test object and evaluation interface. Panel A is a picture of one test object instrumented with the inertial mouse. Panel B is a screenshot of the game screen showing the target object (computer controlled) and game paddle (responds to motion of the test object). Panel C presents the trajectory for one game movement response from target appearance to target disappearance (duration of 2 seconds). Panel D presents overlay plots of the game movement responses for one 60 second game trial. (i.e., 30 game movement responses). The game movement responses are sorted by direction; upward traces are rightward rotations and downward traces are leftward rotations.

CG-UE evaluation interface evaluated patients' performance on 5 test objects, namely Joystick (JS), Mug (MUG), Mounted knob/ball (MB), Bi-manual ball (BiB), and Cross Piece (XP). Objects were chosen to be handled with 2-finger grip, 3-finger grip, whole hand, and both hands, as well as to incorporate a combination of wrist, elbow, and shoulder motion. The following performance outcomes were documented: (a) Response Time (RT), (b) Movement Time (MT), (c) Movement Error (d) Movement Variance (MV) and (e) Success rate (SR) [17].

The operational definitions for the movement metrics are detailed below.

RT (milliseconds): The time from target appearance to the start of the game paddle movement. Values for RT are determined for each individual game movement response, then the average (mean) and the standard deviation is computed over the group of game movement responses for each direction and movement amplitude.

MT (milliseconds): The time from the start of the game paddle movement (RT) to the time it reaches its plateau at the point the target disappears. Values of MT are determined for each individual game movement response and then the average (mean) and the standard deviation are computed over the group of game movement responses for one game session.

ME: The distance between the game paddle and the Target Object at the time of its disappearance. This would be zero if the game paddle touches/catches the moving Target Object. A ME can be either an overshoot or undershoot of the target. The average value for all misses is then computed as the ME. Units are % of screen width.

MV: The individual movement traces for each direction in one game session are averaged and the standard deviation computed for each sampled data point. The standard deviation values for all sampled data point are summed to obtain the total variance. This is reported as the movement variation. Units are % of screen width.

SR (%): The percentage of the total number of target objects that were caught in one game session.

MATLAB (The Math Works, Natick, MA, version 2010a) was used to compute all outcome measures described above.

WMFT was administered according to the standardized testing procedures originally described by Wolf and colleagues. For the WMFT, we used a test template that was fixed to the center of the table for object placements. Timing was recorded using a stopwatch with resolution to the nearest 0.01 second. Participants were seated in a standardized position at a table and received verbal instructions and demonstration for each task. Tasks were performed using the affected upper extremity. Participants were instructed to complete each task as quickly and accurately as possible while maintaining safety. Moreover, if clarification was required, the assessor repeated the standardized instructions without providing feedback regarding performance.

Prior to commencing formal testing, participants were familiarized with the testing procedures. For each task, timing commenced on the assessor's verbal cue ("Go") and ceased when the predefined task completion criterion had been achieved. The WMFT-17 had time based, functional, and strength-based tasks. Before administration, each task was explained and demonstrated to the participants. For all timed tasks, 120 seconds were given to complete each task, and participants were told to perform the tasks as quickly as possible. Following the standard WMFT protocol, if a participant appeared confused, the instructions and demonstration were repeated once. If they performed the task incorrectly or failed to finish within the time limit on the second attempt, a score of 120+ was assigned. WMFT functional ability scores used a 6-point ordinal scale ranging from 0 to 5, with 0 indicating 'no attempt to use the affected extremity' and 5 meaning 'normal use'. The cumulative score was calculated by adding up the individual quality scores for the 15 functional items; a lesser score indicating lower levels of functional recovery and movement quality [27,28]. The hand grip strength was evaluated using the hydraulic Saehan hand held dynamometer in kgs, which is a valid and reliable tool to assess hand grip strength [29]. Participants were positioned according to the WMFT recommendations: Shoulder adducted and slightly flexed, Elbow flexed to 90°, Forearm neutral, and Wrist in slight extension. Participants were instructed: "Squeeze as hard as possible and maintain the contraction for approximately three seconds". Three maximal voluntary contractions were completed, and the average of the 3 trials was recorded. A one-minute rest was provided between trials.

2.4. Clinical trial registration

This study forms a part of a larger research project investigating the effect of computer game-based intervention on hemiparetic hand dexterity functions. It was Registered with CTRI-Reg No. CTRI/2021/01/030170.

