www.editada.org

International Journal of Combinatorial Optimization Problems and Informatics, 17(5), 2026, 138-152. ISSN: 2007-1558.
https://doi.org/10.61467/2007.1558.2026.v17i5.1306

Quantifying Perceptual Uncertainty through Non-Invasive Kinematic Tracking: A Convolutional Neural Network-Based Approach for Identifying Candidate Kinematic Markers

Alberto Nicolás López Moreno[1], Geovanni Hernández Gomez[1], José Manuel López-Villagómez[1], Juan Manuel López-Hernández[1]

[1] División de Ingenierías, Universidad de Guanajuato campus Irapuato-Salamanca, GTO, México

Emails:an.lopezmoreno@ugto.mx,geov.hernandez@ugto.mx,jmlopez@ugto.mx,jm.lopezvillagomez@ugto.mx

Abstract. The analysis of human motor function is considered fundamental in the biomedical and clinical fields, as it allows us to understand how sensory information is transformed into motor responses. In this study, we proposed an analytical design that combined a visual discrimination task with non-invasive tracking of hand trajectories, using convolutional neural networks (CNNs) applied to video analysis. Ten young adults (aged 24 to 34) participated in a perceptual task in which they had to decide whether a pattern of static black bars was regular or irregular. The difficulty of the task was controlled by spatial variation, defined as controlled variations in the spacing between the bars. Behavioral variables, such as accuracy and reaction time, were recorded, along with kinematic parameters such as path length, linearity index, maximum velocity, and variability. The results showed that irregular stimuli were associated with lower accuracy, longer reaction times, and greater variability in motor performance compared to regular stimuli. These findings indicate that perceptual difficulty is reflected not only in behavioral performance but also in the fine structure of motor execution. This work highlights the potential of non-invasive tracking and computer vision for the identification of candidate kinematic markers associated with perceptual uncertainty and decision-making processes, with possible applications in the early detection and monitoring of motor and chronic-degenerative disorders.

Keywords: Computer Vision, Video Analysis, Kinematic Parameters, Human Motor Function, Perceptual Difficulty.

Article Info
Received January 31, 2026
Accepted Aug 11, 2026

1 Introduction

The assessment of human motor function is fundamental in the biomedical and clinical fields for understanding how the body processes sensory information and transforms stimuli into motor responses (Przybyszewski et al., 2023). In this regard, the kinematic study of different parts of the human body is crucial not only for diagnosis but also for monitoring a wide range of neurological and motor disorders (Abasıyanık and Kahraman, 2022). Unlike conventional methods based on hardware or invasive markers, the use of non-invasive tracking techniques offers significant advantages, such as recording movements under more natural (non-invasive) conditions, reducing costs and processing time, and eliminating the discomfort of physical contact with hardware (Schaffelhofer et al., 2015; Di Biase et al., 2020); Li et al., 2023). These characteristics make the analysis of trajectories and movement patterns based on computer vision highly promising for the early detection and monitoring of chronic-degenerative diseases such as Parkinson's, multiple sclerosis, and gait disorders. To evaluate kinematic studies, the use of different decision-making tasks is proposed. These studies are based on models that describe the transformation of stimuli into actions (or movement, in our case), which has allowed for the analysis of the accuracy and speed of kinematic responses (Panconi et al., 2025; Spindler et al., 2022). These have also served as a basis for understanding how individuals respond to perceptual and motor demands at different levels of difficulty, naturally connecting the study of cognition with that of motor performance. Visual pattern discrimination is a fundamental process by which the visual system identifies regularities or irregularities in the spatial distribution of stimuli. This type of task has been widely used to study how the accumulation of perceptual evidence behaves and how this information is converted into a motor reaction (Visser et al., 2025; Gold and Shadlen, 2007).

Other studies have shown that the difficulty of perceptual tasks not only affects accuracy and reaction times, but also influences the variability of motor trajectories or responses. This gives rise to the variable known as learning for decision-making or pattern discrimination, which consists of evaluating the certainty of a choice based on accumulated evidence (Vidal and Lacquaniti, 2021; Deutsch and Newell, 2005). This approach is fundamental not only for understanding cognitive impairments but also for analyzing how they are reflected in movement kinematics during task execution. It has also been studied that it is possible to give correct answers with low confidence, while errors can occur with high confidence (Lin et al., 2021; Di Biase et al., 2022).Currently, there are numerous post-decision models that maintain that confidence is calculated retrospectively from heuristics such as reaction time, and online models that propose that confidence emerges in parallel with the accumulation of evidence, simultaneously with the decision (Villalonga and Sekuler, 2023; Zhang et al., 2024), .For this reason, motion kinematics presents itself as a promising alternative. Motion profiles, such as hand trajectories and velocity profiles, can function as implicit markers of the decision-making process.

Analyzing these kinematic profiles allows researchers to identify choice indicators while solving perception tasks, as well as quantify certainty and the decision-making process (Nath et al., 2019; Zhan et al., 2025; Pecoraro et al., 2025). These analyzed profiles are extracted from systems trained on neural networks Sternad et al. (2011), enabling the generation of online tracking systems (Mathis et al., 2018). Although motion tracking systems based on invasive markers remain the standard in biomechanics, they have significant limitations: high cost, laborious preparation, and the risk of altering natural movement. Mathis et al. (2018) a velocity profile is defined as the temporal representation of the speed of a movement along its trajectory. This is done using the (X,Y) coordinates obtained from each frame of the video, which allows the calculation of instantaneous velocity and the derivation of metrics such as maximum velocity (Vmax) and acceleration to assess the smoothness or irregularity of the movement (Lee et al., 2022), which constitutes a sensitive indicator of perceptual difficulty and the certainty in decision-making. This is done using (X,Y) coordinates obtained from each frame of the video, allowing the calculation of instantaneous velocity and the derivation of metrics such as maximum speed (Vmax) and acceleration to assess the smoothness or irregularity of the motion, which constitutes a sensitive marker of perceptual difficulty and decision-making certainty (Xiang et al., 2022). Non-invasive kinematics based on computer vision and convolutional neural networks (CNNs) has further improved this approach by providing high-precision tools for kinematic analysis (Labuguen et al., 2019; Moro et al., 2022). CNNs are a deep learning architecture widely used in computer vision. Their architecture is based on visual feature extraction and allows the detection of complex spatial patterns in images and videos, enabling the generation of real-time tracking systems. In decision-making systems or tasks, there is a variable called jitter, defined as the random variation in the spatial separation (time, distance) between presented stimuli. In our case, this involves static black bars separated by a certain distance. A regular pattern maintains constant distances between all elements or bars, while an irregular pattern introduces controlled disturbances in these separations. This parameter constitutes the experimental manipulation of perceptual difficulty, since the greater the jitter, the more complex it will be for the participant to identify the regularity in the visual pattern.

1.1- Hypothesis

The present study aims to investigate the relationship between perceptual uncertainty and motor performance during a visual regularity discrimination task with varying levels of spatial variability (jiter). It is hypothesized that increased stimulus irregularity modulates not only perceptual decisions and reaction times, but also kinematic hand trajectories such as straightness and movement variability. Furthermore, it explores whether motion tracking based on convolutional neural networks (CNNs) could provide a potential non-invasive cinematic marker associated with perceptual uncertainty and decision-making processes.

2.- Experimental procedures

In the present study, three main stages were carried out: data acquisition, processing, and analysis and integration of results. During the data acquisition stage, video recordings of participants' hand movements were obtained while they performed a visual discrimination task. For this purpose, a human–machine interface (HMI) was implemented, in which participants were required to classify visual patterns as regular or irregular, as described in more detail in *section 2.1*, based on the level of variability (jitter) in the spacing between stimuli. During each trial, behavioural variables were recorded, including reaction time (RT), response type (respKey), and stimulus condition.

In the video data processing stage, DeepLabCut with a ResNet-50-based architecture was employed. Approximately 300 frames were used for manual annotation of points of interest, which allowed the neural network to be trained for offline automatic tracking. The F1 finger was selected as the primary kinematic marker for trajectory analysis. From this processing stage, variables such as two-dimensional position (x, y), response times, and trajectory rectitude were extracted. In the analysis stage, two types of evaluations were performed. On the one hand, behavioural data were analysed through the construction of psychometric curves, allowing the estimation of the relationship between stimulus variability and response probability. On the other hand, kinematic variables were evaluated as a function of jitter level, with the aim of characterising changes in motor execution.

