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Visual-motor expertise in athletes: Insights from semiparametric modelling of 2317 athletes tested on the Nike SPARQ Sensory Station

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ABSTRACT

Elite athletes not only run faster, hit harder, and jump higher, but also see and react better. However, the specific visual-motor skills that differentiate high-achieving athletes are still not well understood. In this paper we examine 2317 athletes (1871 male) tested on the Nike SPARQ Sensory Station, a digital test battery measuring visual, perceptual and motor skills relevant for sports performance. We develop a multivariate Gaussian transformation model to robustly estimate visual-motor differences by level, gender, and sport type. Results demonstrate that visual-motor performance is superior for athletes at higher levels, with males faster at near-far eye movements and females faster at eye-hand reaction times. Interestingly, athletes who play interceptive sports such as baseball and tennis exhibit better measures of visual clarity, contrast sensitivity and simple reaction time, while athletes from strategic sports like soccer and basketball have higher measures of spatial working memory. These findings provide quantitative evidence of domain-specific visual expertise in athletes.

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KEYWORDS
Vision; motor control; expertise; copula

1. Introduction

Sports place incredible demands on the human visual systems. Hitting a baseball, returning a serve, or blocking a shot on goal all require an athlete to see and react with great efficiency and accuracy. Over the last several decades, scientists have attempted to understand how the eyes and the visual brain contribute to athletic expertise (Gregory, 1997; Yarrow, Brown, & Krakauer, 2009). As captured in two recent meta-analyses (Mann, Williams, Ward, & Janelle, 2007; Voss, Kramer, Basak, Parkash, & Roberts, 2010), higher-achieving athletes are better at detecting perceptual cues, efficiently moving their eyes, processing information quickly, and maintaining attention. Across this literature, elite athletes tend to outperform sub-elite athletes and non-athletes in both sports-specific tasks and component-skill tasks that tap into broad, fundamental visual (Hitzeman & Beckerman, 1993; Laby et al., 1996) and perceptual-cognitive mechanisms (Casanova, Oliveira, Williams, & Garganta, 2009; Starkes & Ericsson, 2003; Williams & Ericsson, 2005; Williams & Ford, 2008). In addition, these expertise-related benefits are largely reflective of the types of demands that are required by the specific roles athletes play. For example, experts in sports that require a greater horizontal distribution of attention (e.g., hockey) demonstrate a greater horizontal breadth of attention than athletes whose sports require more vertical attention (e.g., volleyball), and vice versa (Huttermann, Memmert, & Simons, 2014). Moreover, recent studies have begun to find that measures of visual-motor abilities are able to predict future game performance in professional baseball (Burris et al., 2018; Laby, Kirschen, Govindarajulu, & DeLand, 2018), collegiate hockey (Poltavski & Biberdorff, 2014), and pro basketball (Mangine et al., 2014), making these potentially valuable scouting measures. Collectively, these studies have indicated that high-level athletes may be experts at processing some types of visual information (Klemish et al., 2017) (though see (Eccles, 2006)), making athletes a valuable population to help understand the limits of visual-motor abilities in individuals with considerable training.

While studies of visual-motor expertise represent a fruitful domain for exploring models of learning and determining the limits of human performance, research with experts has been severely limited in impact because of small sample sizes and heterogeneous psychological constructs. In particular, it is difficult to obtain access to high-achieving individuals for research purposes, and therefore inferences about experts are often inconclusive due to the large degree of uncertainty inherent in small sample sizes[1]. In addition, each study uses different tests to measure visual-motor abilities, which has resulted in a disparate set of findings that are difficult to aggregate (Eccles, Walsh, & Ingledew, 2006; Voss et al., 2010). It is also not always clear how performance on controlled laboratory tests maps onto real-world achievement, therefore creating a fundamental disconnect between research and practical applications. Despite these limitations, there remains tremendous interest in understanding the visual, perceptual, cognitive, and motor faculties that differentiate experts from non-experts, and in revealing how these differences relate to specific experiences and outcomes.

In 2011, Nike Inc. launched the SPARQ Sensory Stations as a tool to quantitatively evaluate athlete visual-motor abilities. The Sensory Stations include a battery of nine psychometric tasks administered under standardised conditions with video

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[1]The average sample size across the 62 studies included in the meta-analyses of Mann and Voss consists of 15.39 athletic experts each, for a total of 954 athletic experts across the whole literature.

instructions by trained and certified administrators. Prior to testing, participants complete a registry of information that reports demographic (e.g., age and height), sport (e.g., primary sport and position), concussion history (number and recency), and vision (e.g., eye dominance and eye care history) characteristics (Wang, DeLang, Vittetoe, Ramger, & Appelbaum, 2018). The Sensory Stations operated for four years until 2015 and all assessment data were maintained on a central database. This information was used to provide sport-specific normative information to individuals about their abilities compared to their specific athletic cohort and to monitor learning when coupled with sensorimotor training interventions.

Past research with the Sensory Stations has demonstrated that the battery of tests is reliable (Erickson et al., 2011; Wang et al., 2015), with scores on some tasks demonstrating linear improvements with practice over multiple sessions (Appelbaum, Lu, Khanna, & Detwiler, 2016; Krasich et al., 2016). Furthermore, similar to visual-motor tasks based on other platforms, those on the Sensory Station have also been shown to predict athletic performance. In particular, Burris et al found positive associations between measures of visual-motor control and game statistics such as on-base percentage, strikeout rate, and walk rate in a sample of 252 professional baseball players (Burris et al., 2018). Collectively, as reviewed by Appelbaum and Erickson (Appelbaum & Erickson, 2016), there is a growing body of research pointing to the utility of this battery in both scouting and training of visual-motor skills essential to high-level performance.

