Title
Visual perception principles in constellation creation in individuals

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Authors
Kelly, Bridget A
Kemp, Charles
Little, Daniel R.
et al.

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Visual perception principles in constellation creation

Bridget A. Kelly* (bakelly@student.unimelb.edu.au)
Charles Kemp* (c.kemp@unimelb.edu.au)
Daniel R. Little* (daniel.little@unimelb.edu.au)
Duane Hamacher† (duane.hamacher@unimelb.edu.au)
Simon J. Cropper* (scropper@unimelb.edu.au)

*School of Psychological Sciences & †School of Physics, University of Melbourne Parkville, Victoria, Australia

Abstract

Many cultures share common constellations and common narratives about the stars in the night sky. Previous research has shown that this overlap in asterisms, minimal star groupings inside constellations, is clearly present across 22 distinct culture groups and can be explained in part by properties of individual stars (brightness) and properties of pairs of stars (proximity) (Kemp, Hamacher, Little and Cropper, 2022). The same work, however, found no evidence that properties of triples (angle) and quadruples (good continuation) predicted constellation formation. We developed a behavioural experiment to explore how individuals form constellations under conditions that reduce cultural learning. We found that participants independently selected and connected similar stars, and that their responses were predicted by two properties of triples (angle and even spacing) in addition to the properties of brightness and proximity supported by previous work. Our findings lend further evidence to the theory that commonality of constellations across cultures is not a result of shared human history but rather stems from shared human nature.

Keywords: visual perception; gestalt principles; perceptual grouping; constellations; brightness; proximity; even spacing; good continuation

Introduction

Astrophysicists, anthropologists, and cultural astronomers have identified an intriguing phenomenon; many geopolitically, chronologically, linguistically, and culturally diverse groups across the world share a common perspective on the night sky (Hamacher, 2012; Norris, 2016; Hamacher, 2020). Of particular intrigue is the similarities of night sky constellations and narratives between the Aboriginal and Torres Strait Islander cultures, the world's oldest living cultures (120,000 - 60,000 years old) and the Ancient Greeks (1000 BCE - 31 CE; Gullberg et al., 2019; Hamacher & Norris, 2011; Ruggles, 2005).

While many cultures across the world share common constellations and their narratives (Ruggles, 2005; Kemp, Hamacher, Little and Cropper, 2022; Kemp, Hamacher, Little, and Cropper, 2022a), the commonalities between the Aboriginal and Torres Strait Islander cultures and the Ancient Greeks highlight the tension of an anthropological explanation. Evidence for transfer of constellations and narratives between these groups has not yet been substantiated. Of note, Aboriginal and Torres Strait Islanders cultures are primarily oral based cultures (Kelly, 2016) which would require person-to-person knowledge transfer methods. Given there are significant barriers of geography, culture, language, and time period that separate these groups (Malaspinas, 2016), transfer of night sky knowledge appears unlikely. We suggest that this phenomenon might be better understood through the innate human visual perceptual cognition processes we all share.

Kemp et al. (2022) systematically catalogued the asterisms that repeat across cultures. Asterisms are smaller groups of stars within larger constellations. For example, within the Orion constellation there is Orion's belt, a smaller asterism of three stars. Ten asterisms were identified as featuring strongly across the 22 distinct and unique cultural constellation sets included in the analysis. Of these, asterisms from familiar constellations such as Orion, Pleiades, Hyades (Taurus), Big Dipper, and Southern Cross were found to feature prominently.

Kemp et al. (2022) also sought to investigate if these commonalities could be explained by principles of vision including brightness and Gestalt visual principles of proximity, convexity (collinearity), and good continuation (Metzger, 1936). When incorporated into a computational model (Kemp et al., 2022), the properties of brightness and proximity were enough to account for many of the constellations across cultures. The same analysis, however, provided no evidence that constellations across cultures were influenced by convexity and good continuation.