Finally, an integration stage was carried out in which behavioural and kinematic variables were jointly analysed. *Figure 1* shows the general schematic of the methodology used in this study.

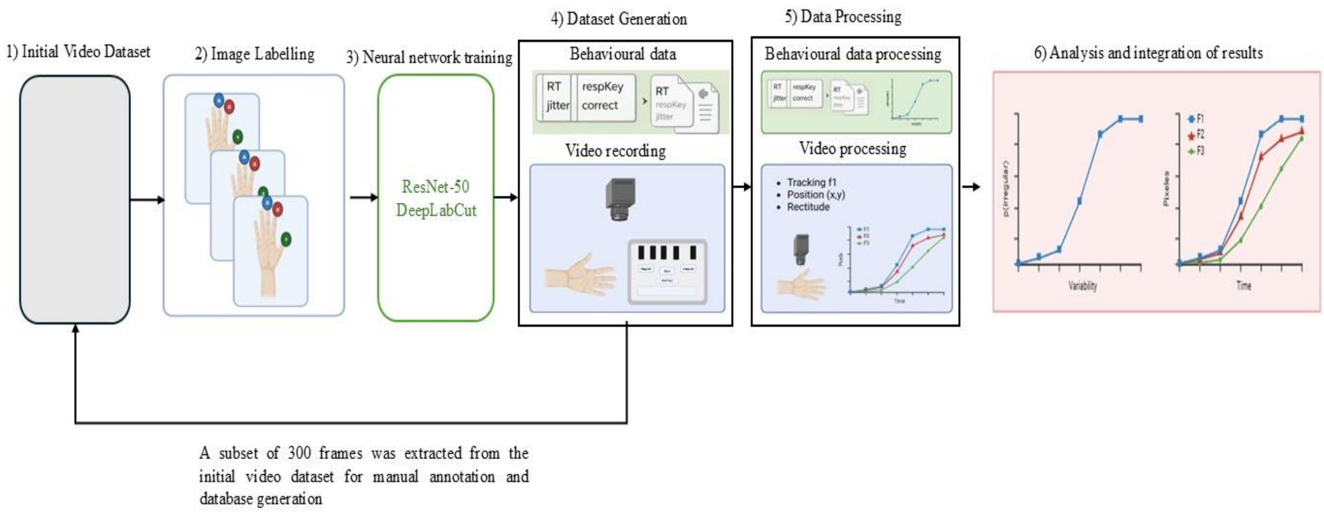

Figure 1. General schematic of the methodology. The process begins with video data acquisition and the generation of an initial image dataset, followed by the manual annotation of a subset of frames for training a DeepLabCut (ResNet-50)-based neural network. In parallel, behavioural data are obtained from a visual discrimination task implemented through a human–machine interface, including reaction time (RT), response type (respKey), and stimulus variability (jitter). Subsequently, video processing is performed to extract kinematic variables such as position, velocity, and trajectory rectitude, using the F1 finger as the primary marker. The behavioural and kinematic data are then integrated through joint analyses, including relationships between RT and rectitude, as well as between jitter and rectitude, enabling the characterisation of the interaction between perceptual processes and motor execution.

2.1- Experimental Task

The task was implemented in software using an interface designed to assess perceptual discrimination between regular and irregular spatial patterns, which, in this specific case, consisted of static black vertical bars, as shown in Figure 2. The interface opened in a window (1100 × 840 px, gray background). This interface displayed a header with the task title, a trial counter, and input fields for the subject (person's name). Below the interface name, the stimulus area occupies the central region of the screen; at the bottom, there are two response buttons, Regular (R) and Irregular (I), located on the left and right, separated by a status LED panel in the center. Further down, a large "Start Trial (SPACE)" button is displayed, followed by a panel with editable stimulus parameters and, finally, a status bar that provides real-time information about the task. To accomplish this task, the following works were analyzed El Iskandarani et al. (2025), Sihn et al. (2025), Villalonga et al. (2025).

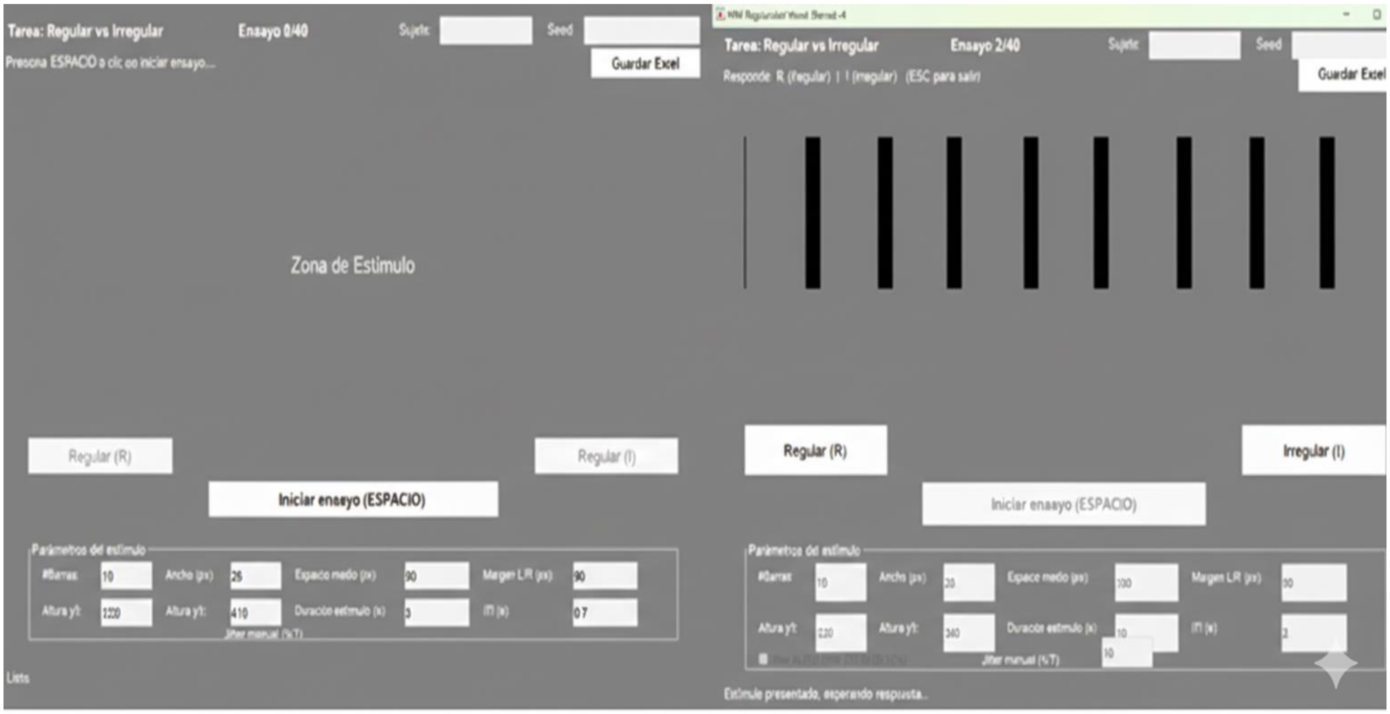

Figure 2. Human–machine interface (HMI) used for the visual discrimination task. The interface displays static vertical bar patterns with either regular or irregular spacing (jitter), allowing participants to classify the stimulus as "Regular" or "Irregular" using dedicated response buttons

During each trial, a set of stimulus parameters was defined, including the number of bars, their width, and the average spacing between them, as well as their spatial arrangement within the display. Participants were presented with static patterns of vertical bars whose regularity depended on the degree of spatial variability introduced in the spacing between adjacent elements. In regular trials, the spacing between bars remained constant, whereas in irregular trials, variability was introduced around the mean spacing, generating perceptual uncertainty.

