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RESEARCH ARTICLE

Feasibility of assessing cognitive impairment via distributed camera network and privacy-preserving edge computing

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Abstract

INTRODUCTION: Mild cognitive impairment (MCI) involves cognitive decline beyond normal age and education expectations. It correlates with decreased socialization and increased aimless motion. We aim to automate detection of these behaviors for improved longitudinal monitoring.

METHODS: We used a privacy-preserving distributed camera network to collect data from MCI patients in an indoor space. Movement and social interaction features were developed using this data to train machine learning algorithms to differentiate between higher and lower cognitive functioning MCI groups.

RESULTS: A Wilcoxon rank-sum test showed significant differences between high- and low-functioning cohorts in the movement and social interaction features. Despite the absence of data linking each person's identity to their specific level of cognitive decline, a machine learning model using key features achieved 71% accuracy.

DISCUSSION: We show that an edge computing-based privacy-preserving camera network can differentiate between levels of cognitive impairment based on movements and social interactions during group activities.

KEYWORDS
computer vision, edge computing, gait, mild cognitive impairment, social interaction, spatial navigation

Highlights

- Movement and social interaction features showed significant differences in high- and low-functioning cohorts.
- Significant features included linear path lengths, walking speed, direction change and velocity entropies, and number of group formations, among others.
- Differences were observed despite the presence of healthy individuals and the lack of individual identifiers.
- Data were collected using a 39-camera privacy-preserving edge computing network covering a 1700-m^2 indoor space.

Hyeokhyen Kwon and Gari D. Clifford are joint senior authors.

1 | BACKGROUND

Mild cognitive impairment (MCI) is a syndrome where cognitive decline exceeds age and education norms without significantly disrupting daily activities. Typically observed in individuals over 65 years,[1] MCI affects memory, executive functions, attention, processing speed, perceptual-motor abilities, and/or language[1] and often precedes dementia, with over half of those with MCI progressing within 5 years.[1] U.S. projections estimate 15 million people with Alzheimer's dementia or MCI by 2060, up from 6.08 million in 2017.[2] Early diagnosis enables patients and caregivers to plan and adapt while individuals remain independent. However, diagnosis and treatment are often delayed due to limited expert access or misattribution of symptoms to normal aging.[3]

MCI and its progression to dementia are linked to lack of physical exercise and infrequent mental or social stimulation.[4,5] Social relationships support cognitive function in aging,[6,7] making the study of social interactions within MCI populations crucial. Changes in motor and gait patterns, including aspects like balance and coordination,[8] gait velocity reduction, increased stride variability, and changes in stride time and length,[9–11] are also evident. These behavioral markers hold promise in identifying signs of cognitive decline in daily settings, potentially prompting timely professional diagnosis and intervention.

Numerous studies have explored the use of machine learning to analyze gait and spatial navigation for prescreening MCI. Typically, these studies involved dual-task assessments, where individuals performed a mental load task, such as simple mathematics, while walking. Gait features such as stride time, step time, single support time, swing time, double support time, stance time, stride length, and step length have been utilized in conjunction with classification models like support vector machines (SVMs) to distinguish between MCI, dementia, and healthy populations.[12–14] However, the data for these studies were collected in controlled environments, which may not generalize well to real-world scenarios. Several studies deployed motion sensors in the homes of elderly individuals living alone, equipping these residences with a range of unobtrusive sensors, including motion detectors and environmental sensors.[14–20] These studies utilized various features such as room activity distribution,[15] an individual's ability to perform daily living activities,[16,17] walking speed, overall activity levels within the home,[18] and the time spent on different activities of daily living.[19] Due to the limitations of motion sensors, which can only detect the presence of individuals in a room, these studies were confined to single-resident households. The sensors were limited in their ability to understand spatial usage and navigation behaviors, only capturing data at the room level without granular details on the motion or activity within the room or interactions with other individuals. Social interactions in the MCI population remain relatively understudied. Previous works often relied on self-reports or caregiver accounts, which may introduce bias or overlook critical details due to the inherent limitations of recalling specific events.

In this feasibility study, we introduce a passive sensing pipeline designed to capture detailed movement (at a resolution of 1–2 m) and social interaction cues during group activities in a MCI population. A distributed camera network spanning 1700 m^2 collected data over 14 months to analyze cognitive function levels within the MCI population, focusing on distinctions within this group rather than between healthy and MCI individuals. In particular, the individuals with MCI were active in a space in which there were also healthy individuals, mimicking a real-world situation involving caregivers and family.