In the current study, we analyse 2317 athletes tested on the Sensory Station to evaluate the relationship between visual-motor abilities and athletic expertise across levels of achievement and sport type, for both men and women. For this purpose, we develop a Bayesian semiparametric transformation model for the analysis of multivariate data (see Section 2 and Appendix). This model has particular value in that it can be applied generally to datasets that contain missing values, negative values, mixed data types, and non-normal marginal distributions (Hoff, 2007). Model estimation is based only on the ranks of the data, which enables robust inference that is invariant to monotonic transformations of the data. Using this methodology, we model athlete scores for seven of the nine sensorimotor tasks, excluding Depth Perception and Go/No-Go due to known limitations with Bluetooth connectivity and a restrictive threshold, respectively (Wang et al., 2015). We consider covariates such as the level of athletic expertise, primary sport type, and gender. Athletic expertise is defined as the self-reported level of the athlete (Middle School, High School, College, Professional). Following past research (Mann et al., 2007; Voss et al., 2010), sports are classified as *interceptive* if the primary athletic actions require coordination between an athlete's body, body parts, or a held implement, and an object in the environment (e.g., tennis, baseball) (Davids, 2002). Conversely, a sport is classified as *strategic* if it is important to divide attention in order to monitor the location of teammates, opponents, and projectiles on the field (e.g., soccer, basketball) (Singer, 2000). We fit two separate models: one including only the main effects for interpretability and the other with all two-way interactions to capture heterogeneous relationships across combinations of level, sport type, and gender.

The present study was therefore conducted to provide new insight into the attributes of visual-motor skill that differ across genders, levels, and sport types. Based on the past literature noted above, it is expected that athletes at higher levels of achievement would demonstrate greater performance scores across all assessment tasks. Based on existing meta-analytic syntheses of athlete perceptual-cognitive expertise (Mann et al., 2007; Voss et al., 2010), it is expected that athletes from interceptive sports would exhibit faster processing speeds, while no strong expectations are present for gender differences.

2. Methods

In this section, we provide a brief description of the participants, the Sensory Station assessment tasks, and the semiparametric modelling approach used in this paper. For the sake of clarity, mathematical details of our statistical model are provided in the Appendix.

2.1. Participants

Data comprising the tested dataset were obtained through two sources. 171 of the participants were evaluated by the author's research team, with informed consent under a research protocol conformed to the standards of the Declaration of Helsinki and approved through both the Duke University Institutional Review Board (B0306) and the Human Research Protection Office of the US Army Medical Research and Materiel Command (A-18957). All other data were shared under a secondary-data protocol approved by the Duke IRB (protocol B0706) and Army MRMC (A-18957). Under this protocol, data were collected for "real world use," without informed consent, and shared with the research team after removal of all protected health information. As such, these data conform to U.S. Department of Health and Human Services, "Regulatory considerations regarding classification of projects involving real world data (DHHS, 2015)", but did not involve direct contact with the research subjects.

The final analysed dataset consists of the task scores, as well as athlete characteristics such as level of expertise, primary sport, and gender for 2317 athletes (1871 male, 446 female). Tables 2 and 3 describe the distribution of gender, sport type, and level of expertise for athletes who completed a Nike Sensory Station evaluation. The dataset was obtained from 28 centres located in English speaking countries (Canada, United States or England). These stations were in operation by professional sports teams (N = 6), collegiate athletic programmes (N = 4), optometrists who provide sports vision care (N = 13), research laboratories (N = 3), and athletic training facilities (N = 4), with two research laboratories also servicing collegiate athletic programmes.

All data was pre-screened to assure consistency in reporting of athlete level and participant age, with 11 (0.5%) excluded because listed ages fell outside acceptable ranges for Middle

School (10–16 yrs), High School (14–19 yrs), College (17–28 yrs), and Professional (14–70 yrs).

2.2. Sensory station tasks and data

The Sensory Stations consist of a battery of nine computerised tasks (Table 1), each designed to evaluate a specific facet of a participant's visual-motor abilities. Evaluation sessions were conducted by Nike-certified technicians who logged into the system to access the testing application. Prior to the behavioural tasks, the technician entered information about the participant including their demographics (e.g., age, gender, height, handedness, eye dominance) and sport participation (e.g., primary sport, primary position, level of achievement). The first five tasks were then presented on a 58 cm display monitor and completed using a handheld Apple iPod Touch, standing 4.9 m from the station. The last four tasks were completed at arm's length on a 107 cm touchscreen monitor placed at eye level. Four of the tasks – Visual Clarity, Contrast Sensitivity, Depth Perception, and Target Capture – operated on staircase schedules in which subsequent trial difficulty increased following a correct response and decreased following an incorrect response. For these tasks, scores were calculated as the final step according to response accuracy on the staircase schedule. All tasks were preceded by video instructions in environments tailored to space and lighting specifications for use of the Sensory Station device. Procedures and descriptions for each task are provided in the Appendix section A1, and detailed descriptions can be found in (Erickson et al., 2011; Wang et al., 2015).