To manipulate perceptual uncertainty, different levels of spatial variability (jitter) were introduced into the spacing of adjacent bars presented in the task. In regular trials, all distances between bars remained constant, while in irregular trials, the spacing varied around the mean distance according to predefined fluctuation levels of 5%, 10%, 20%, and 30%. These percentages represent the variability applied to the average spacing between bars, generating spatial patterns with increasing levels of irregularity. Specifically, the spacing between adjacent bars was calculated by applying a Gaussian scaled random fluctuation according to the level of variation to the spacing, which allowed each condition to have a controlled degree of spatial variability.

During the experiment, jitter levels were presented in a pseudo-random manner between trials to minimize prediction effects and avoid response biases associated with the order of presentation of visual stimuli. The same jitter settings and stimulus generation rules were applied to all participants to maintain consistent difficulty across sessions.Each stimulus was displayed for a limited duration, during which participants were required to classify the pattern as regular or irregular, followed by an intertrial interval before the onset of the next trial.To ensure consistency across trials, constraints were applied to the spatial distribution of the bars, preventing overlap and maintaining a centred configuration on the screen. Figure 3 shows a schematic representation of the task.

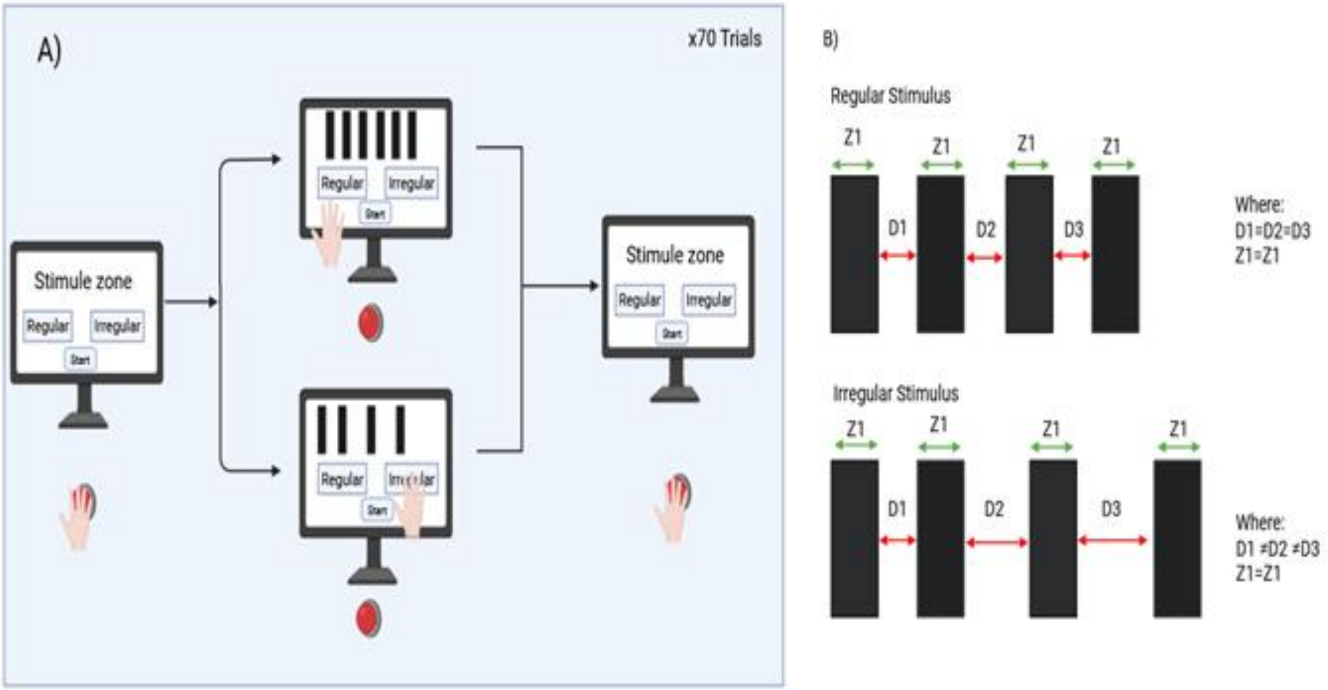

Figure 3.- Diagram of the regularity discrimination task implemented in the interface (A) In each trial, participants observe a sequence of visual flashes in the stimulus area and, at the end, must select between two response options (Regular or Irregular) on the touch screen. Each block consisted of 70 trials. (B) Example of the temporal structure of the stimuli. In the Regular condition, the intervals between flashes (Z1) remain constant (D1=D2=D3). In the Irregular condition, one of the intervals is altered by a controlled fluctuation, which breaks the regularity of the sequence.

Each trial begins when the participant presses the space bar or clicks the digital start button. Then, the graphical interface simultaneously shows all the bars in the stimulus area and records the instant of their appearance with millisecond precision. The central virtual LED changes from gray to green and displays the label "RUN", indicating that the trial es active and awaiting a response. Participants decided between the pattern is Regular (uniform separations) or Irregular (separations with fluctuations) and respond using the interface buttons or the keyboard (R for Regular; I for Irregular). When the response is submitted or the time limit has elapsed, the LED illuminates red (END) for approximately 200 ms before turning gray. The model of computer is Dell Inspirion 2350.

2.2.- Methodology for Non-Invasive Kinematic Tracking

The experiment was conducted over 10 days, divided into sessions. A database comprising four experimental sessions was generated; however, due to computational processing limitations, only one third of this dataset was used for the present analysis. During the sessions, participants performed a visual regularity discrimination task using a graphical interface, described in the Experimental Task section. In each session, participants sat in front of the screen and responded to stimuli displayed on the screen using the interface's keyboard and digital buttons. For each trial, reaction time, stimulus type, and stimulus start time were recorded. In short, the task involved differentiating between static black rectangular patterns and determining whether the spacing between them was regular or irregular. The participant's objective was to choose whether the spacing between the bars was uniform or irregular by randomly changing the distance between them. The trials had irregularity levels of 5, 10, 20, or 30%. Responses were given using digital buttons (R for Regular, I for Irregular), and the exact position of the bars was also recorded. For this study, ten young men, aged between 24 and 34, participated in this study. Furthermore, written informed consent was obtained from all participants for their participation and for the publication of this work, ensuring confidentiality and the voluntary nature of their participation. No additional inclusion criteria were established beyond the volunteer's availability to complete the experimental protocol.

2.3.- Stereo Camera Configuration and Recording Structure

The experiment was conducted under controlled conditions. An experimental system specifically designed and developed for recording participants' hand movements was implemented. The structure was placed on an optical worktable model Newport Integrity 1. It was assembled from 20 x 20 mm aluminum profiles, providing the frame with stability, lightness, and rigidity. The design of this structure was based on database generation studies such as those by Cui et al. (2024) and Zadid et al. (2025). The structure has the following dimensions: 80 cm long, 80 cm wide, and 50 cm deep. For kinematic acquisition, two high-resolution cameras were mounted in a stereoscopic configuration on the top of the frame, horizontally. Only one video camera was used for this study, but the structure is designed to accommodate two to five cameras. The fixed distance between the cameras on the top was 33.5 cm. The automatic positioning system incorporated a lead screw coupled to a DC motor, electronically controlled by a Raspberry Pi 3. an HMI was developed on this board to control the motors that positioned the cameras. This electronic system, implemented within the structure, enabled smooth linear movement and maintained consistent and standardized distances and positioning throughout all recording sessions. The structure also allowed for video capture from two to five synchronized perspectives and provided the necessary precision for non-invasive kinematic tracking of hand trajectories during the behavioral task. The cameras were attached to a 3 mm horizontal support bar connected to the frame via 5 cm sliding blocks, allowing for precise positional adjustments. Automating this adjustment minimizes human error. The camara model used was EKEN 9HR. In Figure 4, the experimental setup can be observed recording structure as shown in Figure 4A-C. For hand tracking, multiple regions of the hand were manually annotated to train the DeepLabCut model as shown in Figure 4A.

