Information Complexity in Material Culture

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Humans invest a substantial amount of time in the creation of artworks. For generations, humans around the world have learned and shared their knowledge and skills on artistic traditions. Albeit large experimental settings or online databases have brought considerable insights on the evolutionary role and trajectory of art, why humans invest in art, what information artworks carry and how art functions within the community still remain elusive. To address these unresolved questions, this present thesis integrates ethnographic accounts with data governance and statistical approaches to systematically investigate a large corpus of art. This thesis specifically focuses on a large corpus of Tamil *kolam* art from South India to provide an exemplary case study of artistic traditions. The foundation for the projects presented in this thesis was the design and construction of a robust data infrastructure that enabled the synthesis of raw data from various sources into one database for systematic analyses. The data infrastructure on the *kolam* artistic system enabled the development of complex statistical methods to explore the substantial investments and information complexity in art. In the first chapter, I examine artists' strategic decisions in the creation of *kolam* art and how they strive to optimize the complexity of their artworks under constraints using evolutionary signaling theory and theoretically guided statistical methods. Results revealed that artists strive to maintain a stable and invariant complexity measured as Shannon information entropy, regardless of the size of the artwork. In order to achieve an optimal artistic complexity "sweet spot", artists trade-off two standard measures of biological diversity in ecology: evenness and richness. Additionally, results showed that although *kolam* art arises in a highly stratified and multi-ethnic society, artistic complexity is strategically optimized across the population and not constrained by group boundaries. Instead, the trade-off can most likely be explained by aesthetic preferences or cognitive limitations. While artistic complexity in *kolam* art can be strategically optimized across the population, distinct styles and patterns can still be employed by artists. Thus, in the second chapter, I focus on how artistic styles in *kolam* art covary along cultural boundaries. I employ a novel statistical method to measure the mapping between styles onto group boundaries on a large corpus of *kolam* art by decomposing the system into sequential drawing decisions. In line with Chapter 1, results demonstrate limited group-level variation. Distinct styles or patterns in *kolam* art can only be weakly mapped to caste boundaries, neighborhoods or previous migration. Both chapters strongly suggest that *kolam* art is primarily a sphere where artists differentiate themselves from others by displaying their unique skill set and knowledge. Thus, variability in *kolam* art is largely dominated by individual-level variation and not reflective of group boundaries or narrow socialization channels. This thesis contributes to an emergent understanding of how artists conceptualize what they are doing and how art functions within the community. Taken together, this thesis serves as an example approach that demonstrates an optimized workflow and novel approaches for the evolutionary study of a large corpus of artistic traditions.

This dissertation is based on the following publications:

Tran, N.-H., Waring, T., Atmaca, S., & Beheim, B. (2021). Entropy trade-offs in artistic design: A case study of Tamil *kolam*. *Evolutionary Human Sciences*, 3, E23. DOI: `https://doi.org/10.1017/ehs.2021.14`

Tran, N.-H., Kucharský, Š., Waring, T. M., Atmaca, S., & Beheim, B. A. (2021) Limited Scope for Group Coordination in Stylistic Variations of *Kolam* Art. *Frontiers in Psychology*, 12, 742577. DOI: `https://doi.org/10.3389/fpsyg.2021.742577`

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"But maybe being their child simply means that I will always feel the weight of their past. Nothing that happened makes me special. But my life is a gift that is too great - a debt I can never repay."

Thi Bui, The Best We Could Do

Cho Ba Mẹ

For Mum and Dad

Summary

Theoretical Background

Complex material culture is one of the many unique achievements that made humans so ecologically successful (Boyd and Richerson, 1985; Cavalli-Sforza and Feldman, 1981; Laland, Odling-Smee, and Feldman, 2000) and thus profoundly shaped human evolution (Ambrose, 2001; Foley and Lahr, 2003). While non-human animals possess cultural traditions (e.g., avian nest construction or stone-tool-aided foraging, see Barrett et al., 2018; Breen, 2021), humans uniquely accumulate knowledge and skills over successive generations (Mesoudi and Thornton, 2018; Boyd and Richerson, 1996). Changes and improvements in human cultural traditions are accumulated over generations. Thus changes in the spatial and temporal coherence of certain material culture attributes have been viewed as indicative of underlying shifts in environmental conditions and population dynamics (Henrich, 2004; Lycett and Norton, 2010).

In the pursuit to better understand the mechanisms underlying cultural persistence and change in ceramic, textile, and lithic traditions documented in the material culture record (Tehrani and Collard, 2009; Roux, 2015; Bettinger and Eerkens, 1999), researchers have implemented tools from population biology and developed theoretical models that drew from cultural evolution and transmission (Boyd and Richerson, 1985; Cavalli-Sforza and Feldman, 1981). An extensive literature has concentrated on understanding the continuities and discontinuities as well as the spatial and temporal distribution of material culture products to classify assemblages and discern (past) identities (Eerkens and Lipo, 2007; Lipo, 2001; O'Brien, 2005). Since educational investments from adults into young novices can be substantial (Shennan and Steele, 1999; Tehrani and Riede, 2008), researchers have further conducted extensive ethnography on how knowledge and skills on material culture productions are learned, taught, and shared among communities and how these mechanisms lead to meaningful variability in material culture productions (Bowser and Patton, 2008; Helbich and Dietler, 2008; Wallaert-Pêtre, 2008).

Until recently, artistic assemblages or traditions have only received limited attention, mostly constrained to specific motifs or designs used as decorations in ceramics or textiles (Tehrani and Collard, 2009; Bowser and Patton, 2008; Wiessner, 1984). Researchers have primarily focused on artifacts contingent on functional sufficiency (e.g., arrowheads, pottery, rugs). In contrast, art is not constrained to satisfy functional requirements, but can be modified in a direction of open-ended complexity and novelty (Mesoudi and Thornton, 2018; Tinits and Sobchuk, 2020). Thus, understanding the standalone creation and appreciation of aesthetics and artistic traditions might be fundamental in understanding what makes humans unique.

In recent years, the availability of large datasets has given rise to the quantitative study of art beyond focusing only on a small number of cases (Sigaki, Perc, and Ribeiro, 2018; Liu et al., 2018). A quantitative and evolutionary approach using population thinking (Mayr, 1959) can be fundamental to explain patterns in artistic production on vast scales, allowing for inferences on population-level cultural dynamics. Access to large scale databases coupled with computational methods has enabled substantial insights into how patterns in art change over time (Youngblood, 2019; Müller and Winters, 2018; Tinits and Sobchuk, 2020) and what information is carried in art (Brand, Acerbi, and Mesoudi, 2019; Pavlek, Winters, and Morin, 2019; Morin and Miton, 2018). Even though online databases and experimental settings have allowed significant advances in understanding the evolutionary role of art, studying artistic traditions in the wild still remain a challenge due to difficulties in systematic quantification on a large scale.

Geometric artistic traditions with their systematic rules amenable to quantification provide an opportunity to investigate a large corpus of art. From Angolan sand drawings (Gerdes, 1988; Gerdes, 1990), Celtic art (Bain, 1973), Vanuatuan sand drawings (Lind, 2017) to Tamil loop patterns (Layard, 1937) — they all display structural properties (i.e., a grammar) that allow for systematic quantification. While geometric artistic traditions arise in different communities worldwide, they are unique and intriguing to study because they enable researchers to synthesize current ethnographic information with novel computational methods to create a high-resolution database of an artistic tradition. A high-resolution database of an artistic tradition would subsequently allow for a systematic study of human investments into art and advance our understanding of communication and the materialization of information in art.

Kolam art is a geometric art form and a Tamil tradition primarily practiced by women in Tamil Nadu, South India (Laine, 2013). In a morning ritual, women would wash the thresholds of their homes and draw intricate *kolam* patterns with rice powder or chalk before sunrise to start the day (Nagarajan, 2018). Women would carefully draw loop patterns around an initial grid of dots, so that the lines do not intersect with the dots, but elegantly and smoothly circle around them (Layard, 1937; Laine, 2013). The presence or absence and the level of simplicity or complexity of *kolam* drawings can communicate various information about the artist, their household, and the community (Nagarajan, 2018, p.37, 52–55, 75–81, 149, 273). Significant time is invested not only on a daily basis to showcase these ephemeral *kolam* artworks, but also to learn, teach and practice them. At a very young age, before menarche occurs, girls typically start to learn and practice *kolam*-making (Nagarajan, 2018, p. 8, 12, 15). Knowledge and expertise are most often transmitted from (grand-)mothers to (grand-)daughters. However, the *kolam* tradition is considered community knowledge, and thus artists frequently share and discuss their *kolam* designs (Nagarajan, 2018, p. 69).

From an evolutionary perspective, the *kolam* tradition provides an intriguing case study to investigate why individuals spent a substantial amount of time learning, practicing, and teaching artistic traditions and what information is embedded in artistic traditions. Importantly, the society in South India is segregated along multiple dimensions that include caste, class, language, region, and religion (Dumont, 1980). Thus, *kolam* art arises in a highly stratified and multi-ethnic society (Waring, 2012a). Since societal partitions have been shown to be displayed in material culture (Kramer and Douglas, 1992; Degoy, 2008; Granito et al., 2019), *kolam* art might also be a venue where social identity is showcased and thus provide interesting insights on how information on group boundaries can be reflected in artistic traditions.

Aims of the present research

The overall objective of this research is to establish a robust data infrastructure and to develop and apply novel approaches to study human behavioral ecology and cultural evolution in an artistic domain. To systematically and quantitatively analyze artistic traditions, careful attention to the specific details of the artistic system coupled with ethnographic background is fundamental. Thus, the overarching goal of this research is to synthesize data governance and statistical knowledge with ethnographic accounts to develop and implement a database and methods to understand the evolutionary role of artistic traditions and what information is entailed in artistic traditions. This thesis is structured as two interconnected projects that strive to deepen our understanding of how artists conceptualize what they are doing and how art functions within the community. To do this, this thesis focuses explicitly on Tamil *kolam* art. Concomitantly, both chapters are developed to serve as an example case study on *kolam* art for workflows optimized for studying geometric artistic traditions.

In the first chapter, I investigated aggregated structural and informational patterns in *kolam* art to understand the strategic investments made by artists and potential constraints operating on them. This paper is published in *Evolutionary Human Sciences*:
Tran, N.-H., Waring, T., Atmaca, S., & Beheim, B. (2021). Entropy trade-offs in artistic design: A case study of Tamil *kolam*. *Evolutionary Human Sciences*, 3, E23. DOI: `https://doi.org/10.1017/ehs.2021.14`.

In the second chapter, I focus on a novel approach to quantify covariation of artistic styles along ethnic or cultural boundaries to elucidate the role of *kolam* art for group coordination. The results are published in *Frontiers in Psychology*:
Tran, N.-H., Kucharský, Š., Waring, T. M., Atmaca, S., & Beheim, B. A. (2021) Limited Scope for Group Coordination in Stylistic Variations of *Kolam* Art. *Frontiers in Psychology*, 12, 742577. DOI: `https://doi.org/10.3389/fpsyg.2021.742577`.

Methods

The detailed data on *kolam* art was collected by Dr. Timothy M. Waring and local research assistants in Kodaikanal, Tamil Nadu in South India in 2009. I designed and created a high-resolution database to synthesize this rich and raw data, including interview surveys, GPS data, *kolam* drawings, network data and practice notebooks. I further developed a robust data pipeline to enable the transcription of *kolam* drawings using a lexicon of gestures (the lexicon was developed by Waring, 2012b). Additionally, I developed and programmed a `kolam` R package (Tran, Waring, and Beheim, 2020) for data consolidation and to specifically import the *kolam* data in a readable format into the software R for analysis. This data infrastructure created the fundamental basis for the novel methods developed and applied in Chapter 1 and Chapter 2. In both chapters, I used a data set of $3,139$ *kolam* drawings from 192 artists.

In the first chapter, I used signaling and optimization theory to investigate individuals' strategic investments into *kolam* art and how constraints might determine behavioral strategies. Since *kolam* drawings can be encoded using a lexicon of gestures, this geometric art system lends itself to focusing on standard ecological and information-theoretic measures: entropy, evenness, and richness distributions. Using a variety of aggregated measures derived from information theory to describe artworks, I investigated whether artistic complexity could be a target of optimization and whether a trade-off model could explain patterns of variations among *kolam* artworks. To understand *kolam* art from the perspective of evolutionary signaling theories of constrained optimization, I employed Shannon information entropy as a measure of artistic complexity. I further applied numerical simulations to show a systematic relationship between Shannon information entropy, richness and evenness that allowed me to detect entropy trade-offs between evenness, and richness. Building on this trade-off model, I subsequently constructed Bayesian hierarchical regression models to investigate how variations in structural and information-theoretic properties of kolam drawings can be accounted for by variation in artists, age, years of practice, and caste membership. Additionally, I employed agent-based simulations to validate the statistical models before model fitting and to check model predictions.

However, focusing merely on the artistic complexity of artistic designs is only an incomplete picture of how art can be linked to social identity, groups, and individuals. Albeit artists may optimize their artistic displays towards a specific complexity "sweet spot", artists can widely differ in *how* they do it. Specifically, artists could strategically use distinct styles or patterns of designs to, on the one hand, optimize their artwork, while on the other hand, communicate their uniqueness, aesthetic preferences or social identity.

Thus, in the second chapter, I focus on styles or patterns in *kolam* art. Specifically, I systematically investigate how styles in art can be mapped onto ethnic and cultural boundaries. As some mapping between stylistic variations and groups can be considered a prerequisite for ethnic markers (see Bell, Richerson, and McElreath, 2009), quantifying the covariation of artistic styles in *kolam* art along cultural boundaries could shed light on the extent to which *kolam* art *could* function as an ethnic marker. To describe and partition the variation in sequential drawing styles, I developed and applied a state-based Markov approach. I exploited the Markovian nature of the art system by decomposing sequential behavior (i.e., gestures) into states in a Markov chain to build a Bayesian hierarchical model that is able to map styles or patterns in art onto group boundaries. The statistical models were validated prior to model fitting and model predictions were checked using agent-based simulations.

Results

The results from the first chapter reveal an optimization sweet spot in terms of Shannon information entropy. Regardless of the size of the *kolam* drawing, most *kolam* drawings center around an entropy "sweet spot" and thus, the variation in their complexity is limited. To maintain this relatively invariant entropy in increasingly large *kolam* drawings, artists strategically increase the richness in gestures, while decreasing the evenness in gestures. The apparent trade-off between richness and evenness further suggests that entropy is the target of optimization, in the same way that, reproductive fitness is the optimization target in the trade-offs between maintenance and reproduction, or offspring number vs. offspring survival, in life-history theory. Thus, individuals strategically decide to invest in *kolam* art and optimize the complexity of their displays to maximize returns. Additionally, results show that *kolam* art does not primarily communicate social stratification or individual-level differences in age or practice. Properties of *kolam* artworks are only weakly associated with underlying social constraints operating on individual artists, indicating a relatively egalitarian information flow of *kolam* knowledge that is not constrained by information networks or social hierarchies.

Results from the second chapter are consistent with the results in Chapter 1 in that it shows minimal variation in styles of *kolam* drawings by social boundaries. Styles or patterns in *kolam* art can only be weakly mapped to caste boundaries, neighborhoods or previous migration. Instead, findings revealed that most of the variation in patterns or styles of *kolam* art is largely dominated by artist-level variations. While the findings do not provide a functional argument about whether *kolam* art actually functions as an ethnic marker (like for example, Smaldino, Flamson, and McElreath, 2018), I make the case that group-level variation and the covariation between patterns or styles of *kolam* art and group boundaries are very limited. Thus, the scope for styles to become embedded in artwork as ethnic markers to signify group boundaries is limited.

Conclusion

From an evolutionary perspective, the substantial investments of humans into artistic traditions is puzzling and intriguing. For generations, humans learn, teach and share their knowledge and skills on the creation of simple to intricate artworks. The operations underlying the creation of artworks are considerably complex, ranging from strategic decisions and manipulations that can include the artwork's size, designs, complexity, or originality. Thus, recurrent patterns in the creation process as well as similarities and differences in artworks are often meaningfully constituted by narrow channels of socialization and strategic decisions of the artist to conform or deviate from the group. To advance understanding of the role of artistic traditions in the community, the information they carry and how artists conceptualize their investments in art, we need systematic approaches to quantify and analyze large corpora of artistic traditions.

As first steps in this direction, this thesis presents a data infrastructure pipeline and two novel empirical approaches to study artistic traditions on a large corpus of data. My work contributes to an emerging picture of the evolutionary role of artistic traditions and the information complexity in artistic traditions. Using state-of-the-art unit tests, version control, and continuous integration to maintain data quality coupled with ethnographic accounts, I was able to extract and lead a team of transcribers to record raw data from various sources collected in Tamil Nadu in 2009 on *kolam* art to build a robust data pipeline. Digital access to a large corpus of art, allowed me to systematically quantify the artistic products and enabled me to develop and apply complex statistical models that are explicit about assumptions and hypothesized processes underlying the creation of the artworks.

In the first chapter, I have presented a comprehensive analysis of artists' strategic investments into art and how the flow of information within an artistic community might be constrained. Artists strategically optimize the complexity of their *kolam* artworks, regardless of their size and unconstrained by group boundaries. This finding is an important step towards understanding individuals' strategic decision-making processes in creating art.

In the second chapter, I demonstrated with a novel approach how covariation of distinctive styles or patterns in *kolam* artworks along cultural boundaries could be systematically investigated. By analyzing sequential drawing decisions, I show that *kolam* artworks only carry limited information on underlying group boundaries. The limited evidence of group-level variation is notable because even in the absence of explicit operationalization of caste-, neighborhood or region-marking in styles in *kolam* art, the various kinds of 'in-group viscosity' mechanisms like caste endogamy, kin-based migration, neighborhood segregation, combined with standard social learning models, would predict structured variation in our data. Thus, this finding further contributes to an emergent picture that the creation of art is not constrained by group or social boundaries.

Both chapters strongly suggest that art is primarily a venue where artists strive to showcase their uniqueness and aesthetic preferences. In contrast to previous findings on material culture (Bowser and Patton, 2008; Helbich and Dietler, 2008; Degoy, 2008; Tehrani and Collard, 2009), narrow information networks or socialization channels are only very weakly displayed in artistic traditions. In conclusion, this thesis provides evolutionary insights into artists' strategic decisions and the information embedded in the creation of artworks. These insights coupled with the novel data infrastructure pipeline and the statistical approaches pave the way towards future applications to other large corpora of visual and geometric artistic traditions, such as Angolan sand drawings (Gerdes, 1988), Vanuatuan sand art (Lind, 2017) or Islamic geometric art (Abdullahi and Embi, 2013). Taken together, this thesis serves as a roadmap-type approach that illustrates workflows optimized for the study of a large corpus of artistic traditions.

Zusammenfassung

Theoretischer Hintergrund

Komplexe materielle Kultur ist eine der vielen einzigartigen Errungenschaften, die den Menschen ökologisch so erfolgreich gemacht haben (Boyd and Richerson, 1985; Cavalli-Sforza and Feldman, 1981; Laland, Odling-Smee, and Feldman, 2000) und damit die menschliche Evolution tiefgreifend geprägt haben (Ambrose, 2001; Foley and Lahr, 2003). Während nicht-menschliche Tiere kulturelle Traditionen besitzen (z.B. Vogelnestbau oder steinwerkzeuggestützte Nahrungssuche, siehe Barrett et al., 2018; Breen, 2021), akkumulieren Menschen in einzigartiger Weise Wissen und Fertigkeiten über aufeinanderfolgende Generationen (Mesoudi and Thornton, 2018; Boyd and Richerson, 1996). Veränderungen und Verbesserungen in menschlichen kulturellen Traditionen werden über Generationen hinweg akkumuliert. So wurden Veränderungen in der räumlichen und zeitlichen Kohärenz bestimmter Attribute der materiellen Kultur als Hinweis auf zugrunde liegende Veränderungen der Umweltbedingungen und der Bevölkerungsdynamik angesehen (Henrich, 2004; Lycett and Norton, 2010).

In dem Bestreben, die Mechanismen besser zu verstehen, die der kulturellen Persistenz und dem Wandel der in der materiellen Kultur dokumentierten keramischen, textilen und lithischen Traditionen zugrunde liegen (Tehrani and Collard, 2009; Roux, 2015; Bettinger and Eerkens, 1999), haben Forscher Werkzeuge aus der Populationsbiologie eingesetzt und theoretische Modelle entwickelt, die sich auf die kulturelle Evolution und Übertragung stützen (Boyd and Richerson, 1985; Cavalli-Sforza and Feldman, 1981). Eine umfangreiche Literatur hat sich auf das Verständnis der Kontinuitäten und Diskontinuitäten sowie der räumlichen und zeitlichen Verteilung von materiellen Kulturprodukten konzentriert, um Assemblagen zu klassifizieren und (vergangene) Identitäten zu erkennen (Eerkens and Lipo, 2007; Lipo, 2001; O'Brien, 2005). Da die Bildungsinvestitionen von Erwachsenen in junge Novizen beträchtlich sein können (Shennan and Steele, 1999; Tehrani and Riede, 2008), haben Forscher darüber hinaus umfangreiche ethnografische Untersuchungen durchgeführt, wie Wissen und Fertigkeiten in Bezug auf die Produktion materieller Kultur erlernt, gelehrt und zwischen Gemeinschaften geteilt werden und wie diese Mechanismen zu einer bedeutsamen Variabilität in der Produktion materieller Kultur führen (Bowser and Patton, 2008; Helbich and Dietler, 2008; Wallaert-Pêtre, 2008).

Bis vor kurzem wurde künstlerischen Assemblagen oder Traditionen nur begrenzte Aufmerksamkeit geschenkt, meist beschränkt auf spezifische Motive oder Designs, die als Verzierungen in Keramiken oder Textilien verwendet wurden (Tehrani and Collard, 2009; Bowser and Patton, 2008; Wiessner, 1984). Die Forscher haben sich in erster Linie auf Artefakte konzentriert, die von funktionaler Suffizienz abhängig sind (z. B. Pfeilspitzen, Töpferwaren, Teppiche). Im Gegensatz dazu ist Kunst nicht auf die Erfüllung funktionaler Anforderungen beschränkt, sondern kann in Richtung offener Komplexität und Neuartigkeit modifiziert werden (Mesoudi and Thornton, 2018; Tinits and Sobchuk, 2020). Daher könnte das Verständnis der eigenständigen Schaffung und Wertschätzung von Ästhetik und künstlerischen Traditionen von grundlegender Bedeutung für das Verständnis dessen sein, was Menschen einzigartig macht.