A summary table of the task scores in the Nike database is provided in Table 4. Raw scores for each of the tasks are recorded on different scales; for example, Visual Clarity scores are expressed in log MAR units and can take on negative values, whereas typical scores for Eye-Hand Coordination are reported in milliseconds and range between 40,000 and 70,000. In addition, lower raw scores are better for some tasks, such as Reaction Time, but worse for others, such as Perception Span. For interpretability, we centre and scale the responses such that a higher standardised score corresponds with superior performance on the task. Figure 1 illustrates the standardised marginal distribution for each of the task scores. The distributions of task scores tend to be left-skewed, with a few outliers in the lower tail. Although all task scores are numeric, many are discrete (e.g., Contrast Sensitivity, Perception Span), while others are continuous (e.g., Reaction

Time, Eye-Hand Coordination). In addition, three of the tasks have missing values: Visual Clarity is missing 15, Contrast Sensitivity six, and Depth Perception 104.

Table 2. Distribution of athlete level and sport type for male athletes.

	Male Athlete Level				
Sport Type	Middle School	High School	College	Pro	Total
Strategic	122	222	459	358	1161
Interceptive	75	123	111	401	710
Total	197	345	570	759	1871

Table 3. Distribution of athlete level and sport type for female athletes.

	Female Athlete Level				
Sport Type	Middle School	High School	College	Pro	Total
Strategic	40	61	86	57	244
Interceptive	39	55	105	3	202
Total	79	116	191	60	446

Table 4. Scores representing the 5th, 25th, 50th, 75th, and 95th percentiles for each of the seven tasks considered in this study. Lower scores are better in the Visual Clarity (VC), Target Capture (TC), EyeHand Coordination (EHC), and Reaction time (RXN) tasks, whereas higher scores are better in the Contrast Sensitivity (CS), Near-Far Quickness (NFQ) and Perception Span (PS).

Percentile	VC	CS	NFQ	TC	PS	EHC	RXN
5%	0.14	1.00	15.00	575.00	15.00	65063.80	418.29
25%	−0.04	1.40	12.00	375.00	28.00	58203.00	379.00
50%	−0.14	1.60	25.00	275.00	34.00	54996.00	355.71
75%	−0.21	1.80	29.00	200.00	41.00	52320.00	335.86
95%	−0.28	2.00	34.00	125.00	56.00	48910.20	309.57

2.3. Semiparametric regression model

In this study, we aim to estimate and quantify the uncertainty about the relationships between performance on the tasks and covariates such as gender, level, and sport type. A standard approach for quantifying these relationships is to specify separate linear regression models for each task, in which the observed task scores are modelled as linear functions of the covariates of interest with normally distributed errors. However, model diagnostics indicate that the residuals are not only correlated within individuals, but also not normally distributed,

Table 1. Brief descriptions of the Nike Sensory Station tasks. # denotes tasks that were performed under a staircase schedule.

Task	Original Units	Label	Description
Visual Clarity ()	log(MAR)	VC	Measures visual acuity for fine details at a distance
Contrast Sensitivity (#)	log(Score)	CS	Measures the minimum resolvable difference in contrast at a distance
Depth Perception (#)	log(Score)	DP	Measures how quickly and accurately participants are able to detect differences in depth at a distance using liquid crystal glasses
Near-Far Quickness	# Correct Responses	NFQ	measures the number of near and far targets that can be correctly reported in a 30 second time interval
Target Capture (#)	milliseconds	TC	Measures the speed at which participants can shift attention and recognise peripheral targets
Perception Span	# Correct Responses	PS	Measures the ability to remember and recreate visual patterns
Eye-Hand Coordination	seconds	EHC	measures the speed at which participants can make visuallyguided hand responses to rapidly changing targets
Go/No-Go	seconds	GNG	Measures the ability to execute and inhibit visually guided hand responses in the presence of "go" and "no-go" stimuli
Reaction Time	milliseconds	RXN	Measures how quickly participants react and respond to a simple visual stimulus