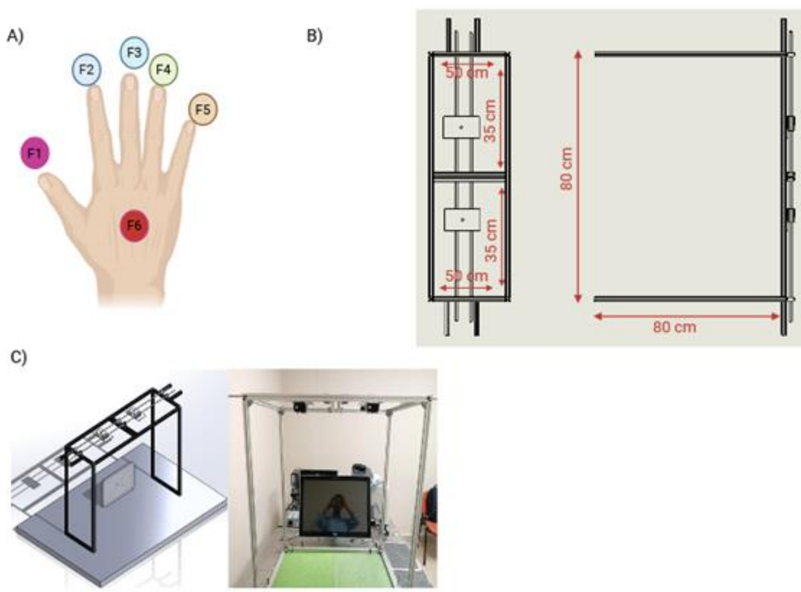

Figure 4.- (A) Diagram of the selected anatomical points on the hand for kinematic analysis: five fingers (F1–F5) and the palm (F6). (B) Design of the stereoscopic aluminum experimental structure; the dimensions of the base (80 × 80 cm) and the position of the cameras, separated by 33.5 cm from the center of each lens, are shown. (C) 3D model of the structure (left) and the experimental setup (right), showing the stimulus display in the central area and the camera system mounted on top for non-invasive recording of hand movements.

3 Results

3.1.- Behavioral Data Extraction

During each session, participants performed the visual discrimination task described in the experimental procedures section. The design of this protocol was informed by the work of Villalonga and Sekuler (2023), Kristensen et al. (2025), Säfström (2025), Lucia and Di Russo (2025), and Gorniak (2019).

To quantify perceptual performance, psychometric curves were constructed from the responses recorded by the human–machine interface (HMI). These curves model the probability of classifying a stimulus as "irregular" as a function of stimulus variability, represented in this study by the jitter level x. The psychometric function was defined using a logistic model with guess and lapse rates:

$$P(C) = \gamma + (1 - \gamma - \lambda) * \frac{1}{(1+e^{-\beta(x-\alpha)})} \quad (1)$$

where P(C) denotes the probability of reporting a stimulus as irregular given a jitter level x. The parameter α represents the perceptual threshold or point of subjective equality (PSE), defined as the value of x at which the stimulus is perceived as ambiguous. The parameter β corresponds to the slope of the function and reflects sensitivity to changes in stimulus irregularity. The parameter γ represents the guess rate, corresponding to the baseline probability of responding "irregular" when no reliable perceptual information is available. Finally, λ denotes the lapse rate, accounting for errors that occur even at high stimulus intensities. In this formulation, α determines the location of the transition between regular and irregular perception, while β controls the steepness of this transition.

The psychometric curve was constructed using the jitter level as the independent variable, which allowed the generation of stimuli with different levels of spatial variability. The participant's response was represented by the variable respKey, encoded in binary form (0 = Regular, 1 = Irregular). All analyses were performed in Google Colab using Python. Empirical probabilities of "irregular" responses were computed for each jitter level, providing the data points used to construct the psychometric curves.

To model the relationship between stimulus variability and perceptual response, a logistic regression model was fitted:

$$P(Irregular|x) = \frac{1}{1 + e^{-(\beta_0+\beta_1 x)}} \quad (2)$$

Equation (2) can be interpreted as a simplified form of the general psychometric function described in Equation (1), obtained by assuming negligible guess and lapse rates ($\gamma \approx 0$, $\lambda \approx 0$). Under this assumption, the function reduces to a standard logistic model. Furthermore, by expanding the term β(x- α) , the model can be reparameterised such that $\beta_1 = \beta$ and $\beta_0 = -\beta\alpha$, resulting in the formulation used in Equation (2). This representation is widely used in behavioural modelling due to its numerical stability and ease of estimation. where β_0 represents the intercept (bias) and β_1 corresponds to the slope

Based on the fitted model, the point of subjective equality (PSE) was computed as:

$$PSE = -\frac{\beta_0}{\beta_1} \quad (3)$$

The individual psychometric curves showed a consistent sigmoidal transition for reporting the probability of perceiving the stimulus as irregular and the level of temporal variability (jitter) Figure 5. In all participants, the probability of an "irregular" response gradually increased as the level of jitter increased, indicating adequate sensitivity to the spatial stimulus. However, differences between subjects were also observed in the position of the curves for the variability of the subjective point of equalization (PSE). The SPEs showed shifts between participants, indicating differences in the perceptual threshold for temporal discrimination.

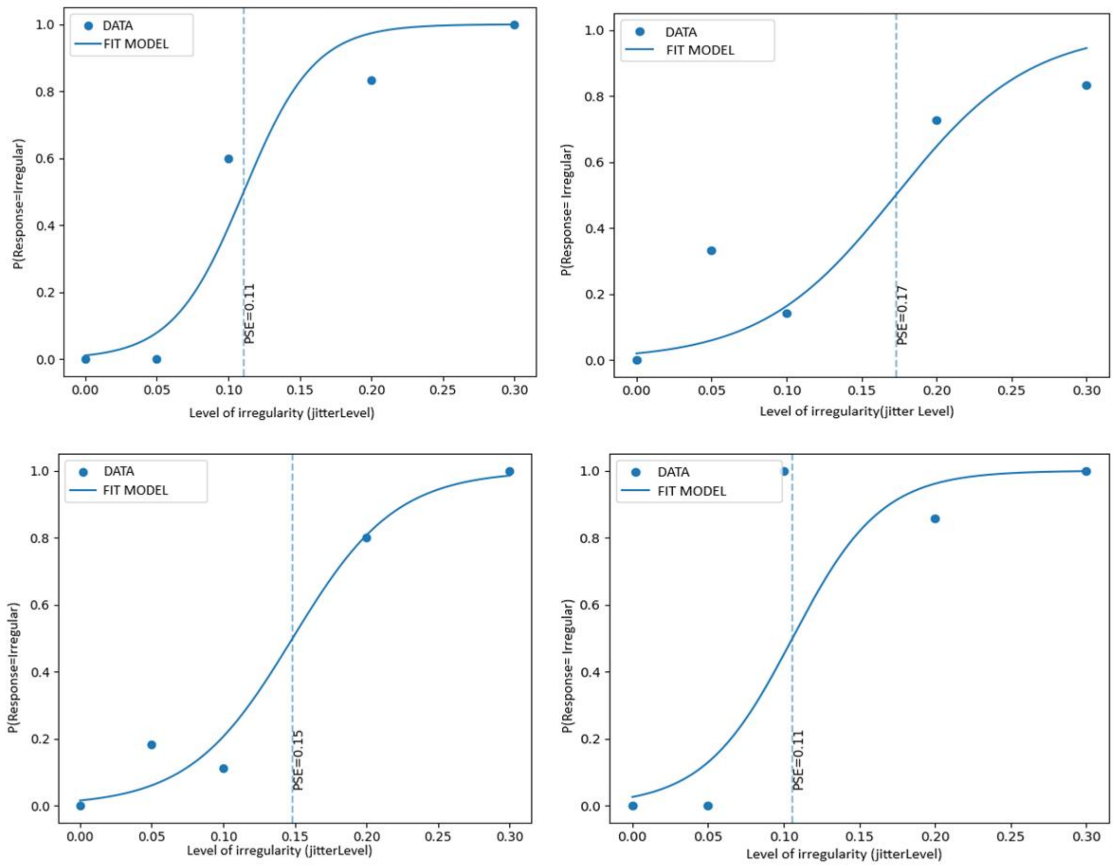

Figure 5.- Each panel displays the corresponding psychometric curve for the participants. The probability of reporting a stimulus as "irregular" is plotted as a function of jitter level. The blue dots correspond to the observed data, while the solid line represents the logistic fit (sigmoid function) used to adjust the relationship between stimulus variability and the perceptual response. The dotted vertical line indicates the point where the probability of responding "irregular" is 0.5. This parameter reflects the participant's perceptual threshold, that is, the level of variability at which the stimulus is perceived as ambiguous between regular and irregular.