Kemp et al. (2022) used 22 cultural data sets that aggregate and collapse individual perspectives down into a singular cultural perspective. Here we collect data on constellation formation from a sample of individuals, which provides us with a greater opportunity to detect the potential influence of principles such as convexity and good continuation. We also introduce an additional principle – even spacing – and evaluate its impact on star grouping. In our setting, even spacing is the tendency to create triples of stars that have two

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internal edges of similar lengths. Individuals are able to identify familiar objects with minimal boundary completion (5%) when they have even spaced dot boundaries (Green and Hautus, 2017). This is in contrast to recognition of objects with randomly spaced dot boundaries (33%) or contiguous dot boundaries (57%; Greene, 2007; Nordberg, Hautus and Greene, 2018). On face value, the sparse dot-boundaries in these experiments (Greene, 2007; Green and Hautus, 2017; Nordberg et al., 2018) have much in common with constellations, which are sparsely distributed stimuli with low-level features that can be connected. Given these results, it is worth considering how the regularity of between-star intervals impacts the grouping of stars into a single constellation.

An additional limitation of the cultural constellation data sets used by Kemp et al. (2022) is that they cannot be used to distinguish between groupings that individuals form on their own and groupings that are the product of prior experience or cultural learning. We sought to examine whether common constellations are independently created by individuals in order to understand how perception influences constellation groupings. To achieve this, we measured star grouping in an environment that examined the perception of individual participants but reduced prior learned knowledge of the star field.

All participants in our experiment viewed the same star field, which controls for a source of variability in the data used by Kemp et al. (2022). Different cultures represent perspectives that vary across locations, elevations, angles, time periods and orientations, and all of these factors are well known to impact how the night sky is seen and interpreted (Hamacher, 2020). In contrast, our experiment allows us to compare how individuals and computational models respond to a stimulus that has a fixed scale and perspective.

In short, the aim of this study is to explore whether the visual principles of brightness, proximity, convexity, good continuation, and even spacing (Kemp et al., 2022; Greene, 2007; Nordberg et al., 2018) can explain how individuals independently group stars into constellations produced in a novel context within a study with fixed perceptual parameters.

Method

Participants

189 members of the public who attended a public science event held in 2019 in Melbourne, Australia participated in the study. Demographic information was not collected as part of this research.

Materials

A novel night-sky scene was taken from the *Stellarium* app; we chose a portion of the night sky that is unfamiliar to the general observer, over an area including the constellations of Carina and Vela, and where these constellations overlap with Volans. We chose this scene as it has ecological validity, yet it does not contain constellations commonly identified across cultures (Kemp et al., 2022). The scene includes 79 stars with sizes ranging from 1 to 15 pixels in diameter and is shown in Figure 1. The image was projected on the ceiling of the large, darkened room in which the event was held.

Procedure and Design

Participants were asked to create a constellation using the stars in the scene and provide their responses via a web app that they accessed on their own device. Each participant created a constellation by tapping on stars in sequence, and the application connected each consecutive pair of stars with a line, see Figure 1. Participants could adjust their responses as they went, adding or deleting lines. Once satisfied, they submitted their final constellation. Participants were then asked to provide a constellation name and narrative describing the meaning of their constellation (not analysed in the current paper).

Figure 1. Screenshots of the web application with research stimulus used by participants to draw their constellations.

Visual Principles Within Star Groups Five visual principles were examined in analysis across four different constellation group sizes; *singletons, pairs, triples, and quads* (see Figure 2 for indication of how each visual principle was applied on each constellation group size). The five visual principles were measured and predicted to impact results as follows.

1. Brightness is measured by star size as proxy for *magnitude.* In stellar *magnitude*, brighter stars have lower *magnitudes*, therefore larger stars have a smaller stellar *magnitud*e. Low *magnitude* (i.e., high brightness) was expected to predict frequency of selection.

2. Proximity is measured by Euclidean *distance* between stars in *pairs*. Pairs with shorter *distances* are expected to be selected more often in comparison to pairs with larger *distance* scores.

3. Convexity is measured by *angle* between three stars in a group, in *triples*. High convexity is when the *angle* between three stars is close to 180°. High convexity is expected to increase selection.