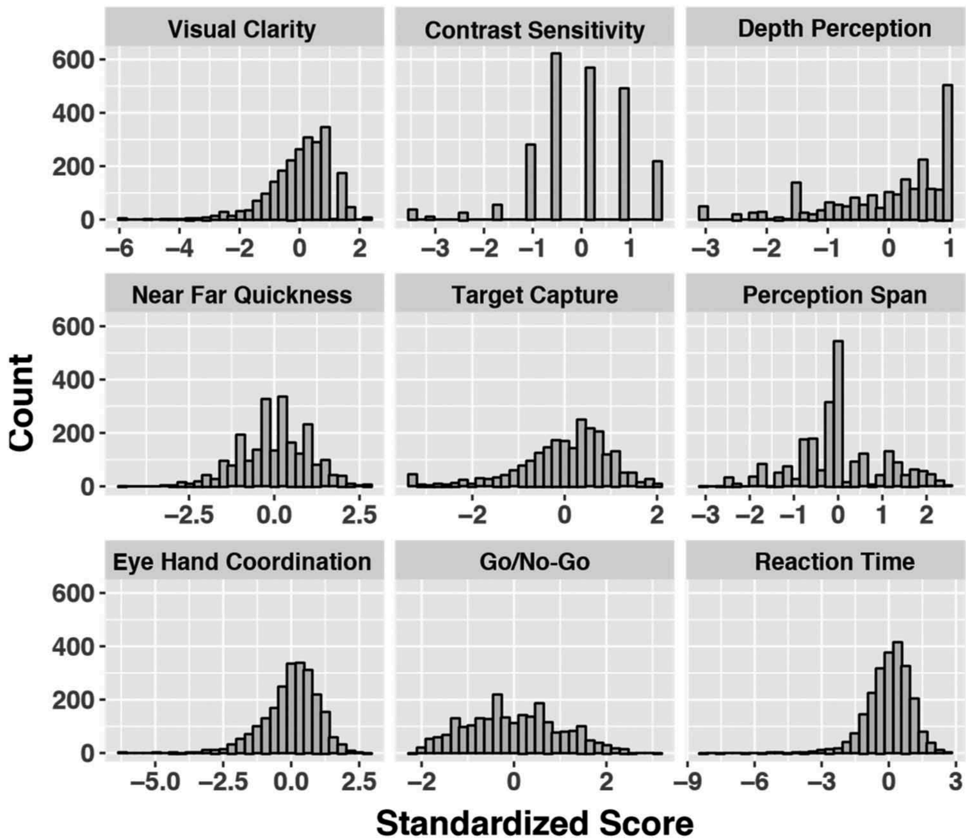

Figure 1. Distribution of standardised task scores for the athletes in the Nike database.

violating the inferential assumptions associated with these models.

Accordingly, we proceed to develop an extension of the semiparametric transformation model introduced by Hoff (2007) for multivariate regression. We choose to do this because we desire a model that (1) models the task scores jointly, rather than separately; (2) is suitable for discrete and/or skewed data; and (3) simultaneously handles data that was assumed missing at random (MAR). Parameter inference for the model is conducted in a Bayesian framework, with approximate samples from the joint posterior distribution obtained via Markov chain Monte Carlo (MCMC) simulation methods. The model we propose is particularly robust, as inference is based only on the ranks of the observed data.

Let y_{ij} represent the task score for athlete i on task j, where there are n athletes and p different tasks. We assume that y_{ij} arises as a monotonically non-decreasing transformation of a latent variable $u_{ij} \in [0,1]$. In context, u_{ij} corresponds to the percentile of performance, so a value of $u_{ij} = 0.99$ means that the athlete i performed in the 99th percentile on the jth task. It is important to note that u_{ij} is not necessarily known even if y_{ij} is observed. To see this, consider a task that consists of a single True/False question, in which 80% of individuals respond correctly. If an individual attempts the task and answers correctly, we only know that $u_{ij} \in [0.2,1]$, since we cannot differentiate among the individuals who answered correctly.

Let $\boldsymbol{z}_i = (\Phi(u_{i1}),\cdots,\Phi(u_{ip}))$, where Φ is the cumulative distribution function (CDF) of the standard normal distribution. As Φ is a monotone increasing function, $\boldsymbol{z}_i$ is a vector that indicates athlete performance on the p tasks. Furthermore, let $\boldsymbol{x}_i \in \mathbf{R}^q$ be a vector of q centred covariates observed about athlete i. We model the relationship between $\boldsymbol{z}_i$ and $\boldsymbol{x}_i$ linearly, such that

$$z_i \sim \mathrm{N}_p\left(x_i^{\mathrm{T}}\boldsymbol{B}, \boldsymbol{C}\right), \tag{1}$$

where $\boldsymbol{B} \in \mathbb{R}^{q \times p}$ is a matrix of regression coefficients, $\boldsymbol{C} \in \mathbb{R}^{p \times p}$ is a correlation matrix, and N_p corresponds to a p-dimensional multivariate normal distribution. In our application, B_{kj} represents the magnitude of the linear relationship between the kth covariate and the transformed performance on the jth task. If $\boldsymbol{C}$ is equal to the identity, then the task scores are not correlated with one another after accounting for the observed covariates. Essentially, our approach involves combining a multivariate regression model and a transformation model and estimating it using only the ranks of the data. For more details about the approach, we refer the reader to the Appendix.

Under this approach, we model athlete scores for $p = 7$ sensorimotor tasks, excluding Depth Perception and Go/No-Go due to known limitations with Bluetooth connectivity and a restrictive threshold, respectively. We consider two models (1) $\boldsymbol{x}_i$ contains indicators for athlete level of expertise, primary sport type, and gender; (2) $\boldsymbol{x}_i$ contains indicators for athlete level of expertise, primary sport type, and gender, along with all two-way interactions. Three-way interactions were not considered due to small sample sizes in some of these subgroups. To ensure identifiability, neither of these models have an intercept term.

For each model, we perform Gibbs sampling to obtain approximate samples of z_{ij}, $\boldsymbol{B}$, and $\boldsymbol{C}$ from their joint posterior distribution. We draw a total of 100,000 samples after a burn-in of 1,000 iterations, storing the values of ***Z, B*** and ***C*** every tenth iteration. All athletes in the data, including those with missing values for Visual Clarity and Contrast Sensitivity, are included due to the fact that the missing values are sampled jointly with the parameters of interest. The model was validated by standard convergence diagnostics and posterior predictive checks. Summaries of the samples from the joint posterior distribution of ***B*** and ***C*** are described in Section 3. Details of the Gibbs sampling approach, including the prior distributions that we used in obtaining the results presented in this study, are provided in the Appendix.

3. Results

3.1. Main effects model

Because we are performing a Bayesian analysis of these data, we analyse approximate samples from the posterior distribution of the model parameters. Based on these samples, we can calculate the mean value of the samples corresponding to a specific model parameter (posterior mean) and calculate uncertainty intervals based on these samples (credible intervals). Throughout this paper, we adopt a convention that a regression coefficient is *significant* if the corresponding symmetric 95% credible interval does not contain zero. This indicates that there is at least a 95% probability that the estimated direction of the monotone association is correct, based on the posterior distribution of the model parameters. Similarly, we call the difference between two groups significant if the 95% credible interval of the difference in predicted group means under the model does not include zero.