2.5. Statistical analysis

JASP statistical software version 0.98.1 was utilized for data analysis. Convergent validity was analyzed using Spearman's rank correlation coefficient (rho) between CG-UE performance measures

and WMFT domains. Mann-Whitney U test was performed to compare performance on game-based movement metrics between stroke survivors and healthy controls. The effect size between groups was analyzed by the Rank biserial correlation method. Statistical significance was $p < 0.05$ (two-tailed). A logistic regression framework was used to derive the Receiver Operating Characteristic (ROC) curve, and the Youden index was calculated to determine the optimal cut-off value.

3. Results

Table 1. Demographic and clinical data of the study population.

Sl. No.	Variables	Stroke group (n = 30)		Healthy Controls (n = 30)	
	Demographics				
2	Age (years), Median (Min-Max)	62 (46–70)		58 (42–69)	
3	Gender (Male/ Female) n (%)	19 (63.3%)	11 (36.7%)	16 (53.3%)	14 (46.7%)
4	Stroke Type (Ischemic/ Hemorrhagic) n (%)	21 (70%)	9 (30%)	NA	
5	Affected Side (Left/Right), n (%)	13 (43.3%)	17 (56.7%)	NA	
6	Time Since Stroke (Weeks), Mean (SD)	10.7 (2.22)		NA	
	Clinical Measures				
7	MOCA-Median (Min-Max)	24 (21–28)			
8	Stroke Severity (Brunnstrom Recovery Stage) n (%)	Stage 4–14 (46.7%)		NA	
		Stage 5–16 (53.3%)		NA	

The study included 60 participants, 30 with stroke and 30 age-matched healthy controls. Among the stroke group, 63.3% were male (n = 19) and 36.7% female (n = 11), while the control group included 53.3% males (n = 16) and 46.7% females (n = 14). The median age of the stroke group was 62 (range 46–70) years, compared to 58 (range 42–69) years in the control group. Age was expressed as median and range due to the skewed distribution. The stroke group consisted 9 cases of hemorrhagic and 21 patients of ischemic etiology (Table 1).

Table 2. CG-UE and WMFT performance outcomes.

Sl. No.	Movement Metrics	Stroke		Healthy Controls	
		Mean	SD	Mean	SD
CG-UE Metrics					
1	Response time (RT) (mS)	664	68.8	515	82.7
2	Movement time (MT) (mS)	320	56.9	291	86.8
3	Movement error (ME) (%)	0.124	0.114	0.0208	0.0323
4	Movement variance (MV) (%)	26.3	13.5	19.3	5.39
5	Success rate (SR) (%)	64.2	21.5	94.8	8.51
WMFT Domains					
1	WMFT Time (sec)	125	74.2	31.8	2.75
2	WMFT-Functional ability (score)	58.7	13.2	75	0
3	WMFT-Strength (kgs)	13.8	7.42	38.5	6.59

In the WMFT, participants with stroke showed a markedly higher mean time to complete the test (125 ± 74.2 sec) than controls (31.8 ± 2.75 sec), along with lower functional ability scores (mean score: 58.7 ± 7.42 vs. 75 ± 0.00) and reduced strength (mean score: 13.8 ± 7.42 vs. 38.5 ± 6.59 kgs).

All participants in both groups followed the instructions and completed the evaluations comfortably. On the computer game-based metrics, stroke participants demonstrated slower RT (664 ± 68.8 mS), prolonged MT (320 ± 56.9 mS), higher ME (0.124 ± 0.114), greater MV (26.3 ± 13.5), and lower success rate (64.2% ± 21.5%) compared to their healthy counterparts (Table 2).

Spearman's rank correlation analysis was performed to examine the relationships between CG-UE outcome metrics: RT, MT, ME, MV, and SR, and the three domains of the WMFT: Time, Functional Ability (FA), and Strength (STR) (Table 3).

Table 3. Correlation of CG-UE metrics with domains of WMFT using Spearman's rho.

		WMFT TIME	WMFT-FA	WMFT-STR
RT	Spearman's rho	0.448	−0.269	−0.055
	p-value	0.013	0.151	0.773
MT	Spearman's rho	−0.169	0.161	0.04
	p-value	0.371	0.395	0.833
ME	Spearman's rho	0.359	−0.354	−0.062
	p-value	0.051	0.055	0.746
MV	Spearman's rho	0.201	−0.294	−0.104
	p-value	0.287	0.115	0.583
SR	Spearman's rho	−0.553	0.531	0.183
	p-value	0.002	0.003	0.334

A statistically significant moderate positive correlation was found between RT and WMFT Time ($\rho = 0.448$, $p = 0.013$), indicating that individuals with longer RTs tended to take more time to complete the WMFT tasks. No significant correlations were observed for RT with either WMFT-FA ($\rho = -0.269$, $p = 0.151$) or WMFT-STR ($\rho = -0.055$, $p = 0.773$).