RESEARCH IN CONTEXT

1. **Systematic review**: The authors conducted a literature review using sources that included Google Scholar and PubMed. Previous studies have primarily employed data from controlled environments to evaluate cognitive impairment severity, particularly through gait and navigation parameters. However, no studies were found that specifically assess cognitive impairment severity based on social interactions and movement patterns in uncontrolled real-world or therapeutic environments, particularly with large indoor spaces where patients and healthy individuals (family and caregivers) mingle.
2. **Interpretation**: This study demonstrates that the proposed social interaction and movement-based features, such as linear path length, walking speed, velocity entropy, and group count, offer valuable insights for evaluating the severity of cognitive impairment in groups, even when these groups include a mix of healthy and cognitively impaired individuals.
3. **Future directions**: Based on our cohort-based analysis findings, we will extend the study to an individual-level analysis using additional sensor data, such as Bluetooth-based localization, to distinguish individual movements and activities. Additionally, we will expand our analysis to include longitudinal monitoring of behavior changes in individuals with varying severity of MCI, according to group therapies, over a 6-month period.

2 | METHODS

We employed a distributed camera system to gather behavioral data from MCI cohorts. Movement and social interaction features were extracted from these data and used with classifiers to categorize cohorts of MCI patients as low or high functioning. Note that this classification was done at the cohort level, categorizing groups as high or low functioning, rather than classifying individual participants. Individual classification will be addressed in future work. The overall system is depicted in Figure 1.

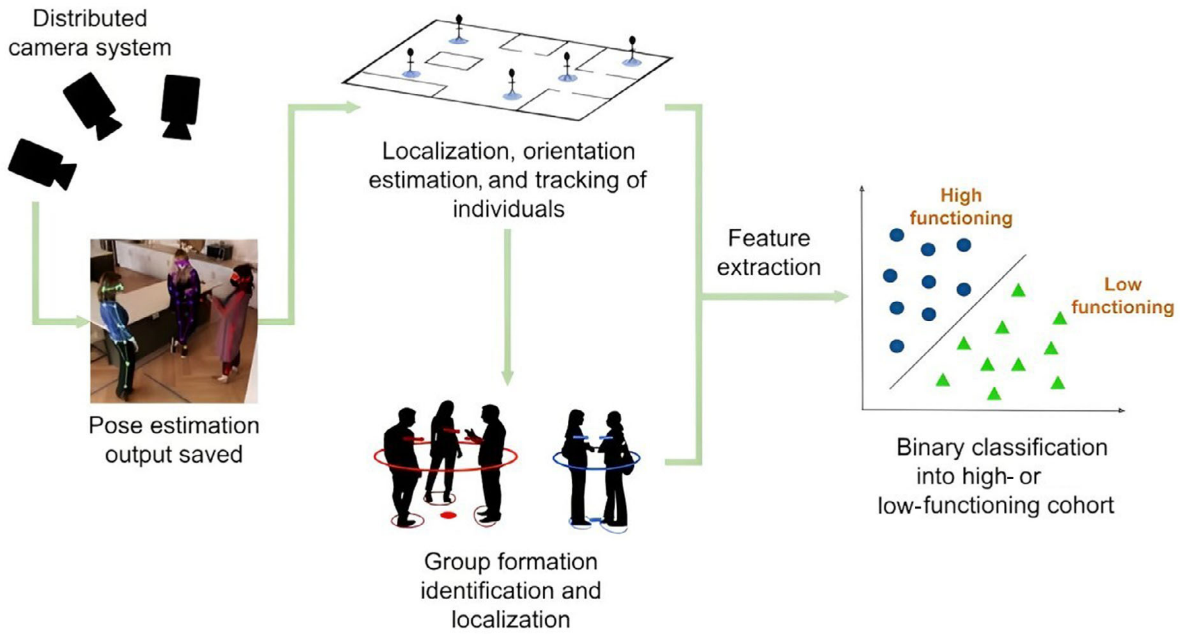

FIGURE 1 Proposed pipeline. A distributed camera network uses real-time pose estimation to collect privacy-preserving data from individuals in an indoor space. These keypoints are used to find the locations, orientations, and tracks of individuals in the indoor space.[21] This is further used to identify and locate group formations.[22] Handcrafted features are extracted from the positions, orientations, tracks, and group formation estimations. These features are used to classify a cohort as either a high- or low-functioning MCI cohort.