Using the model described in Section 2, we use Markov chain Monte Carlo sampling to estimate the posterior distribution of the model parameters. Posterior means of the matrix of regression coefficients are given in Table 5 and significant coefficients are bolded. The coefficients are further visualised in Figure 2, where the baseline group is a middle school male who plays a strategic sport. It is also worth noting that supplementary analyses found that athlete height, which is known to correlate with arm length, did not moderate these gender effects. As such, the present results should not be interpreted in terms of access to the spatial extent of the lightboard on which the task was presented.

Overall, results indicated that athletes with higher levels of expertise perform better for all Nike Sensory Station tasks, with the exception of Target Capture. Interestingly, the largest and most compelling differences were exhibited in tasks that demand greater motor control, such as Eye Hand Coordination, Near Far Quickness, and Reaction Time. In these tasks, meaningful differences existed between middle school and high school athletes, as well as between high school and college athletes. While athlete level differences were much smaller in the Visual Clarity and Contrast Sensitivity tasks, these measures of visual sensitivity also showed small gradations. In general, athletes in the sample with higher levels of expertise were older on averaging, so some of these relationships may be confounded with age.

Table 5. Posterior mean coefficients for the main effects model. These coefficients represent the conditional associations between the covariates and latent variables corresponding to ability on the Visual Clarity (VC), Contrast Sensitivity (CS), Near-Far Quickness (NFQ), Target Capture (TC), Eye-Hand Coordination (EHC), and Reaction Time (RXN) tasks respectively. Coefficients for which the 95% credible intervals do not contain zero are bolded. The baseline corresponds to a middle school male who plays a strategic sport.

	VC	CS	NFQ	TC	PS	EHC	RXN
High School	0.103	0.049	**0.534**	0.002	**0.429**	**0.982**	0.158
College	**0.273**	0.099	**0.799**	0.113	**0.453**	**1.380**	**0.489**
Pro	**0.320**	**0.215**	**0.744**	0.018	**0.436**	**1.664**	**0.553**
Interceptive	**0.187**	**0.123**	**0.121**	0.001	**−0.086**	0.001	**0.143**
Female	−0.002	−0.042	**−0.128**	0.078	**0.105**	**0.193**	0.020

Athletes who play primarily interceptive sports such as tennis and baseball scored significantly better on measures of visual sensitivity such as Visual Clarity and Contrast Sensitivity. In addition, interceptive sport athletes also had significantly higher Near-Far Quickness scores and Reaction Times than strategic sport athletes, the latter of which was also noted by (Mann et al., 2007) in their meta-analysis of the literature.

Interestingly, athletes who play strategic sports tended to do better at Perception Span, which measures the ability to store and recreate visual patterns. This may indicate that spatial working memory (e.g., mentally representing and maintaining the location of teammates and opponents) is of primary importance in strategic sports.

Although the magnitudes of the visual-motor differences between genders were substantially less than those across levels of expertise, significant gender differences in task performance were present. In particular, holding sport type and level of expertise constant, males typically ranked higher than females at Near-Far Quickness, while females typically ranked higher at Eye-Hand Coordination and Perception Span.

3.2. Interaction model

To provide a more systematic look at group-level differences, a second multivariate regression model was fit with both main effects and all two-way interactions. Table 6 presents a summary table of posterior means for this model, and Figure 3 visualises the estimated task score percentile for a typical athlete under each combination of level, sport type, and gender, a table for which is provided in the Appendix.

One finding from the interaction model outcomes was that the sport type differences in measures of visual sensitivity and spatial working memory are compressed at higher levels of athletic expertise. Specifically, interceptive sport athletes scored higher than strategic sport athletes on Visual Clarity and Contrast Sensitivity, with the largest differences exhibited at the middle school level. The same pattern held for Perception Span, though strategic sport athletes outperformed interceptive sport athletes at that task. However, the sport type differences in measures of visual-motor control either remained the same or were amplified at higher levels of athletic expertise. In particular, there was a clear difference in professional athlete reaction times by sport type, with interceptive athletes typically demonstrating quicker responses.

When the groups were clustered hierarchically on the basis of the estimated percentiles across the seven tasks, the groups were primarily divided by level of expertise, with the greatest division occurring between high school and college. The younger cohorts (middle school and high school) separated cleanly into their own