3.2.- Kinematic Data Extraction

To illustrate tracking quality and motion variability, based on the work of Cieślik and Łopatka (2022), Figure 6 shows representative trajectories obtained from two participants during trials of the pattern discrimination task described in the Experimental Task section. For the analysis of all participants' trajectories, marker F1 was selected as the main kinematic feature, as illustrated in Figure 6.

In trials with regular stimuli (jitter=0.0), the trajectories showed smoother and more direct paths between the start and finish points. Compared to the representative trajectories obtained during irregular trials, these showed greater deviations from the direct path and greater variability in movement geometry. These differences can be seen in Figure 6.

It is important to note that the trajectories presented in Figure 6 help to illustrate the qualitative relationship between stimulus variability and movement kinematics. The quantitative relationship between stimulus variability and movement kinematics was subsequently evaluated using the metrics described in the following sections and considering the entire group of participants. Similar to previous studies by Moro et al., 2022, and Papaioannidis et al., 2022, these illustrate how variations in the stimulus can modify the change in movement trajectory.

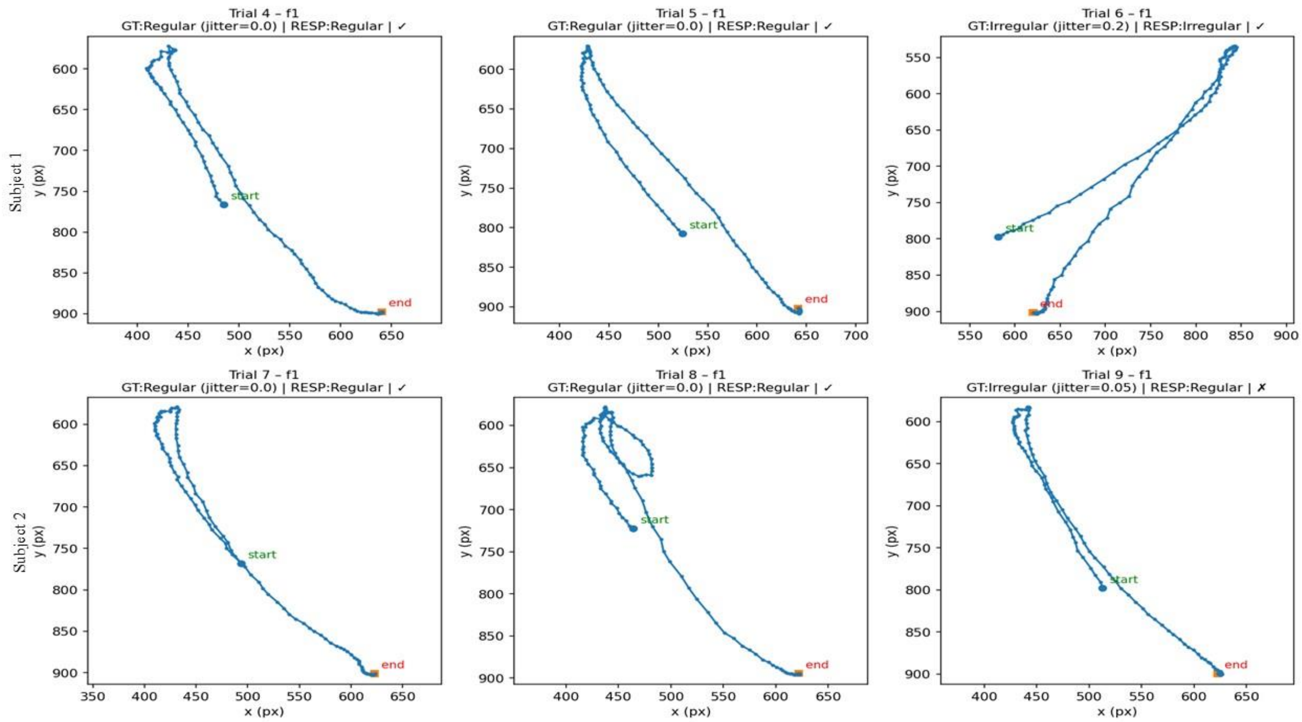

Figure 6.- Representative trajectories of hand movement during the temporal discrimination task. These panels show the two-dimensional (x,y) trajectory of the index finger (F1) during individual trials, under different stimulus conditions (regular and irregular) and levels of variability (jitter). The trajectories were obtained using DeepLabCut from a 60 fps video. The points marked start (green) and end (red) indicate the beginning and end of the movement, respectively.

To obtain these trajectories, kinematic data were extracted from tracking files generated by the Convolutional Neural Network (CNN) trained in DeepLabCut for the detection of points of interest on the hand Figure 4, like the studies by Mathis et al. (2018), Nath et al. (2019), and Li et al. (2023). Each video file was segmented into individual trials by synchronizing events recorded during the experimental task with the corresponding frames in the video. This synchronization was performed using task timestamps, such as stimulus onset and response times, which were converted to frame rates considering an acquisition frequency of 60 fps.

Once the start and end points of each trial were identified and aligned, the two-dimensional (X,Y) coordinates of the hand marker were extracted, following procedures like Ryu et al. (2024). The trajectories were then normalized to ensure comparability between trials of different durations. For each condition (Regular or Irregular), the average trajectories and standard deviation between trials were calculated and represented by shaded regions around the mean curve. This method allowed us to compare the overall shape of the trajectory and also evaluate the spatial dispersion, providing a quantitative description of the variability of the motion between trials.

Figure 7 shows the trajectories obtained during the regular trials, which exhibit more direct paths and less spatial dispersion. On the other hand, the trajectories recorded during the irregular trials show greater variability and spatial distribution. These observations are consistent with the quantitative analyses presented in the following sections, which evaluate the relationship between stimulus variability and kinematic performance.