2.1 | Data collection

2.1.1 | Study site

The data in this study were collected at the Charlie and Harriet Shaffer Cognitive Empowerment Program (CEP) (https://empowerment.emory.edu), a group therapeutic program and space designed for individuals with MCI. In this program, participants engage in weekly activities such as cooking, exercise, and cognitive training from 9 a.m. to 3 p.m. within a designated indoor space designed for therapeutic purposes, as shown in Figure 2A, spanning approximately 1700 m^2. Therapeutic staff and caregivers of participants with MCI are also present to ensure their safety. Demographic information on subjects and healthy individuals present in the study site is presented in Table S1. Our analysis focuses solely on data from three daily breaks (two 15 min, one 30 min), when participants move and socially interact freely.

2.1.2 | Cognitive assessment

Participants in this study were referred from Emory's Cognitive Neurology Clinic, where they were diagnosed with MCI. Clinical criteria for MCI diagnosis are defined by the Uniform Data Set (UDS) in the National Alzheimer's Coordinating Center. The CEP conducted cognitive assessments and functional ability questionnaires, including the 30-point Montreal Cognitive Assessment (MoCA), which evaluates memory, visuospatial abilities, executive functioning, language, attention, and orientation.[23] Scores greater than or equal to 26 indicate normal cognition, 18–25 suggest mild impairment, 10–17 imply moderate impairment, and below 10 indicate severe impairment. Participants were grouped into cohorts based on their enrollment period, with each period comprising two active cohorts. Efforts were made to ensure cohort members had similar cognitive and functional levels at assignment, as determined by Emory's Cognitive Neurology Clinic, creating groups with high or low cognitive functioning.

We examined a total of 66 subjects with MoCA scores ranging from 10 to 29, divided into six cohorts (A to F) as explained above containing 11, 7, 12, 10, 13, and 13 subjects, respectively. Figure 3 illustrates the distribution of MoCA scores within each cohort. Cohorts were categorized as either high-functioning if the mean MoCA score exceeded 21 or low-functioning if the mean MoCA score was 21 or below. This threshold selection of 21 was based on its positioning midway between the upper and lower limits of MoCA scores for MCI, namely 18 and 25. Our interpretation of high- and low-functioning cohorts identified cohorts B, D, and F as low-functioning and cohorts A, C, and E as high-functioning.

2.2 | Behavior sensing framework

2.2.1 | Distributed camera network with on-device pose estimation

We installed 39 edge computing and camera devices, each costing under \$150, throughout the therapeutic space (Figure 2B). Each unit comprised a Raspberry Pi camera module V2 (Sony IMX219 8-