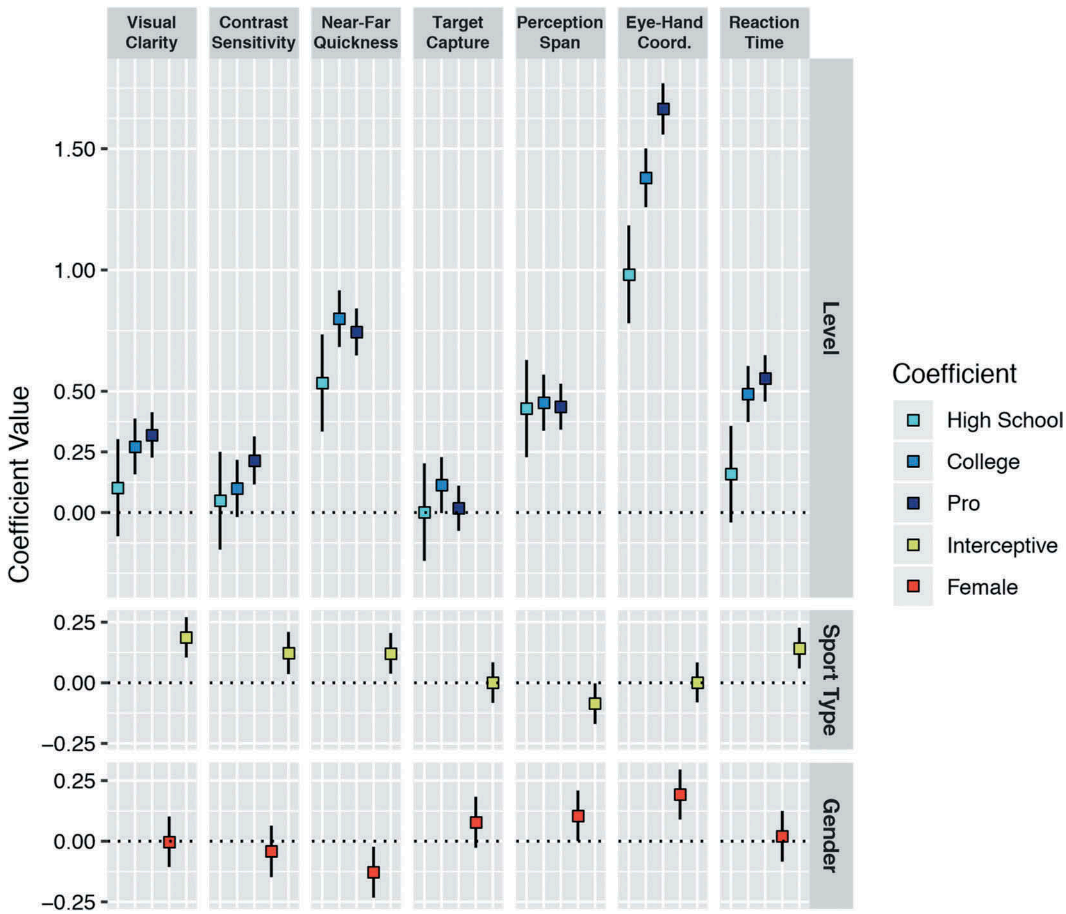

Figure 2. Posterior means, along with 95% credible intervals for the main effects model coefficients of sport level, sport type, and gender. The baseline, marked by a dotted line, corresponds to a middle school male who plays a strategic sport. As such, each row of this figure indicates the regression coefficients in relation to the baseline group. For example, in the gender plots, the females shown in red are in relation to males, shown by the dotted line, holding constant expertise and sport type. In this way, our model enables comparison of magnitudes across both coefficients and tasks.

Table 6. Posterior mean coefficients for the interaction model. These coefficients represent the conditional associations between the covariates and latent variables corresponding to ability on the Visual Clarity (VC), Contrast Sensitivity (CS), Near-Far Quickness (NFQ), Target Capture (TC), Eye-Hand Coordination (EHC), and Reaction Time (RXN) tasks respectively. Coefficients for which the 95% credible intervals do not contain zero are bolded. The baseline is identical to that used in Table 5 and Figure 2, corresponding to a middle school male who plays a strategic sport.

	VC	CS	NFQ	TC	PS	EHC	RXN
High School	0.254	0.121	**0.544**	0.023	0.389	**1.086**	0.198
College	**0.343**	0.199	**0.847**	0.140	**0.380**	**1.458**	**0.565**
Pro	**0.393**	**0.322**	**0.736**	0.027	**0.364**	**1.727**	**0.442**
Interceptive	**0.403**	0.336	0.108	−0.035	−0.233	−0.072	−0.037
Female	0.131	−0.122	0.041	0.010	0.261	**0.597**	0.200
High School × Interceptive	**−0.248**	**−0.211**	0.066	−0.038	**0.269**	0.064	0.101
College × Interceptive	−0.106	**−0.357**	0.066	−0.077	**0.206**	**0.186**	0.060
Pro × Interceptive	**−0.203**	**−0.255**	0.043	0.028	**0.186**	0.077	**0.352**
High School × Female	−0.196	0.058	−0.156	−0.033	**−0.276**	**−0.494**	**−0.289**
College × Female	−0.034	0.113	**−0.279**	−0.050	−0.012	**−0.539**	**−0.446**
Pro × Female	0.081	−0.039	0.084	0.008	−0.043	**−0.336**	0.196
Interceptive × Female	**−0.226**	0.087	−0.075	**0.259**	**−0.184**	−0.036	**0.199**

clusters and subdivided by sport type. There was much more mixing within the collegiate and professional cohorts.

3.3. Relationship between tasks

The tasks comprising the Sensory Station battery were designed to measure sensory and motor abilities using a combination of psychometric methods (e.g., adaptive staircase procedures, speeded reaction tasks, etc.). To explore how these tasks relate to one another, and derive a more holistic picture of the constructs tested in this battery, the posterior distribution of the task correlation matrix $\boldsymbol{C}$ was evaluated. Figure 4 illustrates the location of the tasks along the first two eigenvectors of the maximum a posteriori (MAP) estimate of $\boldsymbol{C}$.