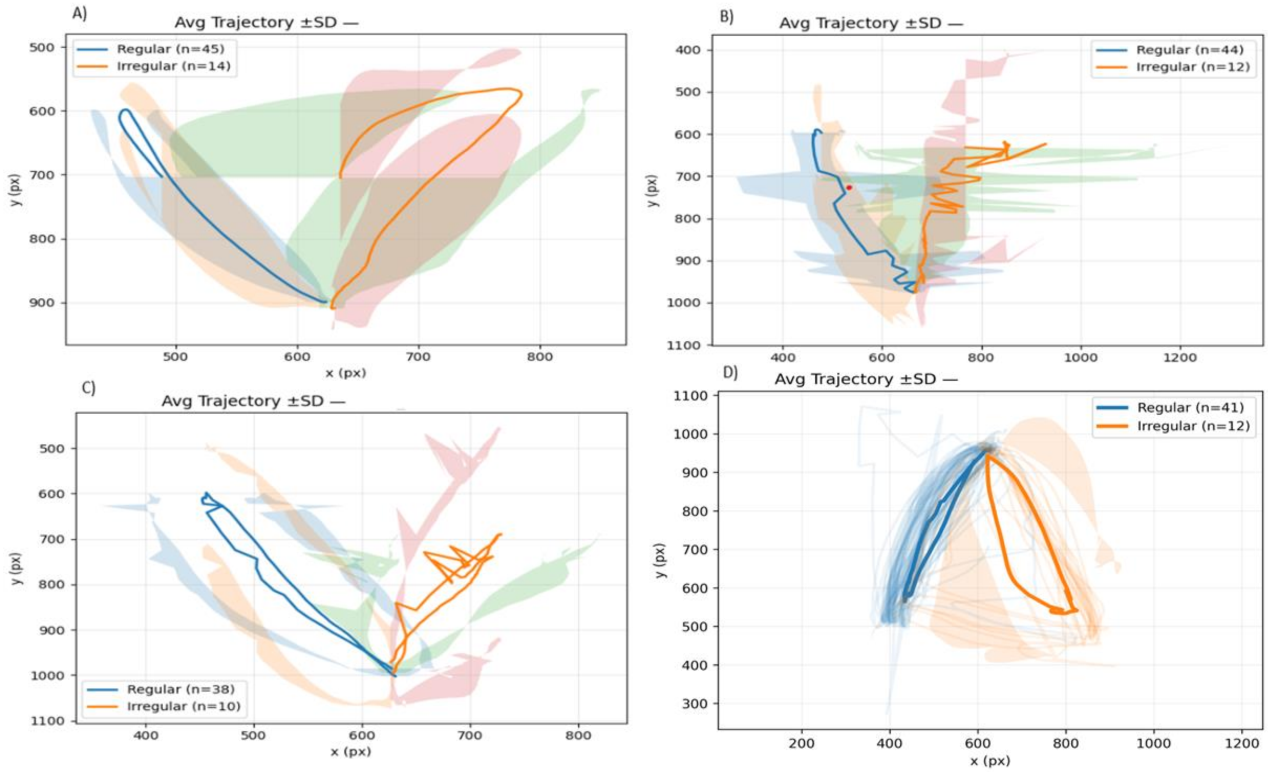

Figure 7.- A-D) Average trajectories of finger F1 at the group level (±SD) for all participants. The conditions are regular stimuli blue and irregular stimuli are orange. The trajectories were normalized and aligned. Greater dispersion and curvature can be observed under irregular conditions.

3.4.- Results analysis

To reinforce the results, the average straightness of the trajectories, defined as the ratio between the straight-line distance and the length of the motion path (D/L), was analyzed as a function of jitter. This relationship is shown in Figure 8A. The results show that the relationship between stimulus variability and kinematics does not follow a linear trend. In this specific case, straightness fluctuates across different jitter levels, decreasing at intermediate levels and partially recovering at higher variability levels. When this behavior is compared to the general psychometric curve Figure 8B, a similar nonlinear behavior can be observed across different jitter levels. These results show that changes in perceptual performance are linked to changes in trajectory straightness.

These results are reinforced when we analyze the retention time (RT) profile, which is defined as the interval between the appearance of the stimulus and the participant's response. This profile is shown in *Figure 8C*, which indicates that with the changes observed in the straightness of the trajectories Figure 8A and in the psychometric function Figure 8B, reaction times increase at intermediate levels of variability, specifically near jitter=0.1, and subsequently decrease at higher levels.

It is also important to emphasize that the results show that the psychometric function exhibits a progressive increase in the probability of classifying stimuli as "irregular" as jitter increases. At low levels of variability (jitter = 0 and jitter = 0.05), responses were classified as regular, while at intermediate levels (jitter = 0.1), a change in response probability was observed. At high levels of jitter variability (0.2 and jitter = 0.3), the probability of irregular responses approached 1, indicating more consistent stimulus discrimination. Analyzing the straightness results Figure 8A, psychometric function Figure 8B, and reaction time Figure 8C, it can be observed that the greatest changes occur around intermediate jitter levels. In this section, lower straightness values and longer reaction times are simultaneously observed, along with a transition in response probability, suggesting a relationship between perceptual performance and motor execution. These findings are consistent with those reported by Villalonga and Sekuler, (2023), and Villalonga et al. (2025).

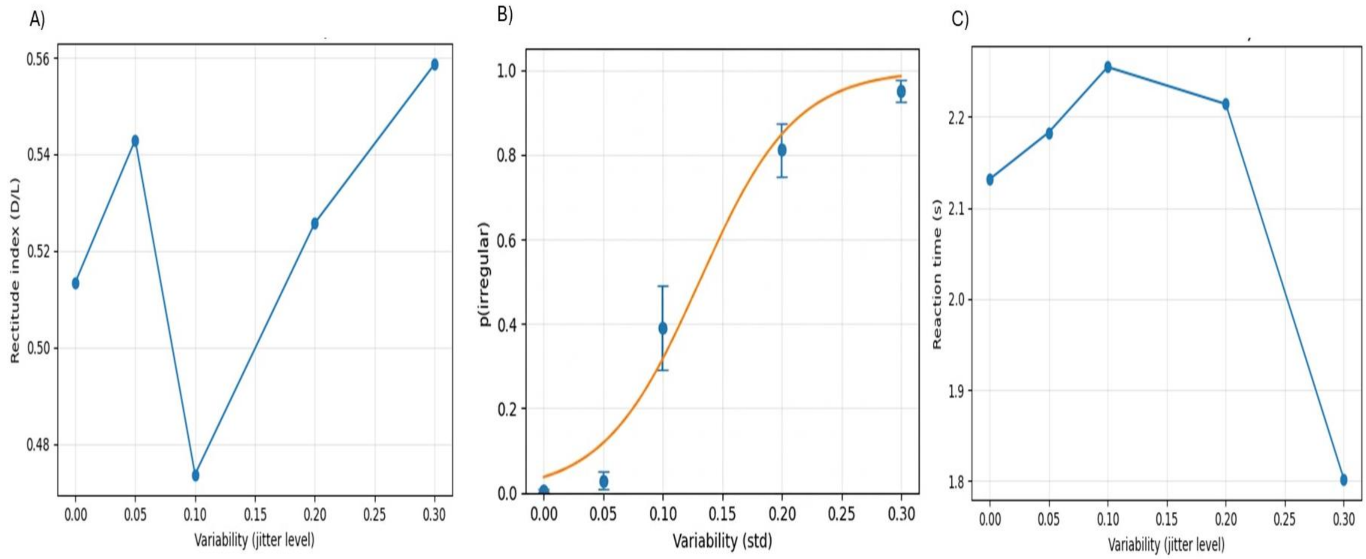

Figure 8.- A) Average trajectory straightness as a function of stimulus variability (jitter level). Each point shows the group average for each jitter level, n=10 participants. Non-monotonic behavior is observed, with a decrease at intermediate levels and an increase at the highest levels of variability. B) Group psychometric curve shows the probability of classifying a stimulus as irregular as a function of jitter. The points represent the average responses, the error bars show the standard error of the mean (± SEM), and the solid line corresponds to logistic adjustment. C) Average reaction time (RT) as a function of jitter. Reaction times increase at intermediate levels of variability and decrease at the highest jitter level. These panels together show the relationship between stimulus variability, perceptual performance, and movement kinematics as a function of jitter levels.

To reinforce the findings presented in Figure 8, Table 1 shows the metrics and quantitative behavioral and kinematic results at the different jitter levels. Accuracy (%) shows a non-linear pattern as a function of stimulus variability. Performance was highest under regular conditions (jitter = 0.00; 99.12 ± 0.45%) and at high levels of irregularity in the task (jitter = 0.30; 95.09 ± 2.62%), while low accuracy (%) values were observed at intermediate levels of variability, particularly at jitter = 0.10 (39.03 ± 10.02%). These results indicate that the participants' perceptual performance varies systematically according to the level of spatial irregularity presented during the task.

Regarding the reaction time (RT) variable, it also showed non-monotonic behavior across the different jitter conditions. The average RT increased progressively from the jitter condition = 0.00 to jitter = 0.10, where the highest value was observed (2.255 ± 0.163 s), and subsequently decreased at higher levels of variability, specifically at the jitter value = 0.30 (1.802 ± 0.180 s). This pattern suggests that intermediate levels of variability could be associated with greater perceptual ambiguity, resulting in longer response times. In comparison, highly irregular stimuli become easier to classify as the participant performs the task and gains experience.

The straightness of the trajectories (D/L) also varied across different jitter levels. The lowest straightness value was observed at jitter = 0.10 (0.474 ± 0.094), while the highest values were observed at jitter = 0.30 (0.559 ± 0.087). These results demonstrate that the movement trajectories became less direct under intermediate variability conditions and more stable under irregular conditions, most likely due to the experience gained by the participants.

Table 1. Behavioral and kinematic metrics of the different jitter levels. Values are reported as mean ±SEM. Accuracy (Accracy %) represents the percentage of correct responses, RT indicates reaction time in seconds, and Rectitude (D/L) indicates the linearity of the trajectory. N indicates the number of participants.