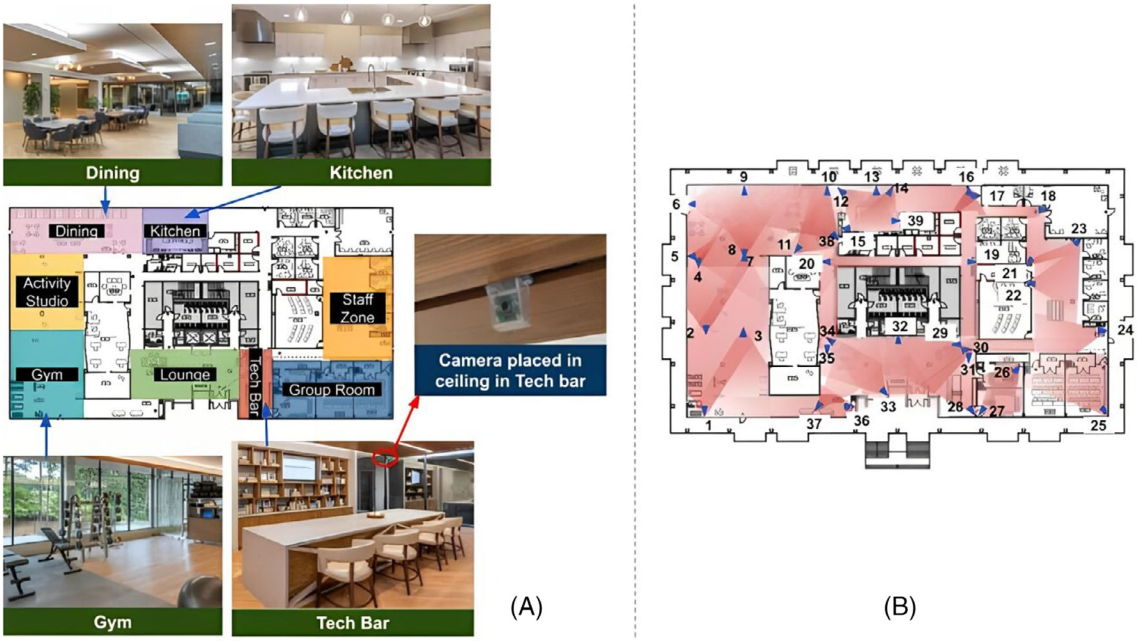

FIGURE 2 (A) Layout of indoor space used in this study, spanning 1700 m^2, along with pictures from various functional areas within this space. Our study site has various regions to provide physical and cognitive training relating to activities in daily living for individuals with MCI. These areas include a gym, dining area, kitchen, lounge, activity area, tech bar, and staff zone. A picture of one of the cameras installed in the ceiling of the tech bar is also shown. (B) Locations and coverage of the 39 edge computing camera systems deployed in the ceiling of the indoor space. The blue triangles depict the camera placement position and orientation. The camera's point in a direction away from the vertex, perpendicular to the short base, with a solid angle viewing region denoted by the shaded red regions. White areas are not covered by cameras, either by choice or infrastructural limitations.

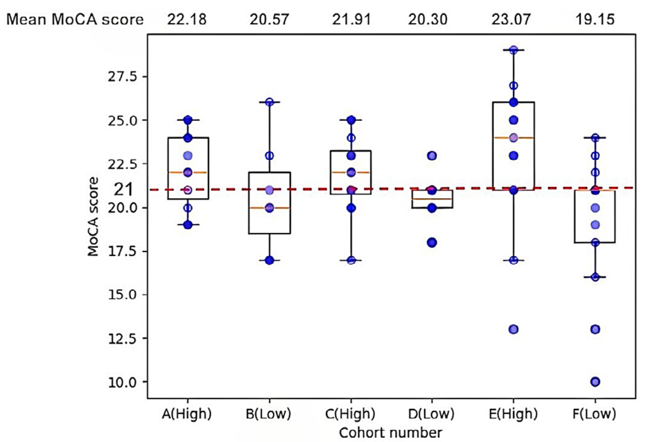

FIGURE 3 Box plot illustrating median, interquartile range, and maximum and minimum MoCA scores for each cohort. The MoCA scores for 66 subjects belonging to one of six cohorts are represented by the blue circles. The mean MoCA score for each cohort is displayed at the top of the plot. The threshold of 21 that is used to assign cohorts as either high-functioning or low-functioning is depicted by the dotted red line. The class that each cohort belongs to, that is, high- or low-functioning, is noted next to the cohort names.

megapixel sensor) and a Google Coral TPU USB Accelerator integrated into a Raspberry Pi 4 model B. These units ran a real-time multiperson two-dimensional pose estimation model[24] at 1 Hz, detecting 17 body keypoints (eg, knees, eyes, nose). Bounding boxes around people were estimated from keypoints. Pose data and bounding box images were stored on an on-premise fog server for analysis, with raw video discarded to protect privacy. See Kwon et al.[21] for details.

2.2.2 | Multiview, multiperson localization, body orientation estimation, tracking, and group localization

Building on our previous work, we used keypoints and bounding boxes for multiview multiperson localization, body orientation estimation, and tracking to capture movements of individuals in the therapeutic space. This resulted in an average localization error of 1.41 m, a tracking accuracy of 88.6%, and a mean body orientation error of 29°. More details can be found in Kwon et al.[21] The estimated locations and orientations were further processed to detect group formations using a clustering method, achieving an F1 score of up to 90% for groups of two or more individuals. More details can be found in Hegde et al.[22]

2.3 | Behavior features for group activities in MCI

We extracted movement and social interaction features to reveal behavioral differences between high- and low-cognitive-function cohorts, motivated by previous works.[12,13,25] The features are detailed in the following section.

2.3.1 | Linear path lengths

These values represent uninterrupted walking path lengths without direction changes, based on individuals' positions. Previous research indicates that linear path lengths (LPLs) in pedestrian settings follow a Levy distribution.[26] We hypothesized that LPL distributions would differ between cognitive function levels. The feature calculations were based on tracked positions (obtained from our multiperson tracking algorithm), with direction changes detected by assessing angle alterations between consecutive positions in the trajectory. For instance, if we consider three consecutive positions in a track denoted by $P_1 = (x_1, y_1)$, $P_2 = (x_2, y_2)$, and $P_3 = (x_3, y_3)$, the angle change, θ, was computed by analyzing the line segments formed by $\overrightarrow{P_{1,2}} = P_2 \ - P_1$ and $\overrightarrow{P_{3,2}} = P_2 \ - P_3$, where $\theta = \arccos$. We considered a 20° change in walking direction to constitute a new linear path, accounting for the noise in position and body orientation estimation. Consequently, consecutive lines with $\theta \leq 20°$ were considered part of a longer, uninterrupted linear path. From the collection of LPLs for all individuals in a cohort, we computed the mean and standard deviation of LPLs for each break duration.