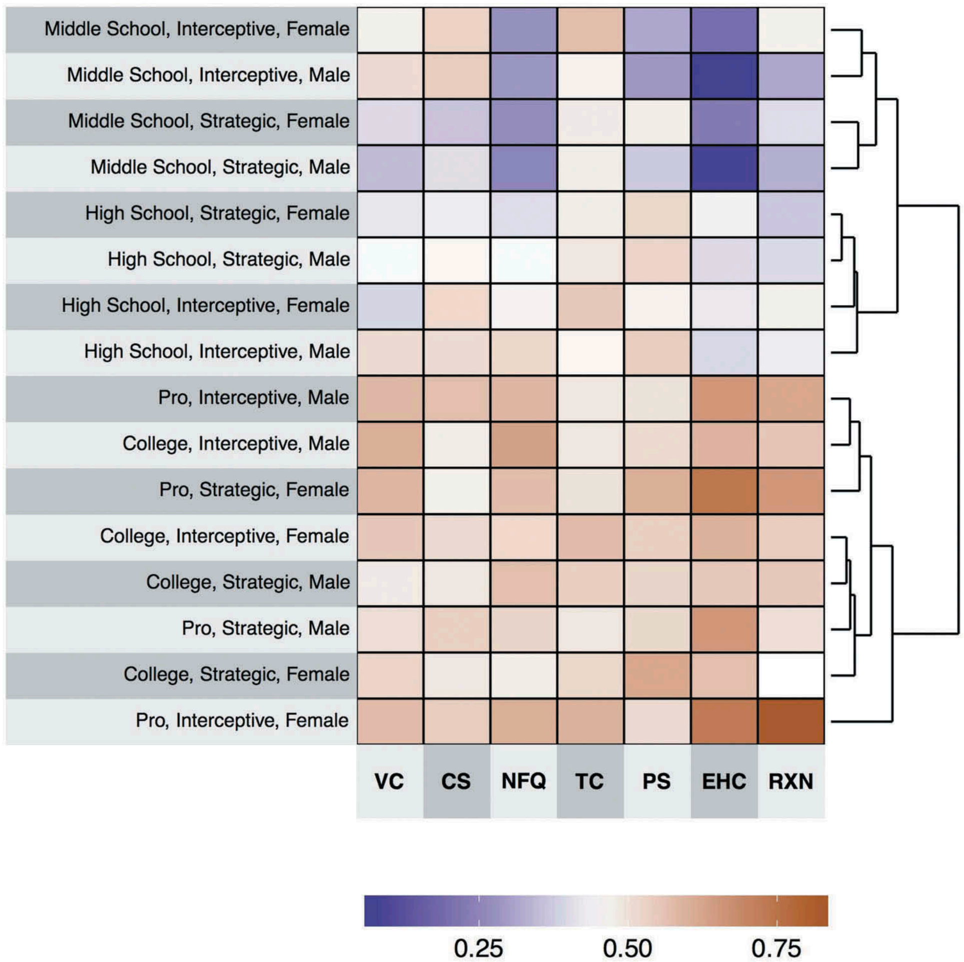

Figure 3. Heat map of the estimated percentiles of task performance for each of the 16 groups of athletes. The groups are clustered hierarchically in the row dendrogram. Note that middle school athletes and high school athletes form their own clusters, subdivided by sport type. College and professional athletes are more mixed, and typically subdivided by gender.

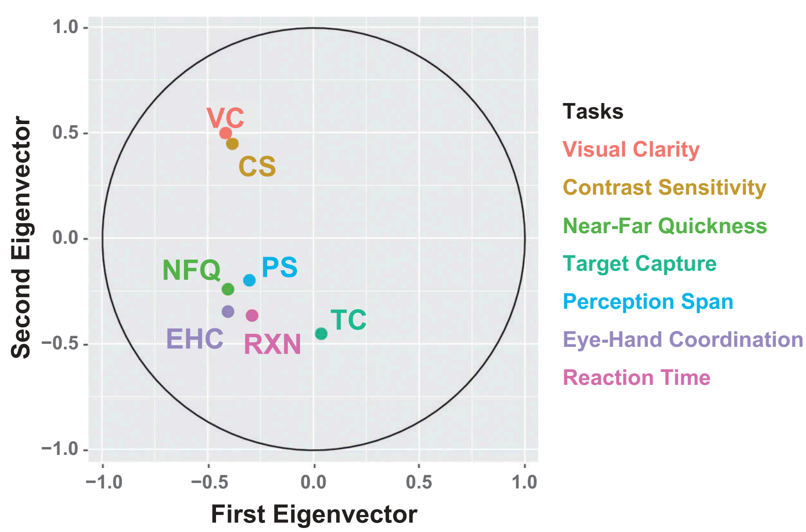

Figure 4. The location of each of the tasks along the first and second eigenvectors of the MAP correlation matrix *C*. Most of the tasks are the same sign along the first eigenvector, whereas VC and CS are different signs than the other tasks along the second eigenvector.

The first eigenvector can be interpreted as capturing overall visual-motor ability, whereas the second eigenvector captures differences between the tasks that measure visual sensitivity (Visual Clarity and Contrast Sensitivity) and the other tasks. An examination of the conditional dependence structure of the task scores is provided in the Appendix.

4. Discussion

In this article, we explored variation in visual-motor abilities across a sample of 2317 athletes tested on the Nike Sensory Station. Each athlete completed a standardised assessment battery designed to capture distinct visual-motor abilities, such as visual-motor control, visual sensitivity, and eye quickness (Wang et al., 2015). By applying a rank-likelihood multivariate regression approach to analyse the relationship between task scores and background variables such as athlete level, sport type, and gender, a number of findings emerge.