None of the correlations involving MT or MV reached statistical significance across any WMFT domains. Similarly, ME was not significantly correlated with WMFT outcomes, although it showed a trend toward a weak to moderate positive correlation with WMFT Time ($\rho = 0.359$, $p = 0.051$), suggesting a possible link between greater ME and slower task performance.

Notably, Success Rate (SR) demonstrated a statistically significant moderate negative correlation with WMFT Time ($\rho = -0.553$, $p = 0.002$), and a moderate positive correlation with WMFT-FA ($\rho = 0.531$, $p = 0.003$). These findings indicate that a higher success rate in the game-based task was associated with faster WMFT performance and better functional ability scores. No significant relationship was found between SR and WMFT-STR ($\rho = 0.183$, $p = 0.334$).

Table 4. Between group comparison of mean CG-UE metrics using the Mann Whitney U test.

Metrics	Objects	Mann Whitney U statistic	p	Rank-Biserial Correlation
Response time (RT)	Long Joy stick (JS)	153	<0.001	0.66
	Mug (MUG)	135.5	<0.001	0.70
	Mounted Ball (MB)	194	<0.001	0.57
	Bi- Manual ball (BiB)	140.5	<0.001	0.69
	Cross-piece (XP)	174	<0.001	0.61
Movement Time (MT)	Long Joy stick (JS)	311.5	0.041	0.31
	Mug (MUG)	272	0.009	0.40
	Mounted Ball (MB)	300.5	0.028	0.33
	Bi- Manual ball (BiB)	365	0.211	0.19
	Cross-piece (XP)	364.5	0.209	0.19
Movement Error (ME)	Long Joy stick (JS)	130.5	<0.001	0.71
	Mug (MUG)	123	<0.001	0.73
	Mounted Ball (MB)	245	0.002	0.46
	Bi- Manual ball (BiB)	234	<0.001	0.48
	Cross-piece (XP)	243	0.001	0.46
Movement Variance (MV)	Long Joy stick (JS)	300	0.027	0.33
	Mug (MUG)	155.5	<0.001	0.65
	Mounted Ball (MB)	255	0.004	0.43
	Bi- Manual ball (BiB)	265	0.006	0.41
	Cross-piece (XP)	249	0.003	0.45
Success Rate (SR)	Long Joy stick (JS)	811.5	<0.001	−0.80
	Mug (MUG)	806.5	<0.001	−0.79
	Mounted Ball (MB)	750	<0.001	−0.67
	Bi- Manual ball (BiB)	755.5	<0.001	−0.68
	Cross-piece (XP)	737.5	<0.001	−0.64

To establish known-group (discriminative) validity, the Mann-Whitney U test was performed to compare performance on CG-UE metrics between stroke survivors and healthy controls across five object interaction tasks: Joystick (JS), Mug (MUG), Mounted knob/ball (MB), Bi-manual ball (BiB), and Cross Piece (XP). The results showed statistically significant differences across all movement parameters for most object tasks, with moderate to large effect sizes, as indicated by rank biserial correlations (Table 4).

- RT showed significant group differences across all five objects (all $p < 0.001$), with large effect sizes ranging from 0.569 to 0.699. This suggests that stroke participants exhibited markedly delayed response initiation compared to healthy controls.
- MT showed statistically significant differences for JS, MUG, and MB (p-values ranging from 0.009 to 0.041), with small to moderate effect sizes (0.308 to 0.396). However, for BiB and XP tasks, group differences in MT were not statistically significant ($p = 0.211$ and $p = 0.209$), indicating object-specific sensitivity in detecting motor execution impairments.
- All five object interactions revealed significant differences in ME (ME) ($p \leq 0.002$), with moderate to large effect sizes (0.456 to 0.727), suggesting considerably lower accuracy in the stroke group.

- For MV, significant differences were found across all object tasks (all $p < 0.01$), with effect sizes ranging from 0.333 to 0.654, indicating less consistent movement patterns among stroke participants.
- The SR metric demonstrated the strongest discriminative ability, with all comparisons yielding highly significant differences ($p < 0.001$) and large effect sizes (0.639 to 0.803). This reflects substantially lower task completion rates in the stroke group across all object types.

These findings collectively provide strong indication of known-group validity for the CG-UE tool, with especially high sensitivity in metrics across varied object manipulation tasks.