In den letzten Jahren hat die Verfügbarkeit großer Datensätze zu einer großangelegten, quantitativen Untersuchung von Kunst geführt, die sich nicht mehr nur auf eine kleine Anzahl von Fällen konzentriert (Sigaki, Perc, and Ribeiro, 2018; Liu et al., 2018). Ein quantitativer und evolutionärer Ansatz, der sich auf das Populationsdenken stützt (Mayr, 1959), kann von grundlegender Bedeutung für die Erklärung von Mustern in der künstlerischen Produktion in großem Maßstab sein und Rückschlüsse auf die kulturelle Dynamik auf Bevölkerungsebene zulassen. Der Zugang zu großen Datenbanken in Verbindung mit dem Zugang zu komplexen Berechnungsmethoden hat wesentliche Erkenntnisse darüber ermöglicht, wie sich Muster in der Kunst im Laufe der Zeit verändern (Youngblood, 2019; Müller and Winters, 2018; Tinits and Sobchuk, 2020) und welche Informationen in der Kunst enthalten sind (Brand, Acerbi, and Mesoudi, 2019; Pavlek, Winters, and Morin, 2019; Morin and Miton, 2018). Auch wenn Online-Datenbanken und Experimente erhebliche Fortschritte beim Verständnis der evolutionären Rolle der Kunst ermöglicht haben, bleibt die Untersuchung von künstlerischen Traditionen in der freien Natur aufgrund der Schwierigkeiten bei der systematischen Quantifizierung in großem Maßstab eine Herausforderung.

Geometrische Kunsttraditionen mit ihren systematischen Regeln lassen sich quantifizieren und ermöglichen daher die Untersuchung eines großen Kunstkorpus. Von angolanischen Sandzeichnungen (Gerdes, 1988; Gerdes, 1990), keltischer Kunst (Bain, 1973), vanuatuanischen Sandzeichnungen (Lind, 2017) bis hin zu tamilischen Schleifenmustern (Layard, 1937) — sie alle weisen strukturelle Eigenschaften (d.h. eine Grammatik) auf, die eine systematische Quantifizierung ermöglichen. Geometrische Kunsttraditionen entstehen zwar in verschiedenen Gemeinschaften auf der ganzen Welt, aber sie sind einzigartig und faszinierend zu untersuchen, weil sie es Forschern ermöglichen, aktuelle ethnografische Informationen mit neuartigen Berechnungsmethoden zu synthetisieren, um eine hochauflösende Datenbank einer künstlerischen

Tradition zu erstellen. Eine hochauflösende Datenbank einer künstlerischen Tradition würde in der Folge eine systematische Untersuchung der menschlichen Investitionen in die Kunst ermöglichen und unser Verständnis von Kommunikation und der Materialisierung von Informationen in der Kunst verbessern.

Die *Kolam*-Kunst ist eine geometrische Kunstform und eine tamilische Tradition, die hauptsächlich von Frauen in Tamil Nadu, Südindien, ausgeübt wird (Laine, 2013). In einem morgendlichen Ritual beginnen Frauen vor Sonnenaufgang die Schwellen ihrer Häuser zu waschen und zeichnen daraufhin komplizierte *Kolam*-Muster mit Reispulver oder Kreide auf den Boden (Nagarajan, 2018). Die Frauen zeichnen sorgfältig Schleifenmuster um ein anfängliches Raster aus Punkten, so dass sich die Linien nicht mit den Punkten überschneiden, sondern elegant und glatt um sie herum kreisen (Layard, 1937; Laine, 2013). Das Vorhandensein oder Fehlen und der Grad der Einfachheit oder Komplexität von *Kolam*-Zeichnungen kann verschiedene Informationen über die Künstlerin, ihren Haushalt und die Gemeinschaft vermitteln (Nagarajan, 2018, S.37, 52–55, 75–81, 149, 273). Es wird nicht nur täglich viel Zeit investiert, um diese flüchtigen *Kolam*-Kunstwerke zu präsentieren, sondern auch, um sie zu lernen, zu lehren und zu üben. In einem sehr jungen Alter, noch vor der Menarche, beginnen Mädchen typischerweise, die Herstellung von *Kolam* zu erlernen und zu üben (Nagarajan, 2018, S. 8, 12, 15). Wissen und Erfahrung werden meist von (Groß-)Müttern an (Groß-)Töchter weitergegeben. Die *Kolam*-Tradition wird jedoch als Gemeinschaftswissen betrachtet, und so tauschen sich die Künstlerinnen häufig über ihre *Kolam*-Entwürfe aus (Nagarajan, 2018, S. 69).

Aus einer evolutionären Perspektive bietet die *Kolam*-Tradition eine interessante Fallstudie, um zu untersuchen, warum Individuen viel Zeit damit verbringen, künstlerische Traditionen zu lernen, zu üben und zu lehren, und welche Informationen in künstlerischen Traditionen eingebettet sind. Außerdem ist die Gesellschaft in Südindien entlang mehrerer Dimensionen wie Kaste, Klasse, Sprache, Region und Religion segregiert (Dumont, 1980). Deshalb entsteht die *Kolam*-Kunst in einer stark geschichteten und multiethnischen Gesellschaft (Waring, 2012a). Da gesellschaftliche Trennungen nachweislich in der materiellen Kultur abgebildet werden (Kramer and Douglas, 1992; Degoy, 2008; Granito et al., 2019), könnte die *Kolam*-Kunst auch ein Schauplatz sein, an dem die soziale Identität abgebildet wird, und somit interessante Erkenntnisse darüber liefern, wie Informationen in künstlerischen Traditionen widergespiegelt werden können.

Ziele dieser Arbeit

Das übergeordnete Ziel dieser Forschung ist der Aufbau einer robusten Dateninfrastruktur und die Entwicklung und Anwendung neuartiger Ansätze zur Untersuchung der menschlichen Verhaltensökologie und kulturellen Evolution in einem künstlerischen Bereich. Um künstlerische Traditionen systematisch und quantitativ zu analysieren, ist eine sorgfältige Beachtung der spezifischen Details des künstlerischen Systems in Verbindung mit ethnographischem Hintergrund von grundlegender Bedeutung. Das übergreifende Ziel dieser Forschungsarbeit ist daher die Synthese von Datenmanagement und statistischem Wissen mit ethnografischen Berichten, um eine Datenbank und Methoden zu entwickeln und zu implementieren, die es ermöglichen, die evolutionäre Rolle künstlerischer Traditionen zu verstehen und herauszufinden, welche Informationen in künstlerischen Traditionen enthalten sind. Diese Arbeit ist in zwei miteinander verbundene Projekte gegliedert, die darauf abzielen, unser Verständnis dafür zu vertiefen, wie Künstlerinnen ihre Arbeit konzeptualisieren und wie Kunst innerhalb der Gemeinschaft funktioniert. Zu diesem Zweck konzentriert sich diese Arbeit explizit auf die tamilische *Kolam*-Kunst. Beide Kapitel dienen als Fallstudien am Beispiel von *Kolam*-Kunst. Sie stellen exemplarisch einen Workflow dar, der für die Untersuchung geometrischer Kunsttraditionen optimiert wurde.

Im ersten Kapitel untersuchte ich aggregierte, strukturelle und informationelle Muster in der *Kolam*-Kunst, um die strategischen Investitionen der Künstlerinnen und die potenziellen Einschränkungen zu verstehen, die auf sie einwirken. Diese Arbeit ist in *Evolutionary Human Sciences* veröffentlicht:
Tran, N.-H., Waring, T., Atmaca, S., & Beheim, B. (2021). Entropy trade-offs in artistic design: A case study of Tamil *kolam*. *Evolutionary Human Sciences*, 3, E23. DOI: `https://doi.org/10.1017/ehs.2021.14`.

Im zweiten Kapitel konzentriere ich mich auf einen neuartigen Ansatz zur Quantifizierung der Kovariation künstlerischer Stile entlang ethnischer oder kultureller Grenzen, um die Rolle der *Kolam*-Kunst für die Gruppenkoordination zu verstehen. Die Ergebnisse wurden in *Frontiers in Psychology* veröffentlicht:
Tran, N.-H., Kucharský, Š., Waring, T. M., Atmaca, S., & Beheim, B. A. (2021) Limited Scope for Group Coordination in Stylistic Variations of *Kolam* Art. *Frontiers in Psychology*, 12, 742577. DOI: `https://doi.org/10.3389/fpsyg.2021.742577`.

Methoden

Die detaillierten Daten zur *Kolam*-Kunst wurden von Dr. Timothy M. Waring und lokalen Forschungsassistenten in Kodaikanal, Tamil Nadu in Südindien im Jahr 2009 gesammelt. Ich entwarf und erstellte eine hochauflösende Datenbank, um diese reichhaltigen Rohdaten zu synthetisieren. Diese Rohdaten enthielten Interviewumfragen, GPS-Daten, *Kolam*-Zeichnungen, Netzwerkdaten und Übungshefte. Darüber hinaus habe ich eine robuste Datenpipeline entwickelt für die Transkription von *Kolam*-Zeichnungen mithilfe eines Gestenlexikons (das Lexikon wurde entwickelt von Waring, 2012b). Außerdem entwickelte und programmierte ich ein `kolam` R-Paket

(Tran, Waring, and Beheim, 2020) zur Datenkonsolidierung und zum gezielten Import der *Kolam*-Daten in einem lesbaren Format in die Software R zur Analyse. Diese Dateninfrastruktur bildete die grundlegende Basis für die neuartigen Methoden, die in Kapitel 1 und Kapitel 2 entwickelt und angewendet wurden. In beiden Kapiteln habe ich einen Datensatz von 3.139 *Kolam*-Zeichnungen von 192 Künstlern verwendet.

Im ersten Kapitel habe ich die Signalisierungs- und Optimierungstheorie verwendet, um die strategischen Investitionen von Individuen in die *Kolam*-Kunst zu untersuchen und um herauszufinden, wie mögliche Einschränkungen die Verhaltensstrategien bestimmen könnten. Da *Kolam*-Zeichnungen mit Hilfe eines Lexikons von Gesten kodiert werden können, eignet sich dieses geometrische Kunstsystem für den Fokus auf ökologische und informationstheoretische Standardmaße: Entropie, Äquität und Vielfalt. Unter Verwendung einer Vielzahl von aus der Informationstheorie abgeleiteten, aggregierten Maßen zur Beschreibung von Kunstwerken habe ich untersucht, ob künstlerische Komplexität ein Ziel der Optimierung sein könnte und ob ein Trade-Off-Modell die Variationsmuster zwischen *Kolam*-Kunstwerken erklären könnte. Um *Kolam*-Kunst aus der Perspektive der evolutionären Signaltheorie der eingeschränkten Optimierung zu verstehen, habe ich die Shannon'sche Informationsentropie als Maß für die künstlerische Komplexität verwendet. Durch numerische Simulationen konnte ich eine systematische Beziehung zwischen der Shannon'schen Informationsentropie, der Äquität und der Vielfalt aufzeigen, die es mir ermöglichte, Trade-offs in Entropie zwischen der Äquität und der Vielfalt zu erkennen. Auf der Grundlage dieses Trade-off-Modells habe ich anschließend Bayes'sche hierarchische Regressionsmodelle erstellt, um zu untersuchen, inwieweit Variationen in den strukturellen und informationstheoretischen Eigenschaften von *Kolam*-Zeichnungen durch Variationen in Bezug auf Künstlerinnen, Alter, Jahre der Übung und Kastenzugehörigkeit erklärt werden können. Zusätzlich habe ich agentenbasierte Simulationen eingesetzt, um die statistischen Modelle vor der Ausführung zu validieren und die Modellvorhersagen zu überprüfen.

Der ausschließliche Fokus auf die künstlerische Komplexität vermittelt jedoch nur ein unvollständiges Bild davon, wie Kunst mit sozialer Identität, Gruppen und Individuen verbunden sein kann. Auch wenn Künstlerinnen ihre künstlerischen Darstellungen auf eine bestimmte Komplexität hin optimieren können, können sie sich in der Art und Weise, wie sie dies tun, stark unterscheiden. Insbesondere können Künstlerinnen strategisch verschiedene Stile oder Muster von Designs verwenden, um einerseits ihr Kunstwerk zu optimieren und andererseits ihre Einzigartigkeit, ästhetischen Vorlieben oder soziale Identität zu kommunizieren.

Im zweiten Kapitel konzentriere ich mich daher auf Stile oder Muster in der *Kolam*-Kunst. Konkret untersuche ich systematisch, wie Stile in der Kunst auf ethnische und kulturelle Grenzen abgebildet werden können. Da eine gewisse Zuordnung zwischen stilistischen Variationen und Gruppen als Voraussetzung für ethnische Marker angesehen werden kann (siehe Bell, Richerson, and McElreath, 2009), könnte die Quantifizierung der Kovariation künstlerischer Stile in der *Kolam*-Kunst entlang kultureller Grenzen Aufschluss darüber geben, inwieweit die *Kolam*-Kunst als ethnischer Marker funktionieren könnte. Zur Beschreibung und Unterteilung der Variationen in sequenzielle Zeichenstile habe ich einen zustandsbasierten Markov-Ansatz entwickelt und angewendet. Ich nutzte die Markov'sche Natur des Kunstsystems, indem ich sequenzielles Verhalten (d.h. Gesten) in Zustände einer Markov-Kette zerlegte, um ein Bayes'sches hierarchisches Modell zu erstellen, das in der Lage ist, Stile oder Muster in der Kunst mit Gruppengrenzen zu verbinden. Die statistischen Modelle wurden vor der Ausführung validiert, und die Modellvorhersagen wurden anhand von agentenbasierten Simulationen überprüft.

Ergebnisse

Die Ergebnisse des ersten Kapitels zeigen einen Optimierungs-Sweetspot in Bezug auf die Shannon'sche Informationsentropie. Unabhängig von der Größe der *Kolam*-Zeichnung zentrieren sich die meisten *Kolam*-Zeichnungen um einen "Sweet Spot" der Entropie und somit ist die Variation ihrer Komplexität begrenzt. Um diese relativ konstante Entropie in immer größeren *Kolam*-Zeichnungen beizubehalten, erhöhen die Künstlerinnen strategisch die Vielfalt an Gesten, während sie die Äquität der Gesten verringern. Der scheinbare Kompromiss zwischen Vielfalt und Äquität deutet darauf hin, dass die Entropie das Ziel der Optimierung ist, so wie in der Theorie der Lebensgeschichte die reproduktive Fitness das Optimierungsziel bei der Abwägung zwischen Erhaltung und Fortpflanzung oder der Anzahl der Nachkommen gegenüber dem Überleben der Nachkommen ist. Die Individuen entscheiden sich also strategisch für Investitionen in die *Kolam*-Kunst und optimieren die Komplexität ihrer Darbietungen, um den Ertrag zu maximieren. Darüber hinaus zeigen die Ergebnisse, dass die *Kolam*-Kunst nicht in erster Linie eine soziale Schichtung oder individuelle Unterschiede in Bezug auf Alter oder Übungsjahre vermittelt. Die Eigenschaften von *Kolam*-Kunstwerken sind nur schwach mit den zugrunde liegenden sozialen Zwängen verbunden, die auf die einzelnen Künstler wirken, was auf einen relativ egalitären Informationsfluss von *Kolam*-Wissen hinweist, der nicht durch Informationsnetzwerke oder soziale Hierarchien eingeschränkt wird.

Die Ergebnisse des zweiten Kapitels stimmen insofern mit den Ergebnissen aus Kapitel 1 überein, da sie zeigen, dass sich die Stile von *Kolam*-Zeichnungen nur geringfügig durch soziale Grenzen unterscheiden. Stile oder Muster in der *Kolam*-Kunst lassen sich nur schwach auf Kastengrenzen, Nachbarschaften oder frühere Migration zurückführen. Stattdessen haben die Ergebnisse gezeigt, dass die meisten Variationen in den Mustern oder Stilen der *Kolam*-Kunst weitgehend von Variationen auf Künstlerinnenebene dominiert werden. Die Ergebnisse liefern zwar kein funktionales Argument dafür, ob die *Kolam*-Kunst tatsächlich als ethnischer Marker fungiert (wie beispielsweise in Smaldino, Flamson, and McElreath, 2018), aber ich lege dar, dass die Variation auf Gruppenebene und die Kovariation zwischen Mustern oder Stilen der *Kolam*-Kunst und Gruppengrenzen sehr begrenzt sind. Daher ist der Spielraum für die Einbettung von Stilen in Kunstwerke als ethnische Marker zur Kennzeichnung von Gruppengrenzen begrenzt.

Schlussfolgerungen

Aus evolutionärer Sicht sind die erheblichen Investitionen der Menschen in künstlerische Traditionen rätselhaft und faszinierend zugleich. Über Generationen hinweg lernen, lehren und teilen die Menschen ihr Wissen und ihre Fähigkeiten bei der Schaffung einfacher bis komplizierter Kunstwerke. Die Vorgänge, die der Schaffung von Kunstwerken zugrunde liegen, sind sehr komplex und umfassen strategische Entscheidungen und Manipulationen, die sich auf die Größe, das Design, die Komplexität oder die Originalität des Kunstwerks auswirken können. Wiederkehrende Muster im Schaffensprozess sowie Ähnlichkeiten und Unterschiede in Kunstwerken werden daher oft sinnvoll konstituiert durch enge Sozialisationskanäle und strategische Entscheidungen der Künstlerinnen, sich der Gruppe anzupassen oder von ihr abzuweichen. Um die Rolle künstlerischer Traditionen in der Gemeinschaft besser zu verstehen, die Informationen, die sie enthalten, und die Art und Weise, wie Künstlerinnen ihre Investitionen in die Kunst konzeptualisieren, benötigen wir systematische Ansätze zur Quantifizierung und Analyse großer Korpora künstlerischer Traditionen.

Als erste Schritte in diese Richtung stellt diese Arbeit eine Dateninfrastruktur-Pipeline und zwei neuartige empirische Ansätze vor, um künstlerische Traditionen anhand eines großen Datenkorpus zu untersuchen. Meine Arbeit trägt dazu bei, ein Bild von der evolutionären Rolle künstlerischer Traditionen und der Informationskomplexität in künstlerischen Traditionen zu zeichnen. Durch den Einsatz modernster Unit-Tests, Versionskontrolle und kontinuierlicher Integration zur Aufrechterhaltung der Datenqualität in Verbindung mit ethnografischen Berichten war ich in der Lage, ein Team von Transkriptionisten zur Datenextrahierung zu leiten. Das Team von Transkriptionisten zeichnete unter meiner Anleitung Rohdaten aus verschiedenen Quellen auf, die 2009 in Tamil Nadu zur *Kolam*-Kunst gesammelt wurden. Unter meiner Führung wurde dadurch eine robuste Datenpipeline aufgebaut. Der digitale Zugang zu einem großen Kunstkorpus ermöglichte es mir, die künstlerischen Produkte systematisch zu quantifizieren. Zudem ermöglichte mir der großangelegte Datensatz komplexe statistische Modelle zu entwickeln und anzuwenden, die explizit auf die Annahmen und hypothetischen Prozesse eingehen, die der Entstehung der Kunstwerke zugrunde liegen.

Im ersten Kapitel habe ich eine umfassende Analyse der strategischen Investitionen von Künstlerinnen in die Kunst präsentiert und dargelegt, wie der Informationsfluss innerhalb einer Künstlerinnengemeinschaft eingeschränkt werden kann. Künstlerinnen optimieren strategisch die Komplexität ihrer Kunstwerke, unabhängig von deren Größe und unabhängig von Gruppengrenzen. Diese Erkenntnis ist ein wichtiger Schritt zum Verständnis der strategischen Entscheidungsprozesse des Einzelnen bei der Schaffung von Kunst.

Im zweiten Kapitel habe ich mit einem neuartigen Ansatz gezeigt, wie die Kovariation von charakteristischen Stilen oder Mustern in *Kolam*-Kunstwerken entlang kultureller Grenzen systematisch untersucht werden kann. Durch die Analyse sequenzieller Zeichenentscheidungen zeigte ich, dass *Kolam*-Kunstwerke nur begrenzte Informationen über die zugrunde liegenden Gruppengrenzen enthalten. Der begrenzte Nachweis von Variationen auf Gruppenebene ist bemerkenswert, denn selbst wenn es keine explizite Operationalisierung von Kasten-, Nachbarschafts- oder Regionsmarkierungen in den Stilen der *Kolam*-Kunst gäbe, würden die verschiedenen Arten von "gruppeninternen Viskositäts"-Mechanismen wie Kastenendogamie, verwandtschaftsbasierte Migration, Nachbarschaftssegregation in Kombination mit Standardmodellen des sozialen Lernens strukturierte Variationen in unseren Daten vorhersagen. Somit trägt dieses Ergebnis zu dem sich abzeichnenden Bild bei, dass die Schaffung von Kunst nicht durch Gruppen- oder soziale Grenzen eingeschränkt wird.

Beide Kapitel deuten stark darauf hin, dass Kunst in erster Linie ein Ort ist, an dem Künstlerinnen ihre Einzigartigkeit und ihre ästhetischen Vorlieben zur Schau stellen wollen. Im Gegensatz zu früheren Erkenntnissen zur materiellen Kultur (Bowser and Patton, 2008; Helbich and Dietler, 2008; Degoy, 2008; Tehrani and Collard, 2009) sind enge Informationsnetzwerke oder Sozialisationskanäle in künstlerischen Traditionen nur sehr schwach ausgeprägt. Zusammenfassend lässt sich sagen, dass diese Arbeit evolutionäre Einblicke in die strategischen Entscheidungen von Künstlern und die in die Schaffung von Kunstwerken eingebetteten Informationen liefert. Diese Erkenntnisse in Verbindung mit der neuartigen Dateninfrastruktur-Pipeline und den statistischen Ansätzen ebnen den Weg für künftige Anwendungen auf andere große Korpora visueller und geometrischer Kunsttraditionen, wie z. B. angolanische Sandzeichnungen (Gerdes, 1988), vanuatuanische Sandkunst (Lind, 2017) oder islamische geometrische Kunst (Abdullahi and Embi, 2013). Insgesamt dient diese Arbeit als Roadmap-ähnlicher Ansatz, der Arbeitsabläufe veranschaulicht, die für die Untersuchung eines großen Korpus an künstlerischen Traditionen optimiert sind.

Chapter 1

Entropy Trade-offs in Artistic Design: A Case Study of Tamil *Kolam*

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Abstract

From an evolutionary perspective, art presents many puzzles. Humans invest substantial effort in generating apparently useless displays that include artworks. These vary greatly from ordinary to intricate. From the perspective of signaling theory, these investments into highly complex artistic designs can reflect information about individuals and their social standing.

Using a large corpus of *kolam* art from South India (N = 3,139 *kolam* from 192 women), we test a number of hypotheses about the ways in which social stratification and individual differences affect the complexity of artistic designs.

Consistent with evolutionary signaling theories of constrained optimization, we find that *kolam* art tends to occupy a "sweet spot" at which artistic complexity, as measured by Shannon information entropy, remains relatively constant from small to large drawings. This stability is maintained through an observable, apparently unconscious trade-off between two standard information-theoretic measures: richness and evenness. Although these drawings arise in a highly stratified, caste-based society, we do not find strong evidence that artistic complexity is influenced by the caste boundaries of Indian society. Rather, the trade-off is likely due to individual-level aesthetic preferences and differences in skill, dedication, and time, as well as the fundamental constraints of human cognition and memory.