2.3.2 | Speed of walking

Studies indicate that walking speed decreases in people with cognitive impairment.[12,13] We calculated walking speed for each individual by dividing the LPL by the number of positions along the path $S_i = LPL_i / n_i$, for the ith LPL, where n_i represents the number of positions and corresponds to the traversal time at a 1-Hz sampling rate. The mean and standard deviation of walking speeds for all individuals in a cohort during a break period were then used for classification.

2.3.3 | Direction change

We hypothesized that frequent changes in direction could be a sign of confusion and, hence, correlate to cognitive decline.[27] Specifically, we computed the mean and standard deviation of θ computed from the LPL for all individuals' movement from a cohort observed during the break times.

2.3.4 | Entropy of walking velocity

Velocity entropy, a measure of complexity, was determined as the sample entropy of the speed computed between consecutive estimated locations, $V_t = \overrightarrow{P_{t,t+1}} \vee$, where $\overrightarrow{P_{t,t+1}}$ represents the distance moved between two consecutive position samples. We hypothesize that walking velocity will change more dynamically in individuals with severe cognitive impairment due to the aimless movements associated with MCI.[14] During the break periods, we computed sample entropy from speed changes, $E_v = SampleEntropy(V_{1:T})$, where T is the number of locations estimated for the vth trajectory during the break session. Finally, we extracted the mean and standard deviation of $E_{v=1,\dots,K}$ from all individuals in a cohort for each break period.

2.3.5 | Entropy of orientation change

We calculated the entropy from orientation changes $\Delta\ \theta_{t-1,t} = \theta_t \ - \theta_{t-1}$ between each timestep detected from the trajectory. This entropy of orientation change is denoted by $E_o = SampleEntropy(\Delta\theta_{1:T})$. Similar to velocity entropy, we derived the mean and standard deviation of E_o from multiple trajectories available for each cohort within a break period.

2.3.6 | Levy distribution parameters for linear path lengths

We hypothesized that the distribution of LPLs of healthy individuals followed a Levy distribution, while those of individuals with MCI exhibited more Brownian motions.[14,28] We fit a Levy distribution to the LPLs of each individual, extracting the location (μ) and scale (c) parameters. The mean and standard deviation of these parameters for all individuals of a cohort, observed during the break sessions, were used for classification.

2.3.7 | Overall group formations

Studies have shown that the total number of social interactions is lower in individuals with MCI from self-reports and surveys.[25] We used the detected group formations as a proxy for social interactions. First, we counted the number of detected groups, g_t, and the number of individuals participating in group activities, n_t, at time t. Then, for a cohort, we normalized the number of detected groups with the number of individuals participating in group activities, $G_t = g_t / n_t$. This is to take account of the varying size and dynamics of group activities occurring over time. Smaller G_t can potentially mean that a large group was detected ($g_t \downarrow \wedge n_t \uparrow$), and larger G_t can mean that multiple small groups were detected ($g_t \uparrow \wedge n_t \downarrow$). Lastly, we derived the mean and standard deviation of $G_{1:T}$ over each break duration for a cohort.

2.3.8 | Region-specific group formations

As shown in Figure 2A, the therapeutic space includes regions for cooking, dining, exercise, and classroom sessions. We hypothesized groups with different cognitive functioning levels would use these spaces differently during break times. At a specific region of the therapeutic space, r, at time t, we computed the number of groups formed in each region of the facility, ${g_t}^r$, and normalized it by the number of individuals in that region, ${n_t}^r$, to obtain the normalized region-specific group formation ${G_t}^r = {g_t}^r / {n_t}^r$. These data were collected over each break period for each cohort, with mean and standard deviation calculated for each region.

The movement features included LPLs, walking speed, direction change, walking velocity entropy, orientation change entropy, and Levy distribution parameters. The social interaction features encompassed overall group formations and region-specific group formations.

2.4 | Cohort-level classification of cognitive impairment

The derived features were used for binary classification of high and low levels of cognitive function of each cohort according to Figure 3. Before model training and testing, the behavior features were rescaled to lie between 0 and 1 to account for the different ranges of values in each feature. The rescaled features were then fed to classification models, such as SVMs.