4. *Even spacing* is measured by Euclidean *distance* between two stars in a *Pair*. *Even spacing* is the similarity of

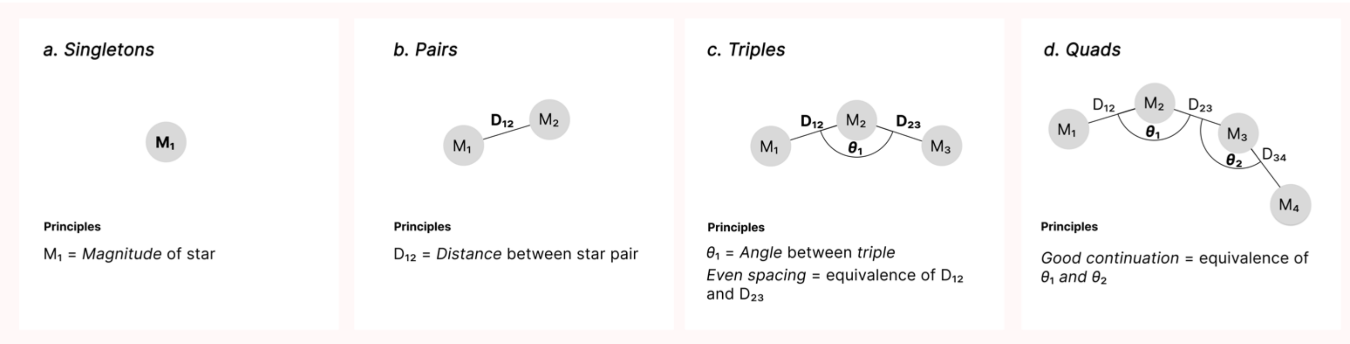

Figure 2. Five visual principles were examined in analysis across four different star group sizes

the two *distances* in a *Triple*. High *even spacing* is when the *distances* in star *pairs* inside a *Triple* are equal. High *even spacing* is predicted to increase likelihood of selection.

5. *Good continuation* is calculated by smoothness of figures or edges. This is measured by similarity of both *angles* of the two *triples* in *quads.* High *good continuation* is expected to increase selection.

Results

Responses for 20 participants who submitted inappropriate or nonsensical text responses, or entries marked 'test' were removed. 169 responses remained for analysis; four of them are shown in Figure 4.

A consensus plot summarising responses across all participants is shown in Figure 3. Edge widths denote the frequency with which edges were selected, and the plot includes only edges selected 10 or more times. The most frequent subgroup is the central quadruple of stars called "Jason's cross" in Figure 4, and a second common subgroup is the circle ("Wheel of time").

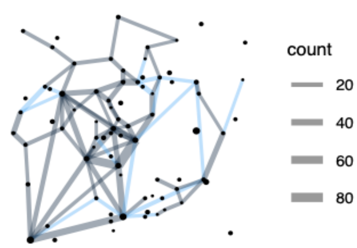

Figure 3. Consensus plot showing edges selected by at least 10 participants. Edge width denotes selection frequency, and non-multiscale Delaunay triangulation edges are shown in blue.

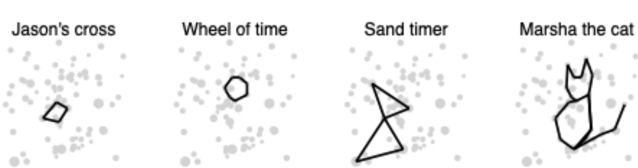

Figure 4. Responses of four participants that exemplify common star edges selected

Previous work on the organization of random dot patterns (van den Berg, 1998) and constellation perception (Dry et al., 2009; Kemp et al., 2022) has suggested that people tend to construct constellation figures out of edges belonging to a Delaunay triangulation of the stimulus. A Delaunay triangulation is a network created by connecting all of the stars into triangles in a way that disfavours triangles with small angles. We generated a multiscale Delaunay triangulation by thresholding at all magnitudes between 1 and 15, computing Delaunay triangulations for each thresholded set of stars, and taking the union of all of these triangulations. Most of the frequently chosen edges in Figure 3 belong to this multi-scale Delaunay triangulation, and those that do not are shown using blue.

We used a multi-scale Delaunay triangulation to generate sets of candidate *pairs*, *triples,* and *quads* for analysis. A *pair*, *triple* or *quad* was included if it was provided by at least one participant or if it can be constructed using the multi-scale Delaunay triangulation. Including Delaunay structures means that we have *pairs*, *triples,* and *quads* in the analyses that were never chosen by participants. This allows us to ask how well the five perceptual features identified earlier distinguish between *pairs*, *triples,* and *quads* that were selected and those that were never chosen.