Of fundamental interest, both the main effects and interaction models consistently reveal that visualmotor abilities, especially those with strong visual-motor control demands, are greater at higher levels of athletic achievement. This gradation of expertise level is unique in the literature, given that past research predominantly involves comparing small numbers of athletes to non-athletes on divergent choices of tasks (see Mann et al., 2007; Voss et al., 2010). By estimating the performance difference on an identical task battery from athletes ranging from middle school to high school, to college, and to professional level, the current study provides important data regarding visual-motor variability across different age groups and competitive levels. While caution must be taken in interpreting these effects given the self-reported nature of the demographic and sport characteristics, this study does provide exploratory evidence of cross sectional differences in the visual-motor skills of athletes. As, such, future hypothesis-driven research may use the characteristics identified here to guide studies testing talent identification or training studies aimed at improving on-field performance.

In addition, the current results indicate that performance on the battery of tasks differs by sport type. The distinction between strategic and interceptive sports has been made in several meta-analytic reviews (Lebeau et al., 2016; Mann et al., 2007; Voss et al., 2010), reflecting a strong research interest in understanding how competition demands are reflected in athlete's underlying abilities. However, in the past it has been difficult to infer such differences because of the small sample sizes and varied assessments used across studies. Our findings indicate that athletes playing interceptive sports exhibit better Visual Clarity, Contrast Sensitivity, Near-Far Quickness, and Reaction Times than those playing strategic sports. In contrast, athletes playing strategic sports tend to score higher on the Perception Span task. This suggests that different visual-motor abilities are engaged by the situational demands of each sport type. Specifically, for interceptive sports, the importance of interacting with a fast-moving object may demand an enhanced ability to see the object, distinguish it from its environment, and react to its movement (Davids, 2002). In strategic sports such as soccer, athletes must simultaneously maintain an array of information about teammates, opponents, and the ball. As such, players with a high ability in Perception Span can quickly code and preserve spatial information, obtaining a performance advantage in pattern recognition and recall (Abernethy, Burgess-Limerick, & Parks, 1994), decision-making (Starkes & Ericsson, 2003), and development of team mental model (Mohammed & Dumville, 2001).

The current findings indicate that female athletes are better, on average, at Perception Span and Eye-Hand Coordination than their male counterparts, holding constant the level of expertise and sport type. This is particularly true at the middle school level. The female advantage in Perception Span may be attributed to the combination of rapid development of spatial working memory during the middle school years (Gathercole, Pickering, Ambridge, & Wearing, 2004) and earlier developmental acceleration in females. The female advantage in Eye-Hand Coordination is surprising, though previous studies have found that women are faster at programming a sequence of manual movements (Nicholson & Kimura, 1996) and more accurate at controlling arm movements under time pressure (Liu, Eklund, & Tenenbaum, 2015). These female advantages may also be related to past demonstrations that females exhibit faster perceptual processing speeds and greater verbal fluency (e.g., Kimura, 1999; Voyer, Voyer, & Bryden, 1995), though other studies have shown that gender differences in perceptual and attentional processing observed in non-athletes are not present in athlete populations (Lum, Enns, & Pratt, 2002). While it is important to note that the current sample is substantially larger than any of these past study cohorts, it is also the case that the current sample (like in most other athlete studies) contains many more males. In particular, there are only three professional female athletes in the sample who play interceptive sports. Moreover, despite the fact that the our methods account for sample size heterogeneity in each category, there were particularly few professional female athletes, as compared to their male counterparts. As such, the current conclusions mirror those of Voss et al. (2010) who state that, "future studies should try to recruit both males and females to permit more within-study and across-study comparisons of gender."

The methods and results in this paper have many strengths, but also limitations. First, while the present study is based on a very large sample of athletes, this programme was not available to all athletes. As such, this does not reflect a random sample of all athletes, but rather only of athletes who either individually paid for the services, participated in programmes that did, or were at institutions where research was being conducted with the device. Second, information provided about the athletes was made through entry of self-reported information by the athletes, such as their age, sport, level and position. While it is expected that of the responses were accurate, it is possible that some percentage of data was mislabelled. Despite this, a large percentage of the centres contributing to the dataset were verified by the authors through discussions or published research studies from groups using the systems (e.g., Burris et al., 2018; Erickson et al., 2011; Gilrein, 2014; Poltavski & Biberdorff, 2014). Third, though it would be valuable to infer new information about the developmental trajectories of athletes in this sample, the fact that athlete level and age are highly confounded makes it impossible to separate developmental effects from expertise effects. Fourth, the correlational nature of the study makes it difficult to discern potential causal relationships; for example, participation in the sport may improve performance on some visual-measures. Lastly, due to the real-world nature of these data and the desire to capture meaningful relationships among variables (that do not necessarily conform to the assumptions inherent in linear regression models), a novel model was developed to use only the ranks of the data, making it robust to the marginal distributions of the task scores. Although using ranks would result in the loss of some information this was not a substantial concern due to the large sample size of this dataset (Hoff, Niu, & Wellner, 2014).

Collectively, these findings provide quantitative evidence, from a very large, real-world test battery, of domain-specific visual expertise in athletes. By analysing data collected on athletes, spanning from developing adolescents to many of the most elite professional athletes in the world, this study provides a unique lens into the visual and motor capabilities that differentiate individuals with different levels of expertise and types of athletic experience. While it is not possible to infer causal relationships, these findings do open intriguing questions about the influences of nature and nurture on athletic achievement. To arbitrate these challenging, but important questions, future research should look to longitudinal developmental and interventional designs to further investigate the findings observed here.

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