Keywords: Art, Signaling, Entropy, Skill, Material Culture, Bayesian inference

1.1 Introduction

From the perspective of human evolution, art is mysterious. People in all known populations invest substantial time, energy, and effort into generating abstract patterns and performances (Brown, 1991), to no obvious benefit. In biology, the study of seemingly non-functional traits in social communication relies on the evolutionary theory of signaling, a framework for understanding how reproductive trade-offs produce phenomena such as warning displays, mating calls, and specialized adaptations such as bright, colorful plumage (Zahavi, 1975). It is currently unclear whether human art is comparable to signaling behaviors, what features they have in common with each other, or if art is even something that can be usefully understood using an evolutionary approach.

In recent years, the availability of large art datasets has enabled large-scale quantitative analysis (Müller and Winters, 2018; Liu et al., 2018; Sigaki, Perc, and Ribeiro, 2018), which is the cornerstone of the "population thinking" approach characteristic of evolutionary thinking in modern biology (Mayr, 1959). Here we present such an analysis of a large corpus of material art from South India: the *kolam* drawings created by the women of Tamil Nadu in South India. Because this long-standing artistic tradition follows systematic rules amenable to quantification, statistical models allow us to characterize the strategies pursued by individual artists, detect the existence of a theoretically derived entropy trade-off between richness and evenness, and weigh the importance of particular constraints on the flow of information within an artistic community.

1.1.1 Theoretical Background

In evolutionary theory, signals can successfully coordinate behavior between organisms by reliably indicating skill (Hawkes and Bird, 2002), commitment (Bulbulia and Sosis, 2011; Soler, 2012), social status (Smith, Bird, and Bird, 2003), strength (Sosis, Kress, and Boster, 2007) and cooperativeness (Gintis, Smith, and Bowles, 2001; Granito et al., 2019). Courtship behaviors, such as the ornate nest structures built by bowerbirds, often have no practical use, but their great cost itself is a signal of underlying phenotypic quality and potential mate value (Zahavi, 1975; Schaedelin and Taborsky, 2009; Madden, 2003). Some human behaviors, such as inefficient and unnecessarily difficult spearfishing in Meriam communities (Bliege Bird and Douglas, 2002), have been nominated as having a similar purpose, to enhance a signaler's social status and thus mating success (Bird, Smith, and Bird, 2001). More generally, costly public signals can lead to improved status and reputational standing (Power, 2017), reproductive success (Smith, Bird, and Bird, 2003), or increased social support (Bird et al., 2012). Beyond latent properties of the individuals, signals can evolve to indicate persistent group memberships, which become the basis for cooperative assortments. Especially in multi-ethnic populations, ethnic marker theory has become substantial to understand how individuals coordinate their norms and behaviors with others using identity or group membership signals (Boyd and Richerson, 1987). These signals, referred to as ethnic markers, have evolved to prevent individuals from interacting with others with different norms in coordination games (McElreath and Boyd, 2007; Moffett, 2013; Granito et al., 2019).

As a medium of communication, human art might reflect fitness-relevant qualities and capacities (e.g., preferences, skills, or personality traits such as patience, creativity, commitment) as well as promote social standing and mating qualities (e.g., health and fertility) (Davies, 2012; Grasseni, 2018). The signal is manifested as the aesthetic appeal or value of the artwork, and as such, it makes sense to see artists compete with each other in producing the most appealing and aesthetically pleasing artwork (Varella and Fernández, 2015; Gustafsson, 2018; Grasseni, 2018) that reflects their qualities and social status. Information on an artist's capacities, social standing, or mating qualities is judged by the apparent costs of the artistic production reflected in its complexity (Varella and Fernández, 2015; Grasseni, 2018).

A number of quantitative approaches have been used to measure cultural diversity on some distribution of traits. In economics and anthropology, a popular distributional measure is the Gini index of inequality (Zoli, 1999; Ravallion, 2014). A Gini index value of 0 represents a state of total equality, while a value of 1 represents total inequality. In ecology, three common methods of biological diversity are richness (the number of unique variants present), evenness (the relative abundance of variants), and Shannon information entropy, which weights richness by the relative abundance. For a low-entropy, low-diversity state, the representation of alternative variants is highly unequal, and in the limiting case in which only one variant is present, entropy is 0. At the other extreme, all n variants are represented equally, maximizing evenness, and so the entropy is also maximized to the value of $\log(n)$ (Jost, 2006; Jost, 2009). Entropy has also been used in several recent papers quantifying artistic diversity, where an artwork can be represented by an empirical probability distribution of variants (Pavlek, Winters, and Morin, 2019; Müller and Winters, 2018; Winters and Morin, 2019).

Although the Gini index in economics and diversity in ecology quantify the relative abundance in a very similar way, to our knowledge no systematic relationship has been described between the Gini index and Shannon information entropy, richness, or evenness. If we define evenness as $v = 1 - g$, for a given Gini index g, numerical simulations show the relationship between Shannon information entropy, richness and evenness is quite strict, so that the maximum entropy $\widehat{H}$ is given by evenness v and richness n as

$$\exp(\widehat{H}) \approx n - (n-1)v^{1+\frac{2}{2+a}+\frac{a}{a+n}} \tag{1.1}$$

where $a = \exp(0.51390628)$ (see the derivation A.5 in Appendix A for more details). This approximation allows us to detect *entropy trade-offs* between evenness and richness, which we use as analog to fitness trade-offs and can be applied to the study of any well-defined artistic system.

1.1.2 *Kolam* Art of South India

Kolam drawings are geometric art practiced by women in the Kodaikanal region of Tamil Nadu, Southern India (Layard, 1937). A *kolam* consists of one or more loops drawn around a grid of dots (in Tamil called *pulli*). On a typical morning, a Tamil woman will prepare a grid of dots on the threshold of her home and then draw a *kolam* with rice powder or chalk. During the day, the drawing weathers away, and a new *kolam* is created the next day. *Kolam* drawings are historically a tradition of matrilines, but more recently are also a topic of cultural education in Tamil schools. Girls in Tamil Nadu begin practicing *kolam*-making from an early age, and competency in this art is considered necessary for the transition into womanhood (Nagarajan, 2018). Although the primary medium is the threshold of the home, women practice *kolam*-making in notebooks, and it is common for artists to share, copy and embellish each other's *kolam* designs. Such unrestrained artistic exchange is fostered by the fact that *kolam* designs are not considered to belong to any one person, but rather to be a type of community knowledge (Nagarajan, 2018). However, the ability to successfully draw aesthetically pleasing (i.e., diverse, complex, large) *kolam* drawings is said to reflect certain qualities of a woman (e.g., her degree of traditionalness or patience), and as such, her capacity to run a household and become a good wife and mother (Nagarajan, 2018; Laine, 2013).

Kolam drawings further broadcast meaningful information about a household to neighbors and visitors. Nagarajan, 2018 argues that the presence or absence of *kolam* drawings help mark important events and the emotional or physical state of the artist and its household. Auspicious events, such as weddings or community festivals, warrant unusually large and complex *kolam* drawings, while inauspicious events such as death or illness are marked by the absence of *kolam* drawings, and might communicate the inability to receive or host visitors or the need for social support (Nagarajan, 2018; Laine, 2013).

Overall, *kolam*-making plays an integral role in the Tamil community and is deeply embedded in the Tamil culture with playful or even large-scale competitions among women (Nagarajan, 2018, p. 179-203). Women often come together to carefully examine and critique each other's *kolam* drawings in terms of aesthetic qualities (e.g., geometric complexity or density Nagarajan, 2018, p. 189) or consult each other on designs to optimally showcase their skills (Nagarajan, 2018, p. 182). Contemporary interpretations of the *kolam* in Tamil movies even use "the motif of the heroine's beautiful kolam in attracting the male gaze of the hero. The romance is either initiated by a strikingly beautiful kolam or sustained during the nocturnal hours when a kolam is being made by the heroine [....].”, (Nagarajan, 2018, p. 179-267)

1.1.3 Current Study

Kolam drawings are highly diverse and contain multiple distinct artistic families. Here we study the *ner pulli nelevu* or *sikku kolam* family because of its unique form. Because *sikku kolam* drawings represent an unusually strict system of artistic expression, *kolam* drawings can be mapped onto a small identifiable set of gestures and are therefore well-suited to systematic, quantitative analyses as a naturalistic model system of cultural evolution. A given *kolam*'s gesture sequence can be characterized by a number of informative summary statistics which capture aspects of *kolam* itself: the sequence length (i.e., the total number of gestures), the discrete canvas size (measured by the grid of dots, or *pulli*), the gesture density per unit canvas area, and gesture diversity as measured by evenness (here, the Gini index), richness, and Shannon information entropy.

With the ability to calculate standard measures and properties to describe artworks derived from information theory, we can explore the possible functions of signaling in *kolam* drawing. Specifically, we wish to understand better the social and strategic landscape within which artists work. Moreover, we seek to understand how realized *kolam* drawings result from the conflicting pressures of the need to communicate social signals, and various constraints on artistic production, among them the skill and experience of the artist and the social system she lives within.

Since these trade-offs are properties of the design space of the art itself, a substantial amount of variation may be explained simply by understanding strategic decisions, conscious or unconscious, made by the artist. Thus, two major research questions arise: first, can a trade-off model explain the pattern of variation among *kolam* drawings, as is commonly done in behavioral ecology? And second, can we relate structural and information-theoretic properties of *kolam* designs to underlying social and cognitive constraints operating on individual artists?

1.2 Methods

1.2.1 *Kolam* Dataset

We (TW) interviewed 312 artists in the Kodaikanal region in Tamil Nadu in 2009, collecting a total of 6,393 *kolam* drawings from the *ner pulli nelevu* or *sikku kolam* family, along with details of each woman's education, *kolam*-making experience, place of origin, and household demographic background, including caste.

Using the lexicon of 29 *kolam* gestures developed in Waring, 2012b, each *kolam* was digitally transcribed into a sequence of gestures and transferred into a database using the *kolam* R package (see `http://github.com/nhtran93/kolam` for more details).

An example of transcribed *kolam* drawings can be seen in Figure 1.1. The geometry of the *kolam* can be divided into three geometric spaces (orthogonal, diagonal, transitional) with their specific corresponding gestures. Each set of gestures is represented by a letter (O, D, T, respectively), while special variations of these moves are given special letters (C, H, P). Topologically, diagonal and transitional gestures are chiral with distinct left and right versions because rotations of these gestures in space cannot yield their exact mirror image (Waring, 2012b). The detailed lexicon of gestures can be consulted in Figure A.2 in Appendix A.

We excluded 674 *kolam* drawings that could not be matched to an artist, 695 *kolam* drawings because they included non-lexical gestures and another 17 *kolam* drawings due to transcription errors. We further excluded 120 women because their survey data was incomplete, with substantial missing data in key variables: age, GPS, duration of practice, or caste membership. In total, $3,139$ *kolam* drawings (on average 16 *kolam* per woman) from 192 artists were included in the analysis (age: $M = 31.83$, *sd* = 9.93 years, range = $15 - 60$; married: 75%). The artists are from 19 different castes, spanning from low-, middle- to high-castes. Of the $3,139$ *kolam* drawings, 1801 *kolam* drawings came from artists of a low-caste, 593 *kolam* drawings from artists of a middle-caste, and 745 *kolam* drawings from artists of a high-caste.

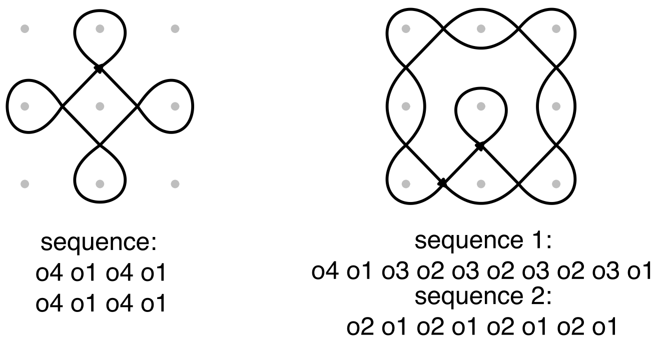

FIGURE 1.1: Example of two orthogonal *kolam* drawings and their corresponding encoding using a lexicon of gestures.

1.2.2 Information-theoretic Measures

We use Shannon information entropy $H(p)_j$ as a measure of artistic complexity or diversity for each *kolam* drawing j and probabilities p_i for each possible, discrete gesture i, computed as the average log-probability: $H(p)_j = -\sum_i^n p_i \log(p_i)$. Entropy as a measure for complexity is continuous, additive and increases as the number of possible gestures increases. While the lexicon of 29 gestures (Waring, 2012b) decomposed the *diagonal* and *transitional* gesture types into distinct left and right versions, we did not distinguish between them because they are a property of the transcription and not of the artist. Thus, information-theoretic measures were computed based on 18 distinct gestures (with each chiral pair counted as only one) and the theoretical upper bound of the entropy in our analyses is $\sum_i^{18} \frac{1}{18} \log(\frac{1}{18})) = 2.89$ log units. In

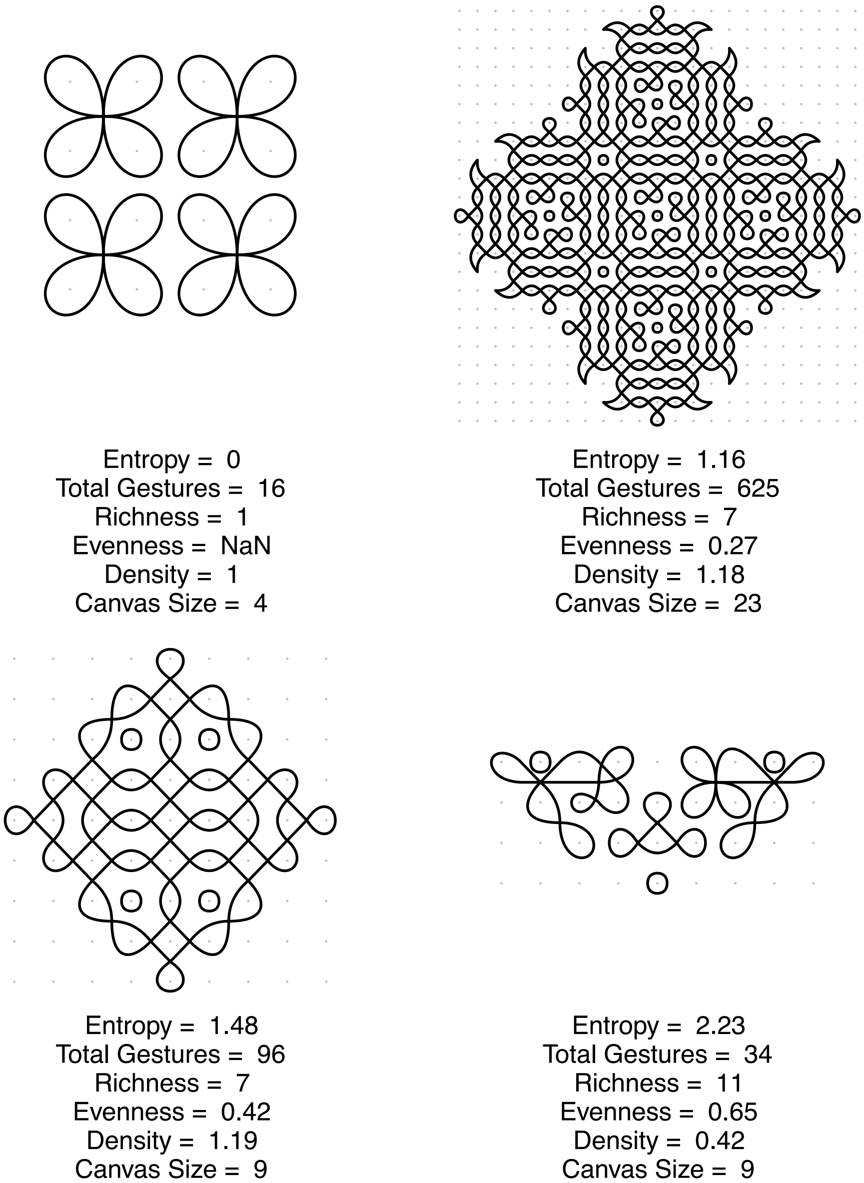

FIGURE 1.2: Structural and information-theoretic properties of *kolam* drawings. The Figure shows four *kolam* examples and their respective information-theoretic measures and structural properties.

contrast, the theoretical lower bound of entropy is 0 for a *kolam* that consists only of one gesture (see Figure 1.2).

Richness represents the number of unique gestures (accounting for chirality) present in a *kolam* drawing and evenness represents the relative abundance of each gesture. We computed evenness v using the Gini index of inequality g: $v = 1 - g$, where $g(n)\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|p_i - p_j|}{2(n-1)}$, where n is the richness and p the frequency of specific variants or gestures. Figure 1.2 illustrates how these properties or information-theoretic measures correspond to specific *kolam* drawings.

1.2.3 Statistical Analysis

To investigate the scope for viewing *kolam* art as a signaling system for aesthetic value, we modeled five information measures of each kolam in our sample using a variety of predictor variables. The five properties used as dependent variables to describe a *kolam* drawing were the canvas size, the gesture density per unit canvas area, evenness, richness, and Shannon information entropy. The canvas size of a *kolam* is a discrete count variable measured by the grid of dots, or *pulli*, and captures the dimension of the *kolam*. Since kolam drawings always start with an initial square grid of dots, the canvas size is equal to the width or length of this initial dot matrix, regardless of whether the resulting kolam is not maximally spanning both the width and length of this grid. The gesture density reflects the number of gestures by canvas area: density $= \frac{\text{sequence length}}{\text{canvas size}^2}$. Age, duration of practice, and caste were used as predictor variables to explain individual variation. Age and duration of practice were standardized to be centered on zero with a standard deviation of one.

Since our data contains repeated observations for artists and castes (i.e., multiple *kolam* drawing from an artist or from any given caste), we partially pooled information across these two units using hierarchical modeling in order to account for imbalances in sampling and to yield more reliable and precise estimates (Efron and Morris, 1977). While information was pooled across artists to avoid over-dispersed parameter estimates, we estimated a random intercept (i.e., offset) for each artist. Caste is comprised of 19 different categories and was modeled as a varying effect to estimate individual offsets for each caste category.

Evenness and richness are related to entropy by a mathematical identity (shown in the derivation A.5 in Appendix A) and subject to an optimization process. This theoretical guide motivates the specific choice of predictor variables in our statistical models, which is why we would not include, e.g., canvas size as predicted by richness. Including these predictors would not address our larger question of modeling information entropy or mapping its potential trade-offs, nor would such an analysis add an adequate potential alternative explanation of the invariance in entropy and the richness/ evenness trade-offs because the system does not prevent artists from drawing *kolams* with minimal or maximum entropy.

The statistical models were implemented in the probabilistic programming language Stan (v2.18) (Carpenter et al., 2017), using 6000 samples in four independent chains. We applied an iterative process of model building, inference, model checking and evaluation, and model expansion to ensure a principled and robust Bayesian workflow (Gabry et al., 2019; Talts et al., 2018). Prior predictive simulations and fitted models to simulated data were used to determine reasonable and regularizing priors for the parameters that respects the parameter type's bounds. We present a complete description of the statistical models and the priors in Appendix A. Analyses were performed in R (Team, 2019). Data and analyses can be found here: `http:`

//github.com/nhtran93/kolam_signaling. All $\widehat{R}$ values were less than 1.01, and visual inspection of trace plots, rank histograms and pairs plots indicated convergence of all models. Visual MCMC diagnostics can be found in Appendix A.

1.3 Results

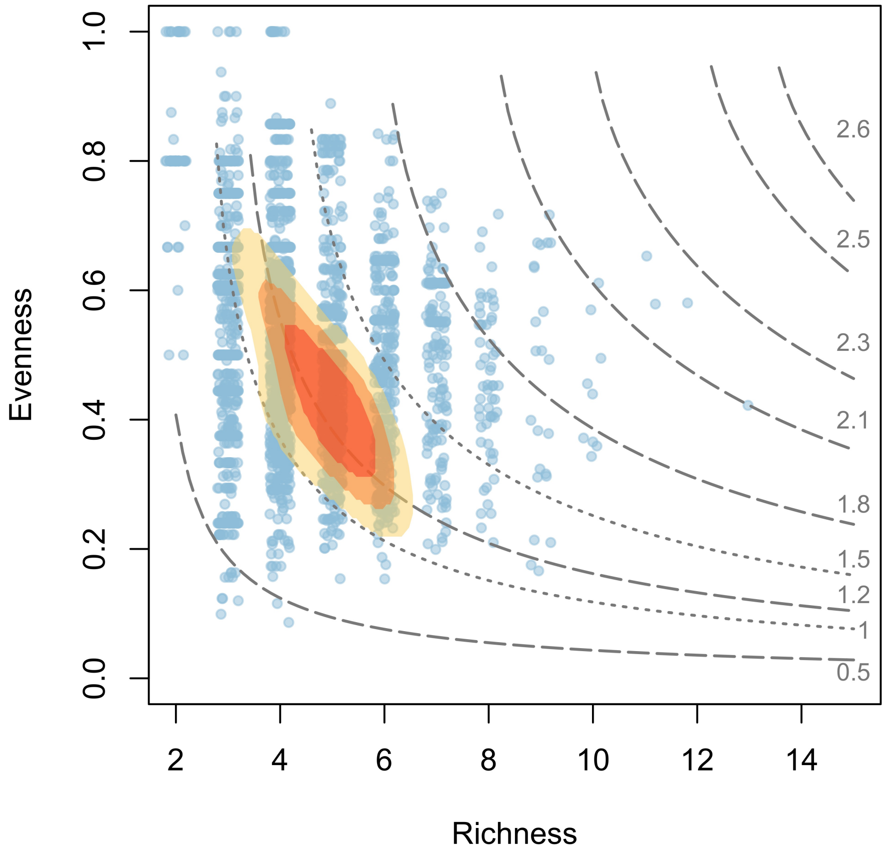

FIGURE 1.3: Trade-off between the Evenness and the Richness. The grey lines measure maximum entropy isoclines. The raw *kolam* data are jittered and illustrated in blue (light blue = low density, dark blue = high density). The (90%, 75%, 50%) kernel-density of the average richness and evenness for each canvas size of the data are depicted in the orange area (light orange to dark orange).

Consistent with the entropy trade-offs implied by equation 1.1, we find that as *kolam* drawings concentrate around an entropy of 1.17 log units regardless of their size, they systematically vary in evenness and richness as they increase in size (see Figure 1.3). Larger *kolam* drawings employ a greater richness of gestures, on average, but also have greater inequality between gestures in such a way that entropy remains tightly bounded between 1.1 and 1.4. As illustrated further in Panel A and C in Figure 1.4, evenness decreases with increasing canvas size, while richness increases with increasing canvas size.

In characterizing the artist-level variation, we also find similar patterns. Figure 1.4 illustrates artist's offsets on the different structural and information-theoretic properties on *kolam* drawings. Artist means cluster between an entropy of 1.1 and 1.4 log-units. Thus, very plain (entropy < 1) as well as highly complex *kolam* drawings (entropy > 1.5) are very rare. Individuals who draw larger *kolam* drawings tend to use more different gestures but, in turn, repeat a few gestures disproportionately (Figure 1.4, panel B).