Visual Principles Within Star Groups Analysis

Figure 5 shows the relationship between the five perceptual features and star selection frequency. In all cases, low feature values are expected to be associated with groups of stars more frequently chosen by participants.

1. *Magnitude.* The first panel focuses on the *magnitude* as a feature of single stars, *singletons*, where *magnitude* is defined as the negative logarithm of the star's radius. Our *magnitude* variable is therefore comparable to stellar *magnitude*, where brighter stars have lower *magnitudes*. As expected, the figure shows that the stars selected most frequently tend to be large stars (i.e., low in *magnitude*). Large stars, however, are not inevitably selected, and the plot reveals that one of the largest stars (the star just left of the tip of Marsha's tail in Figure 4) is never selected.

2. *Distance.* The second panel shows the Euclidean *distance* between *pairs* of stars. As expected, the most frequently selected *pairs* tend to be relatively close to each

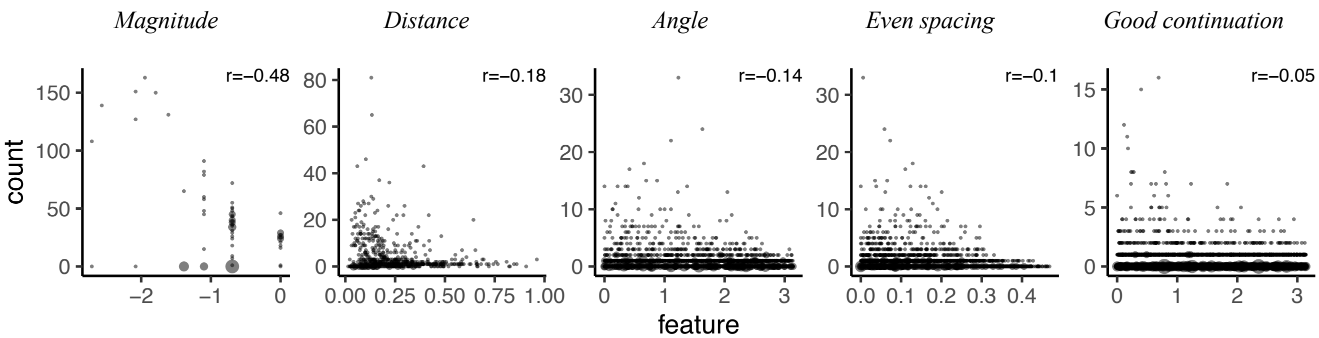

Figure 5. The five transformed variables plotted against frequency to examine prevalence in star selections. Larger markers indicate cases where multiple data points lie at the same location.

other. There are many nearby *pairs*, however, that are never or rarely selected.

3. *Angle.* The third panel is based on the *angle* in star *triples*. The *angle* $\angle 123$ in radians between three stars in a *triple* is transformed using $abs(\pi - \angle 123)$ so that larger *angles* have smaller feature values, and collinear triples have a feature value of 0. Among commonly selected *triples* there are more points to the left of the plot than the right, suggesting that participants tend to select *triples* that form large *angles*.

4. *Even spacing.* The fourth panel shows a variable defined as $abs(0.5 - d_{12}/(d_{12}+d_{23}))$, where d_{12} is the *distance* between the first two points in a *triple* and d_{23} is the *distance* between the final two points. If these two *distances* are identical, then the even spacing variable takes value 0. The most frequent *triples* tend to have small feature values, suggesting a preference for *even spacing*.

5. *Good continuation.* The fifth panel focuses on *quads*, and the perceptual variable is defined as $abs(\angle 123 - \angle 234)$, where $\angle 123$ is the signed *angle* (in radians) for the first three stars in a *quad* and $\angle 234$ is the signed *angle* for the final three points. If these two *angles* are identical, then the *good continuation* variable takes value 0. The most frequently chosen *quads* tend to have small feature values, suggesting a preference for *quads* formed from *triples* with similar *angle*s.

