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Beyond error reduction: Dimensional analysis reveals qualitative differences in motor expertise

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A R T I C L E I N F O

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A B S T R A C T

This study explores how motor expertise transforms across spatial dimensions. Three hundred data points were collected from twenty participants (ten experts and ten novices) who performed identical tasks across one-dimensional (1D) linear accuracy, two-dimensional (2D) planar precision, and three-dimensional (3D) angular coordination, captured by custom-built motion capture as participants executed strokes toward a suspended ball. The results revealed a progressive pattern of expertise effects. In 1D, experts showed moderately lower error; in 2D, the advantage became more pronounced; and in 3D, a qualitative difference emerged, as experts exploited larger movement angles while maintaining greater consistency. Dynamical systems analysis confirmed this distinction, with experts developing stable coordination patterns and novices exhibiting unstable ones. These findings extend traditional conceptualizations of expertise by showing that advanced skill transcends error reduction and involves the strategic organization of movement variability, providing a foundation for complexity-specific training protocols.

1. Introduction

Understanding how expertise develops remains a central concern in human performance research. Ericsson's influential theory emphasizes that expertise emerges through deliberate practice, defined as structured activities designed to improve specific performance aspects (Ericsson & Pool, 2016; Macnamara & Maitra, 2019). Expert–novice comparison studies consistently demonstrate that experts outperform novices across diverse domains. They execute actions more accurately, respond faster to task-relevant information, and maintain consistency under varying conditions (Musculus & Lobinger, 2018; Runswick et al., 2022; Williams & Ford, 2024).

1.1. Nature of motor expertise and measurement challenges

Although conventional assessments show that experts produce smaller errors, they provide limited insight into whether experts and novices organize movements fundamentally differently or simply execute similar strategies with greater precision (Buszard et al., 2020). Bernstein's (1967) degree-of-freedom problem suggests that skill acquisition requires the ability to coordinate redundant movement possibilities into functional synergies. The contemporary dynamical systems approach proposes that experts develop stable coordination patterns rather than simply reducing variability (Button et al., 2020). However, empirical evidence for qualitative organizational differences remains limited, partly because of methodological constraints in measuring expertise (Komar et al., 2019).

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A critical limitation in expertise research is the predominant reliance on single-dimensional performance measures. Most studies evaluate expertise through individual outcome indicators such as accuracy or error magnitude, which capture only one aspect of performance (Cañal-Bruland & Mann, 2015). Although these values effectively quantify performance differences, they may obscure qualitative differences in how movements are organized and executed (Hristovski et al., 2011). If experts and novices achieve similar outcomes through fundamentally different coordination strategies, single-variable assessments would fail to detect these organizational differences.

This limitation is particularly problematic for complex motor skills involving multiple spatial scales. Reducing movement to a single score discards information about trajectory characteristics, coordination patterns, and movement variability exploitation (Davids et al., 2003; Seifert et al., 2013). A systematic approach for examining whether expertise manifests differently across spatial complexity levels, from simple linear control to full three-dimensional organization, is lacking. Addressing this gap requires multiscale analyses that capture both quantitative improvements and qualitative changes in movement organization.

1.2. Dimensional analysis as an information-processing aspect

Multiscale spatial analysis is a foundational methodological approach in scientific research that enables systematic evaluation and classification of data based on spatial attributes and inherent complexity (Wagner et al., 2011). Researchers can strategically tailor data collection procedures, analytical models, visualization techniques, and interpretive strategies to align with the complexity of observed phenomena. This tailoring is achieved by conceptualizing the hierarchical structure of data, such as one-dimensional (1D), two-dimensional (2D), or three-dimensional (3D) representations (Davamani et al., 2024). Such that integrated complexity considerations guide methodological rigor and enhance the validity of the resulting conclusions (Harrison, Reilly, & Creswell, 2020), identifying appropriate statistical models, performance indices, and inferential strategies.

From an information-processing perspective, hierarchical spatial analysis offers a mechanical principle for complexity management in human performance systems. By systematically decomposing multidimensional behavior into constituent levels (1D→2D→3D), researchers can examine how different information-processing demands emerge as task complexity increases. This progressive approach parallels established principles in computational systems: simple features are processed before complex patterns and hierarchical decomposition exposes organizational structures that aggregate measures obscure (Marr, 1982; Patel et al., 2022). Applied to expertise research, this logic enables distinction between consistent effects across complexity levels (quantitative scaling) and qualitative transitions at higher spatial scales that suggest fundamental reorganization of information-processing strategies. This way also aligns with reduction principles in adaptive systems, where hierarchical feature representation enables efficient processing of high-dimensional data (Newell & Liu, 2014).

Multiscale analysis principles apply across diverse computational and behavioral domains, whereas motor control provides a particularly tractable empirical context for demonstrating methodological utility. Human movement studies offer particularly illustrative applications of spatial progression analysis (Winter, 2009). Kinematic data are frequently categorized according to their spatial characteristics, which influence the methodological tools used in behavioral neuroscience, biomechanics, robotics, and sports sciences (Bartlett, Wheat, & Robins, 2007; Stergiou, 2016). In 1D analyses, tracking linear motion along an axis might involve examining positional data over time to identify deviations from a target or an ideal trajectory (Henry, 1953; Newell, Liu, & Mayer-Kress, 2001). In 2D contexts requiring planar accuracy or coordination, researchers apply measures that concurrently consider lateral and vertical deviations. Such measures offer a comprehensive view of skill execution and control strategies (Glazier, 2017; Latash, 2008). In more complex scenarios involving whole-body movements in athletic, rehabilitative, or ergonomic contexts, 3D motion capture enables the analysis of intricate joint–coordination patterns. Such analysis yields insights into motor synergies, skill acquisition, and injury prevention (Federolf et al., 2014; Roberts et al., 2014). Furthermore, direct comparisons across 1D, 2D, and 3D levels within the same experimental setting remain novel. Such comparisons highlight how each additional layer of complexity can uniquely influence accuracy and coordination, moving beyond the conventional treatment of spatial scale as a methodological tool (Kulik et al., 2020).

1.3. Research gap and analytical challenges

The selection of error indices appropriate for spatial complexity is critical for movement analysis. Traditional 1D measures such as absolute error (AE) and constant error (Schmidt & Lee, 2011) quantify deviations along a single axis, yielding straightforward performance indicators. However, multidimensional movement requires more comprehensive assessment approaches. For 2D and 3D tasks, indices such as the radial error (RE) and mean radial error (MRE) integrate positional variance across multiple axes, capturing the complexity of spatial coordination (Stergiou & Decker, 2011). These complexity-matched indices enable researchers to align analytical precision with task demands (Latash, 2010).

Researchers increasingly seek to understand complex human system interactions in motor control and biomechanics. To support this research, recent analytical advancements have emerged to address common methodological challenges (Manakitsa et al., 2024). These advances offer new solutions for data scarcity, class imbalances, and the need for controlled experimental conditions, which are persistent issues in movement science. For example, probabilistic diffusion models simulate realistic multivariate time series data derived from inertial measurement units. This enables researchers to augment limited datasets and improve the statistical power of their analyses (Llauradó Crespo, 2024). In addition, machine learning has been integrated with synthetic data approaches to enhance signal processing, motion classification, and error quantification in tasks spanning multiple complexity scales (Chen et al., 2021). These integrative methodologies streamline analyses and offer scalable solutions for studying human movement in diverse contexts, from clinical rehabilitation to elite athletic performance, by simulating various movement patterns and environmental conditions

(Vinciarelli et al., 2015).

Within information systems research, these computational advances provide powerful pattern recognition capabilities. However, they lack systematic principles for interpreting how information-processing demands scale with spatial complexity. Despite these advancements, a significant gap remains in the absence of a unified analytical structure that systematically examines how performance characteristics change across complexity levels. Although studies have individually addressed specific dimensional contexts, only a few have explicitly compared the same movement behaviors across 1D, 2D, and 3D analyses within a single experimental paradigm (Kulik et al., 2020). This omission limits the understanding of how expertise manifests differently depending on task complexity (Aguilar et al., 2016). Furthermore, guidance on selecting complexity-appropriate analytical tools that can detect qualitative differences in movement strategies rather than merely quantifying error magnitudes is limited (Tolk, Harper, & Mustafee, 2021). Table tennis provides a particularly suitable empirical context for addressing this gap. A single racket swing toward a suspended ball generates measurable data simultaneously across three analytical levels: linear accuracy along the contact axis, planar precision across horizontal and vertical planes, and angular coordination captured through continuous upper-limb kinematics (Bootsma & van Wieringen, 1990; Sheppard & Li, 2007). This synchronized data acquisition from identical movement events enables direct cross-dimensional comparisons, offering a tractable model for examining whether expertise effects transform qualitatively as spatial complexity increases.