Jitter level	Accuracy (%)	RT (s)	Rectitude (D/L)	N
0	99.12 ± 0.45	2.131 ± 0.147	0.514 ± 0.091	10
0.05	2.93 ± 2.02	2.183 ± 0.142	0.543 ± 0.097	10
0.1	39.03 ± 10.02	2.255 ± 0.163	0.474 ± 0.094	10
0.2	81.06 ± 6.37	2.214 ± 0.233	0.526 ± 0.086	10
0.3	95.09 ± 2.62	1.802 ± 0.180	0.559 ± 0.087	10

3.5.- Mathematical modeling

To quantify the effect of perceptual difficulty on behavioral performance, reaction time (RT) was analyzed as a function of stimulus variability as a function of jitter level x. Reaction time represents the time required for the participant to accumulate perceptual evidence and perform a motor task.

A linear model is proposed to describe this relationship:

$$RT = \alpha_0 + \alpha_1 x \qquad (4)$$

Where α_0 corresponds to the baseline reaction time under conditions of minimal difficulty (jitter = 0), and α_1 quantifies the increase in reaction time as a function of the increase in stimulus irregularity, and x is the jitter level.

This equation indicates that a positive value of α_1 suggests that higher levels of perceptual difficulty are associated with longer reaction times, which is consistent with reported accumulation models for evidence of perceptual decision-making.

4 Conclusions

This study investigated the relationship between perceptual decision-making and motor performance during a visual discrimination task with varying levels of spatial uncertainty, defined as jitter. The results showed a non-linear relationship between behavioral and kinematic variables, demonstrating that changes in stimulus variability are linked to changes in both perceptual performance and the physical characteristics of the trajectories.

One of the main findings is that trajectory straightness did not vary monotonically with stimulus variability; on the contrary, straightness decreased at intermediate jitter levels and partially recovered at higher levels. Reaction time and psychometric performance showed nonlinear patterns across different jitter conditions, but the most pronounced changes in both were observed at intermediate levels of variability. Taking together, these results demonstrate that perceptual performance and movement kinematics are closely related during task execution.

Although the results show a systematic correlation between stimulus variability and motor behavior, which coincides with previous studies by Villalonga and Sekuler (2023) and Ofir and Landau (2025), demonstrating that performance is influenced by stimulus properties and sensory uncertainty, future work requires the implementation of mathematical and computational models such as evidence accumulation and diffusion drift to provide a more in-depth description of the mechanisms responsible for the correlation between motor behavior and perceptual ability.

Despite the results obtained, it is important to highlight the limitation of the sample size. Although N=10 participants allowed for the identification of consistent trends between behavioral and kinematic variables, future studies with larger populations are necessary to generate better fits and mathematical models.

4.1.- Comparison with classic perceptual discrimination tasks

Table 2 shows a comparison of the studies conducted, where we can agree that as the difficulty of the stimulus increases, the ability to distinguish the correct option decreases. It can also be said that as the level of difficulty decreases, the trajectories for choosing the correct option become more linear. These studies use other types of models, such as accumulation of evidence and diffusion models (Luacia & Di Russo, 2025), but they do not use a non-invasive tracking system, which allows us to apply these models to our data. Another important conclusion is that reaction time varies with the difficulty.

Table 2.- Comparation summary of experimental studies

Study	Task type	Manipulation Delaware	Behavioral metrics	Key findings
Gold & Shadlen (2007)	Discrimination of coherent movements	Movement coherence (%)	Accuracy, RT, psychometric curves	Greater difficulty results in lower accuracy and increased RT. Accumulated evidence with drift-diffusion dynamics.
Wong & Haith (2017)	Perceptual-Motor intregation tasks	Perceptual difficulty	RT distributions, movement curvature	Kinematics reflects the perceptual difficultybefore the decision.
Säfstöm (2025)	Sequential reaching task with multisensory feedback	Unexpected elimination of visual and auditory feedback	Variability of movement, efficiency of corrective actions	Sequential actions depend critically on discrete multisensory feedback at the end of each phase
Kristensen et al. (2025)	Psychophysical studies modeled with psychometric functions	Intensity of the adaptively selected stimulus	Psychometric curves and parameter estimation	Adaptive designs produce greater efficiency, but introduce sampling bias, especially in the slope of the psychometric function. .
Our Job	Discrimination of spatial regularity with non-invasive tracking	Jitter (%) in the separation of bars	Accuracy, RT, psychrometric curves XY trajectories, straightness	Generation of mathematical models for response times and trajectory databases

4.2.- Analysis of neural networks

The implementation of artificial intelligence, specifically convolutional neural networks applied to offline video-based cinematic tracking, is a promising, low-cost, and non-invasive methodology for capturing motion trajectories associated with perceptual decision-making tasks. By enhancing tracking without the need for physical markers or specialized hardware, it facilitates the extraction of relevant cinematic measurements such as trajectory length, speed, and acceleration, without affecting the naturalness of the movement. The results obtained in this study show that kinematic measures vary according to changes in stimulus variability, providing information about the correlation between perceptual performance and motor execution. Therefore, this work contributes to the development of scalable and low-cost methodologies that could be useful in future applications focused on motor and cognitive functions.

4.3.- Future work

As future work, kinematic analysis should be applied to include more complex dynamic models that capture not only average metrics, such as straightness, but also variables like velocity and acceleration. This will allow for a more detailed study of how perceptual performance relates to the configuration of motion profiles under different experimental conditions. Another promising area involves evaluating clinical populations, such as individuals with Parkinson's disease, gait disorders, or mild cognitive impairment, to determine if these methodologies could contribute to clinical assessment and monitoring. This also includes integrating techniques that can aid in the three-dimensional (X,Y,Z) reconstruction of movement. The results presented show that both behavioral performance and kinematic variables change depending on stimulus variability. However, to develop a mathematical model that relates perceptual uncertainty and motor performance, future work is needed that incorporates evidence accumulation models, such as Drift Diffusion Models, to more accurately evaluate variables associated with decision-making, confidence, and adaptive processes.

References

Abasıyanık, Z., & Kahraman, T. (2022). Effect of dual-task training on cognitive functions in persons with multiple sclerosis: A systematic review and meta-analysis. *Multiple Sclerosis and Related Disorders, 62*, Article 103801. https://doi.org/10.1016/j.msard.2022.103801

Cieślik, K., & Łopatka, M. J. (2022). Research on speed and acceleration of hand movements as command signals for anthropomorphic manipulators as a master-slave system. *Applied Sciences, 12*(8), Article 3863. https://doi.org/10.3390/app12083863

Cui, C., Sunar, M. S., & Su, G. E. (2024). A dataset of egocentric and exocentric view hands in interactive senses. *Data in Brief, 57*, Article 111003. https://doi.org/10.1016/j.dib.2024.111003

Deutsch, K. M., & Newell, K. M. (2005). Noise, variability, and the development of children's perceptual-motor skills. *Developmental Review, 25*(2), 155–180. https://doi.org/10.1016/j.dr.2004.09.001

di Biase, L., Di Santo, A., Caminiti, M. L., De Liso, A., Shah, S. A., Ricci, L., & Di Lazzaro, V. (2020). Gait analysis in Parkinson's disease: An overview of the most accurate markers for diagnosis and symptoms monitoring. *Sensors, 20*(12), Article 3529. https://doi.org/10.3390/s20123529

di Biase, L., Raiano, L., Caminiti, M. L., Pecoraro, P. M., & Di Lazzaro, V. (2022). Parkinson's disease wearable gait analysis: Kinematic and dynamic markers for diagnosis. *Sensors, 22*(22), Article 8773. https://doi.org/10.3390/s22228773

El Iskandarani, M., Bolton, M., & Riggs, S. L. (2025). Examining dual-task interference effects of visual and auditory perceptual load in virtual reality. *International Journal of Human-Computer Studies, 205*, Article 103619. https://doi.org/10.1016/j.ijhcs.2025.103619

Gold, J. I., & Shadlen, M. N. (2007). The neural basis of decision making. *Annual Review of Neuroscience, 30*, 535–574. https://doi.org/10.1146/annurev.neuro.29.051605.113038

Gorniak, S. L. (2019). The relationship between task difficulty and motor performance complexity. *Attention, Perception, & Psychophysics, 81*(1), 12–19. https://doi.org/10.3758/s13414-018-1634-4