As indicated by Figure 1.5, there is also some small distinct variation between artists on the average entropy of their *kolam* drawings σ_{artist} = 0.04, 90% CI [0.02, 0.05]). This between-artist variability is most pronounced in canvas size (σ_{artist} = 0.15, 90% CI [0.13, 0.17]) and in density (σ_{artist} = 0.10, 90% CI [0.08, 0.11]) with individuals showing differences in the average canvas size and density of their *kolam* drawing. Between-individual variation the evenness (σ_{artist} = 0.05, 90% CI [0.04, 0.06]) and in the richness (σ_{artist} = 0.01, 90% CI [0.00, 0.03]) were estimated with high certainty to be non-zero, but very small (see right panel in Figure 1.5).

We detected very small effects of caste membership on density, evenness, richness, and entropy, with varying-effect deviations estimated near zero with high certainty as illustrated in Figure 1.5 (density σ_{caste} = 0.02, 90% CI [0.00, 0.04]; evenness σ_{caste} = 0.03, 90% CI [0.02, 0.05]; and richness σ_{caste} = 0.01, 90% CI [0.00, 0.03]; entropy σ_{caste} = 0.03 90% CI [0.01, 0.05] respectively). However, evidence for caste differences in canvas sizes of *kolam* drawings was more pronounced (σ_{caste} = 0.11, 90% CI [0.06, 0.16]).

Evidence for an effect of age and an effect of duration of practice on the five outcomes is also very weak. Figure 1.5 shows that both predictor variables have a very small effect on the five outcome variables. Age and the duration of practice are estimated with high uncertainty to be close to zero across the five models.

Only a small amount of variation in the information statistics we employed can be accounted for by variation in artists, their age, years of practice, and caste membership: about 15% for canvas size, 13% of the evenness, 11% of the variation in the gesture density, 0.01% for the richness and 0.03% for entropy as measured by the Interclass Correlation Coefficient (Gelman and Hill, 2006) (see Appendix A for more details). Residential proximity and regional origin of artists hardly account for any variation in the structural and information-theoretic properties (see Appendix A for more details). In contrast, the residual variance of the outcomes is large and dominates model inference more than the variation explained by our fixed and random effects combined.

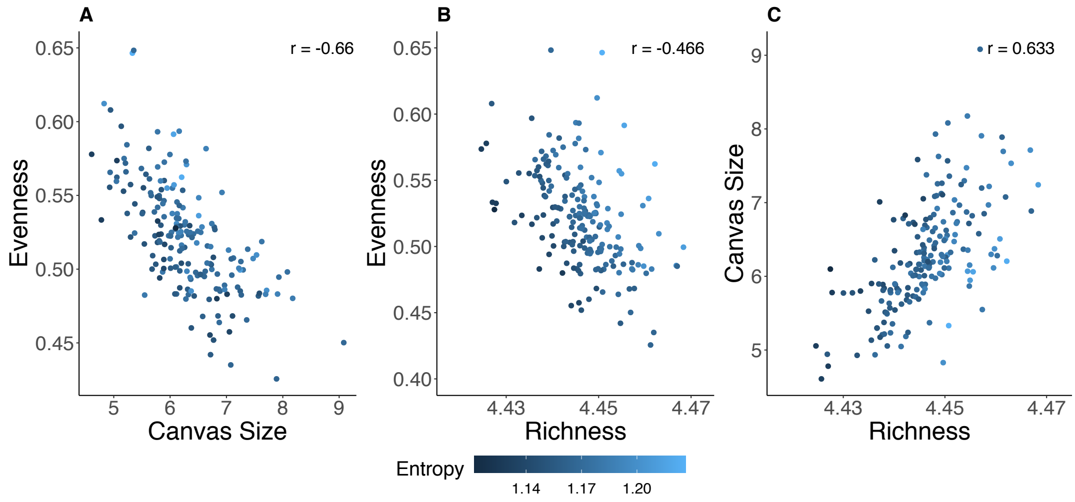

Figure 1.4: Scatter plot of posterior estimates of individual intercepts (sum of individual offsets and population mean). The posterior estimates of individual variation of two models are plotted against each other to illustrate the correlation between outcomes. The blue colour gradient reflects the posterior estimates of individual variation of entropy. Pearson's correlation *r* between the posterior estimates of the two variables is shown on the upper left for each panel. A. The canvas size and the evenness model. B. The evenness and the richness model. C. The canvas size and the richness model.

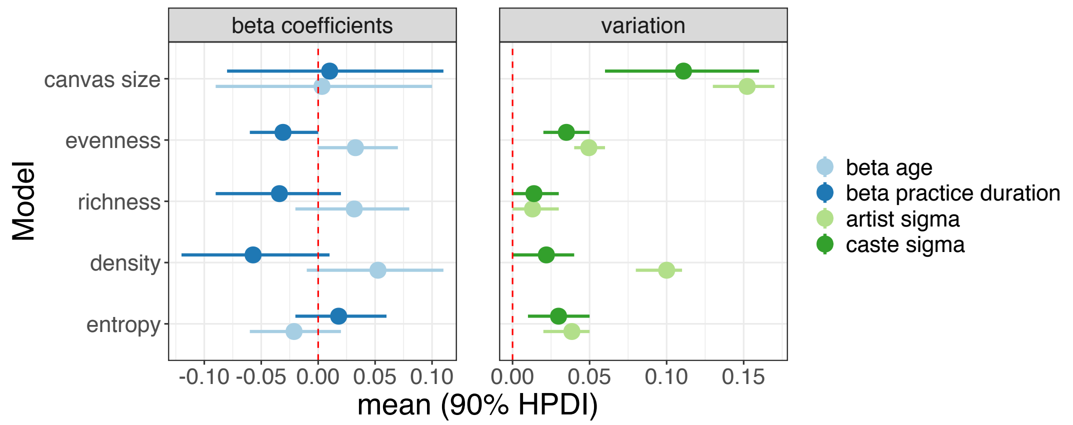

Figure 1.5: Prior-Posterior Coefficient Plots. All panels have the same y-axis indicating the five models. The left panel (beta coefficients) illustrates the estimated beta coefficients for the two predictors, duration of practice (dark blue) and artist's age (light blue) for each model. The right panel (variation) illustrates the estimated population level standard deviation for the effect of caste (dark green) and the estimated individual variation (light green) for each model. The 90% Highest Posterior Density Interval (HPDI) was computed for each posterior.

1.4 Discussion

Viewed at the population scale, the complexity of *kolam* drawings is quite invariant, suggesting the existence of an entropy "sweet spot" at which most artists and most *kolam* drawings center around, regardless of the design's size or gesture richness. The observed increase in gesture richness in bigger *kolam* drawings is compensated for almost exactly by a corresponding decrease in gesture evenness, such that as *kolam* drawings increase in size, richness is traded off against evenness so as to maintain nearly constant entropy. Our findings are consistent with the general view of signaling in behavioral ecology as an attempt at optimization under constraints and lend support that entropy is optimized through an observable and apparently unconscious trade-off between richness and evenness (shown theoretically and empirically).

In this interpretation, *kolam* drawings that are generally more diverse are more valuable art products (Nagarajan, 2018, p. 189). For this reason, we see very few *kolam* drawings with an entropy below one, which would be unusually simplistic or repetitive, regardless of their size. Conversely, artists seem to hit an upper entropy constraint around 1.5 log units, regardless of the size of the *kolam*, which suggests some form of constraint on more complex (and more valuable) artwork.

Although the nature and origin of these constraints are unclear, our analysis can rule out a few possibilities. Almost no meaningful information about caste stratification is visible in the information metrics we employ. Members of different caste categories tended to create distinct *kolam* drawings of different canvas sizes, but no clear differences in other major structural or information-theoretic properties. Indeed, our findings are consistent with ethnographic accounts of *kolam* as a form of community knowledge and suggest that, as a public art form drawn on a home's threshold, *kolam* drawings enjoy a relatively egalitarian information flow even in a stratified, multi-ethnic society (Waring, 2012a).

Based on the above, we believe that complexity in *kolam* design is more likely constrained by aesthetic preferences and cognitive limitations, rather than by information networks or social hierarchies. Although we were able to observe variation in average entropy between artists, with some highly complex *kolam* above an entropy score of 1.5 log units, we were not able to map this variation to patterns of age or experience. This could reflect cultural selection pressures to make traditional practices of artistic ornamentation and design, such as *kolam* art, more learnable or transmissible (Müller and Winters, 2018; Tamariz and Kirby, 2015; Ravignani, Delgado, and Kirby, 2017; Kirby, Cornish, and Smith, 2008; Tylén et al., 2020) or limitations in procedural and working memory capacities (Oberauer and Kliegl, 2006; Oberauer, 2010) unrelated to the action of experiential memory or cognitive senescence (Gurven et al., 2017).

An overly complex and large *kolam* with rich and diverse gestures might be too difficult, time-consuming, or too risky to execute successfully because options for revisions and corrections are limited. Artists might want to avoid highly complex *kolam* drawings because they draw them in front of their house, and hesitation, pauses, or corrections could be interpreted by the audience as imperfection or as a lack of skill (Nagarajan, 2018, p. 53, p.156). This avoidance of maximally complex artistic designs due to increased risk of deficiency and failure might also be relevant to other practices of ornamentation or decorations where mistakes often last and cannot be rectified easily (e.g., polychrome bowl designs, Bowser, 2000 or Angolan *sona* drawings, Gerdes, 1990). Alternatively, it might also be that more diverse *kolam* drawings are simply not as aesthetically appealing to artists and their audience because individuals often tend to prefer a certain extent of regularity and repetition rather than complete randomness and thus highly complex *kolam* drawings (Voloshinov, 1996; Huang et al., 2018). Other artistic designs, such as loop patterns for decorations in Japan or Angolan sand drawings have already been known to be influenced by the aspiration for symmetry (Nagata, 2015; Gerdes, 1990). Therefore, the artist's aesthetic preferences are the final constraint.

In fact, geometric art like *kolam* displays structural properties (e.g., symmetry, rotation, and repetition) and can correspond to distinct complexity measures (Sigaki, Perc, and Ribeiro, 2018). Aesthetic preferences can determine these distinct structural properties and reflect shared attention and learning (Tomasello, Kruger, and Ratner, 1993). Artists can deliberately choose to impose structural constraints according to their and consumers' preferences on an artwork. For instance, artists can strive for symmetry, only use the same type of variants (i.e., gesture types), or decide to primarily use the same two variants (i.e., gestures) and only add very low frequencies of other special variants as decoration. All these decisions underlie the time, skills, and aesthetic preferences of the artist and can profoundly shape the distribution of information-theoretic properties of the resulting artwork (Grasseni, 2018; Gustafsson, 2018). Beyond measures of entropy, we do not have direct ratings of the aesthetic quality of *kolam* drawings or whether the artist has employed a particularly appealing style. Other information metrics, such as bilateral or rotational symmetry, or fractal scaling, might reveal specific details beyond diversity or complexity and should be an endeavor for future studies.

While the observed patterns in *kolam* art imply a certain degree of invariance in complexity across different canvas sizes and only small traces of individual variation and social stratification, they exhibit what has been called "equifinal" behavior (Barrett, 2018; Bertalanffy, 1969). Equifinality means that inferring the generative processes that might have given rise to the observed cultural frequency data is difficult because we only have cross sectional data (Kandler and Powell, 2015; Barrett, 2018). Temporal data could allow us to narrow the subset of causal mechanisms that underlie the observed distribution of information-theoretic properties. Generative simulations could approximate temporal data and provide a more in-depth understanding of how artistic traditions could have theoretically evolved, specifically in regards to the diversity or the complexity and the stability of the *kolam* in the population across time. In order to infer the underlying generative processes, a probabilistic model, in which the hypothesized causal mechanisms (i.e., cognitive constraints, aesthetic preferences, or other potential constraints) are explicitly defined, needs to be built (Kandler and Powell, 2015). Such a probabilistic model can allow us to repeatedly simulate datasets with known parameters and compare the resulting distribution with observed data to infer the most likely hypothesized causal mechanisms. Furthermore, measuring the signaling value of specific *kolam* motifs for coordinating using classification tasks (Bell, 2020) could be a promising endeavor to explain the role of *kolam* art for social coordination. A comparison of the signaling value of culturally salient *kolam* motifs between the Tamil population in South India and the Tamil diaspora in the U.S. could further reveal divergent functions of *kolam* art for different communities. Another promising future endeavor could be to focus specifically on how *kolam* drawings are perceived and whether the processing efforts of *kolam* drawings (visual complexity measured by perimetric complexity or algorithmic complexity) (Miton and Morin, 2019; Pelli et al., 2006) are in alignment with the actual production efforts (e.g., gesture complexity measured by Shannon entropy) invested in kolams. These perception and processing efforts of a consumer or learner of kolams could even have implications on the transmission of *kolam* knowledge in terms of learning and reproduction (Tamariz and Kirby, 2015).

Our results on entropy trade-offs and various constraints on complexity operating on *kolam* art encourage us to distance ourselves from underspecified and vague attempts to explain the evolution of art (Pinker, 2003; Miller, 2011) and think deeply about artistic traditions in terms of evolutionary signaling theories of constrained optimization. Further investigations of how evolutionary signaling theories of constrained optimization could be applied to other art forms in other communities, such as Vanuatuan sand art (Lind, 2017; Zagala, 2004), Angolan sand drawings (Gerdes, 1993; Gerdes, 1988), or Islamic geometric art (Abdullahi and Embi, 2013), could advance our evolutionary understanding of investments in and constraints on art. A careful synthesis of evolutionary signaling theory with ethnography can help us understand individual's strategic investments into mastery of specific artistic skills and how they optimize their artistic displays (e.g., size, novelties, color diversity) within certain constraints (e.g., aesthetic preferences, cognitive constraints or motor constraints), allowing us to elucidate properties of art. Importantly, evaluating evolutionary constraints on cultural productions beyond functional sufficiency is integral to understanding how cultural productions have evolved (e.g., motor constraints in music production Miton et al., 2020). All these future directions will be time consuming and computationally challenging, but we believe that the long-term gains for an evolutionary understanding of artistic traditions will make this enterprise worthwhile.

1.5 Conclusion

Using quantitative measures to systematically study material art in a large-scale anthropological dataset, our findings inform discussions on entropy trade-offs and various constraints on complexity operating on artistic traditions.

In the case study of the hand-drawn Tamil artistic tradition, our findings are consistent with evolutionary signaling theories of constrained optimization and lend support that artistic complexity, measured by Shannon information entropy, is optimized through an observable, apparently unconscious trade-off between two standard ecological and information-theoretic measures: richness and evenness. This trade-off between richness and evenness can potentially be explained by cognitive constraints and aesthetic preferences. Variation in structural and information-theoretic properties of *kolam* drawings are small, and evidence of social structures reflected in the information measures we employ, are weak. This corroborates our understanding of *kolam* art as a signal that does not primarily communicate social stratification or individual differences in age or practice, but rather aesthetic preferences, dedication, time and skill, as well as constraints of human cognition and memory.

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Author Contributions
TMW collected the data, designed the *kolam* lexicon and wrote the Netlogo transcription software. SA led the data transcription team. NHT, BAB and TMW designed the analysis. NHT wrote data processing and statistical software and conducted the analysis. NHT and BAB wrote the manuscript, and all authors provided edits and revisions.

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Research Transparency and Reproducibility

The *kolam* data and code for this study are available and can be found on GitHub: `http://github.com/nhtran93/kolam_signaling`. The R package to analyzekolam drawings can be further found on GitHub: `http://github.com/nhtran93/kolam`.

Chapter 2

Limited Scope for Group Coordination in Stylistic Variations of *Kolam* Art

This work has been published in *Frontiers in Psychology:*

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Abstract

In large, complex societies, assorting with others with similar social norms or behaviors can facilitate successful coordination and cooperation. The ability to recognize others with shared norms or behaviors is thus assumed to be under selection. As a medium of communication, human art might reflect fitness-relevant information on shared norms and behaviors of other individuals, thus facilitating successful coordination and cooperation.

Distinctive styles or patterns of artistic design could signify migration history, different groups with a shared interaction history due to spatial proximity, as well as individual-level expertise and preferences. In addition, cultural boundaries may be even more pronounced in a highly diverse and socially stratified society. In the current study, we focus on a large corpus of an artistic tradition called *kolam* that is produced by women from Tamil Nadu in South India ($N = 3,139$ *kolam* drawings from 192 women) to test whether stylistic variations in art can be mapped onto caste boundaries, migration, and neighborhoods. Since the *kolam* art system with its sequential drawing decisions can be described by a Markov process, we characterize variation in styles of art due to different facets of an artist's identity and the group affiliations, via hierarchical Bayesian statistical models.

Our results reveal that stylistic variations in *kolam* art only weakly map onto caste boundaries, neighborhoods, and regional origin. In fact, stylistic variations or patterns in art are dominated by artist-level variation and artist expertise. Our results illustrate that although art can be a medium of communication, it is not necessarily marked by group affiliation. Rather, artistic behavior in this context seems to be primarily a behavioral domain within which individuals carve out a unique niche for themselves to differentiate themselves from others. Our findings inform discussions on the evolutionary role of art for group coordination by encouraging researchers to use systematic methods to measure the mapping between specific objects or styles onto groups.

Keywords: Art, Material Culture, Ethnic Markers, Coordination, Cooperation, Bayesian inference

2.1 Introduction

Cooperation in humans requires groups of individuals to successfully coordinate and work together toward common or mutually beneficial goals. With the transition to agricultural societies, populations have become larger and more complex (Moffett, 2013; Richerson and Boyd, 1999). Thus, in these large, multi-ethnic societies, assorting with others with similar social norms or behaviors can facilitate successful coordination and cooperation (Axelrod and Hamilton, 1981; Hamilton, 1964b; Hamilton, 1964a). In evolutionary biology, an abundance of research has focused on mechanisms that allow individuals to interact preferentially with each other, showing that cooperation can evolve and stabilize when individuals preferentially interact with close kin or have a recognition mechanism to interact with other individuals with cooperative traits or shared norms (McElreath, Boyd, and Richerson, 2003; Gintis, 2014). Thus, the ability to recognize others with similar social norms or behaviors is presumably under selection (Riolo, Cohen, and Axelrod, 2001; Jansen and Van Baalen, 2006).

As a medium of communication, human art might reflect fitness-relevant information on shared norms and behaviors of other individuals, thus facilitating successful coordination and cooperation. Distinctive styles or patterns of artistic design could signify migration history, different groups with a shared interaction history (e.g., kin, neighbors, or members of the same caste), or individual-level variation and expertise (i.e., duration of practice). To investigate the long standing and growing interest in quantitative detection of ethnic markers across disciplines, we present a Bayesian analysis of a large corpus of material art created by women from Tamil Nadu in South India, called *kolam* drawings. Using this corpus of *kolam* art, we test whether stylistic variations in art can be mapped onto caste boundaries, migration and neighborhoods, and how much variation in styles can actually be accounted for by these factors. Specifically, we illustrate how we can exploit the Markovian nature of the art system to our advantage to build a hierarchical model that is able to describe and partition the variation in the complex, sequential drawing compositions in order to better understand the role of art for social coordination.

2.1.1 Theoretical Background

In ethnic marker theory, it is assumed that human groups have developed distinct and overt ethnic markers or tags to signal group membership to preserve cultural boundaries (Moffett, 2013; McElreath, Boyd, and Richerson, 2003; Barth, 1969). The use of ethnic markers can help solve coordination and collective action problems because they communicate interaction norms. Ethnic markers can be manifested in various forms, from sartorial cues, dialectic variations, special adornments to distinct styles in production (Wobst, 1977). Thus, mastering different styles of weaving (Tehrani and Collard, 2009), arrowhead production (Wiessner, 1983), or pottery

(Bowser, 2000) could be fundamental for social interaction because of the fitness-relevant information about with whom, when, and how to interact. For instance, in the Ecuadorian Amazon, women's pottery style reflects their social identity and group membership as part of their political strategies (Bowser and Patton, 2008). Learning to identify, create, and modify stylistic symbols in pottery play a fundamental role in women's lives and social standing with Achuar and Quichua society.

While theoretical models and experiments in the laboratory demonstrate the mapping between group membership and objects for the purpose of social coordination (Efferson, Lalive, and Fehr, 2008; McElreath and Boyd, 2007; McElreath, Boyd, and Richerson, 2003), evidence from the field has been more ambiguous about the link between objects or styles and groups for social coordination (Wiessner, 1984; Hodder, 1977; Moya and Boyd, 2016). Thus, Bell (2020) have pointed out the need for a systematic method that is able to measure the mapping between a specific object or style onto groups because such a statistical measure of an object's role in social coordination has been largely elusive. In fact, Bell and Paegle (2021) presented a three-step ethnographic field method, consisting of scans, surveys, and classification tasks, to assess the role of motifs for social coordination. Specifically, the triad classification task was demonstrated to systematically measure whether motifs have information content as a result of population-specific socialization. This approach from Bell and Paegle (2021) is well-suited for systems with a finite set of motifs. A complementary approach to the field methods from Bell and Paegle (2021) — however, still elusive — would be a quantitative approach on the corpus of artistic productions that is able to identify styles or patterns that are salient de novo, not constrained by functional requirements and associated with groups or individuals.

2.1.2 *Kolam* Art

Kolam designs are ritual patterns that Tamil women draw with rice powder or chalk on the threshold of their houses in South India (Layard, 1937; Durai, 1929). Each morning before sunrise, women typically clean the thresholds of their homes and then start to draw *kolam* loop patterns by initializing a grid of dots (Laine, 2013). Subsequently, continuous lines are drawn around the dots to form intricate loop patterns.

While Hindu women draw threshold designs throughout India (e.g., rangoli in Uttar Pradesh or mandana in Rajasthan; Kilambi, 1985; Saksena, 1985), *kolam* designs are specific to Tamil Nadu (Laine, 2013; Layard, 1937). As a symbol of generosity, *kolam* drawings are a ritual offering to animals "to feed a thousand souls" (Nagarajan, 2018, p. 56, 243–255). Most importantly, the *kolam* communicates the state of the artist and its household, and marks important events within the household as well as in the village (Nagarajan, 2018, p. 37, 52–55, 75–81, 267). On the one hand, *kolam* designs communicate to neighbors and visitors that the household is healthy with sufficient food and able to host guests and be hospitable. Thus, especially large and complex *kolam* loop patterns are drawn on auspicious events, such as weddings or births. In contrast, the absence of *kolam* drawings typically indicates inauspicious events, such as death or menstruation, and thus signifies the inability to host visitors. On the other hand, *kolam* designs are further understood to convey information on the artist's personality (e.g., womanliness, traditionalness, and patience) and their competency to run a household and become a good wife and mother.