3 | EXPERIMENTS

Three hundred fifteen break sessions (15–30 min each) were recorded over 14 months across six cohorts. Each break session served as a single sample for deriving behavior features. Based on the mean MoCA score of each cohort, they were labeled as either high or low cognitive functioning, serving as the gold-standard measures. Of the 315 samples, 168 were high-functioning, and 147 were low-functioning, yielding a near-balanced ratio of 1:1.14. Since datasets where the most common class is less than twice the rarest are considered only marginally imbalanced,[29] we deemed our dataset reasonably balanced and did not apply class imbalance handling. We report F1 score and area under the receiver operating characteristic curve (AUROC) metrics, which account for slight class imbalances. For classification, we employed radial basis function-based non-linear SVM, XGBoost (XGB), logistic regression (LR), and lasso binary classification algorithms in a leave-one-sample-out cross-validation manner. Further, to evaluate the model's robustness, we performed sensitivity analyses using stratified 10-fold cross-validation, with the results reported in Table S2 and the details in Supplementary Document. Model performance was compared using all features, only movement features, and only social interaction features, evaluated by precision, recall, F1 score, and accuracy. The Wilcoxon rank-sum test assessed statistical differences in raw feature distributions between high- and low-functioning cohorts. The null hypothesis stated that the feature distributions for both groups were similar, with a significance threshold set at $p < .05$. It is important to note that the features examined in this test were raw features' distributions, not their means and standard deviations.

4 | RESULTS

Table 1 shows leave-one-sample-out classification results for SVM, XGBoost, LR, and lasso binary classifiers using different feature sets. XGBoost achieved the highest F1 score (0.68) using all features, slightly outperforming SVM (0.67). The SVM demonstrated the highest performance and stability across all feature combinations. LR and lasso binary classifier both reached 0.65 F1 score with all features, outperforming their scores with social interaction features by 3% and 2% and movement features by 5% and 3%, respectively. XGBoost's performance decreased by 4% with only social interaction features and 7% with only movement features. In Table 2, the p values for each tested feature are presented to assess their statistical significance in differentiating cohorts based on cognitive function levels. All features except "Levy μ parameter" demonstrated statistical significance ($p < .05$).

5 | DISCUSSION

5.1 | Classifying high- and low-functioning cohorts

Table 1 shows that for leave-one-sample-out classification, the SVM slightly outperforms the LR and lasso binary classifiers in F1 score across all feature combinations, with the difference seen with movement features. It also surpasses XGBoost when using only social interaction or movement features. XGBoost, LR, and lasso perform best when using all features, followed by social interaction and movement features, while SVM maintains consistent performance across all combinations. These results suggest that the most informative results are obtained when all features are used. Precision remains stable across SVM, LR, and lasso, but XGBoost's precision drops by 5% when using only social interaction or movement features. Recall drops significantly for XGBoost, LR, and lasso binary classifier when using movement features, suggesting a higher rate of missed "low-functioning" samples (false negatives) with this feature combination. The dataset includes 14 movement features and 18 social interaction features (see Figure 4 for features), which likely explains this performance degradation. SVM, being a complex non-linear model, effectively distinguishes between classes even with fewer features, showing minimal improvement when all features are used. With balanced $N = 315$ samples from high- and low-functioning groups, XGB showed an area under the receiver operating characteristic curve (AUROC) of 0.77 when using all features. This showed a power of 80% with a 0.05 significance level, assuming a 0.104-width confidence interval and a null hypothesis AUROC of 0.65.

5.2 | Feature analysis

The Wilcoxon rank-sum test results in Table 2 show statistically significant differences in most features between high- and low-functioning MCI cohorts, indicating their potential predictive value. Lower-functioning groups had slower walking speeds, especially at higher speeds, consistent with prior research linking slower walking to cognitive impairment.[30,31] Mean LPLs were slightly longer in lower-functioning groups (≈ 4.9 vs ≈ 4.5 m), suggesting more directed movement in higher-functioning cohorts. Velocity and orientation change entropies were greater in lower-functioning groups, indicating

TABLE 1 Precision, recall, F1 score, and accuracy, along with 95% confidence intervals for leave-one-sample-out cross-validation when SVM, XGBoost, logistic regression, and lasso binary classifications were used with all features, only social interaction features, and only movement features.