The exploratory analyses in Figure 5 provides some initial evidence that people's responses may be influenced by all five perceptual features considered here. To build on these results we considered regression models that attempt to predict the frequency of *singleton*, *pair*, *triple* and *quad* selection using the five perceptual features as predictors. The predictors included in each model are listed in the second column of Table 1. For example, when predicting the frequency with which *quads* were selected, all five perceptual features were included as predictors, and the model formula was *count ~ magnitude + distance + angle + even_spacing + good_continuation.*

Because *magnitude* is a feature of *singletons*, an aggregation function is needed to combine the *magnitude* of the four members of a *quad* into a single *magnitude* value for the *quad*. Following Kemp et al. (2022) we used a *max* function as the aggregation function, which means that the *magnitude* of a *quad* corresponds to the largest *magnitude* for any of its members (i.e., the magnitude of the least bright star of the star set). For example, if a *quad* has three bright stars and one very faint star using the *max* function for *magnitude* would exclude that *quad* from analysis. The same aggregation function was used to combine *distance*s, *angles*, and *even spacing* scores. For example, the value of *even spacing* for a *quad* is the maximum of the *even spacing* values for its two component *triples*.

The following subsections describe two families of regression models that used identical model formulas but made different assumptions about the distribution of the dependent variable (*count*).

Linear Regression Models We first implemented a set of linear regression models that are closely related to the Graph Clustering model presented by Kemp et al. (2022). That model includes an additional step in which the predictor variables are scaled within a local neighbourhood, and the linear regression models here omit that step for simplicity.

Each linear regression model uses a log link function. The purpose of these models was to fit weights to the perceptual features that maximised the correlation between predicted and observed counts. These correlations are shown in Figure 6, and the coefficients responsible for these correlations along with confidence intervals are shown in Table 1. All perceptual features were scaled to have zero mean and unit variance, so the coefficients for different perceptual features can be directly compared.

Figure 6 reveals that the regression models for *singletons* and *pairs* achieve moderate correlations (0.49) with the observed counts. The model for *pairs* is closely related to the Graph Clustering model presented by Kemp et al. (2022), although that model includes a single parameter that controls the relative strengths of *magnitude* and *distance* but here a parameter is estimated for each feature. The coefficients for the *pairs* model (see column 3 of Table 1) are consistent with the suggestion in Kemp et al. (2022) that *distance* has a stronger effect on perceptual grouping than star *magnitude*, because the coefficient for *distance* has higher absolute value than the coefficient for *magnitude*. The 95% confidence intervals for the two coefficients, however, overlap each other.

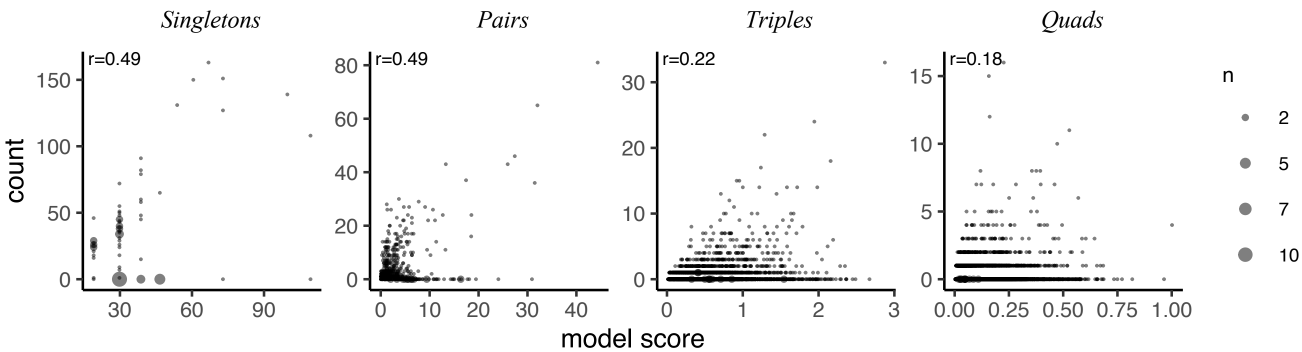

Figure 6. Observed counts against linear regression fits for *Singletons, Pairs, Triples* and *Quads*

The results for *triples* and *quads* reveal weak positive correlations of 0.22 and 0.18 respectively. For *triples* the coefficients suggest that *angle* and *even spacing* carry roughly equal weight as predictors, and for *quads* the coefficients suggest that *good continuation* carries less weight than *distance*, *angle* and *even spacing*.