Kolam-making is not formally taught in school or training institutions, but knowledge is mostly transmitted from (grand-)mothers to (grand-)daughters and accumulated through practice and exposure over time (Nagarajan, 2018, p. 67-69). Since *kolam*-making and mastery are considered necessary for the transition into womanhood, women start to learn and practice *kolam*-making from an early age of about six years (Nagarajan, 2007, p. 8, 12, 156). Diligent practice in private notebooks would be required until a *kolam* design is finally showcased on the threshold of the household. It takes approximately six years to master the ability to draw a beautiful and complex *kolam* with continuous lines that do not intersect with the dots, uniform line widths, and invisible starts and stops of loops (Nagarajan, 2007, p. 128, 156). While hand-drawn *kolam* designs are never for sale (Nagarajan, 2018, p. 36), women can buy design books that display a variety of printed example *kolam* designs. Since the *kolam* traditions and the designs are considered community knowledge (Nagarajan, 2018, p. 69), women would often come together to share their designs with each other. In anticipation of an auspicious event, women in the household would share their ideas and carefully plan the especially complex *kolam* pattern of that day. At the same time, women would compete with each other to draw the most innovative, dense, and geometrically complex pattern during festivals or contests (Nagarajan, 2018, p. 179-203).

2.1.3 Current Study

In the current study, we focus on Tamil *kolam* art to demonstrate a novel approach to quantify covariation of artistic styles along cultural boundaries. The *kolam* system is well-suited to study social coordination because *kolam* art is observable (e.g., women display *kolam* drawings on their thresholds), recognizable (e.g., *kolam* art is specific to Tamil Nadu and has a specific grammar) and plays an important role in Tamil culture with an abundance of artists (and their multitude of group identities) learning and producing *kolam* drawings from a young age. Social learning and the accumulation of *kolam* knowledge across generations could have led to the covariation of styles or patterns in *kolam* art along certain cultural boundaries. Since *kolam* drawings arise in a highly stratified, caste-based society, the question arises whether different styles in *kolam* art may communicate group membership for social coordination.

Kolam designs actively broadcast information about the household to neighbors and visitors. For instance, a consistent absence of *kolam* patterns on the threshold indicates that the household is not Hindu (Nagarajan, 2018, p. 75). Furthermore, caste distinctions are reported among *kolam* designs with, for example, certain styles dominating between different subgroups of the Brahmin caste (Saroja, 1988; Nagarajan, 2018). According to Nagarajan (2018, p. 149), "regional variations are recognized and regularly discussed among women". Thus as predicted by ethnic marker theory (McElreath, Boyd, and Richerson, 2003), the mapping between *kolam* styles and group identities should become more salient at these cultural boundaries. However, a concrete quantification whether and to what extent differences in *kolam* styles are associated with caste, region, or other variables is still elusive (Nagarajan, 2018, p. 273) and requires a systematic investigation.

Kolam drawings cannot only be mapped onto a small identifiable set of gestures[1] "with systematic procedures and techniques" to create them (Ascher, 2002, p. 5), but their beauty is also characterized by continuous lines and loops with smooth transitions between gestures (Nagarajan, 2018, p. 128, 156). Thus, this naturalistic art system can be described by a state-based Markov process due to its series of sequential and dependent decisions. This Markovian nature of the art system allows us to build hierarchical statistical models that are able to account for variation in styles in art (i.e., the complex composition of gesture sequences that result in motifs, patterns, or styles in artistic design) due to different facets of an artist's social identity or their group membership, thus elucidating the role of the complex composition of gestures in social coordination. In the current study, we describe (1) the general styles or patterns of *kolam* designs, and further investigate (2) whether stylistic variations in artistic design can be linked to caste boundaries, migration and groups of individuals with a shared interaction history due to spatial proximity (neighborhood), and (3) how much of the stylistic variations in artistic design can be accounted for by artist-level variation and group affiliations relative to each other.

2.2 Methods

2.2.1 Data

We used a data set of $3,139$ *kolam* drawings (on average 16 *kolam* per woman) from 192 artists (age: mean $= 31.88$ years, sd $= 10.08$ years, range = $15 - 60$ years; married: 73%, non-native $\approx 18\%$) that were collected in Kodaikanal, Tamil Nadu in South India in 2009 by TMW and local research assistants. A survey was conducted on artists' *kolam* drawing abilities and behavior and other demographic information, such as their age, marital status, caste membership, number of children, the years of *kolam* practice, and their migration background (i.e., nativity). Artists in our data set self-identify with a total of 19 different caste categories. These caste categories are

[1] Nagarajan (2018, p. 53) describes *kolam*-making in the following way: "While the woman is creating it [kolam], she exhibits a set of gestures as a visual art form — a sequence of bodily movements requiring a quality of attentiveness akin to dance or yoga."

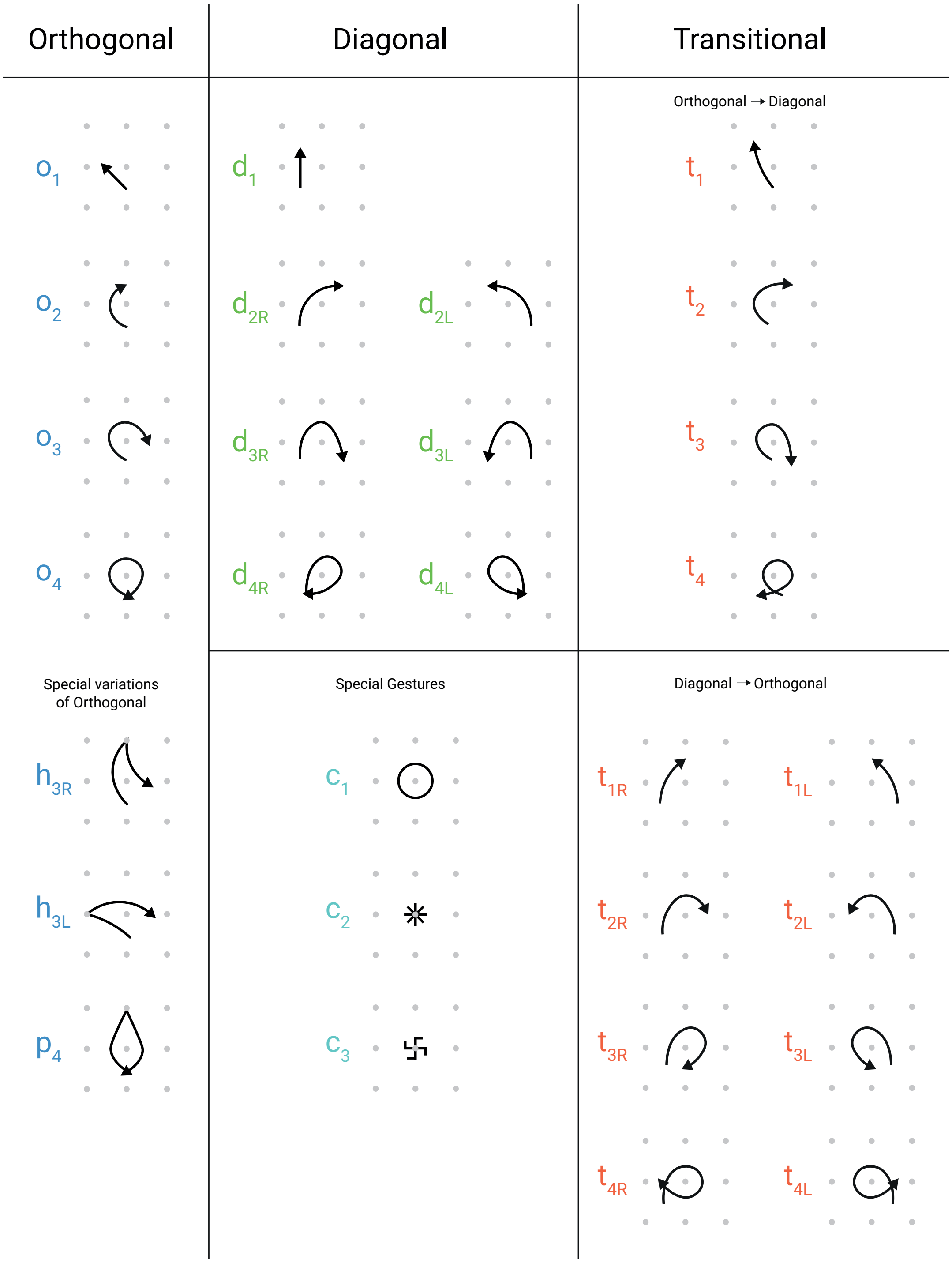

FIGURE 2.1: The Lexicon of *Kolam* Gestures. The Figure illustrates the gestures and the corresponding code to encode *kolam* drawings. Taken and adapted with permission from Waring (2012b).

associated with varying privileges and include local and migrant caste groupings. Additionally, the spatial proximity of each artist to each other was measured.

A *kolam* drawing can be constituted of one or more closed loops. Each loop can be decomposed into a sequence of gestures using a lexicon of gestures (Waring, 2012b).

A complete description of the lexicon can be found in Figure 2.1. The lexicon of gestures contains 29 gestures, denoting the geometric space of the gestures as well as the chirality of gestures with distinct left and right versions since rotations of these gestures in space cannot yield their exact mirror image (see Figure 2.1, lower row right). The gestures that constitute a loop and the *kolam* drawings can be categorized into three different geometric spaces with distinct characteristics: orthogonal, diagonal, and transitional (each set of gestures represented by O, D, T, respectively). Additionally, there are three special single gestures that serve as decoration and are not part of a loop. We transcribed the *kolam* data using the lexicon.

2.2.1.1 Geometric Spaces in *Kolam* Art

Kolam patterns have a grammar that contains many mathematical principles (Siromoney, Siromoney, and Krithivasan, 1974; Ascher, 2002; Waring, 2012b). Specifically, we refer to three geometric spaces that determine the starting and ending positions of a loop as well as the orientation of the loops: orthogonal, diagonal, and transitional space. Figure 2.2 illustrates orthogonal and diagonal spaces with example *kolam* drawings each. While orthogonal loops (i.e., loops in orthogonal space) start and end between two neighboring dots, diagonal loops (i.e., loops in diagonal space) start and end in the center of four dots. Furthermore, orthogonal gestures are oriented towards 45°, 135°, 225°, or 315° angles, and diagonal are oriented towards 0°, 90°, 180°, 270° angles. Gestures that start in orthogonal space, end in orthogonal spaces. Gestures that start in diagonal space, end in diagonal space. Thus, orthogonal and diagonal gestures are disjoint, but can be connected with each other using transitional gestures. Transitional gestures can either start in diagonal space and end in orthogonal space or they start in orthogonal space and end in diagonal space. Since orthogonal and diagonal gestures have distinct starting and ending positions and orientations, and transitional gestures share orthogonal and diagonal positions and orientations, switching between these different geometric spaces requires practice in order to still maintain smooth transitions, continuous loop closures, and uniform line-widths. Thus, *kolam* designs in only one geometric space tend to be easier to create, especially if the *kolam* design only consists of orthogonal gestures.

2.2.1.2 *Kolam* Art as a Markov System

Since each *kolam* loop pattern[2] can be decomposed into a sequence of gestures and artists strive to form uniform and smooth loops, the system can be described by a state-based Markov process, whereby the conditional probability distribution for the system at the next step depends only on the current state of the system, and not on the state of the system at a previous step (Gagniuc, 2017).

[2]Note: For the purpose of our analysis, we neglected the three special, single gestures: c1, c2 and c3.

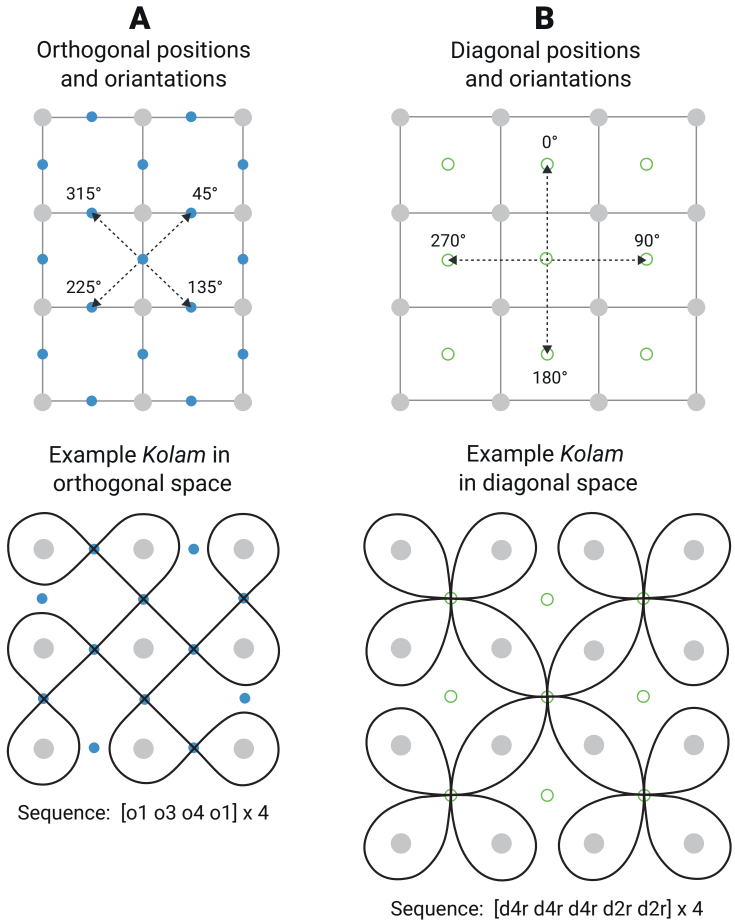

FIGURE 2.2: Explanation of the geometric spaces in *kolam* art. Taken and adapted with permission from Waring (2012b). Panel A shows the orthogonal geometric space with an example *kolam* drawing and Panel B shows the diagonal space with an example *kolam* drawing. In Panel A, the dashed arrows illustrate the possible orthogonal starting and ending positions of gestures (blue dots) and loops as well as the orthogonal orientations of gestures: 45°, 135°, 225°, 315° angles. In Panel B, the dashed arrows illustrate the possible diagonal starting and ending positions of gestures (green circles) and loops as well as the diagonal orientations of gestures: 0°, 90°, 180°, 270° angles. Sequence: The sequence of gestures that the specific *kolam* designs can be decomposed into (see lexicon in Figure 2.1).

Each gesture within a geometric space can be considered a state and thus, each loop and *kolam* drawing can be described by a probabilistic state transition matrix $m \times m$ where the row vector $m \times 1$ describes the state (i.e., gesture) and column vector the transition to the next state (i.e., gesture). Every gesture is accessible from itself. Furthermore, the gestures in this Markov system can be partitioned into communicating classes such that gestures of the same geometric space communicate with each other (accounting for chirality), and gestures of orthogonal and diagonal space are only connected via gestures of transitional space (see Figure B.2 in Appendix B for more details). Figure 2.3 illustrates the transition count matrix for *kolam* drawings from two example artists.

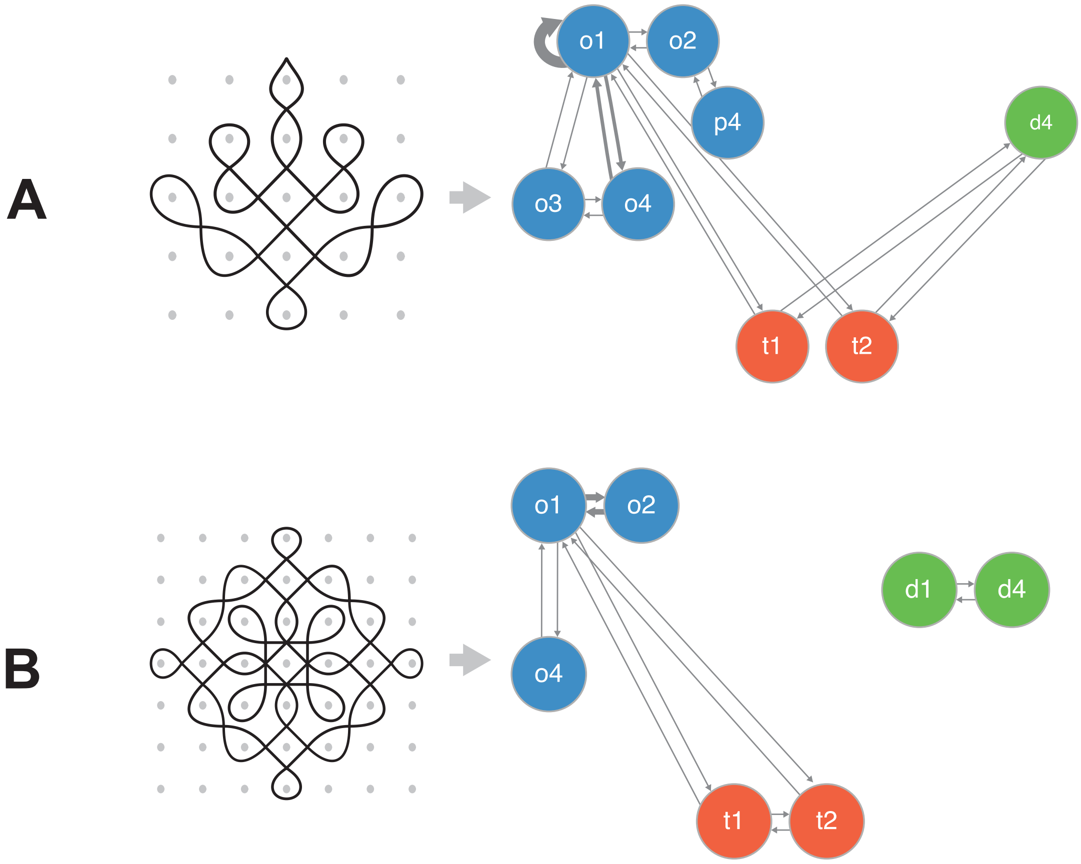

FIGURE 2.3: Example of a transition (count) networks for *kolam* drawings. Each row (Panel A and B) corresponds to an example *kolam* drawing from an artist. The edge width represents the count, whereby an increased width implies a higher transition count. The three colours represent the different geometric spaces: orthogonal (blue), diagonal (green) and transitional (orange). Each node represents a gesture used by the artist from the lexicon of gestures (see Figure 2.1).

We computed the transition counts for each loop of a *kolam* drawing across all the *kolam* drawings of an artist. The three special, single gestures were not considered because they are not part of a loop. Since each of the sequences of gestures represents a loop and the artists' starting location of a loop or *kolam* drawing is unknown, we further counted the transition from the last gesture in the sequence to the first gesture in the sequence. These transition counts not only reflect the distribution of gestures for each artist, but further artists' preferences or biases towards specific patterns or motifs (i.e., specific sequence of gestures). We first computed an aggregated transition count matrix y_i for each artist i of size 14×14. In order to fit our full model, we further computed four transition matrices y — one for each of the different geometric spaces and one for the transitions between geometric spaces: transitions between geometric spaces of size 3×3, transitions within orthogonal space of size 6×6, transitions within diagonal space of size 4×4 and transitions within transitional space of size 4×4. These transition matrices y_{ijk} represent the count of transitions from state (i.e., gesture) j to state (i.e., gesture) k for artist i. Thus, distinct patterns of *kolam* drawings can arise from different transition probabilities *within* geometric spaces and *between* geometric spaces — if any transition between geometric spaces occurs at all.

2.2.2 Statistical Analyses

To investigate the variation in *kolam* patterns and motifs due to individual variation, social stratification reflected by caste membership, nativity or neighborhood (i.e., place of residence), and expertise measured by the years of practice, we fitted a total of seven Bayesian statistical models. Here, we will only focus on the full model, but the interested reader can see the details of all the models in the supplementary information. For each artist, we modeled four transition matrices. The statistical model reflects the process of how the *kolam* drawings arise; the probability of the next state (gesture in a geometric space) is conditional on the current state. In the current model, the conditional probability of the next state given another state is factored into two components. One component encodes the probability of transitioning between geometric spaces; the other encodes the probability of transitioning between gestures within a geometric space. For instance, given that the current state is the gesture *o1*, then the probability that the next gesture will be *o2* is comprised of the probability of staying in the current orthogonal geometric space O times the conditional probability of choosing gesture *o2* given being currently in gesture *o1*: $P(o2|o1) = P(O|O) \times P(o2|o1, O|O)$.

Each row of each transition matrix is probabilistic and modeled on the logit scale using the softmax link (i.e., multinomial logistic regression). Caste was modeled as a varying effect with 19 categories to estimate individual offsets for each caste category. Since there are multiple *kolam* drawings for each individual, caste group and neighborhood, information across individuals, castes and neighborhoods was partially pooled using hierarchical modeling to account for imbalances in sampling and yield more reliable and precise estimates (Efron and Morris, 1977). The duration of practice was standardized to be centered on zero with a standard deviation of one. The native place was a binary indicator predictor variable (0 = native, 1 = non-native). A geodesic distance matrix was computed between the GPS coordinates and subsequently hierarchically clustered with a distance threshold of 500m, resulting in 8 neighborhood clusters. The neighborhood clusters were modeled as a varying effect with 8 categories to estimate individual offsets for each neighborhood.

The models can be parameterized differently by including or excluding predictors as well as setting equality constraints for various parameters between rows of the transition matrices. We used leave-one-out cross-validation (Vehtari, Gelman, and Gabry, 2017) and computed Pseudo-Bayesian model averaging[3] and stacking weights (Yao et al., 2018) using the log-likelihood evaluated at the posterior simulations and the `R`

[3]Pseudo-Bayesian model averaging computes the relative model weights using Bayesian bootstrap. (For more details, see the manual, Vehtari et al., 2020).

package `loo` (Vehtari et al., 2020) to estimate and compare out-of-sample prediction accuracy of our fitted models.

The statistical models were implemented in the probabilistic programming language Stan (v2.18) (Carpenter et al., 2017), using 4000 samples in four independent chains. All $\widehat{R}$ values were less than 1.01, and visual inspection of trace plots, rank histograms and pairs plots indicated convergence of all models (see Appendix B for more details). A principled and robust Bayesian workflow with an iterative process of model building, inference, model checking and evaluation, and model expansion was used (Gabry et al., 2019; Talts et al., 2018). Prior predictive simulations were used to determine weakly informative priors for the parameters. Thus, there were no indication of convergence issues and the models were optimally calibrated. We present a complete description of the statistical models and the priors in Appendix B. Data and analyses can be found at `http://github.com/nhtran93/kolam_coordination`.

2.2.3 Intraclass Correlation (ICC)

The intraclass-correlation coefficient (ICC) can be calculated to determine the proportion of the total variance explained by random and fixed effects (Nakagawa, Johnson, and Schielzeth, 2017). We calculated a modification of the ICC using variance decomposition of the model predictions[4]. We drew predictions of the transition probabilities on the logit scale using the posterior samples for each of our fixed (i.e., migration, duration of practice) and random (i.e., neighborhood, caste, individual variation) terms separately, using the estimates from the full model. Thus, for each fixed or random term, we obtain the transition probabilities (on the logit scale) implied by that term in isolation for each individual. The ICC is then the ratio between the variance of the predictions across individuals from a single term divided by the sum of the variances of predictions across individuals for all terms ($ICC_i = \frac{Var(\text{predictions}_i)}{\sum Var(\text{predictions}_j)}$). This calculation was done per each MCMC iteration and each cell of the transition matrix separately. The final estimates are based on the average over the MCMC iterations and all cells in the transition matrix.[5] The value of ICC corresponds to the proportion of total variance of the model's transition probabilities on the logit scale that is accounted for by a particular term in the model. By construction, the coefficient cannot be smaller than 0 and the sum of all ICCs is equal to 1. Thus, the ICC quantifies the proportion of the total variance explained and is suitable to compare relative strength of the model terms. However, the absolute strength of each predictor is dependent on all other terms in the model.