1.4. Study objectives and contributions

Therefore, this study proposes a unified analytical design that systematically incorporates spatial complexity into the selection of error indices and modeling strategies (Figure 1, top row). This principle aligns with the interpretation of movement and performance data across multiple domains (Da'u & Salim, 2020).

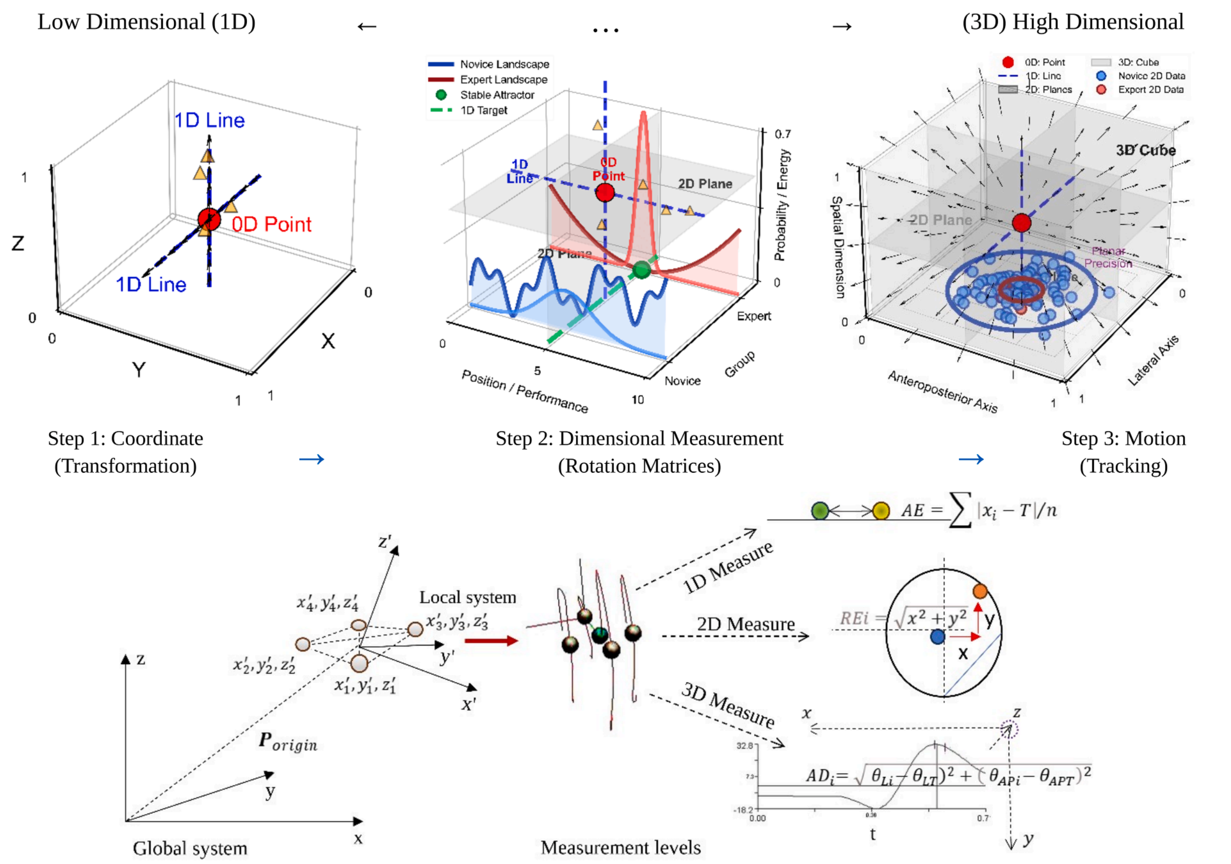

Fig. 1. Conceptual framework and measurement system for dimensional analysis of motor expertise. Top row: Dimensional progression across spatial complexity: Left, three-dimensional coordinate system with 0D point (red) and 1D lines (blue dashed); Middle, energy landscape integrating 2D plane with novice pattern (blue, multiple shallow wells) versus expert pattern (red, single deep well with stable attractor); Right, complete 3D cube with integrated dimensional elements and base-plane precision patterns showing novice scatter (blue, wider ellipse) versus expert scatter (red, tighter ellipse). The progression illustrates expertise transitions from fundamental dimensional elements through energy optimization to integrated spatial organization. Bottom row: Coordinate transformation and measurement system: Left, relationship between local (x', y', z') and global system (x, y, z) coordinate systems via position vector (P_{origin}) and rotation matrix R; Middle, three measurement complexity levels (1D, 2D, 3D) used in the experimental protocol (see Appendix A); Right, fundamental rotation matrices R_x, R_y, and R_z combined into the transformation equation $P_{global} = R \cdot P_{local} + P_{origin}$, for rigid body motion tracking.

The proposed structure was evaluated by comparing the performances of novice and expert participants in tasks involving 1D, 2D, and 3D measurements. Under 1D conditions, the AE quantifies the linear deviations (Park & Kim, 2014). In a 2D context, RE captures planar discrepancies, reflecting the complexity of controlling performance in two spatial planes (Chiari et al., 2005). The 3D condition incorporates kinesthetic features, evaluating participants' movement angles along the lateral and anteroposterior axes, thereby illuminating how expertise influences performance accuracy when navigating complex spatial demands (Jeffery et al., 2013). This multilevel approach validates the theoretical underpinnings of the proposed conceptual idea and demonstrates its application in understanding the influence of various complexity scales on error structures and learning processes.

By unifying these analytical strategies under coherent spatial progression, this study advances methodologies in diverse fields, including motor control, biomechanics, robotics, and human−computer interaction (Padilla, 2023). It promotes the adoption of standardized complexity-specific indices that enable cross-study comparisons, foster interdisciplinary collaboration, and drive innovation in the analysis of complex system behaviors (Halilaj et al., 2018). For the information processing and management community, this study offers a transferable methodological principle of systematic dimensional decomposition as a tool for complexity management. Similar to how aggregate motor performance measures obscure qualitative organizational differences that emerge at higher spatial scales, aggregate evaluation in information systems can mask complexity-dependent patterns in how users process and interact with data (Marr, 1982; Patel et al., 2022). Our empirical evidence that experts reorganize behavior qualitatively when spatial demands increase has direct implications for adaptive interfaces, multidimensional data visualization, and interactive systems that require cross-scale information coordination (De Giorgis, Gangemi, & Russo, 2025; Ikhwantri et al., 2023). By grounding this principle in rigorous motor control experimentation, the present study provides an empirically validated case for dimensional analysis as a general-purpose diagnostic tool applicable to the broader study of human performance in complex information environments.

1.5. Research objectives

Based on the gaps identified in the dimensional analysis of motor expertise, this study addresses the following objectives:

- Examine whether expertise effects strengthen progressively across 1D, 2D, and 3D movement dimensions and identify where qualitative organizational differences emerge.
- Develop dimension-appropriate measurements that distinguish quantitative accuracy improvements from qualitative changes in movement organization.
- Establish practical implications for training protocols, rehabilitation approaches, and human–computer interaction design.

By simultaneously measuring the same movement behavior across 1D (linear), 2D (planar), and 3D (angular) levels, this study provides direct cross-dimensional comparisons that are absent from existing motor control research. The five figures support this progressive analysis, from conceptual foundations (Figure 1) through empirical comparisons (Figure 2), three-dimensional spatial organization (Figure 3), and dynamical systems analysis (Figure 4) to the integrated dimensional progression principle $C \propto D$ (Figure 5).

2. Methods

We employed a comparative experimental design with two participant groups (experts and novices) performing identical motor tasks. The performance was assessed across three analytical models: one-dimensional (1D) linear accuracy, two-dimensional (2D) planar precision, and three-dimensional (3D) angular coordination (Schmidt et al., 2018). To ensure clarity, we distinguished between related variability terms used throughout this study: movement variability (general variation in execution), functional variability (adaptive variation supporting task goals), trajectory variability (angular consistency quantified as CV%), and variable error (statistical consistency measure). These distinctions are essential because experts simultaneously exhibit high functional variability while maintaining low trajectory variability. This pattern distinguishes qualitative movement organization from simple error reduction. The complete operational definitions are presented in Appendix I.