Negative Binomial Regression Models The linear regression models used in the previous section are useful because the results provide an upper bound on the correlations that can be achieved between predicted and observed counts. However, these models do not acknowledge that the dependent variable is a count. We therefore implemented an additional set of negative binomial models that are specifically designed for hypothesis testing of count data. These negative binomial models use the same formula as the linear regression models, and the key difference is that the dependent variable (*count*) is now assumed to follow a negative binomial distribution.

To test the contributions of the five perceptual features, we fit Bayesian regression models using the *brms* package in R (v2.18.0, Burkner et al., 2019). Default priors were used in all cases. For each model, we compute 95% credible intervals for all coefficients. Credible intervals that exclude zero are taken as evidence that the perceptual feature in question predicts people's responses.

Point estimates and credible intervals for all models are shown in the right-hand side column of Table 1. The credible intervals for the majority of the predictors exclude zero (i.e., are either positive or negative in their range). The two exceptions to this observation are *good continuation* and *magnitude* as predictors of *quads* frequency. Our Bayesian analysis therefore does not support the conclusion that perceptual grouping for *quads* is influenced by *good*

Table 1. Impact of five visual perception features on each star set size within two regression models. For the negative binomial model, estimates with a 95% credible interval that excludes zero are shown in bold.

Data set size	Term	Linear Regression (Log link)		Negative binomial model	
		Estimate	Confidence Interval	Estimate	Credible Interval
Singleton	(Intercept)	3.5	3.21 , 3.72	3.5	**3.16 , 3.88**
Singleton	Magnitude	-0.41	-0.54 , -0.27	-0.43	**-0.78 , -0.1**
Pair	(Intercept)	0.53	0.07 , 0.89	1.27	**1.16 , 1.39**
Pair	Magnitude	-0.98	-1.17 , -0.82	-0.39	**-0.5 , -0.29**
Pair	Distance	-1.14	-1.42 , -0.89	-0.57	**-0.69 , -0.44**
Triple	(Intercept)	-0.79	-1.02 , -0.63	-0.62	**-0.68 , -0.55**
Triple	Magnitude	-0.37	-0.55 , -0.22	-0.16	**-0.22 , -0.09**
Triple	Distance	-0.62	-0.87 , -0.42	-0.23	**-0.31 , -0.15**
Triple	Angle	-0.31	-0.39 , -0.24	-0.37	**-0.43 , -0.3**
Triple	Even spacing	-0.24	-0.33 , -0.16	-0.27	**-0.34 , -0.2**
Quad	(Intercept)	-3.03	-3.15 , -2.93	-2.88	**-2.95 , -2.82**
Quad	Magnitude	0.13	0.07 , 0.19	0.02	-0.04 , 0.08
Quad	Distance	-0.35	-0.47 , -0.24	-0.16	**-0.23 , -0.08**
Quad	Angle	-0.49	-0.54 , -0.44	-0.49	**-0.55 , -0.43**
Quad	Even spacing	-0.37	-0.42 , -0.31	-0.42	**-0.48 , -0.36**
Quad	Good continuation	-0.17	-0.23 , -0.11	-0.05	-0.11 , 0.01

continuation or *magnitude*, and suggests that *quads* are best explained through perceptual features of *distance, angle* and *even spacing*. However, *magnitude* does influence perceptual groupings for *singletons, pairs* and *triples.* Overall, we find evidence that the features of *magnitude, distance, angle* and *even spacing* are robust predictors of people's responses.

The relative magnitudes of the Bayesian estimates are broadly comparable with the results of the linear regression analysis. For example, the Bayesian analysis provides additional evidence that *distance* carries more weight than *magnitude* as a predictor of pair frequency, and that *angle* and *even spacing* carry roughly equal weight as predictors of triple frequency.

Discussion

The results from this study show that individuals are likely to identify and cluster stars in manners that have shared features, both in the stars selected and connections between stars, to form common constellations. Furthermore, this agreement occurs independently between individuals and without prior learned knowledge of the night sky scene. This resolves two potential confounding factors that were present with the prior study by Kemp et al. (2022) and lends further evidence to support the theory that visual perceptual processes contribute to the commonality of constellations across the world's cultures.