[4]For more details, see `icc` and `variance_decomposition` functions in the `performance` R package (Lüdecke et al., 2021)

[5]Note that we have four transition matrices, so we computed the ICC separately according to the above described procedure for each of the transition matrices: across geometric space, orthogonal space, diagonal space and transitional space.

2.3 Results

According to Pseudo-Bayesian model averaging and stacking weights in leave-one out cross-validation, our full model has the best predictive performance (see Appendix B for more details).

TABLE 2.1: Population-level Estimated Posterior Transition Matrix across Geometric Spaces

	orthogonal	transitional	diagonal
orthogonal	0.99	0.01	0.00
transitional	0.51	0.30	0.19
diagonal	0.00	0.51	0.49

On the population-level, our results illustrate that although artists are unconstrained in their patterns or stylistic variation in *kolam* drawings and they can freely transition back and forth between geometric spaces and gestures, artists have evident preferences and biases towards certain gestures and geometric spaces. *Kolam* patterns that arise in orthogonal geometric space are predicted to stay in orthogonal geometric space with a probability of 0.99, and transitioning to a different geometric space from orthogonal space to access a greater diversity of gestures hardly occurs with a probability of 0.01 (see Table 2.1). As seen in Table 2.1, if an artist draws a *kolam* artwork in diagonal space, they are predicted to equally likely switch to transitional space (probability of 0.51) or remain in the current diagonal space (probability of 0.49), while artists that draw a *kolam* artwork in transitional space are predicted to remain in the current space with a probability of 0.30 and switch to orthogonal or diagonal space with a probability of 0.51 and 0.19, respectively. Therefore, when an artist draws kolam patterns in orthogonal space, they are unlikely to transition between different geometric spaces and only draw patterns with different gestures within the orthogonal space. However, if artists draw kolam patterns in diagonal or transitional space, they tend to use a diverse set of gestures that span across multiple different geometric spaces. For a more in-depth analysis of the population-level tendencies in gesture compositions that result in specific gesture equilibria and styles in artistic design, please consult Appendix B.

Figure 2.4 shows the estimated individual-level transitions between orthogonal, diagonal, and transitional gestures from two artists and an example *kolam* artwork each from their repertoire. As seen in Figure 2.4, artists' styles in drawing *kolam* artwork can be very divergent between artists. While the artist corresponding to the estimated transitions and example *kolam* artwork in Panel A of Figure 2.4 would draw *kolam* artworks that arise and remained in orthogonal space with a probability of 0.846 at equilibrium, she would only occupy diagonal (0.041) and transitional (0.113) spaces at equilibrium. The artists corresponding to Panel B would create *kolam* artworks that

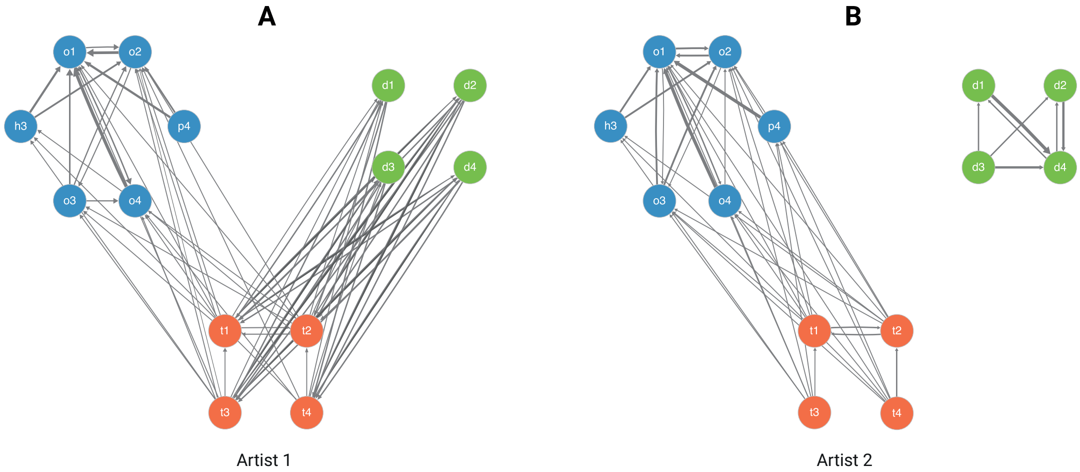

FIGURE 2.4: Estimated individual-level transitions between orthogonal, diagonal and transitional gestures for two example artists. Each panel represents an example artist (Panel A: artist 1, Panel B: artist 2) with her corresponding estimated transition probabilities between gestures. The width of the edges reflects the probability of transition, whereby a wider or bolder edge implies an increased probability of transition. Self-loops are not displayed.

occupy orthogonal (0.53), diagonal (0.35), and transitional (0.12) spaces at equilibrium. Furthermore, in contrast to the artist corresponding to Panel A, the artist corresponding to Panel B draws diagonal gestures in isolation without connecting their gestures to gestures from other geometric spaces. In fact, the *kolam* designs displayed in Figure 2.3 correspond to the artists from Panel A and B in Figure 2.4 respectively. Thus, the vastly different transition probabilities between gestures among artists can thus give rise to diverse patterns or motifs in *kolam* artwork.

Even though the estimated population-level transition matrices reveal a tendency in how kolam patterns arise, our results show that there is substantial variation in kolam drawing styles and patterns between artists. Whether styles in kolam drawings comprise of one or more transitions between geometric spaces or only arise and remain in the same geometric space, our results reveal that most of the variation in styles or patterns of kolam artwork is driven by individual differences and their expertise (see Figure 2.5 and Table 2.2). Figure 2.5 shows the size of the variance estimates (i.e., random effects) in transitioning to the next gesture from a given geometric space (Panel A) or gesture (Panel B, C, D). The variance parameters for the transition probabilities in *kolam* artwork are dominated by artist-level variation, whereby the artist-level variation has consistently the largest estimate on all four transition matrices. As illustrated in Figure 2.5, caste membership and neighborhood have smaller estimates on the four transition matrices. The duration of practice shows large estimates on the gesture transitions within diagonal and transitional space and moderately large estimates in transitions between diagonal and transitional space (see Appendix B for more details). Former migration history further only shows small estimates on the transition between geometric spaces, while the estimates for within orthogonal and

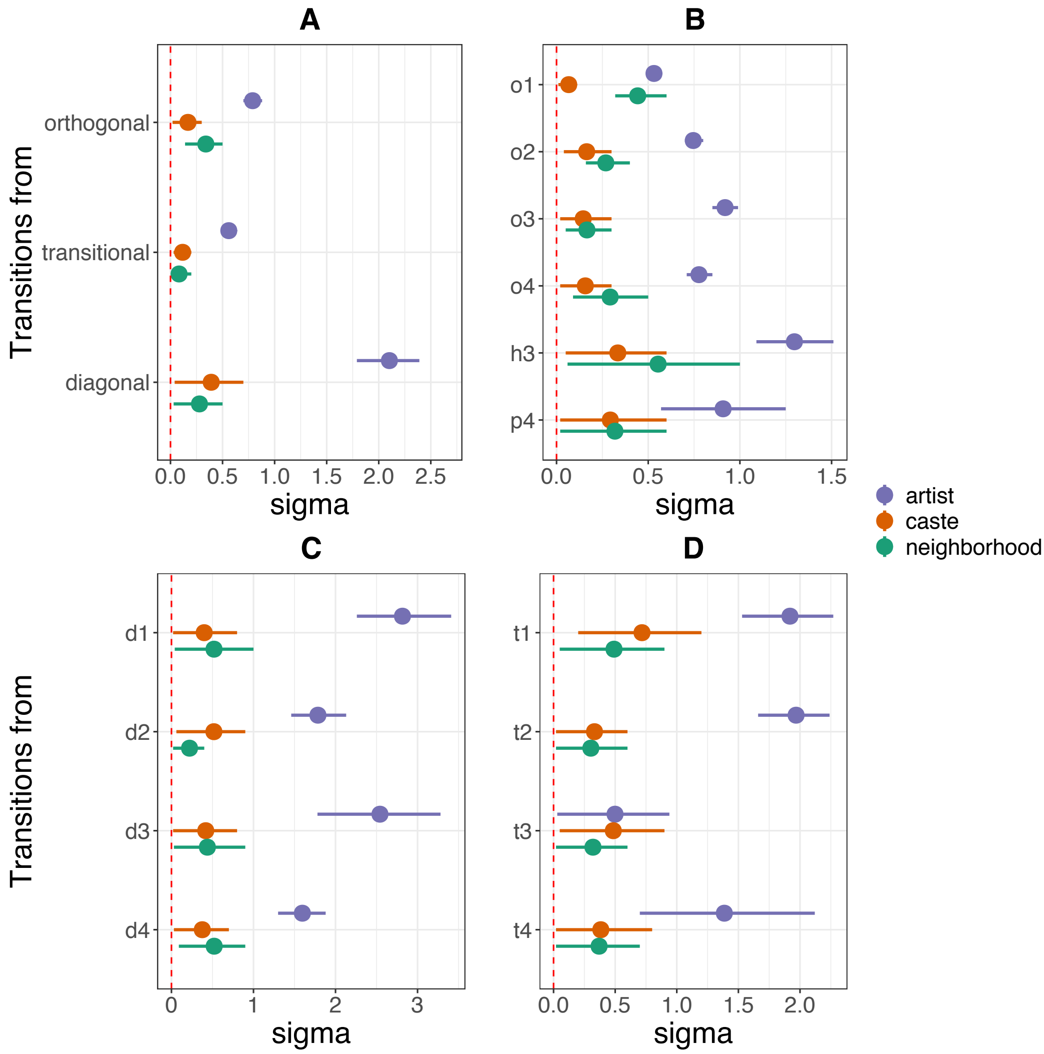

FIGURE 2.5: Posterior Coefficient Plots displayed as the 90% Highest Posterior Density Interval (HPDI) of the posteriors of sigma estimates (i.e., standard deviation of the random effects) associated with variation due to artists, caste, and neighborhood. Transitions *from* geometric spaces (Panel A) and *from* individual gestures (Panel B, C, D) are shown on the y-axis.

transitional space transitions are moderately large (see Appendix B for more details).

According to the computed ICCs, *kolam* drawing styles with one or more transitions between different geometric spaces largely map onto individual variation (63%), so that the variance of predictions from a model with just individual artists' intercepts make up 63% of the total variance; the expertise of the artist accounts for additional 25% of the total prediction variance (see Table 2.2). In other words, on average 63% of the variation in the predicted transition patterns between geometric spaces can be attributed to the variation between distinct artists unexplained by other predictors, and a further 25% can be attributed to their expertise, measured as the duration of practice. Individual variation (62%) paired with artist's expertise (20%) further primarily accounts for styles of *kolam* artwork that arise and remain in orthogonal space

TABLE 2.2: Explained Variation (Intraclass Correlation)

	individual	expertise	nativity	caste	residence
across geometric spaces	0.63	0.25	0.06	0.03	0.04
orthogonal	0.62	0.20	0.05	0.03	0.10
diagonal	0.83	0.07	0.02	0.05	0.03
transitional	0.60	0.16	0.06	0.12	0.06

(see Table 2.2). Caste membership can account for 12% of the variation in transitions between transitional gestures in *kolam* artwork, but can only account for very little variation in the rest of the estimated transition probabilities (see Table 2.2). Similarly, previous migration history or the neighborhood of the artist can explain 10% of the variation in transitions between orthogonal gestures, but only little in the rest of the estimated transition probabilities in *kolam* artwork (see Table 2.2).

2.4 Discussion

Our statistical model revealed that styles or patterns in *kolam* artwork can only be very weakly mapped onto group affiliations, such as caste boundaries, neighborhoods, or previous migration. Styles or patterns in *kolam* artwork show group-level variation; however, the group-level variation is limited. Hence, it is unlikely that styles or patterns in this artistic tradition operate as ethnic markers. Albeit artists can relatively freely choose their styles or patterns in a *kolam* artwork, at the population-level, artists prefer and are biased towards specific (sequences of) gestures and prefer to remain in orthogonal gesture space. While a general tendency for specific gestures and geometric spaces exists on the population-level, artists can still widely differ in their stylistic variations or patterns in *kolam* art. In fact, the variation in styles and patterns in *kolam* art is dominated by artist-level variation and expertise. Thus, styles and patterns in *kolam* art can be mapped onto artists and their expertise and presumably their preferences.

Group-level variation can emerge naturally and become embedded in art through strategic decisions to communicate group affiliations and even through an unconscious population-level process of iterative learning and performance (McElreath, Boyd, and Richerson, 2003). In contrast to predictions from ethnic marker theory that ethnic markers should be most prominent along cultural boundaries (McElreath, Boyd, and Richerson, 2003), we show that *kolam* artworks only weakly covary along caste, neighborhood, or migration boundaries using a statistical approach. While the mapping between styles in *kolam* artworks and group affiliations is very limited, we still provide empirical evidence that there is scope for styles to become embedded in artwork as ethnic markers to signify group boundaries (for more details, see Bell, Richerson, and McElreath, 2009). However, how much group-level variation is actually needed to function as an ethnic marker in a population is still unresolved.

Although art is a medium of communication and assorting with others with similar social norms or behaviors can facilitate successful coordination and cooperation, we believe that styles in art in this context do not play a coordinating role. One possible reason for the lack of covariation of artistic styles along cultural boundaries is that artists might have grown more similar to each other over time due to increased interactions (Healey et al., 2007; Granito et al., 2019). Due to the cross-sectional nature of our data, we might have not been able to see such a change over time. However, since the *kolam* tradition is considered community knowledge and artists share their designs with each other (Nagarajan, 2018), the development of styles might have been influenced by frequent intergroup contact, and shared attention and learning (Granito et al., 2019; Tomasello, Kruger, and Ratner, 1993). Precisely, the notion of *kolam* art as community knowledge might have led to pressures to make artistic styles accessible and transparent to any potential audience.

The lack of migration history reflected in styles in *kolam* artwork could further indicate a pressure to conform to the dominant style in the region and the pressure to conform to the patrilocal style in the household. (Postmarital) Relocated *kolam* artists might adopt stylistic choices that are dominant in the region to communicate their belonging and similarity for successful group cooperation (Helbich and Dietler, 2008; Wallaert-Pêtre, 2008). Furthermore, the Tamil community in South India has a strongly patrilocal system of postmarital residence, thus relocated *kolam* artists might want to avoid communicating dissimilarity by adopting the local dominant style from their in-laws.

Avoiding conflicts with dissimilar others might be yet another reason why art, specifically styles in *kolam* art, have not developed to strongly map onto group boundaries and only show a limited scope for group coordination. Since individuals from different castes are often forced to cooperate with each other in the domain of farming in South India (Waring, 2012a), foreclosing valuable partnerships by using overt signals might not be desirable for successful cooperation (Smaldino, 2016). Art, specifically *kolam* art, might not be the preferred domain for ethnic markers to signal group membership since individuals have a multitude of (social) identities and group affiliations. Different situations and audiences might require different social identities that the artist can deliberately choose to occupy and display when suitable.

Instead, art might be a stage specifically reserved to promote artists' knowledge and expertise as well as their aesthetic preferences for symmetry, specific motifs, or gesture sequences through individual patterns and styles. Albeit artists may optimize their artistic displays towards a specific complexity "sweet spot" (Tran et al., 2021), our findings illustrate that they additionally strive to leave their individual mark on the artwork using their unique and distinct style for optimal distinctiveness (Brewer, 1991; Pickett et al., 2011). In fact, research in music has already shown that the probability of adopting a specific style disproportionately can be determined by frequency-based biases like conformity and novelty or prestige, success, and content biases

(Youngblood, 2019; Brand, Acerbi, and Mesoudi, 2019). Since *kolam* art is culturally transmitted between artists, patterns or motifs might be subject to these transmission biases in social learning. For example, a novelty bias towards favoring unique patterns or motifs in *kolam* art could explain the substantial variation in kolam drawing styles between artists. Specifically, counter-dominance signaling could be a driving mechanism behind the cross-sectionally observed distinct styles between artists, since this mechanism posits that lower-status artists use highly unique styles to counter the currently dominating styles (Klimek, Kreuzbauer, and Thurner, 2019). In order to investigate the cultural transmission of artistic traditions like *kolam* art and to disentangle the different biases at play, longitudinal data, explicit generative models, and careful consideration of the cost of adoption are required. Thus, our current data and analyses are insufficient to draw conclusions about cultural transmission processes and future research should explore this avenue in more detail.

How art can be mapped onto ethnic and cultural boundaries for the purpose of group coordination, and how much group-level variation is necessary to function as an ethnic marker are still vital questions to elucidate the coordinating role of art, and they require further investigations. Certainly, art and different aspects of art can actually play a crucial coordinating role depending on the context and the community. However, in Tamil Nadu, *kolam* designs might not be used as ethnic markers because there are already a variety of other ethnic markers that signify group membership. For instance, clothing, grooming, names, or the pottu (also known as bindi; see Davis, 1992, p. 25, for more information) can signify a woman's caste, religion, regional origin, class, and marital status (Mosse, 2018; Nagarajan, 2018). Furthermore, *kolam* designs might not be preferred as visual ethnic markers because their primary audiences are neighbors and visitors who most likely already know each other. This factor could explain a limited utility of *kolam* artwork serving as ethnic markers and further explain the lack of group mappings onto styles in *kolam* art. Another important consideration would be whether the groups are sufficiently distant to entail information about ethnic and cultural boundaries in the present sample. While we collected data from three different neighborhoods, the maximum distance between households was only slightly above 3 km. Additionally, caste endogamy persists, and thus women often still stay in the same caste community after postmarital relocation, even though artists in our sample migrated from different villages or cities of the states Karnataka, Kerala and Tamil Nadu to Kodaikanal. Furthermore, although our sample consists of a mix of Scheduled Castes, Backward Castes and Forward Castes, some caste groups within each of these categories are closely associated with each other or branches of the same caste community. Thus, our research only serves as an example of a systematic investigation of how styles in art can be mapped onto ethnic and cultural boundaries for group coordination by decomposing sequential behavior into states in a Markov chain. We demonstrate how describing a cultural system as a Markov chain can help us partition variation in styles to gain new evolutionary insights on the role of art for social coordination.

Certainly, loop patterns and motifs in *kolam* art are not limited to a sequential description using Markov chains, since ethnomathematicians have been intrigued by the many mathematical properties in *kolam* art (Ascher, 2002; Nagata, 2015; Layard, 1937). *Kolam* loop patterns are often structured by bilateral symmetry (i.e., vertical or horizontal symmetric) and rotational symmetry (see *kolam* drawings in Figures 2.2 and 2.3). Furthermore, some complex *kolam* designs even exhibit fractal scaling by continuously repeating specific patterns. Symmetry, fractal scaling, geometric complexity, canvas size as well as the density of a *kolam* are all appreciated aesthetic qualities by Tamil women (Nagarajan, 2018, p. 165-167, 189), but not considered in the current analyses using Markov models. While the relation between complexity, density, and canvas size to individual and group-level variation has already been investigated (Tran et al., 2021), the relation between symmetrical and fractal properties of *kolam* designs to individual and group-level variation is still elusive and requires future explorations.

Future research should focus more on a synthesis between theoretical and statistical models and ethnographic methods in the field. For instance, classification tasks can be applied to motifs in art to gain a better understanding of the (cultural–historical) significance of specific motifs in art for social coordination (Bell, 2020). Bell (2020) demonstrated how triad classification tasks could be used to measure the signaling value of specifically selected Tongan motifs that are not constrained by functional sufficiency and thus elucidate their role for social coordination and the implied signaling dynamics. Similarly, specific *kolam* motifs with specific meaning, such as the "temple lamp" (see Figure 2, Panel A; Waring, 2012b) or auspicious symbols like the swastika (see Figure 1, left; Thomas, 1880) could be selected to measure their signaling value using the triad classification tasks. Our statistical approach and the methods proposed by Bell and Paegle (2021) could complement each other in future investigations of the coordinating roles of other art forms and material culture products. Another promising future avenue would be to expand ethnic marker theory and fieldwork to explain the dynamics between costly investments and ethnic markers. Since complex *kolam* designs require years of learning and practice, they can be considered costly. Similarly, Polynesian tattoos are markers of identity and political status, but costly due to their permanent and painful nature (Gell, 1993; Schildkrout, 2004). In these ritual examples, the evolutionary dynamics and trajectory of ethnic markers could deviate from current predictions of ethnic marker theory, and thus future research needs to consider costly ethnic markers.

In archaeology and evolutionary anthropology, a substantial amount of research has been dedicated to study the step-by-step production of lithics (e.g., stone tools) and pottery (chaîne opératoire; Sellet, 1993). Our state-based Markov analysis could be extended and applied to investigate the technical processes and operational sequences involved in the production of material culture. Stylistic variations in *kolam* art and other artistic traditions can transcend specific motifs and patterns, and manifest themselves in methodological and technical processes of the art production. For instance, *kolam* artists can systematically differ in their use of rice powder or chalk or their sequence of loop additions with the potential aid of applying scaffolding techniques. According to Gosselain (1999), different technological stages in pottery production can be associated with different stylistic displays of groups of Bafia potters in Cameroon. Thus, different sequences or stages of the production can further reflect stylistic expressions along ethnic or cultural boundaries due to shared learning. In the context of art, methodological and technological differences, such as brushstroke, pigment or contouring sequences and technique could be investigated by describing the different behavioral sequences as states in a Markov system to elucidate whether stylistic variations follow cultural and ethnic boundaries. We believe that the potential application of our state-based Markov approach to material culture and art is vast and could lead to compelling new insights into the evolutionary importance and coordinating role of art and other cultural artifacts.

2.5 Conclusion

Using a state-based Markov approach to systematically study the link between styles or patterns in art and group affiliations, our findings inform discussions on the evolutionary role of art for group coordination by encouraging researchers to use systematic methods to measure the mapping between specific objects or styles onto groups.

We show on a Tamil artistic tradition case study that although art can be a medium of communication, it is not necessarily dominated by group affiliation. While distinctive styles or patterns of artistic design are not apparently linked to caste boundaries, neighborhoods, or previous migration, they are linked to artist-level variation, such as expertise and presumably preferences. Our findings corroborate our understanding that artistic traditions and behavior in this context are primarily a domain where individuals carve out a unique niche for themselves to differentiate themselves from others.

Acknowledgements
We specifically want to thank the many Tamil *kolam* artists who were willing to share their repertoires, and the local collaborators who participated in data collection, including: Kousalia Devi, Subashini Vetrivel, Matthew, Shankar, Arun, Sudarshan, Senthil, and Michael. We thank the team of transcribers Anja Becker, Anne Büchner, Carlotta Rück, Claudia Bavero, Franziska Meier, Kristina Kunze, Karin Kämmerling, Leonie Ette and Maria Fröhlich.