2.1. Participants

Twenty participants were recruited and divided equally into novice and expert groups based on verified expertise criteria. The expert group ($N = 10$; mean age = 26.1 years, standard deviation (SD) = 4.2) comprised professional table tennis players who were active Korea National League participants and officially registered members of the Korean Table Tennis Association. All expert participants engaged in structured daily training and competed regularly in officially sanctioned tournaments, with a minimum of 7 years of competitive experience (range: 7–15 years). These professionals have been previously recognized for their exceptional standing as elite athletes within the national competitive structure (Baker & Young, 2014; Ericsson, Krampe, & Tesch-Römer, 1993). The novice group ($N = 10$; mean age = 25.3 years, $SD = 3.8$) had neither prior technical instruction nor organized training experience in table tennis. This ensured clear group separation, which is consistent with the established expert–novice comparison methodology in motor control research (Musculus & Lobinger, 2018; Williams & Ford, 2024). All participants had normal or corrected-to-normal vision and no musculoskeletal impairments that would affect task performance.

2.2. Experimental design

Each participant performed a standardized racket–ball contact task. A ball was suspended by a thread at a fixed height (1.5 m from the floor; 30 cm from the racket), and participants executed racket swings following a metronome beat (see Appendix A for details). The racket (standard table tennis racket, 85 g) was instrumented with reflective markers to track position and orientation throughout the movement. The participants were instructed to make contact with the ball accurately, prioritizing precision over power. This task generated synchronized data across all three measurement levels from a single movement execution.

Three analytical measurements were extracted from each task execution (Figure 1): (i) 1D measurement, participants estimated the linear distance representing their point of ball contact along the anterior−posterior axis. No feedback was provided. (ii) In the 2D measurement, participants used a computer cursor to indicate the planar coordinates of ball contact on a screen display, matching randomly generated target positions in the horizontal and vertical planes. (iii) In the 3D measurement, upper-limb kinematics, including angular displacement along the lateral and anteroposterior axes, were recorded via motion capture throughout the entire movement sequence. Reflective markers placed at standard anatomical landmarks were tracked via a Vicon motion capture system (Vicon Motion Systems, UK) throughout each movement. The complete swing trajectory was recorded, enabling the extraction of 1D (linear distance), 2D (planar coordinates), and 3D (angular kinematics) data from the same movement execution. The participants completed five trials without feedback. The measurements were analyzed in order of increasing spatial complexity (1D, 2D, and 3D).

2.3. Dimensional data integration

To ensure that all three analytical measurements are derived from identical task executions, we developed an integrated data-acquisition system that synchronizes motion capture recordings with participants' perceptual estimates. For each trial, as the participants executed the racket swing to hit the ball, the system simultaneously carried out the following: (1) recorded the linear distance of contact for 1D analysis, (2) captured the planar coordinates of contact in the horizontal and vertical planes for 2D analysis, and (3) tracked the full angular kinematics of the arm and racket throughout the entire movement for 3D analysis (Figure 1, bottom row). This synchronization was achieved through a custom software interface (MotionSync v2.3) that time-stamped all the data streams and aligned them to the moment of ball contact. The system's temporal resolution (1000 Hz sampling rate) ensured that the discrete contact point used for 1D and 2D analyses was precisely embedded within the continuous 3D trajectory, allowing us to examine the same movement at different levels of dimensional complexity. This approach eliminated potential confounds from task variation and provided direct comparability across the dimensional measurements (Table 1).

2.3.1. Dataset characteristics

The dataset comprised motion capture recordings and performance measurements from 20 participants (10 experts and 10 novices). Each participant completed five trials per analytical task, yielding 300 data points (5 trials × 10 participants × 2 groups × 3 measurements) (see Appendix B). Expertise verification occurred through the documented performance history and professional credentials Section 2.1, which confirmed significant differences between the novice and expert groups. Motion capture data were recorded via a Vicon system (Vicon Motion Systems, UK) at a sampling rate of 1000 Hz throughout the entire movement cycle for each trial, as specified in Section 2.3. Reflective markers placed at standardized anatomical landmarks tracked upper-limb kinematics as participants performed the racket–ball contact task. For the 1D and 2D components, the system extracted the moment of ball contact with precise temporal resolution, allowing accurate measurement of the position at impact. For 3D analysis, continuous angle–time data were filtered via a fourth-order Butterworth low-pass filter with a 10 Hz cutoff frequency to remove measurement noise while preserving the movement characteristics, which is consistent with the processing detailed in Appendix F.

The data preprocessing included outlier identification and removal according to standard kinematic analysis protocols, maintaining data integrity while preserving the maximum number of valid trials. Reliability analyses via Cronbach's alpha confirmed high measurement consistency across all three measurement dimensions, with values exceeding the 0.80 threshold considered acceptable, as specified in Section 3.4. This confirmed the stability and repeatability of our data collection protocol across all participants and conditions. The dataset is structured hierarchically, with individual trials nested within participants, grouped by expertise level, and containing synchronized measurements across the three-dimensional progressions. This structure enabled direct comparisons of the same movement events across different tasks while maintaining the independence of observations for statistical analysis. The integrated data-acquisition system (MotionSync v2.3) ensured temporal alignment of all measurements to the moment of ball contact, as described in Section 2.3, allowing direct cross-dimensional comparisons of the same physical events.

Table 1
Study procedures and data collection.

Task	Procedure	Data Collected	Units
1D Measurement	Estimate contact point displayed on screen	Estimated absolute error size	Lengths
2D Measurement	Estimate contact point to targets on screen	Estimated radial error size	Coordinates X, Y
3D Measurement	Prescribe movement sequence with motion capture	Self-produced movement angles	Angular deviation

Note. Each measurement (1D, 2D, and 3D) was derived from the same racket–ball contact task. X and Y denote the horizontal and vertical screen coordinates, respectively.

2.4. Apparatus and procedures

Apparatus: The equipment and materials were carefully selected for accuracy and reliability across all the tasks. Standardized computer software displayed lines of fixed length to the participants in the 1D task, maintaining consistency across trials by presenting lines of identical length without variations. Custom-developed spatial tracking software enabled precise coordinate recording within a 2D plane for planar analysis. The interface was designed to record accurately, capturing their ability to navigate randomized target coordinates on the screen. A motion capture setup comprising reflective markers and an array of cameras strategically positioned to capture movements from multiple angles was used for the 3D task. This system records kinematic data with high precision, allowing for a detailed analysis of the participants' movement angles along the specified axes. Data recording was automated across all tasks, minimizing human error and maintaining the accuracy and reliability of the measurements. Procedures: The participants participated in a single testing session under standardized conditions. The study objectives and procedures were explained at the beginning of the session. The equipment was calibrated before each session for measurement accuracy. For the 1D and 2D measurements, calibration verified that the visual displays corresponded to the physical measurements. For 3D measurement, the motion capture system underwent standardized wand calibration following the manufacturer's protocols for spatial coordinate and angular measurement precision across all the sessions (see Appendix B for more details of the data collection).

2.5. Ethical considerations

This study was conducted in accordance with the Declaration of Helsinki and approved by the Seoul National University Institutional Review Board (SNUIRB No. 1509/002–002; Report ID: 20481572). After receiving comprehensive information about the study's purpose, procedures, potential risks, and their rights, all the participants provided written informed consent. The consent process included an explanation of motion captures and data usage, confirmation of the right to withdraw at any time without penalty, and a description of confidentiality protections. Participant data were anonymized via coded identifiers (E1–E10 for experts, N1–N10 for novices) to protect privacy. Raw motion capture files were stored on secure, password-protected servers accessible only to the research team. No personally identifiable information appeared in the published materials. The experimental task posed minimal physical risk, involving standard racket swing motions similar to routine table tennis practice. The participants could request breaks at any time. No adverse events occurred during data collection. The authors declare that they have no conflicts of interest related to this research.

3. Data analysis

To clarify the analytical workflow, each racket swing simultaneously generated the following three data streams from the same physical movement. (1) Linear contact distance for 1D accuracy analysis, (2) planar contact coordinates for 2D precision analysis, and (3) continuous angular kinematics for 3D coordinate analysis (see Figure 1). This synchronized extraction, achieved through the integrated data-acquisition system described in Section 2.3, ensures that all cross-dimensional comparisons reflect identical movement events rather than separate task executions. The following subsections detail the specific calculations applied to each data stream.