In addition, this study further elucidated which visual principles underpin the formation of constellations across cultures (Kemp et al., 2022; Greene, 2007; Nordberg et al., 2018). Previously, it was found that proximity (*distance)* and brightness (*magnitude)* explained commonly identified constellations across cultures, with proximity (*distance)* having the strongest effect (Kemp et al., 2022). Here, we found that brightness within *singletons* and proximity within *pairs* were predictive of selection*.* The Gestalt principles of convexity (collinearity, *angle)* and *even spacing* carried similar weight as predictors in three-star (*triples)* and four-star (*quads)* sets. As star groups size grow larger, the number of features present increased and the level of a feature's influence on star selections varied. Notably, as the star set increased in size, the ability for *magnitude* to predict star selections decreased in influence and was found not to predict star selection in the largest star set, *quads*. Similarly, the ability of *distance* to explain star selection decreased in influence in models for *triples* and *quads* compared to *singletons* and *pairs*. One explanation for this may be that as perceptual grouping grows more complex, features such as *even spacing* are prioritised by the visual system over other features, such as *magnitude*. This aligns with previous research on the inter-related nature of these visual principles and their variable interdependent conditions for activation (Lezama et al., 2016; Wagemans, Elder et al., 2012; Wagemans, Feldman et al., 2012; Wilder et al., 2016).

Contrary to our expectations, we found that the Gestalt principle of *good continuation* did not explain selections of stars in sets of four (*quads).* The largest star group sets consisting of four stars may have not reached a threshold where this property is critical (Wagemans, et al, 2012; Field, Hayes & Hess, 1993). Gestalt principles can fail to be activated in laboratory or non-naturalistic studies due to isolation of principles from one another (Lezama et al., 2016; Wagemans et al., 2012; Wagemans et al., 2012; Wilder et al., 2016). Our study was designed to minimise these methodological limitations. We used naturalistic images and conditions, captured individual independent responses, and created a singular scale perspective for the stimulus to create robust conditions for data capture and our analyses. Additionally, given the strength of the models' ability to predict the selections using four of the five visual principles, we believe our analyses are capable of identifying the core components that underpin this phenomenon. Given that *good continuation* appeared to be present in the initial exploratory analysis of the constellations but did not have explanatory power in the model, it may be beneficial to explore this principle in larger star group sets to assess for contexts where it may be present to a greater degree. Additionally, future research design could allow for multiple constellations to be drawn and include other visual features, such as Gestalt principle of symmetry in the analysis to further expand on these findings and increase the explanatory power of the models.

The mystery of why cultures from across the world have common constellations has been documented for some time but it is not yet well explained. This research supports the hypothesis that common constellations do have a shared origin story, not in our history but in our human nature. Throughout history, humans have existed under different environmental, geo-political, cultural, and linguistic conditions – but we all share a common, evolved visual perception system that strives to construct meaningful, stable, and shared representations of the world. However, we know that an individual's personality traits (Partos, Cropper, and Rawlings, 2016) and cultural or ethnographic background can impact their perceptions of visual stimuli (Goto, Ando, Huang, Yee, & Lewis, 2010; Masuda and Nisbett, 2006). Future research should consider measuring or controlling for these factors to understand how these may impact the creation of shared constellations. In addition, we did not examine in this paper the shared narratives that co-exist alongside shared constellation. For example, the commonly identified constellation of Orion also has a commonly shared narrative of chasing the Pleiades across the night sky (Kemp et al., 2022a). Narrative has shown to be a feature of oral cultures' ways of sharing, knowing, and remembering, notably within the Aboriginal and Torres Strait Islander cultures (Hamacher, 2020). It is worth investigating if the similarly strong human preference for sense-making through narrative is working in tandem with the visual system's preferences. Together, these two components could allow us to derive a strong evidence-based explanation for the cross-cultural overlap of constellations and their narratives across the world. In doing so, we will better understand how we came to share in our experience of the night sky and be given a glimpse into the innate human forces that unite us throughout history.

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