Metric		Precision	Recall	F1 score	Accuracy	AUROC
All features	SVM	0.62 ± 0.054	0.72 ± 0.050	0.67 ± 0.052	0.66 ± 0.052	0.72
	XGB	0.69 ± 0.051	0.66 ± 0.052	0.68 ± 0.052	0.71 ± 0.050	0.77
	LR	0.65 ± 0.053	0.65 ± 0.053	0.65 ± 0.053	0.68 ± 0.052	0.70
	Lasso	0.67 ± 0.052	0.64 ± 0.053	0.65 ± 0.053	0.68 ± 0.051	0.66
Social interaction features	SVM	0.63 ± 0.053	0.71 ± 0.050	0.67 ± 0.052	0.67 ± 0.052	0.71
	XGB	0.64 ± 0.053	0.64 ± 0.053	0.64 ± 0.053	0.67 ± 0.052	0.74
	LR	0.62 ± 0.054	0.62 ± 0.054	0.62 ± 0.054	0.64 ± 0.053	0.68
	Lasso	0.63 ± 0.053	0.63 ± 0.053	0.63 ± 0.053	0.66 ± 0.052	0.68
Movement features	SVM	0.64 ± 0.053	0.70 ± 0.051	0.67 ± 0.052	0.68 ± 0.052	0.71
	XGB	0.64 ± 0.053	0.59 ± 0.054	0.61 ± 0.054	0.65 ± 0.053	0.70
	LR	0.65 ± 0.053	0.57 ± 0.055	0.60 ± 0.054	0.65 ± 0.053	0.68
	Lasso	0.66 ± 0.052	0.59 ± 0.054	0.62 ± 0.054	0.66 ± 0.052	0.67

Highlighted cells show the best performance.

TABLE 2 *P* values of Wilcoxon rank-sum test performed on features for distinguishing high- and low-functioning cohorts.

Feature name	*p*
Linear path length	<.0001*
Walking speed	<.0001*
Direction change	<.0001*
Velocity entropy	<.0001*
Orientation change entropy	<.0001*
Levy μ parameter	.0676
Levy *c* parameter	.0364*
Number of groups in therapeutic space	<.0001*

The *p* values with an asterisk (*) indicate features with statistically significant differences ($p < .05$) in distributions between low- and high-functioning groups.

more movement confusion. Higher-functioning cohorts had a higher number of group formations. The "Levy μ parameter" feature had $p < .05$, indicating comparable distributions across low- and high-functioning cohorts, possibly due to the inclusion of individuals with normal cognition (such as care partners and therapeutic staff), diluting the discriminatory power of Levy features. Most features, except walking speed, have not been studied in detail and could serve as new parameters to assess MCI.

Figure 4 shows feature importance obtained using the permutation feature importance method for SVM across three feature combinations: all features (top), social interaction features (middle), and movement features (bottom). These plots highlight features that contributed most to SVM's classification task, emphasizing the relative importance of each feature within the model. The SVM model identified mean and standard deviation of direction change, velocity entropy, Levy location parameter, standard deviation of walking speed, mean number of group formations in the activity area, kitchen, staff area and gym, and standard deviation of number of group formations in the lounge as most important when using all features (Figure 4, top). When considering social interaction features (Figure 4, middle), the most important features were mean number of groups in the dining area and gym and standard deviation of the number of groups in the kitchen and gym. The lounge, gym, and activity areas are specifically designed to encourage social interactions, providing open spaces and seating. When considering movement features (Figure 4, bottom), the most useful features were mean LPL, direction change, walking speed and scale parameter of Levy distribution, and standard deviation of orientation change entropy and direction change. These results are consistent with previous studies linking aimless movements and frequent angle changes to MCI.[14,27,32] Interestingly, Levy parameters were significant in both the all-features and movement-only models, despite contrasting Wilcoxon rank-sum results, suggesting their utility when combined with other movement metrics. We also hypothesize that Levy parameters will provide useful information when used on individual-level data, which will be part of our future work.

Our results are promising, indicating valuable information in the extracted features, even in noisy settings with multiple actors. An F1 score of 0.68, well above random chance, and an AUROC of 0.77, exceeding 0.5, demonstrate the features' discriminative power. This is further supported by the small *p* values from the Wilcoxon rank-sum test for most features. However, there is significant room for improvement, as discussed in the next subsection.

5.3 | Limitations and future direction

Our study uniquely focused on group analysis of cohorts with varying cognitive impairment levels coexisting with healthy individuals in a real-world setting. Despite higher noise in group-based data, we