3.1. One-dimensional calculation

Accuracy and consistency were quantified via the following indices (Stemler, 2019):

$$AE = \frac{1}{n}\sum_{i=1}^{n}|x_i - T| \tag{1}$$

where x_i is the participant's estimation, T is the true length, and n is the number of trials. AE measures how close the observed values are to the true values, reflecting the accuracy of the overall performance.

$$VE_{1D} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - M)^2} \tag{2}$$

where M is the mean of the participants' estimates. VE_{1D} measures the variability of observations around the mean, representing consistency.

3.2. Two-dimensional calculation

The spatial accuracy and consistency in the 2D task (Put et al., 2014) were assessed via RE, which is calculated as follows:

$$RE_i = \sqrt{x^2 + y^2} = \sqrt{(x_i - x_T)^2 + (y_i - y_T)^2} \tag{3}$$

where $(x_i,\ y_i)$ is the point at which the participant reached and $(x_T,\ y_T)$ denotes the target point.

The MRE was calculated as follows:

$$MRE = \frac{1}{n}\sum_{i=1}^{n} RE_i \tag{4}$$

The SRE is given by

$$SRE = \sqrt{(x_c - x_T)^2 + (y_c - y_T)^2} \tag{5}$$

where $(x_c,\ y_c)$ represents the centroid coordinates of the points reached by the participants. Finally, VE_{2D} was calculated as follows:

$$VE_{2D} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[(x_i - x_c)^2 + (y_i - y_c)^2\right]} \tag{6}$$

3.3. Three-dimensional calculation

The 3D measurements focused on the angular accuracy and consistency of participants' movements (Van der Kruk & Reijne, 2018). AD was calculated as

$$AD_i = \sqrt{(\theta_{Li} - \ \theta_{LT})^2 + (\ \theta_{APi} - \ \theta_{APT})^2} \tag{7}$$

where $(\ \theta_{Li},\ \theta_{LT})$ represents the angles measured by the participants along the lateral and anteroposterior axes and $(\ \theta_{APi},\ \theta_{APT})$ represents the target angles.

The MAD was calculated as follows:

$$MAD = \frac{1}{n}\sum_{i=1}^{n} AD_i \tag{8}$$

The angular deviation consistency (VE_{3D}) was then calculated as follows:

$$VE_{3D} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\theta_{Li} - \ \theta_{Lc})^2 + (\theta_{APi} - \theta_{APc})^2} \tag{9}$$

where $(\ \theta_{APi},\ \theta_{APT})$ represents the mean angle across trials.

3.4. Statistical analysis

All analyses were conducted using IBM SPSS Statistics (version 18). The data were screened for normality (Shapiro–Wilk test) and homogeneity of variance (Levene's test). Measurement reliability was assessed using Cronbach's alpha for each analytical measurement, with values above 0.80 considered acceptable for internal consistency.

Independent sample t tests compared novice and expert groups within each analysis at a significance level of $p < 0.05$. Effect sizes (Cohen's d) quantified the magnitude of group differences. Repeated-measures ANOVA was used to examine the interaction effects of skill level (novice vs. expert) and analytical complexity (1D, 2D, and 3D) on performance indices. Where assumptions were violated, appropriate adjustments or nonparametric tests were applied.

4. Results

Comparisons of performance between expert and novice participants were conducted across three analytical processes. Table 2 presents descriptive statistics and inferential test results for one-dimensional (1D) AE, two-dimensional (2D) RE, and three-dimensional (3D) angular measurements.

Table 2
Average 1D, 2D, and 3D values and standard deviations for novices and experts.

Measurement	Absolute Error (1D)		Radial Error (2D)		Angle Degree (3D)	
	Experts	Novices	Experts	Novices	Experts	Novices
M	2.52	3.14	2.13	4.19	14.14	5.80
SD	1.27	1.52	0.96	2.09	6.55	9.66
t(18)	2.13, $p < 0.05$*		3.42, $p < 0.01$**		4.52, $p < 0.001$**	

* $p < 0.05$, ** $p < 0.01$; *M* = mean; *SD* = standard deviation; *t* = *t* value; 1D = one-dimensional analysis; 2D = two-dimensional analysis; 3D = three-dimensional analysis (see Appendix B for the dataset).

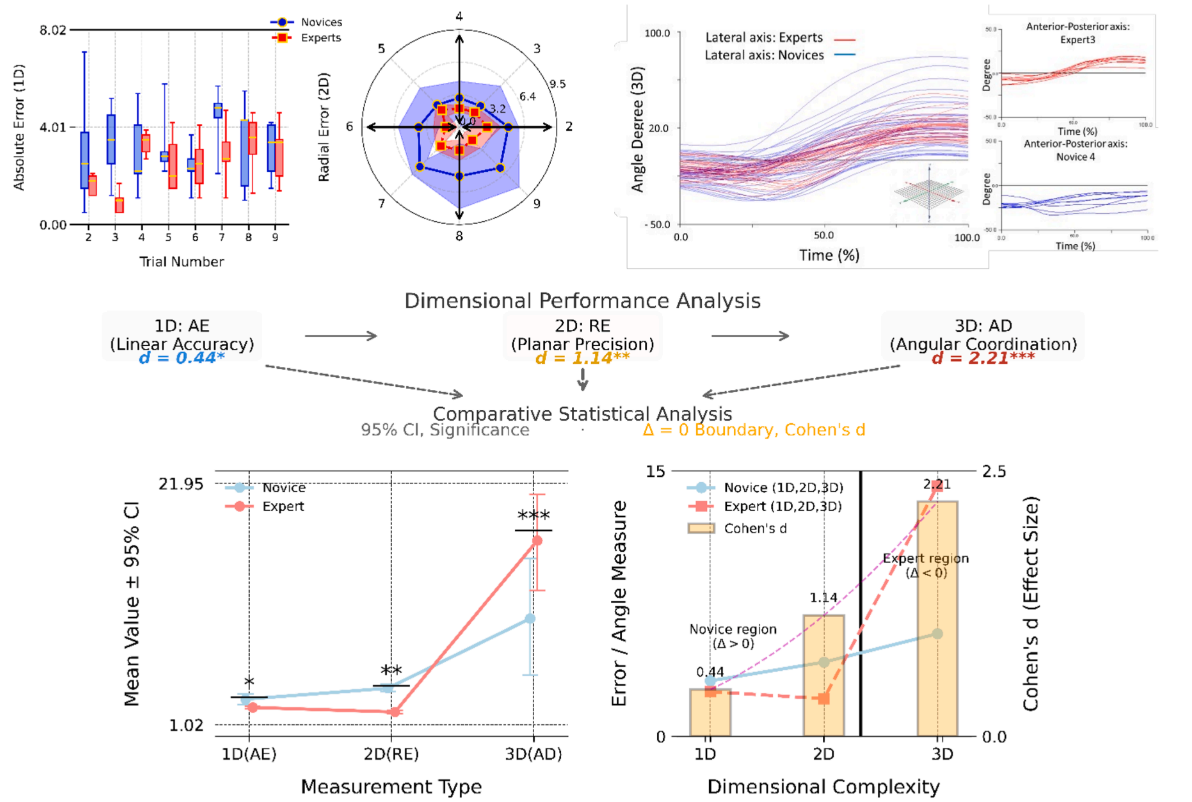

Fig. 2. Performance comparisons across trials in 1D AE, 2D RE, and 3D angle degree measurements. Upper panels: (Left) Mean AE with SD error bars for novices (blue) and experts (red) over trials. (Middle) Polar plot of mean RE with shaded SD areas across trials. (Right) Kinesthetic features profile in 3D, illustrating lateral and anterior-posterior axis racket angle trajectories throughout the movement cycle, where experts (red) demonstrate larger angular excursions with reduced variability, particularly during the impact phase (70–80% of movement time). Flowchart: Dimensional performance analysis connecting raw measurements across three analytical levels (1D: Linear Accuracy, 2D: Planar Precision, 3D: Angular Coordination) to comparative statistical analysis, with effect sizes ($d = 0.44, 1.14, 2.21$) annotated at each level and increasing arrow thickness illustrating the progressive strengthening of expertise effects across dimensional complexity. Bottom panels: (Left) Statistical comparison across 1D(AE), 2D(RE), and 3D(AD) with 95% confidence intervals for novices (light blue) and experts (light coral), with significance levels marked by asterisks (*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). (Right) Phase-like diagram with black boundary ($\Delta = 0$) separating novice-favored from expert-favored regions; orange bars on right y-axis show Cohen's d effect sizes (0.44, 1.14, 2.21) with quadratic fit line (dashed magenta), demonstrating progressive increase in expertise effects across dimensional complexity.