Kristensen, S. B., Bødkergaard, K., & Bibby, B. M. (2025). Analysing the bias introduced by adaptive designs to estimates of psychometric functions. *Journal of Mathematical Psychology, 124*, Article 102899. https://doi.org/10.1016/j.jmp.2025.102899

Labuguen, R., Bardeloza, D. K., Negrete, S. B., Matsumoto, J., Inoue, K., & Shibata, T. (2019). Primate markerless pose estimation and movement analysis using DeepLabCut. In *2019 Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision & Pattern Recognition (icIVPR)* (pp. 297–300). IEEE. https://doi.org/10.1109/ICIEV.2019.8858533

Lee, M.-F. R., Chen, Y.-C., & Tsai, C.-Y. (2022). Deep learning-based human body posture recognition and tracking for unmanned aerial vehicles. *Processes, 10*(11), Article 2295. https://doi.org/10.3390/pr10112295

Li, J., Kang, F., Zhang, Y., Liu, Y., & Yu, X. (2023). Research on tracking and identification of typical protective behavior of cows based on DeepLabCut. *Applied Sciences, 13*(2), Article 1141. https://doi.org/10.3390/app13021141

Lin, L. P. Y., Plack, C. J., & Linkenauger, S. A. (2021). The influence of perceptual-motor variability on the perception of action boundaries for reaching in a real-world setting. *Perception, 50*(9), 783–796. https://doi.org/10.1177/03010066211038406

Lucia, S., & Di Russo, F. (2025). Identification of anticipatory brain activity in a time discrimination task. *Brain and Cognition, 183*, Article 106243. https://doi.org/10.1016/j.bandc.2024.106243

Mathis, A., Mamidanna, P., Cury, K. M., Abe, T., Murthy, V. N., Mathis, M. W., & Bethge, M. (2018). DeepLabCut: Markerless pose estimation of user-defined body parts with deep learning. *Nature Neuroscience, 21*(9), 1281–1289. https://doi.org/10.1038/s41593-018-0209-y

Moro, M., Marchesi, G., Hesse, F., Odone, F., & Casadio, M. (2022). Markerless vs. marker-based gait analysis: A proof of concept study. *Sensors, 22*(5), Article 2011. https://doi.org/10.3390/s22052011

Nath, T., Mathis, A., Chen, A. C., Patel, A., Bethge, M., & Mathis, M. W. (2019). Using DeepLabCut for 3D markerless pose estimation across species and behaviors. *Nature Protocols, 14*(7), 2152–2176. https://doi.org/10.1038/s41596-019-0176-0

Ofir, N., & Landau, A. N. (2025). A drift-diffusion model of temporal generalization outperforms existing models and captures modality differences and learning effects. *Behavior Research Methods, 57*(12), Article 334. https://doi.org/10.3758/s13428-025-02819-8

Panconi, G., Grasso, S., Guarducci, S., Mucchi, L., Minciacchi, D., & Bravi, R. (2025). DeepLabCut custom-trained model and the refinement function for gait analysis. *Scientific Reports, 15*, Article 2364. https://doi.org/10.1038/s41598-025-85591-1

Papaioannidis, C., Mademlis, I., & Pitas, I. (2023). Fast CNN-based single-person 2D human pose estimation for autonomous systems. *IEEE Transactions on Circuits and Systems for Video Technology, 33*(3), 1262–1275. https://doi.org/10.1109/TCSVT.2022.3209160

Pecoraro, P. M., Marsili, L., Espay, A. J., Bologna, M., & di Biase, L. (2025). Computer vision technologies in movement disorders: A systematic review. *Movement Disorders Clinical Practice, 12*(9), 1229–1243. https://doi.org/10.1002/mdc3.70123

Przybyszewski, A. W., Śledzianowski, A., Chudzik, A., Szlufik, S., & Koziorowski, D. (2023). Machine learning and eye movements give insights into neurodegenerative disease mechanisms. *Sensors, 23*(4), Article 2145. https://doi.org/10.3390/s23042145

Ryu, J., Nejatbakhsh, A., Torkashvand, M., Gangadharan, S., Seyedolmohadesin, M., Kim, J., Paninski, L., & Venkatachalam, V. (2024). Versatile multiple object tracking in sparse 2D/3D videos via deformable image registration. *PLOS Computational Biology, 20*(5), Article e1012075. https://doi.org/10.1371/journal.pcbi.1012075

Säfström, D. (2025). The multisensory control of sequential actions. *Experimental Brain Research, 243*(1), Article 13. https://doi.org/10.1007/s00221-024-06962-0

Schaffelhofer, S., Agudelo-Toro, A., & Scherberger, H. (2015). Decoding a wide range of hand configurations from macaque motor, premotor, and parietal cortices. *Journal of Neuroscience, 35*(3), 1068–1081. https://doi.org/10.1523/JNEUROSCI.3594-14.2015

Sihn, D., Kim, J., Kim, M. J., & Kim, S.-P. (2025). The intrinsic propagation directionality of fMRI infra-slow activity during visual tasks. *Neuroscience, 564*, 52–59. https://doi.org/10.1016/j.neuroscience.2024.11.041

Spindler, P., Alzoobi, Y., Truckenmüller, P., Hahn, S., Manzoni, Y. N., Feldmann, L., Hermann, K.-G., Kühn, A. A., Faust, K., Schneider, G.-H., Vajkoczy, P., & Schmidt, H. (2022). A noninvasive method to quantify the impairment of spinal motion ability in Parkinson's disease. *European Spine Journal, 31*(12), 3316–3323. https://doi.org/10.1007/s00586-022-07401-w

Sternad, D., Abe, M. O., Hu, X., & Müller, H. (2011). Neuromotor noise, error tolerance and velocity-dependent costs in skilled performance. *PLOS Computational Biology, 7*(9), Article e1002159. https://doi.org/10.1371/journal.pcbi.1002159

Vidal, P.-P., & Lacquaniti, F. (2021). Perceptual-motor styles. *Experimental Brain Research, 239*(5), 1359–1380. https://doi.org/10.1007/s00221-021-06049-0

Villalonga, M. B., & Sekuler, R. (2023). Keep your finger on the pulse: Better rate perception and gap detection with vibrotactile compared to visual stimuli. *Attention, Perception, & Psychophysics, 85*(6), 2004–2017. https://doi.org/10.3758/s13414-023-02736-y

Villalonga, M. B., Noyce, A. L., & Sekuler, R. (2025). Dynamic modulation of spatial selection: Online and anticipatory adjustments in the flanker task. *Attention, Perception, & Psychophysics, 87*(3), 794–814. https://doi.org/10.3758/s13414-025-03026-5

Visser, Y. F., Medendorp, W. P., & Selen, L. P. J. (2025). Corticomuscular and intermuscular coherence during evidence accumulation in sensorimotor decision-making. *Physiological Reports, 13*(6), Article e70237. https://doi.org/10.14814/phy2.70237

Wong, A. L., & Haith, A. M. (2017). Motor planning flexibly optimizes performance under uncertainty about task goals. *Nature Communications, 8*, Article 14624. https://doi.org/10.1038/ncomms14624

Xiang, L., Wang, A., Gu, Y., Zhao, L., Shim, V., & Fernandez, J. (2022). Recent machine learning progress in lower limb running biomechanics with wearable technology: A systematic review. *Frontiers in Neurorobotics, 16*, Article 913052. https://doi.org/10.3389/fnbot.2022.913052

Zadid, T. H., Tanim, S. A., & Mridha, M. F. (2025). A dataset of exocentric images capturing hand gestures in multiplayer games. *Data in Brief, 63*, Article 112182. https://doi.org/10.1016/j.dib.2025.112182

Zhan, W., Ke, Z., Wang, C., Pan, Y., Sun, Y., & Yin, X. (2025). Application of the Deeplabcut for the analysis and study on the crawling behavior of *Henosepilachna vigintioctopunctata* (Fabricius). *IEEE Access, 13*, 44024–44040. https://doi.org/10.1109/ACCESS.2025.3543311

Zhang, H., Xiong, G., Cai, S., & Wu, S. (2024). A causal role of right temporoparietal junction in prosocial learning: A transcranial direct current stimulation study. *Neuroscience, 538*, 59–67. https://doi.org/10.1016/j.neuroscience.2023.12.008