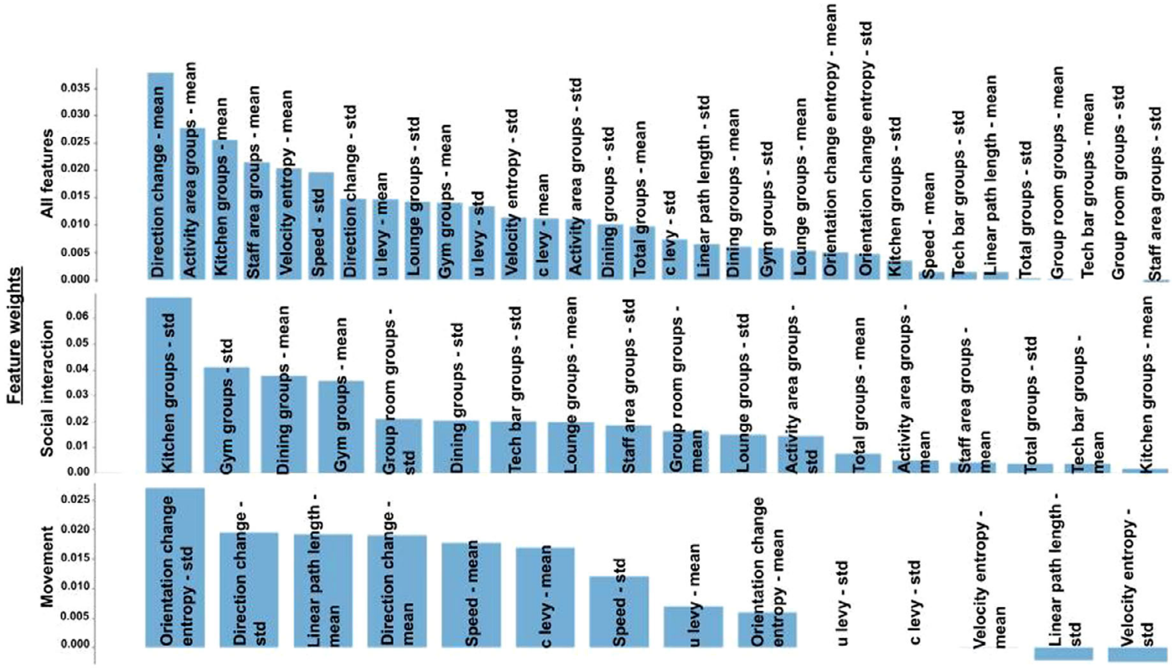

FIGURE 4 Feature importance analysis for SVM models used for classification. The top figure shows the feature weights when using all features, the middle figure shows the feature weights when using only social interaction features, and the bottom figure shows the feature weights when using only movement features.

achieved a 68% F1 score in distinguishing low- and high-functioning cohorts, laying the groundwork for further exploration of the proposed passive monitoring system for MCI. This study takes an initial step toward real-world identification and monitoring of individuals with MCI, exploring whether the extracted features can distinguish MCI in group settings, even among healthy individuals, as typically seen in care facilities or home environments.

However, this study has certain limitations. Cohorts were formed on a rolling basis, assigning participants to one of two active cohorts based on similar cognitive functioning. While most cohort members had MoCA scores above or below the threshold for high- and low-functioning groups, significant score variability within each cohort introduced noise to the classification task. Reducing MoCA score overlap or identifying individuals could improve performance.

Our future work will integrate Bluetooth and video tracking for detailed individual-level analysis, building on our prior work using Bluetooth sensors for localization with a 4.4-m error.[33] This approach addresses MoCA score variability by analyzing individuals instead of cohorts. Cameras offer contextual data on movement and social interactions, while Bluetooth sensors provide identity, enabling privacy-preserving individual-level analysis. Future iterations of this system could monitor behavioral changes in nursing homes or hospitals. Additionally, we plan to conduct an in-depth study of Levy parameters at the individual level for MCI, dementia, and normal cognition populations. The Wilcoxon rank-sum test shows a p value less than .05 for the Levy c parameter, and Figure 4 suggests that both the Levy c and μ parameters aid in classification. This indicates that Levy parameters provide valuable information for distinguishing between high- and low-functioning cohorts, even with overlapping feature distributions and healthy individuals, and may be more informative at the individual level. We also intend to apply temporal deep learning methods, like recurrent neural networks,[34] to track movement and group activity changes over time.

6 | CONCLUSION

In an aging society, passive monitoring of older adults' movements and social interactions is vital for objectively assessing cognitive impairments. While previous studies relied on controlled lab settings or surveys,[14,18,25] our work demonstrated that a distributed camera system in a large 1700-m^2 therapeutic environment could quantify group interactions and movements in MCI cohorts over 14 months. Movement and social interaction features like LPL, walking speed, direction change, velocity and direction change entropy, Levy parameters, and number of group formations were found to be discriminative, consistent with previous studies,[14,18,25] even in noisy, privacy-constrained real-world settings with mixed populations. This approach enables cognitive function assessment beyond controlled tests, potentially detecting early dementia signs through long-term passive monitoring.

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Informed consent to collect and use data was obtained from all human subjects in this study.

CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interests related to this publication. Author disclosures are available in the supporting information.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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