The performance patterns across all three analyses are presented in Figure 2. The upper panels show group differences in one-dimensional (left), two-dimensional (middle), and three-dimensional (right) measurements, with error bars representing 95% confidence intervals. The bottom panel shows increasing separation between groups from one-dimensional ($d = 0.44$, $p < 0.05$) to two-dimensional ($d = 1.14$, $p < 0.01$) to three-dimensional ($d = 2.21$, $p < 0.001$) analyses.

4.1. One-dimensional analysis: linear accuracy

The AE in the one-dimensional analysis differed significantly between groups (see Appendix C for calculation details). Novices produced a greater mean AE ($M = 3.14$, $SD = 1.52$) than experts did ($M = 2.52$, $SD = 1.27$), $t(18) = 2.13$, $p < 0.05$, $d = 0.44$. Novices also exhibited greater variability across trials ($SD = 1.52$) than experts did ($SD = 1.27$), indicating less consistency in linear accuracy performance.

4.2. Two-dimensional analysis: planar precision

The RE in the two-dimensional analysis revealed larger group differences than those observed in the one-dimensional measurements (see Appendix D for calculation details). The experts produced a lower mean RE ($M = 2.13$, $SD = 0.96$) than the novices did ($M = 4.19$, $SD = 2.09$), $t(18) = 3.42$, $p < 0.01$, $d = 1.14$. Compared with the novices ($SD = 2.09$), the experts also demonstrated markedly lower variability ($SD = 0.96$), indicating a large difference in standard deviation. The effect size for two-dimensional analysis ($d = 1.14$) exceeded that of one-dimensional analysis ($d = 0.44$), and the significance level increased from $p < 0.05$ to $p < 0.01$.

4.3. Three-dimensional analysis: angular coordination

Three-dimensional analysis was used to examine angular kinematics throughout the complete movement cycle, yielding distinct patterns across multiple kinematic parameters.

4.3.1. AD patterns

Three-dimensional angular measurements revealed the greatest group differences (see Appendix E for calculation details). The experts produced greater mean angles ($M = 14.14°$, $SD = 6.55°$) than the novices did ($M = 5.80°$, $SD = 9.66°$), $t(18) = 4.52$, $p < 0.001$, $d = 2.21$. Notably, the experts presented both higher mean values and lower variability ($SD = 6.55°$) than the novices did ($SD = 9.66°$), a pattern differing from the one- and two-dimensional analyses where the experts presented lower means with lower variability. The effect size for three-dimensional analysis ($d = 2.21$) substantially exceeded those for two-dimensional ($d = 1.14$) and one-dimensional ($d = 0.44$) analyses.

Table 3
Kinematic features of racket angle trajectories for experts and novices.

Trajectory Features	Experts (n =10)	Novices (n =10)	t(18)	p values	Cohen'sd
Maximum angle (°)	32.86 ± 5.27	21.39 ± 7.83	3.98	<.001**	1.78
Minimum angle (°)	-7.52 ± 3.14	-11.94 ± 4.36	2.72	.014*	1.22
Angular range (°)	40.38 ± 6.83	33.33 ± 9.57	2.15	.046*	0.96
Angular velocity (°/s)	65.23 ± 12.41	57.85 ± 18.76	1.19	.249	0.53
Time to peak angle (% of movement)	72.64 ± 4.93	68.17 ± 9.82	1.38	.187	0.61
Trajectory variability (CV %)	16.25 ± 4.86	28.73 ± 7.15	4.94	<.001**	2.21

* $p < 0.05$, ** $p < 0.01$; CV = coefficient of variation, representing the relative standard deviation of the angles throughout the movement trajectory. (see the terminology paragraph at the beginning of Section 2 and Appendix F for calculation details).

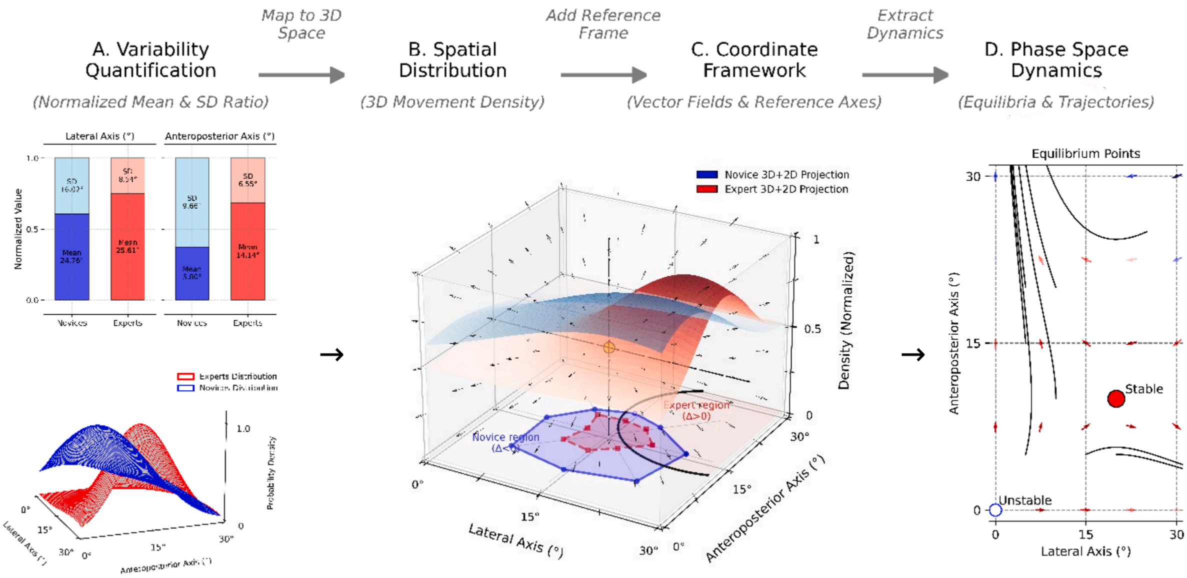

Fig. 3. Advanced comparison of novice and expert performance in 3D data collection. The top flowchart illustrates the analytical progression from variability quantification (A) through spatial distribution mapping (B) and coordinate framework establishment (C) to phase space dynamics extraction (D). Upper-left: Normalized mean and SD of racket angles for novices and experts along the lateral and anteroposterior axes. Each bar represents a group (novices or experts) and is divided into two segments. The lower and upper segments indicate the normalized mean racket angle and the normalized SD, with values annotated directly on the bars. Novices have a larger SD, indicating greater variability compared to experts, especially along the lateral axis. Lower-left: Movement angle distributions for experts (red surface) and novices (blue surface), illustrating spatial density patterns in 3D space. Middle: Coordinate reference including a central point, vector fields along the x-axis and y-axis, a semi-transparent plane at $z = 0.5$, and a surrounding cube. The thin black arrows forming a radial vector field represent movement directions. Experts' distributions are more concentrated, suggesting greater precision and consistency in their movements compared to novices. 2D polar projection at base ($z \approx 0$) shows; novice trajectory (blue circles with solid line), expert trajectory (red squares with dashed line). Right: Phase diagram illustrating the dynamical system of the lateral and anteroposterior axes. The slope field depicts the direction and magnitude of changes in racket angles, while the trajectories represent the evolution of racket angles from various initial conditions. Equilibrium points are marked, with the origin (0,0) identified as an unstable equilibrium and the point (20,10) as a stable equilibrium, highlighting the system's tendency towards a steady-state configuration in expert performance.

4.3.2. *Kinematic trajectory features*

Table 3 presents the kinematic parameters extracted from the racket angle trajectories throughout the movement cycle. Six parameters characterize the temporal and spatial aspects of movement execution.