Author Contributions

NHT and SK designed the analysis. NHT, TMW and BAB wrote data processing software. NHT wrote the statistical software, conducted the analysis and write the manuscript. SK reviewed the code. TMW collected the data and designed the *kolam* lexicon. SA led the data transcription team. BAB and TMW provided critical feedback. All authors provided edits and revisions.

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Research Transparency and Reproducibility

The *kolam* data and code for this study are available and can be found on GitHub: `http://github.com/nhtran93/kolam_coordination`. The R package to analyze *kolam* drawings can be further found on GitHub: `http://github.com/nhtran93/kolam`.

Appendix A

Supplementary Information for Chapter 1: "Entropy Trade-offs in Artistic Design: A Case Study of Tamil *Kolam*"

A.1 Approximation of Entropy using Richness and the Gini Index

For any discrete probability distribution with n possible outcomes, each i of which occurs with probability p_i, we can calculate a number of information measures. In ecology, Shannon information entropy is a popular measure of biological diversity because it contains two different aspects: richness and evenness. The Shannon information entropy is a measure of the expected "surprise" or uncertainty, given in the discrete case by

$$H(p) = -\sum_{i=1}^{n} p_i \log(p_i) \tag{A.1}$$

for each outcome i. In economics, the Gini index (Zoli, 1999; Ravallion, 2014) is used to describe relative inequality in the probability distribution, calculated as the mean absolute difference between all pair of variants,

$$g(n) = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |p_i - p_j|}{2(n-1)} \tag{A.2}$$

where n is the richness (the number of unique variants) and p the frequency of specific variants.

Entropy and the Gini index capture variation in the relative abundance of each outcome following the focal probability distribution. That is, when one outcome $p_j \to 1$

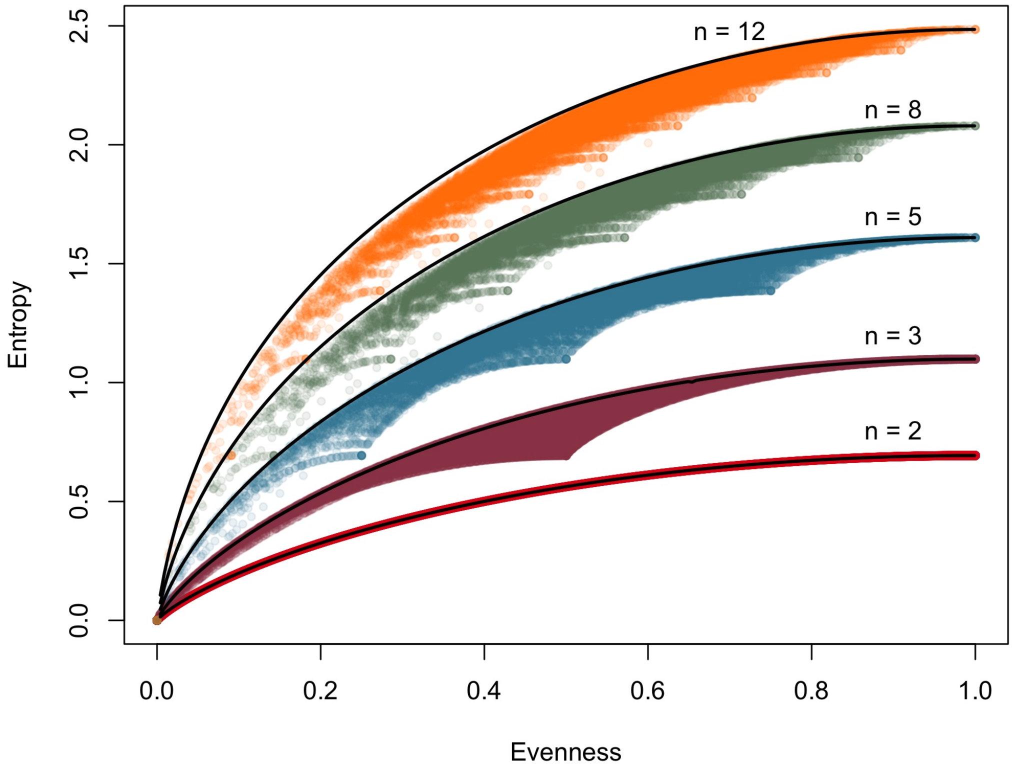

FIGURE A.1: High-resolution simulations showing the entropy distribution of a given richness and evenness. The black lines show the maximum entropy for a given number of variant. The differently coloured points represent the entropy distribution corresponding to the different number of variants. Equation A.3 defines the curve for $n = 2$.

and all $p_j \to 0$, the Shannon entropy goes to its lower asymptote of 0, and the Gini index goes to its upper asymptote of 1. Likewise, when $p_j = \frac{1}{n}$ for all j, the entropy is maximized at $\log(n)$ and the Gini index is minimized at 0.

In the special case of $n = 2$ with two variant frequencies p and $q = 1 - p$, such that $p > q$, the Gini index simplifies to $g_2 = p - q$. Using the fact that $p + q = 1$, we can rewrite each as: $p = \frac{1-g_2}{2}, q = \frac{1+g_2}{2}$. Thus, there is an exact relationship between H_2 and g_2, such that entropy is maximized when the Gini index is minimized, and vice versa.

$$H_2 = \left(\frac{1+g}{2}\right) \log\left(\frac{2}{1+g}\right) + \left(\frac{1-g}{2}\right) \log\left(\frac{2}{1-g}\right) \tag{A.3}$$

.

Equation A.3 defines the curve for $n = 2$ in Figure A.1.

However, the relationship between a Gini index and an entropy is indefinite if $n > 2$ because multiple distributions with the same n with different entropy could take the same Gini index value. Figure A.1 illustrates the relationship between the entropy and Gini index calculated for 100,000 simulated probability distributions.

To understand the relationship between entropy, the Gini index and the richness further, the location of the minimum and maximum entropy within this wing-shaped "envelope" are important. Given any particular value of g, and number of variants n, we can describe the range of possible distributions between a maximum and minimum entropy. Although analytic solutions for the minimum or maximum entropy are elusive for $n > 3$, numerical solutions are readily available using simulation and non-linear optimization algorithms. In the supplementary codebase, we use the `Rsolnp` package to run the non-linear optimization algorithm and find maximum-entropy solutions for the cases in Figure A.1.

The lower "tips" of each distribution in Figure A.1 represent the minimum-entropy limits at which the least-common non-zero variant tends to a zero frequency. In the case of $n = 3$, the minimum-entropy boundary can be approximated by noting that the minimum entropy (i.e., the "tip") occurs when $g = \frac{1}{2}$. At a closer look at Figure A.1, the minima of the entropy distribution lie at $\{\frac{0}{n-1}, \frac{1}{n-1}, \ldots, \frac{n-1}{n-1}\}$, following a limiting boundary described by the equation:

$$H_{min} = \log\left(n - (n-1)g\right). \tag{A.4}$$

More precisely, the minimum entropy boundaries can be defined by generalizing the entropy equation for n = 2 in equation A.3 to: $p = \frac{y-a}{b-a}, q = \frac{b-y}{b-a}$, where $v = 1 - g$ in the special case of $n = 2, a = 0$ and $b = 2$. Empirical exploration of the entropy envelope by the simulation of 100,000 gesture distributions indicates that no distribution can occupy a lower entropy than defined by this boundary. This can be used to decompose entropy using g and n because if g is known, $H_{n,g}$ varies between boundaries defined by the equation:

$$\exp(\widehat{H}) \approx n - (n-1)v^{1+b} = n - (n-1)v^{1+\frac{2}{2+a}+\frac{a}{a+n}}, \tag{A.5}$$

where evenness is $v = 1 - g$. If $b = 0$, this equation gives the lower theoretical boundary on entropy for any given g and n described by equation A.4 and the "tips" in Figure A.1. The numerically-calculated maximum entropy values are described by the equation $b = \frac{2}{2+a} + \frac{a}{a+n}$ with $a \approx \exp(0.5139)$. Thus, if we assume that a distribution tends towards maximum entropy (Frank, 2009), we can calculate a distribution's entropy knowing only its richness n and the evenness $v = 1 - g$.

As evenness and richness are now related to entropy by a mathematical identity (and so have no single causal direction to their relationship), we can aspire to understand what actually could explain why the observed *kolam* patterns follow the entropy isoclines.

A.2 *Kolam* Data

A.2.0.1 Lexicon of Gestures

One specific class of *kolam* are those with loop patterns, called square loop *kolam* drawings (i.e., the *ner pulli nelevu* or *sikku kolam* family) (Waring, 2012b). These *kolam* drawings are composed of an initial grid of dots (*pulli*) that reflect the canvas size. Lines consisting of multiple gestures are sequentially drawn around the dots to form loops. We only focus on these square loop *kolam* drawings because the patterns can be mapped onto a small identifiable set of gestures which is suitable for analyses.

The geometry of the *kolam* can be divided in two fundamental geometric spaces and a transitional geometric space with their specific corresponding positions, orientations and gestures. All gestures are always located in relation to the neighboring dots, called *pulli*. For a detailed description of the sequential encoding of *kolam* drawings with the gestural lexicon, please consult Waring (2012b).

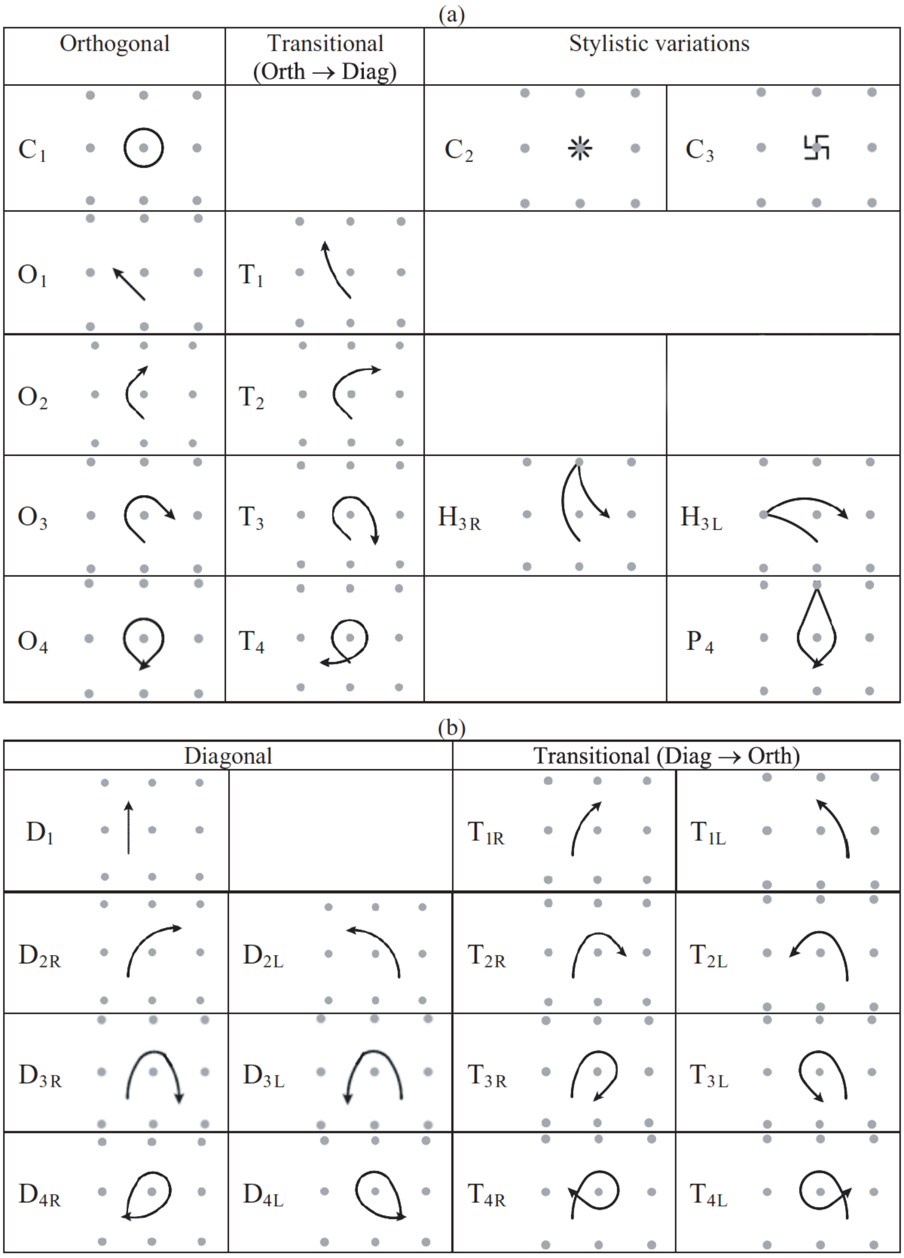

FIGURE A.2: The Lexicon of *Kolam* Gestures. The Figure illustrates the gestures and the corresponding code to encode *kolam* drawings. Taken and adapted with permission from Waring (2012b)

A.2.1 Database

A.2.1.1 Survey Information

Information on individuals' *kolam* drawing abilities and behavior were gathered as well as demographic information. Demographic information entailed data such as GPS data of the current residency, marriage status, native places and measures of socio-economic status. To investigate individual's *kolam* practice, survey questions included information on individual's frequency of drawing *kolam* drawings in front of their doorstep or in their practice book and the age of initial learning.

A.2.1.2 GPS

The geographical position of each individual's current residency was measured. A GPS tracker of type Garmin GPSmap 60 CSx was used. The interviewer only asked for the name of the native place and during data pre-processing the name of the native place and if needed other demographic information was then used to manually map the name of the native place to a GPS position. All GPS positions of the current residency and the native place were recorded allowing distances between points to be calculated by applying the distance formula to the x-y-z coordinates of the two points.

A.2.1.3 *Kolam* Drawings

A corpus of *kolam* drawings was compiled by soliciting individual's to draw *kolam* drawings as part of the survey. Each individual was asked to draw a minimum of a total of 20 *kolam* drawings.

A.3 Statistical Analyses

A.3.1 Random Intercept Models

A.3.1.1 Statistical Model

$$
\begin{aligned}
\text{Density} &\sim \text{Log-Normal}(\mu_i, \sigma) \\
\mu_i = \alpha_{density} + \alpha_j + \beta_{caste} + \beta_{age} \times \text{age} + \beta_{\text{practice duration}} &\times \text{practice duration} \\
\beta_{caste} &= \sigma_{caste} \times z_{caste} \\
\alpha_j &= \sigma_{artist} \times z_{artist} \\
\alpha_{density} &\sim \text{Normal}(1, 2) \\
\sigma_{caste} &\sim \text{Normal}(0.5, 1) \\
\sigma_{artist} &\sim \text{Normal}(0, 0.5) \\
\sigma &\sim \text{Normal}(0.5, 0.5) \\
\beta_{caste} &\sim \text{Normal}(0, 1) \\
\beta_{age} &\sim \text{Normal}(0, 1) \\
z_{caste} &\sim \text{Normal}(0, 1) \\
z_{artist} &\sim \text{Normal}(0, 1)
\end{aligned}
\tag{A.6}
$$

$$
\begin{aligned}
\text{Evenness} &\sim \text{Truncated Normal}(\mu_i, \sigma)[0,1] \\
\mu_i &= \alpha_{evenness} + \alpha_j + \beta_{caste} + \beta_{age} \times \text{age} + \beta_{\text{practice duration}} \times \text{practice duration} \\
\beta_{caste} &= \sigma_{caste} \times z_{caste} \\
\alpha_j &= \sigma_{artist} \times z_{artist} \\
\alpha_{evenness} &\sim \text{Normal}(1, 2) \\
\sigma_{caste} &\sim \text{Normal}(0.5, 1) \\
\sigma_{artist} &\sim \text{Normal}(0, 0.5) \\
\sigma &\sim \text{Normal}(0.5, 1) \\
\beta_{caste} &\sim \text{Normal}(0, 1) \\
\beta_{age} &\sim \text{Normal}(0, 1) \\
z_{caste} &\sim \text{Normal}(0, 1) \\
z_{artist} &\sim \text{Normal}(0, 1)
\end{aligned} \tag{A.7}
$$

$$
\begin{aligned}
\text{Richness} &\sim \text{Poisson}(\lambda_i) \\
\log(\lambda_i) &= \alpha_{richness} + \alpha_j + \beta_{caste} + \beta_{age} \times \text{age} + \beta_{\text{practice duration}} \times \text{practice duration} \\
\beta_{caste} &= \sigma_{caste} \times z_{caste} \\
\alpha_j &= \sigma_{artist} \times z_{artist} \\
\alpha_{richness} &\sim \text{Normal}(1, 2) \\
\sigma_{caste} &\sim \text{Normal}(0.5, 1) \\
\sigma_{artist} &\sim \text{Normal}(0, 0.5) \\
\beta_{caste} &\sim \text{Normal}(0, 1) \\
\beta_{age} &\sim \text{Normal}(0, 1) \\
z_{caste} &\sim \text{Normal}(0, 1) \\
z_{artist} &\sim \text{Normal}(0, 1)
\end{aligned} \tag{A.8}
$$

$$\begin{aligned}
\text{Canvas Size}_i &\sim \text{NegBinom}(\mu_i, \phi) \\
\log(\mu_i) &= \alpha_{size} + \alpha_j + \beta_{caste} + \beta_{age} \times \text{age} + \beta_{\text{practice duration}} \times \text{practice duration} \\
\beta_{caste} &= \sigma_{caste} \times z_{caste} \\
\alpha_j &= \sigma_{artist} \times z_{artist} \\
\alpha_{size} &\sim \text{Normal}(1, 2) \\
\sigma_{caste} &\sim \text{Normal}(0.5, 1) \\
\sigma_{artist} &\sim \text{Normal}(0, 0.5) \\
\phi &\sim \text{Normal}(1.5, 3) \\
\beta_{caste} &\sim \text{Normal}(0, 1) \\
\beta_{age} &\sim \text{Normal}(0, 1) \\
z_{caste} &\sim \text{Normal}(0, 1) \\
z_{artist} &\sim \text{Normal}(0, 1)
\end{aligned} \tag{A.9}$$

$$\begin{aligned}
\text{Entropy}_i &\sim \text{Truncated Normal}(\mu_i, \sigma)[0, 1] \\
\mu_i &= \alpha_{entropy} + \alpha_j + \beta_{caste} + \beta_{age} \times \text{age} + \beta_{\text{practice duration}} \times \text{practice duration} \\
\beta_{caste} &= \sigma_{caste} \times z_{caste} \\
\alpha_j &= \sigma_{artist} \times z_{artist} \\
\alpha_{entropy} &\sim \text{Normal}(1, 2) \\
\sigma_{caste} &\sim \text{Normal}(0.5, 1) \\
\sigma_{artist} &\sim \text{Normal}(0, 0.5) \\
\phi &\sim \text{Normal}(1.5, 3) \\
\beta_{caste} &\sim \text{Normal}(0, 1) \\
\beta_{age} &\sim \text{Normal}(0, 1) \\
z_{caste} &\sim \text{Normal}(0, 1) \\
z_{artist} &\sim \text{Normal}(0, 1)
\end{aligned} \tag{A.10}$$

A.3.1.2 Visual MCMC Diagnostics

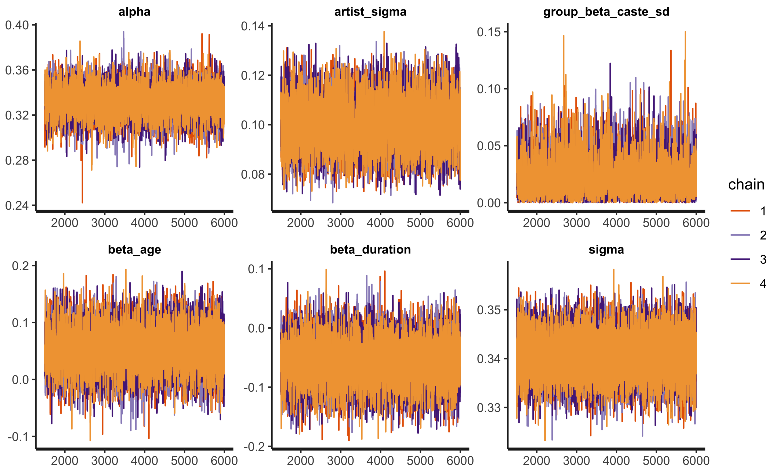

FIGURE A.3: Traceplot for the random intercept model on density showing mixing across chains and convergence.

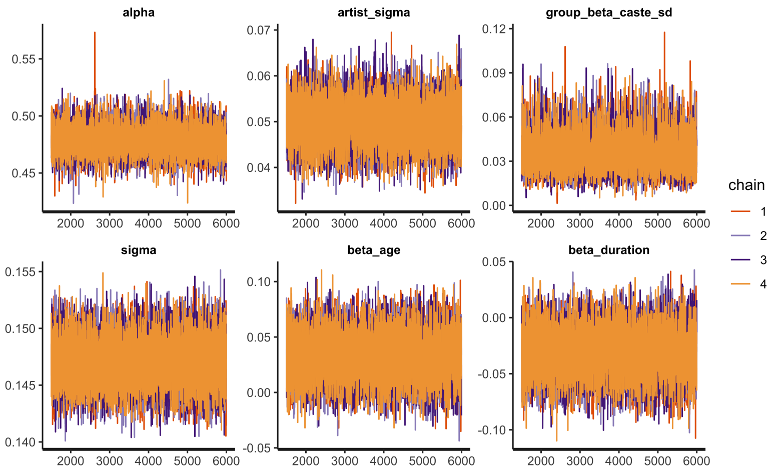

FIGURE A.4: Traceplot for the random intercept model on evenness showing mixing across chains and convergence.

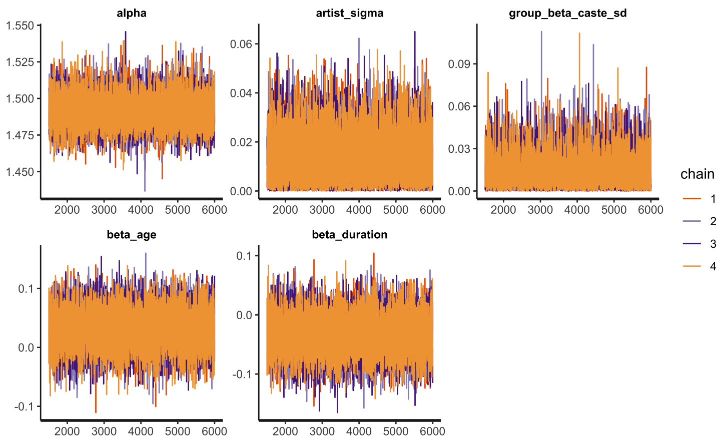

FIGURE A.5: Traceplot for the random intercept model on richness showing mixing across chains and convergence.