To establish an optimal classification threshold for the CG-UE, a Receiver Operating Characteristic (ROC) analysis was utilized into the logistic regression framework. Based on the validation test set performance, the metric demonstrated excellent discriminative capacity with an overall classification accuracy of 91.67%. The visual trajectory of the ROC curve (Figure 2) approached the upper-left quadrant of perfect separation, mathematically confirming the robust discriminant validity of this hand function metric for neuro-rehabilitation screening.

Table 5. Classification performance of the logistic regression model for upper limb kinematic evaluation.

Sl. No.	Performance Metric	Statistical Value/ Count
	Model Fit Parameters	
1	Training Sample Size (n)	48
2	Validation Test Sample Size (n)	12
3	Overall Prediction Accuracy	91.67%
	Confusion Matrix (Test Set Validation)	
1	True Positives (Observed Stroke predicted as Stroke)	6
2	False Negatives (Observed Stroke predicted as Control)	1
3	True Negatives (Observed Control predicted as Control)	5
4	False Positives (Observed Control predicted as Stroke)	0
	Derived Clinical Metrics	
1	Sensitivity (True Positive Rate)	85.71%
2	Specificity (True Negative Rate)	100.00%
3	Youden Index (J)	0.86

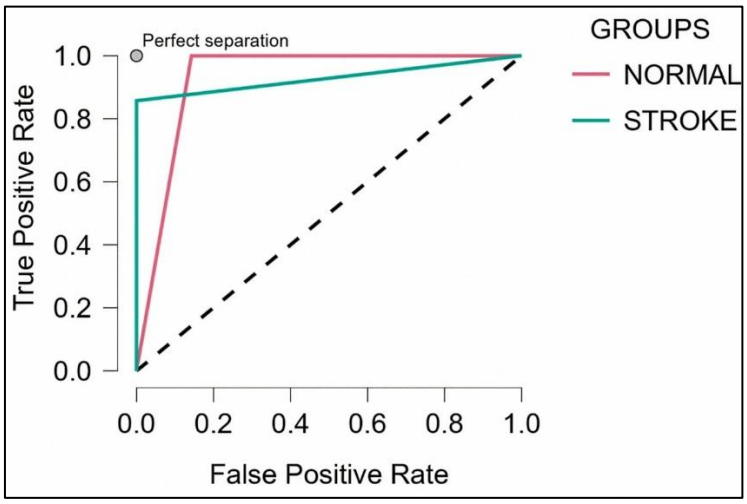


Figure 2. Receiver Operating Characteristic (ROC) curves evaluating classification performance between post-stroke patients and healthy controls.

Using the Youden Index (J = 0.86), we found that the classification threshold (probability of 0.50) provided the best balance between sensitivity and specificity. At this cutoff, the model correctly identified 85.71% of stroke cases (6/7) and 100% of healthy controls (5/5) (Table 5).

4. Discussion

The interactive CG-UE software provides several standardized computer-guided activities to objectively quantify performance metrics. Importantly, the CG-UE assessment tool enables one to test many objects with varied physical and functional demands.

The five manipulation tasks tested in this study were chosen to span a broad range of functional properties and anatomical requirements of hand functions. All manipulation tasks required finger-thumb or hand/palmar surface contacts and involved various combinations of wrist, elbow, and shoulder motions. Multiple objects with different sizes, shapes, weights, surface properties, and friction and functional needs for accuracy (manipulation using 2/3-finger grip, whole hand grip and bimanual tasks) were used. The objects fixed with the miniature motion mouse using Velcro worked like a computer mouse and were sensitive to movement. The varied physical properties of the objects demanded diverse dexterous skills using pinch grip, power grip, whole hand grasp, and bilateral movements. In addition, the game activities of the CUE assessment tool have specific goals and time constraints that can be adjusted. The speed of the game objects, paddle size, and movement amplitude can be varied depending on the task requirements and level of impairment.

Thus, the CG-UE assessment tool has a number of advantages over the existing assessment methods. A thorough knowledge of objects and their geometrical properties and functional and anatomical demands, will help set specific movement goals, gain objective outcome measures, and monitor progression.

The results demonstrated that slower game-based responses align with longer completion times, with RT showing a significant positive correlation with WMFT time. In contrast, success rate (SR) demonstrated a strong negative correlation with WMFT time and a positive correlation with WMFT functional ability, suggesting that higher in-game success rates are associated with tasks achieved faster and with better functional scores.

Specifically, low correlation was observed between most CG-UE performance measures and other WMFT domains. This indicates that the two assessment tools represent separate qualities of hand-arm functions. While the CG-UE assessment tool measures the actual movement parameters and metrics of fine and gross motor skill tasks with different functional demands, the WMFT records the time to complete a task and scores the performance ordinally.