Significant group differences emerged for four of the six kinematic parameters. The experts produced larger maximum angles ($M =$ 32.86°, $SD =$ 5.27°) than the novices did ($M =$ 21.39°, $SD =$ 7.83°), $t(18) = 3.98$, $p < 0.001$, $d = 1.78$, and, correspondingly, larger angular ranges ($M =$ 40.38°, $SD =$ 6.83° vs. $M =$ 33.33°, $SD =$ 9.57°), $t(18) = 2.15$, $p = .046$, $d = 0.96$. The experts presented lower trajectory variability ($CV =$ 16.25%, $SD =$ 4.86%) than the novices did ($CV =$ 28.73%, $SD =$ 7.15%), $t(18) = 4.94$, $p < 0.001$, $d = 2.21$. The minimum angles also differed significantly, with experts showing less-negative values ($M =$ -7.52°, $SD =$ 3.14°) than the novices ($M =$ -11.94°, $SD =$ 4.36°), $t(18) = 2.72$, $p = .014$, and $d = 1.22$. By contrast, no significant group differences emerged for angular velocity, $t(18) = 1.19$, $p = .249$, $d = 0.53$, or time to peak angle, $t(18) = 1.38$, $p = .187$, $d = 0.61$.

4.3.3. *Movement spatial organization*

The spatial distributions and phase space analysis of three-dimensional movements are presented in Figure 3. The normalized comparison (upper left panel) shows that the experts produced larger mean angles with smaller proportional variability along the

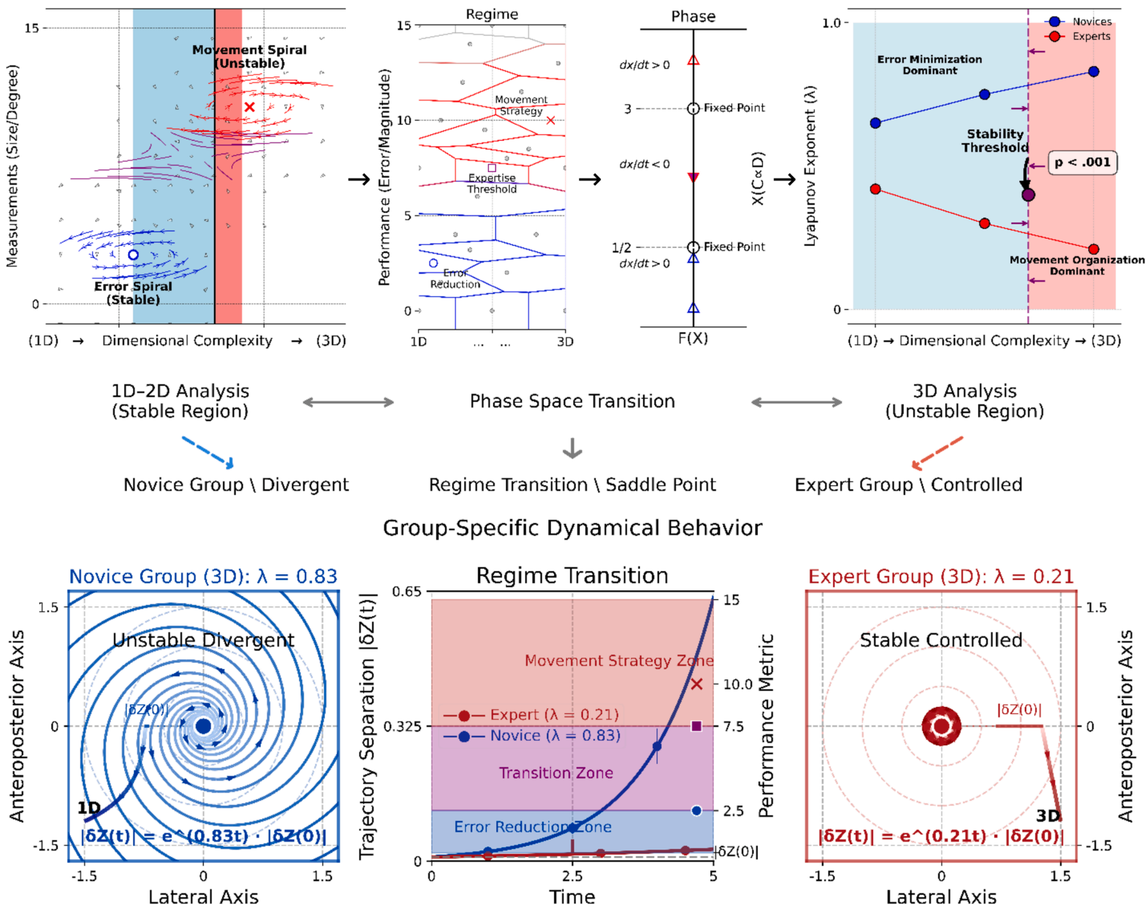

Fig. 4. Dynamical systems analysis of expertise across dimensions. Upper set: (Left) Phase diagram showing flow fields across 1D–3D complexity, with blue region (stable spiral, converging trajectories) representing 1D-2D dominance and red region (unstable spiral, diverging patterns) representing 3D dominance. (Middle left) Spatial organization of performance regions across dimensional complexity, where blue indicates error reduction domains (stable fixed point) and red indicates movement strategy domains (unstable fixed point). (Middle right) Phase space equilibria with fixed points at $x = 1/2$ (stable, 1D-2D) and $x = 3$ (unstable, 3D). (Right) Lyapunov exponent transitions, with novices (blue) showing increasing instability and experts (red) demonstrating decreasing instability; purple threshold marks the shift from error reduction to strategic movement organization (see Appendix G). Flowchart connects analysis (upper set) to empirical observations (bottom set), illustrating how dimensional complexity reveals the transition from error reduction strategies (1D-2D stable region) through phase space transition to movement organization strategies (3D unstable region), manifesting in group-specific dynamical behaviors. Bottom set: (Left) Novice group ($\lambda = 0.83$) displays exponentially diverging spiral trajectories indicating unstable dynamics. (Middle) Trajectory separation curves showing three regime zones (error reduction, transition, movement strategy) with performance metrics on right y-axis. (Right) Expert group ($\lambda = 0.21$) exhibits tightly controlled spiral trajectories demonstrating stable dynamics. This integrated visualization reveals how expertise transitions from error-focused to movement-organization strategies across dimensions, with critical transition at the saddle node (see Appendix H).

anteroposterior axis ($M = 14.14°$, $SD = 6.55°$) than the novices did ($M = 5.80°$, $SD = 9.66°$), with expert variability representing 46% of their mean value compared with the novices' variability of 167%. Spatial distributions of movement (bottom left and middle panels) revealed that expert movements (red surface) were concentrated within a narrower spatial region, with movement vectors converging toward a common area. Novice movements (blue surface) were distributed across a wider spatial region with more variable vector directions. Phase space analysis (right panel) revealed that expert trajectories converged toward coordinates (20, 10), whereas novice trajectories were distributed throughout the phase space without consistent convergence patterns. The concentration of expert trajectories toward a specific region contrasted with the dispersed pattern of novice trajectories.

4.4. Comparative analysis across analytical dimensions

Systematic progression emerged when group differences were compared across analyses. The effect sizes increased monotonically from $d = 0.44$ (one-dimensional) to $d = 1.14$ (two-dimensional) to $d = 2.21$ (three-dimensional), representing a fivefold increase from the smallest to the largest effect sizes. Similarly, the significance levels increased from $p < 0.05$ (one-dimensional) to $p < 0.01$ (two-dimensional) to $p < 0.001$ (three-dimensional) (Figure 4). A repeated-measures ANOVA was used to examine the interaction effects of skill level (expert vs. novice) and the analytical dimension (1D, 2D, and 3D) on performance indices. The interaction effect reached significance, $F(2,36) = 8.73$, $p < 0.001$, indicating that the magnitude of group differences varied systematically with dimensional complexity.

5. Discussion

This study examines how motor expertise manifests differently across dimensions of complexity. The central question is whether skilled performance represents uniform error reduction or whether expertise transforms qualitatively as task complexity increases, a fundamental issue in expertise research (Ericsson & Lehmann, 1996; Seifert et al., 2013). Drawing on analyses of motor control and biomechanics (Stergiou, 2016; Winter, 2009), we compared 1D, 2D, and 3D measurements, each demanding progressively more complex spatial and temporal coordination. Our findings extend traditional expertise conceptualizations emphasizing uniform performance improvements (Araújo & Davids, 2011; Fitts & Posner, 1967). In 1D and 2D, the experts reported the expected error reductions. However, 3D analysis revealed qualitatively different movement organizations.

5.1. Summary and interpretation of findings

The dimensional progression illustrates how different complexity levels expose distinct expertise aspects. For the 1D case, the AE serves as a direct measure of accuracy (Equation 1), where x_i is the participant's estimate in trial i and T is the true value. Experts demonstrated lower AE values than novices did, which is consistent with the classical expectation that extended practice reduces one-dimensional deviations (Lohse et al., 2014; Mitra, Amazeen, & Turvey, 1998; Schmidt & Lee, 2011). The difference in error magnitudes between the two groups can be considered

$$\Delta AE = AE_{novices} - AE_{experts} \tag{10}$$

However, the modest effect size ($d = 0.44$) suggests that 1D measurements capture only limited expertise aspects, which is consistent with recent critiques (Pacheco & Newell, 2018). For 2D analysis, the radial error provides a more comprehensive accuracy measurement by incorporating the x- and y-axes:

$$RE_i = \sqrt{x^2 + y^2} = \sqrt{(x_i - x_T)^2 + (y_i - y_T)^2} \tag{11}$$

$$MRE = \frac{1}{n} \sum_{i=1}^{n} RE_i \tag{12}$$

The experts displayed significantly lower MRE, reflecting more stable planar performance (Crawford, Medendorp, & Marotta, 2004; Sherwood, Lohse, & Healy, 2014). The substantially larger 2D effect size confirms that multidimensional coordination differentiates expertise levels more effectively (Profeta & Turvey, 2018). The 3D analysis revealed a qualitative shift. Rather than quantifying positional deviations, angular deviations capture movement characteristics along multiple axes (Equation 9), where the participant's lateral and anteroposterior angles are compared against the centroid (mean) angles across trials. Unlike AE or RE, angular deviations (summarized as MAD in Equation 8) do not represent conventional error but instead capture how participants explore and use available degrees of freedom (Williams & Ericsson, 2005). The counterintuitive finding that experts employ larger movement amplitudes despite lower 1D and 2D errors represents a fundamental shift in expertise manifestation. Experts exploit broader, more flexible movement ranges instead of constraining them to smaller displacements. Thus,

$$\Delta AD = MAD_{novices} - MAD_{experts} \tag{13}$$

may not reflect a conventional performance gap but rather a shift in the influence of complexity on movement coordination strategies (Kraiger, Ford, & Salas, 1993). This exemplifies what previous studies describe as functional variability (Davids et al., 2003), defined as strategic exploitation of movement variability to create adaptable solutions as opposed to stereotyped responses. Unlike trajectory variability (which measures consistency), functional variability represents purposeful variation that enhances performance adaptability.

5.2. Dimensionality and motor control complexity

Expertise effects do not scale linearly across dimensions. At lower-dimensional levels (1D or 2D), enhanced performance is reflected through straightforward reductions in error metrics such as AE or MRE, indicating a direct translation of practice into perceptual–motor precision (Schmidt & Lee, 2011). However, as dimensional complexity increases to 3D and beyond, expertise may be expressed as a greater capacity to organize, stabilize, and flexibly adapt to complex movement patterns instead of simply minimizing errors (Stergiou, 2016).

This pattern aligns with Bernstein's (1967) degree-of-freedom problem, which positioned skill acquisition as a strategic organization of available movement possibilities (Park, 2025). Our findings demonstrate this principle empirically: as dimensional complexity increases from 1D to 3D, experts harness rather than eliminate movement options, shifting from error reduction to strategic exploitation of variability. Although Bernstein's theory has been influential conceptually, quantitative evidence across systematically varying dimensional complexity has remained limited (Golomer et al., 2020; Pacheco, Lafe, & Newell, 2019). The relationship between the task dimension and the coordination complexity can be expressed proportionally as follows:

$$C \propto D \tag{14}$$

where C represents the motor coordination complexity and D represents the task dimensionality. This proportional relationship captures the fundamental principle that coordination demands increase with increasing dimensional complexity (Figure 5 and Appendix J). The dynamic behavior underlying this relationship can be modeled as a parameter-dependent system where angular coordination (θ) changes based on dimensional complexity. The key insight is that the system parameter $\alpha(D)$ changes sign from negative (stable, 1–2D) to positive (unstable, 3D) as the dimension increases. This sign change represents a fundamental bifurcation in the dynamic structure governing movement coordination (Kelso, 1995; Kostrubiec et al., 2012). The complete mathematical formulation of this parameter-dependent system, including the coupled differential equations and eigenvalue analysis, appears in Appendix G. The stability characteristics of these dynamical patterns can be quantified through Lyapunov exponents:

$$\lambda = \frac{1}{\Delta t \cdot N} \sum_{i=1}^{N} \ln\left(\frac{d_i(t + \Delta t)}{d_i(t)}\right) \tag{15}$$

where d_i represents the distance between neighboring trajectories. Lower λ values indicate more stable, predictable movement patterns (see Appendix G for details). This explains the observed transition from convergent to divergent patterns with increasing dimensionality (Rosenstein et al., 1993). For higher-dimensional tasks, the dynamics of motor coordination have become increasingly complex. In these tasks, mathematical features such as phase transitions (shifts between different coordination states) and fixed points (stable or unstable equilibrium positions) become critical. These features define important performance characteristics, including

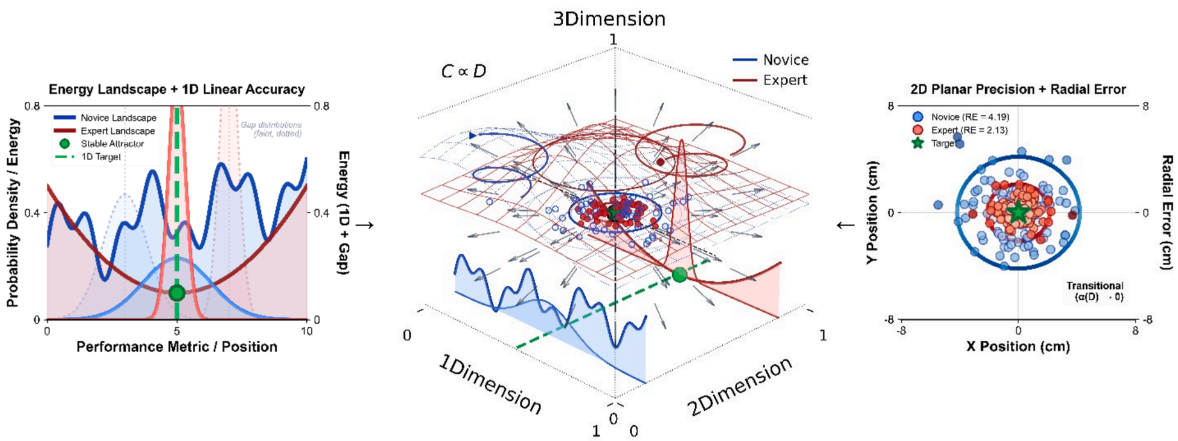

Fig. 5. Dimensional progression ($C \propto D$) integrating empirical evidence across complexity levels. (Left) 1D linear accuracy. Novice (blue) shows multiple shallow energy wells while expert (red) shows a single deep well with stable attractor (green circle). Filled distributions reveal novices' wider spread versus experts' tighter concentration around the target (green dashed line). (Middle) Integrated $C \propto D$ panel synthesizing all dimensional levels within a unified 3D cube, with 1D distributions at the base, 2D bullseye precision at the mid-plane ($z = 0.5$), and 3D angular coordination wireframes at the upper level (novice dotted blue; expert solid red with half-max contour ring). The diverging novice spiral ($\lambda = 0.83$) versus converging expert spiral ($\lambda = 0.21$) illustrates the stability bifurcation. (Right) 2D planar precision (radial error). Novice scatter (hollow blue, wider confidence ellipse) versus expert scatter (filled red, tighter ellipse) around the target (green star), with concentric rings indicating radial-error distances. The dimensional decomposition isolating $D = 1, 2, 3$ appears in Appendix J.

movement stability and adaptability to changing conditions. The phase diagrams in Figure 4 illustrate these dynamic differences. By plotting the lateral axis angle (θ_L) against the anteroposterior axis angle (θ_AP), these diagrams display vector fields that represent movement trajectory evolution. Stability analysis revealed two key equilibrium points: a stable point at (20,10), where expert trajectories consistently converged, and an unstable point at (0,0), where novice trajectories failed to be maintained.

In lower-dimensional cases (1D), expert performance aligns with stable spiral characteristics, converging toward fixed points that minimize variability and error. Conversely, higher-dimensional cases (3D) exhibit features akin to unstable spirals, with divergent patterns reflecting greater flexibility and exploratory strategies. The transition between these features is marked by saddle points, where performance reflects a delicate balance between stability and instability. Experts leverage motor synergies, specifically coordinated muscle and joint recruitment, to exploit inherent redundancies for enhanced stability and functional adaptability (Latash, Scholz, & Schöner, 2007).