This pattern aligns with other studies that suggest movement metrics of CG-UE, and such technology tools may capture impairments that are not fully reflected in time-based clinical tools like the WMFT [30,31]. Therefore, taken together, these results support the potential clinical utility of CG-UE, not only in classifying clinical populations but also in tracking functional improvements during rehabilitation.

As expected, the group comparison revealed significant differences between healthy adult and stroke groups in most of the performance measures. Notably, RT consistently showed statistically significant differences between groups across all object conditions with large effect sizes, aligning with studies that have revealed delayed initiation of voluntary movements in stroke populations as a core impairment of motor control due to corticospinal tract damage and sensorimotor integration deficits [32,33].

Similarly, ME and MV, indicators of movement accuracy and consistency, were significantly higher in the stroke group, reflecting deficits in proprioceptive feedback, motor planning, and coordination [34]. Moderate to large effect sizes further support the sensitivity of CG-UE in capturing subtle upper limb impairments that might not be evident on traditional time-based assessments alone.

MT) did not significantly differentiate the groups in bimanual ball and cross piece movements. We observed a likely contribution of the non-paretic side and/or the associated trunk movement aiding the bimanual task execution. Similarly, the cross-piece activity impairment could be masked by the involvement of and compensation by proximal hand movements leading to better outcomes. These findings support reports that indicate that timing alone may be insufficient to detect all types of impairment, especially when accuracy or movement quality is more telling [30].

The success rate (SR) emerged as the most discriminative parameter, showing highly significant differences across all tasks with the largest effect sizes. This demonstrates that SR may capture meaningful performance changes better than another metric. The Fitts Law framework explains that motor performance is constrained by the speed-accuracy trade-off [35]. SR seems to implicitly capture this trade-off as optimal success rates that occur when speed and accuracy are well balanced and thus supports the utility of SR as a compound outcome. Importantly, these results highlight that SR could serve as a single summary metric for real-time feedback in game-based interventions or be extended to telerehabilitation [36].

Further, the high sensitivity (85.71%) and specificity (100%) demonstrate that CG-UE movement metric provides exceptional diagnostic precision. Clinically, this suggests that rather than relying on subjective clinical observation of movement quality, clinicians can utilize the CG-UE as an accurate, objective tool to confirm the presence of upper extremity dexterity deficits post stroke.

5. Conclusions

In summary, CG-UE demonstrated distinctions in the way hand function deficits were objectively presented, which is advanced compared to earlier tools like WMFT. It also effectively differentiated stroke survivors from healthy controls across key movement parameters and a range of object manipulation tasks. The outcomes strongly support the potential of CG-UE as an

interactive, technology driven system for objective assessment and real-time feedback in neurorehabilitation settings.

CG-UE promises to be a tool for clinical use and in gamified neurorehabilitation, offering objective, engaging, and scalable parameters for upper limb evaluation. It holds promise for integration with telehealth platforms to make the most of patient engagement and remote accessibility.

The limitations of this study

CG-UE is a technology tool and needs apparatus like the motion mouse and a computer. Further, the CG-UE cannot assess certain fine motor tasks like buttoning a shirt or tying a shoe lace. Another limitation is that the device, while it can detect angular motion, cannot track movements that are purely linear (straight line).

CG-UE evaluates the motor performance, i.e., the activity levels as per ICF, but how this translates as a measure of participation (how it impacts patients' life) should be understood with further studies. CG-UE's ability to quantify clinically meaningful change in response to targeted therapy, which is crucial for its clinical utility, could be prioritized in future research.

Use of Generative-AI tools declaration

The authors declare they have not used any generative Artificial Intelligence (AI) tools in the creation of this article. However, AI support was utilized from platforms like Language tool as was suggested and was restricted to language and grammar edits.

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Conflict of interest

The authors declare no conflict of interest.

Authors' contributions

Sudhir Bhatbolan was the primary investigator, responsible for conceptualization, study design, data collection, analysis and writing the original draft of the manuscript and is the guarantor for the overall content. Dr. Sanjay Parmar contributed substantially to the methodology design, oversaw the data curation and significantly contributed to the data interpretation and manuscript revision. Dr. Tony Szturm and Dr Sharmila Dudhani contributed to data interpretation, critically reviewed/ edited sections of the final manuscript and supervised the overall study. Dr. Basavaraj Banakar, Dr. Girish Babu G and Dr. Sunil KM were responsible for overall supervision of the study and provided critical review of the manuscript.

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