Studies employing principal component analysis, uncontrolled manifold analysis (Scholz & Schöner, 1999), and nonlinear measures show that expert performers navigate dynamic solution landscapes instead of constraining them to single control dimensions (Federolf et al., 2014; Glazier, 2017). Our dimensional analysis extends these findings by demonstrating that optimal movement strategies fundamentally differ across dimensional complexity. Specifically, what constitutes an "optimal" solution in 1D differs qualitatively from what is optimal in 3D contexts. Particularly, experts in 3D tasks exploit functional variability (adaptive coordination strategies) while simultaneously reducing trajectory variability (CV%; see Table 3 and Appendix I), demonstrating that skilled performance involves strategic management over simple elimination of movement variability.

5.3. Comparison with computational approaches

Dimension-specific perspectives prove necessary when conventional measures fail to capture the subtleties of complex motor tasks (Park, 2023; Stergiou & Decker, 2011). Our dimensional approach, which reveals how expertise manifests across complexity levels, is complemented by recent computational methods offering pattern recognition capabilities. Transformer-based models achieve over 90% accuracy in human activity recognition (Kwon et al., 2021), diffusion models generate realistic movement sequences (Tevet et al., 2023), and deep learning architectures predict motor performance with notable precision (De Giorgis et al., 2025; Zheng et al., 2025). However, these approaches typically collapse multidimensional data into latent representations, obscuring the dimensional characteristics our analysis explicitly addresses (Rajwar et al., 2023).

A practical example illustrates this distinction. A neural network might accurately classify expert versus novice movements, achieving 95% accuracy, but outputs only a categorical label without insight into the developmental pathway. By contrast, our approach reveals a specific progression: modest improvement in 1D (error reduction, $d = 0.44$), significant improvement in 2D (coordination, $d = 1.14$), and qualitative reorganization in 3D (variability exploitation, $d = 2.21$). This specificity enables targeted interventions addressing dimensional deficits instead of generic recommendations that classification alone cannot provide. This design maintains transparency by explicitly analyzing movement across spatial complexity levels and provides theoretical grounding connecting statistical findings to established motor control principles (Bernstein, 1967). Further, it reveals qualitative coordination differences potentially obscured in data-driven methods optimized for prediction accuracy (Bacciu et al., 2020). Future research could productively integrate both approaches. Machine learning could enhance dimensional analysis through automated dimension extraction and predictive identification of when qualitative transitions occur during skill acquisition. Conversely, dimensional analysis could improve computational models through theoretically grounded feature engineering and interpretable latent space scales corresponding to spatial complexity levels (Karpatne et al., 2017).

5.4. Implications

Our study provides three conceptual advances. First, expertise transforms qualitatively with spatial complexity, challenging error-centric models (Ericsson & Lehmann, 1996). Second, our Lyapunov exponent findings ($\lambda = 0.21$ vs. $\lambda = 0.83$, $p < 0.001$; see Appendix H) provide empirical support for Bernstein's (1967) degree-of-freedom problem, demonstrating functional stability despite larger movement amplitudes (Golomer et al., 2020; Profeta & Turvey, 2018). Third, our analysis connects information-processing models (lower dimensions) with dynamical systems principles (higher dimensions), suggesting that these perspectives address different dimensional aspects of the same phenomenon (Latash, Scholz, & Schöner, 2007; Pacheco & Newell, 2018). This integration offers methodological guidance for information processing and management readership. When studying expertise in domains involving spatial complexity, including data visualization and human–computer interaction, researchers should consider whether dimensional decomposition might expose organizational distinctions that aggregate measures obscure.

Whereas our findings directly demonstrate that expertise manifests differently across dimensional complexity and that 3D analysis reveals qualitative organizational differences invisible at lower-dimensional scales, several promising applications merit further investigation. In training contexts, our results suggest that dimension-progressive protocols could be designed to focus initially on 1D accuracy, advance to 2D coordination, and then introduce 3D complexity where experts' organizational advantages emerge (Guadagnoli & Lee, 2004; Pacheco et al., 2019). Feedback strategies may similarly benefit from dimensional calibration, emphasizing error correction for novices in simple tasks and coordination patterns in complex tasks where reducing variability could impair performance (Kleynen et al., 2015; Wulf & Lewthwaite, 2016). In rehabilitation, the observed dimensional progression points toward potential scaffolding approaches that initially constrain movement to single dimensions and systematically introduce degrees of freedom as recovery progresses. Such approaches could help clinicians distinguish dysfunctional movement from functional movement variability (Stergiou et al., 2006; Vereijken et al., 1992; Wu et al., 2014). For human–computer interaction, our findings raise the possibility that adaptive systems could modulate dimensional complexity based on demonstrated user stability, although empirical validation in interface design contexts remains necessary (Ikhwantri et al., 2023; Oudah et al., 2020).

5.5. Limitations and future directions

Our sample size (three hundred data points were collected from twenty participants) is consistent with that of motion-capture expertise studies that typically employ 8–12 participants per group (Komar et al., 2019; Van der Kruk & Reijne, 2018). The large 3D effect size ($d = 2.21$) supports statistical confidence in the observed dimensional progression. However, these findings reflect a specific motor domain and skill contrast (elite professional versus complete novice). Generalization to other motor tasks, intermediate skill levels, or broader populations requires larger multisite samples incorporating diverse motor domains and developmental skill trajectories (Pacheco, Lafe, & Newell, 2019). This cross-sectional design did not track developmental trajectories. Longitudinal studies could reveal when dimensional transitions occur during skill acquisition (Kostrubiec et al., 2012). Our controlled laboratory setting eliminated environmental unpredictability; future research should examine whether dimensional progression patterns persist under ecologically complex conditions (Araújo et al., 2006). Promising avenues include integrating different scale analysis with computational pattern recognition (Karpatne et al., 2017), developing real-time multilevel assessments for adaptive training systems (Sigrist et al., 2013), and examining whether behavioral expertise dimensions correspond to neural control organization (Diedrichsen et al., 2010). This observation could also extend to information-processing domains where spatial complexity influences performance, such as data visualization, virtual environment navigation, or gesture-based interfaces.

6. Conclusion

This study advances our understanding of expertise by demonstrating that skill manifests differently across dimensional complexity levels (Davids et al., 2003; Seifert et al., 2013). Whereas 1D and 2D analyses reveal expected reductions in error magnitude among experts, our 3D analysis reveals a more sophisticated reality: expertise reflects the strategic organization of movement variability over simple error minimization. As detailed in our theoretical implications, this finding represents a paradigm shift in how we should conceptualize and measure expertise (Ericsson & Lehmann, 1996).

The design we have developed provides both theoretical and practical contributions to the field. Theoretically, it extends the conventional view that expertise universally reflects error reduction, demonstrating instead that advanced skill involves qualitatively different movement organization strategies as dimensional complexity increases. Our quantitative findings provide concrete evidence for what Bernstein (1967) theoretically described as the degree-of-freedom problem. The practical applications of our work span training protocols, rehabilitation approaches, and technology design. Although our study has limitations, including the sample size typical of motion capture research, the large effect sizes and strong significance levels support our core findings. Each of these application domains can benefit from recognizing that expertise manifests differently across movement contexts, requiring dimension-appropriate assessment tools and instructional strategies.

As detailed in Section 5.5, future research should apply this dimensional analysis to other complex skills and environments. This could potentially incorporate real-time adaptation analysis that captures how performers adjust their coordination strategies in response to changing constraints (Saltzman & Kelso, 1987). By integrating insights from motor control, biomechanics, neuroscience, and computational modeling, we can expect more reliable approaches to understanding, measuring, and developing expertise across the spectrum of human movement activities (Roupa et al., 2022).

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Data availability statement

The data and analysis code supporting the findings of this study are openly available in the GitHub repository 'Dimensional-motor-expertise' at https://github.com/pcw8531/Dimensional-motor-expertise. The repository includes: (1) complete Jupyter notebook with all dimensional analyses (1D, 2D, 3D), (2) raw performance data for all participants, and (3) code for statistical analyses and visualizations presented in the manuscript.

CRediT authorship contribution statement

Chulwook Park: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no conflicts of interest.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ipm.2026.104951.

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