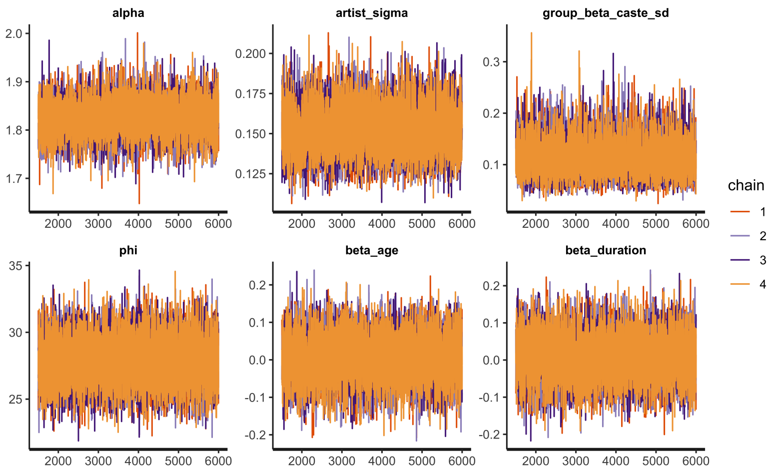

Figure A.6: Traceplot for the random intercept model on canvas size showing mixing across chains and convergence.

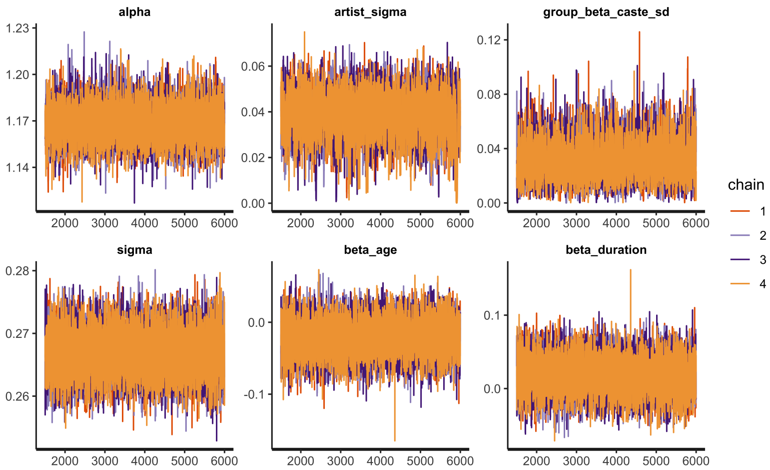

Figure A.7: Traceplot for the random intercept model on entropy showing mixing across chains and convergence.

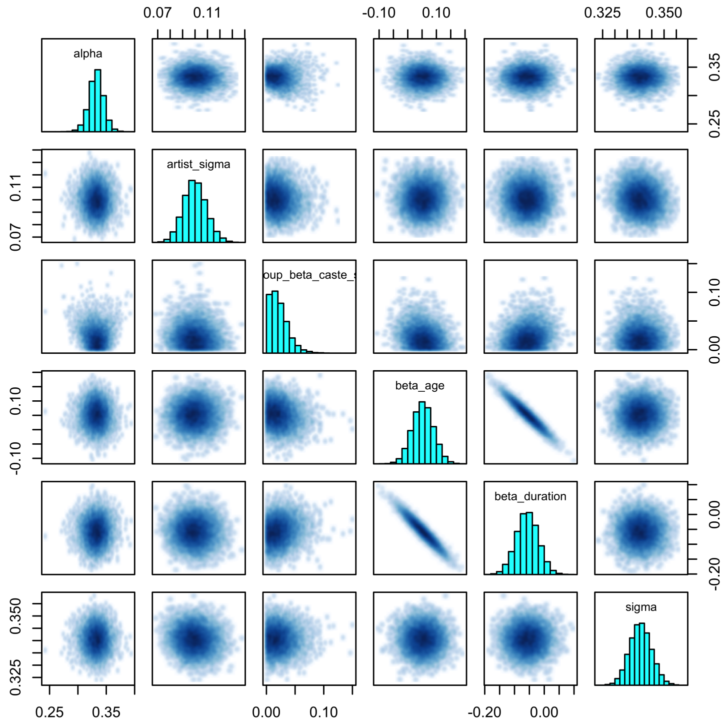

FIGURE A.8: Pairs plot for the random intercept model on density showing correlation among parameters and no sampling problems.

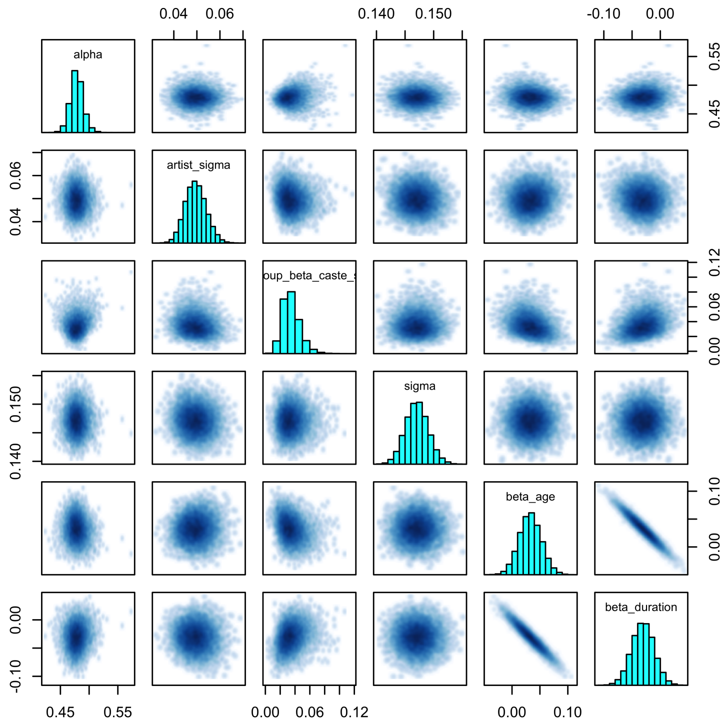

FIGURE A.9: Pairs plot for the random intercept model on gini showing correlation among parameters and no sampling problems.

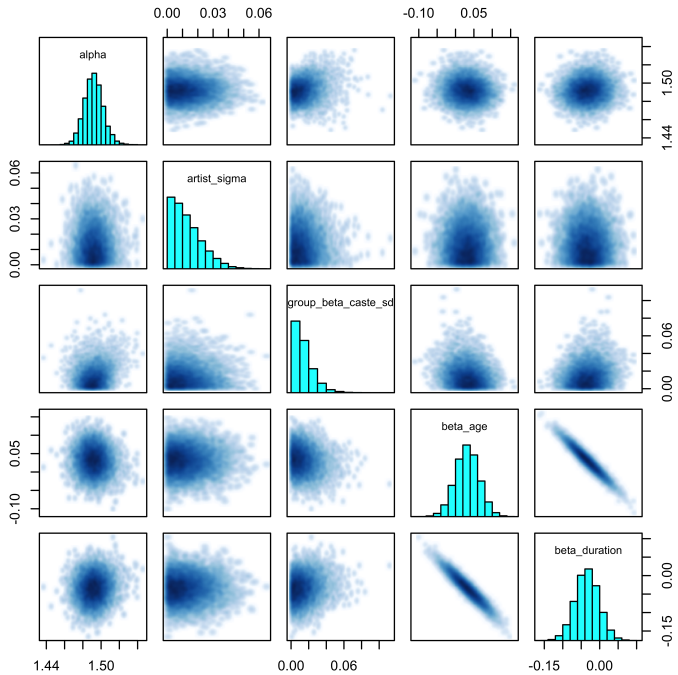

FIGURE A.10: Pairs plot for the random intercept model on richness showing correlation among parameters and no sampling problems.

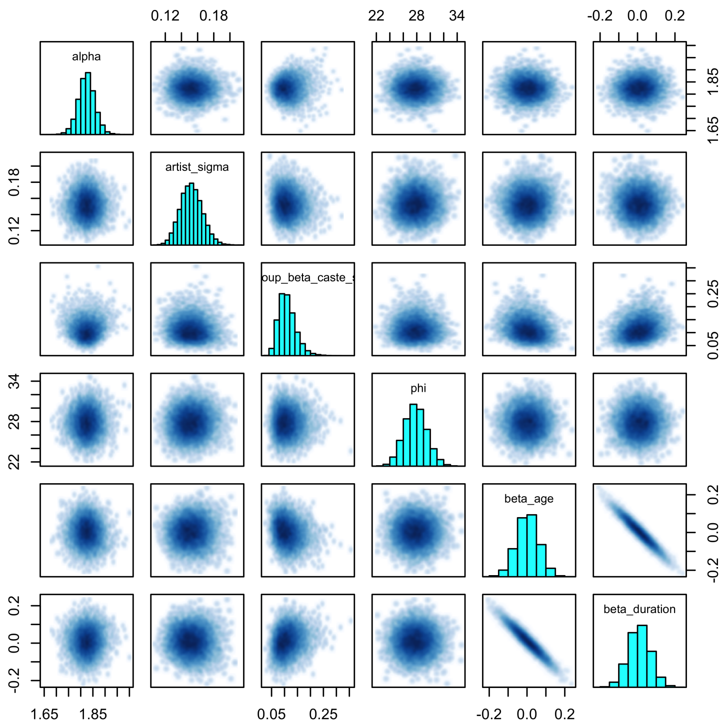

FIGURE A.11: Pairs plot for the random intercept model on canvas size showing correlation among parameters and no sampling problems.

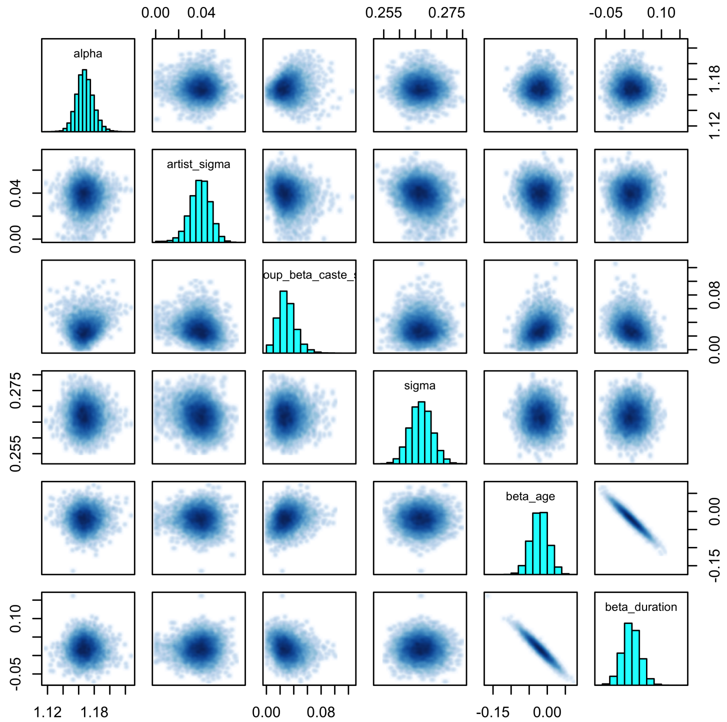

FIGURE A.12: Pairs plot for the random intercept model on entropy showing correlation among parameters and no sampling problems.

A.3.1.3 Intraclass Correlation (ICC)

The intraclass-correlation coefficient (ICC) can be calculated for Gaussian models to determine the variance explained by random and fixed effects (Gelman and Hill, 2006, p.258). Since our five models are non-Gaussian, we approximated the ICC using variance decomposition based on the posterior predictive distribution. We first drew from the posterior predictive distribution not conditioned on our fixed (i.e., age and duration of practice) and random effect (i.e., caste and individual variation) terms and then drew from the posterior predictive distribution conditioned on all fixed and random effects. Subsequently, we calculated the variances for both draws. The pseudo-ICC is then the ratio between these two variances. Occasionally, the variance ratio can be negative due to very large variance of the posterior predictive distributions.

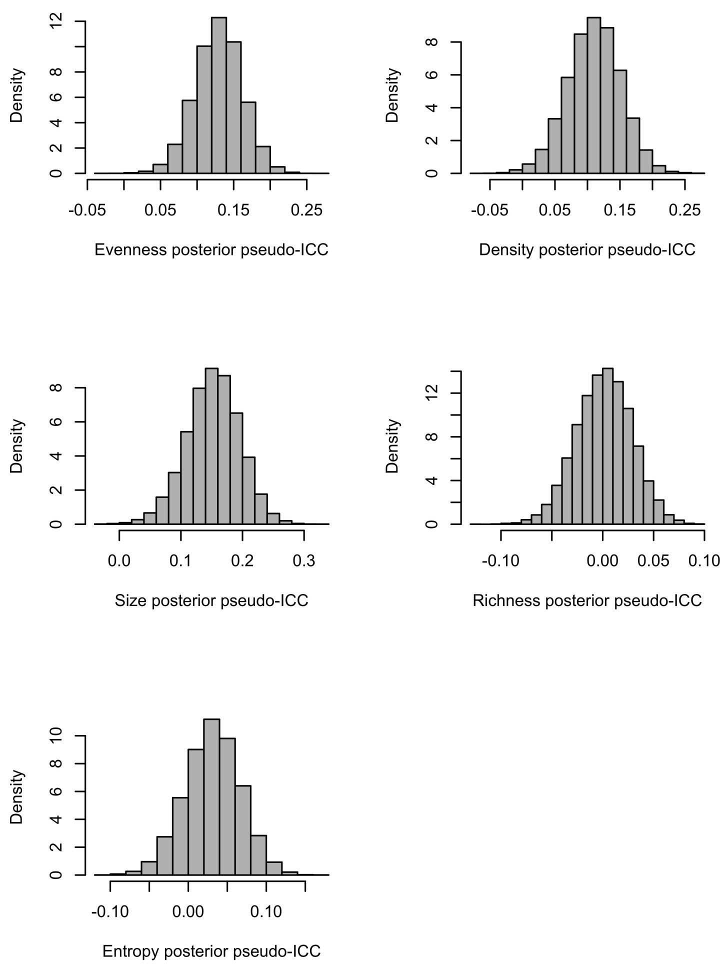

FIGURE A.13: Intraclass Correlation Coefficients (ICC) for individual random-effect variances for the four outcome variables. The variance decomposition is based on the posterior predictive distribution, which is the correct way for Bayesian non-Gaussian models.

A.3.1.4 Illustration of Random Effect Estimates for Caste

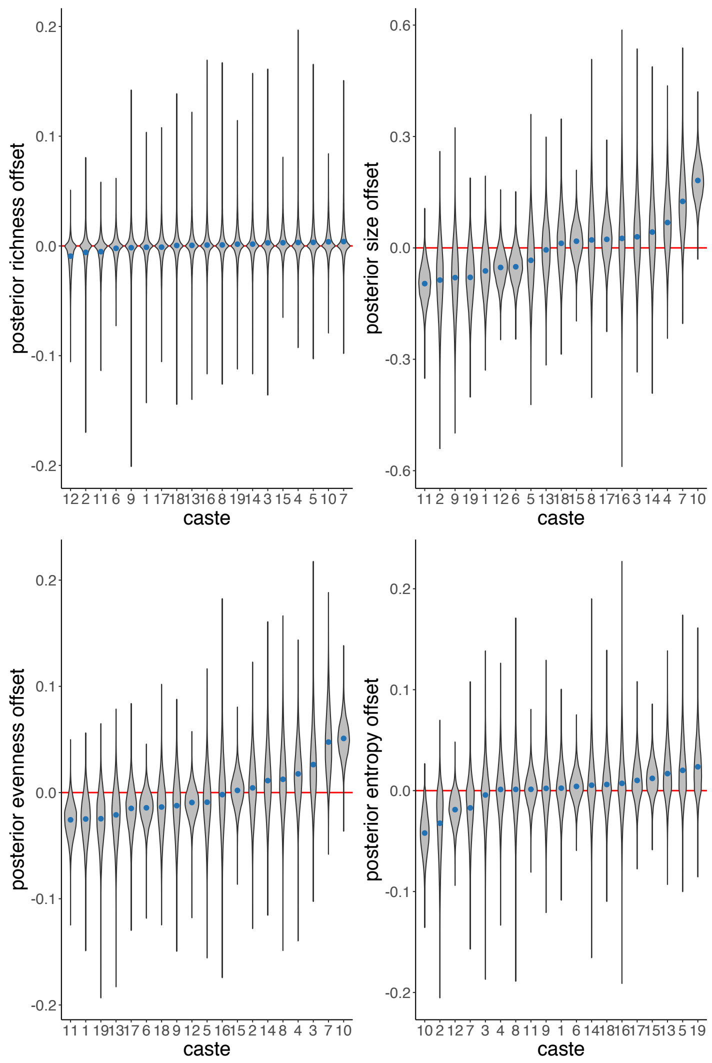

FIGURE A.14: Caste random effect offsets for each outcome variable. The red line reflects zero offset. Each violin probability density plot displays the variation within each caste on the corresponding outcome variable (i.e., richness, canvas size, density, evenness and entropy). The posterior mean offset is illustrated in blue. The range of the violin plots reflect the 90% HPDI.

A.3.2 Gaussian Process Models

To investigate whether the observed variation in structural and information-theoretic properties of *kolam* drawings is structured by the residential or native place proximity between individuals, we used a Gaussian process (GP) model to estimate a function for the covariance between pairs of individuals at different spatial distances of their residency as well as their native place. We fit the GP model on the five outcome variables entropy, canvas size, gesture density, richness and evenness. To foreshadow the conclusions drawn from the GP model, results from the GP model are in line with our main results from the random-intercept models. The GP model further indicates no major differentiation between artists originally from the community and those who emigrated from other parts of India, and no spatial association between artist's *kolam* drawings.

A.3.2.1 Statistical Model

We estimated unique intercepts for each individual with a varying effects approach to continuous categories using a Gaussian process (GP) model. A GP can be seen as a distribution of nonlinear functions. Placing a GP prior over the covariance, allows us to estimate a function for the covariance between pairs of individuals at different variable distances (McElreath, 2016). The individual-level covariance matrix α_i was modeled using an exponentiated quadratic kernel. This covariance function implies that the covariance between any two individuals j and k declines exponentially with the squared distance between them. No variation between individuals would correspond to a covariance of zero or close to zero. The parameter ρ^2, also referred to as length scale, determines the rate of decline. If ρ^2 is large, then the covariance decreases slowly with squared distance, while if ρ^2 is small it decreases rapidly with squared distance. This length-scale ρ^2 prior is constrained to be between zero and one because the distances were normalized to be between zero and one. η^2 is the maximum covariance between any two individuals. Automatic relevance determination (Neal, 1996) was performed where multiple predictors with corresponding length-scale parameters for each dimension were merged into the GP.

Statistical models on the five structural and information-theoretic properties of *kolam* drawings were implemented. The predictor variables to investigate the partition of variation across individuals and the population was the same in all models. Age, duration of practice, caste, and residential and native place proximity between individuals were used as predictor variables to explain individual variation on the structural and information-theoretic properties. The residential and native place distances as well as age and practice duration were normalized, such that the minimum value was zero and the maximum value was one. The pairwise Euclidean distances between each pair of individuals along each predictor variable dimension was then computed for age, duration of practice and residential and native place proximity between individuals. GPS coordinates were used to compute residential and native place distance matrices between individuals. Distances correspond to Euclidean distance between individuals for the specific variable dimension. For example, the residence or native place distance matrix are spatial distances. Caste was modeled as a hierarchical non-centred categorical variable with 19 categories.

$$
\begin{aligned}
\text{Density} &\sim \text{Log-Normal}(\mu_i, \sigma) \\
\mu_i &= \alpha_{density} + \alpha_j + \beta_{caste} \\
\alpha_j &\sim \text{MVNormal}(0, K(x)) \\
K_{jk} &= \eta^2 \text{exp}\left[-\left(\frac{\text{Residence}^2}{2 \times \rho_R^2} + \frac{\text{Native Place}^2}{2 \times \rho_N^2} + \frac{\text{Age}^2}{2 \times \rho_A^2} + \frac{\text{Duration}^2}{2 \times \rho_D^2}\right)\right] + \delta_{jk} \times 0.001 \\
\beta_{caste} &= \sigma_{caste} \times z \\
\eta^2 &\sim \text{Normal}(5, 2) \\
\rho_R^2 &\sim \text{Beta}(1, 2) \\
\rho_N^2 &\sim \text{Beta}(1, 2) \\
\rho_A^2 &\sim \text{Beta}(1, 2) \\
\rho_D^2 &\sim \text{Beta}(1, 2) \\
\sigma &\sim \text{Normal}(0.5, 0.5) \\
\alpha_{density} &\sim \text{Normal}(0.5, 1) \\
\sigma_{caste} &\sim \text{Normal}(0.5, 0.5)
\end{aligned}
$$

$$
\begin{aligned}
\text{Evenness} &\sim \text{Truncated Normal}(\mu_i, \sigma)[0, 1] \\
\mu_i &= \alpha_{evenness} + \alpha_j + \beta_{caste} \\
\alpha_j &\sim \text{MVNormal}(0, K(x)) \\
K_{jk} &= \eta^2 \text{exp}\left[-\left(\frac{\text{Residence}^2}{2 \times \rho_R^2} + \frac{\text{Native Place}^2}{2 \times \rho_N^2} + \frac{\text{Age}^2}{2 \times \rho_A^2} + \frac{\text{Duration}^2}{2 \times \rho_D^2}\right)\right] + \delta_{jk} \times 0.001 \\
\beta_{caste} &= \sigma_{caste} \times z \\
\eta^2 &\sim \text{Normal}(5, 2) \\
\rho_R^2 &\sim \text{Beta}(1, 2) \\
\rho_N^2 &\sim \text{Beta}(1, 2) \\
\rho_A^2 &\sim \text{Beta}(1, 2) \\
\rho_D^2 &\sim \text{Beta}(1, 2) \\
\sigma &\sim \text{Normal}(0.5, 0.5) \\
\alpha_{evenness} &\sim \text{Normal}(0.5, 1) \\
\sigma_{caste} &\sim \text{Normal}(0.5, 0.5)
\end{aligned}
$$

$$
\begin{aligned}
\text{Richness} &\sim \text{Poisson}(\lambda_i) \\
\log(\lambda_i) &= \alpha_{richness} + \alpha_j + \beta_{caste} \\
\alpha_j &\sim \text{MVNormal}(0, K(x)) \\
K_{jk} = \eta^2 \text{exp} \left[- \left(\frac{\text{Residence}^2}{2 \times \rho_R^2} + \frac{\text{Native Place}^2}{2 \times \rho_N^2} + \frac{\text{Age}^2}{2 \times \rho_A^2} + \frac{\text{Duration}^2}{2 \times \rho_D^2} \right) \right] &+ \delta_{jk} \times 0.001 \\
\beta_{caste} &= \sigma_{caste} \times z \\
\eta^2 &\sim \text{Normal}(5, 2) \\
\rho_R^2 &\sim \text{Beta}(1, 2) \\
\rho_N^2 &\sim \text{Beta}(1, 2) \\
\rho_A^2 &\sim \text{Beta}(1, 2) \\
\rho_D^2 &\sim \text{Beta}(1, 2) \\
\alpha_{richness} &\sim \text{Normal}(0.5, 1) \\
\sigma_{caste} &\sim \text{Normal}(0.5, 0.5)
\end{aligned}
$$

$$
\begin{aligned}
\text{Canvas Size}_i &\sim \text{NegBinom}(\mu_i, \phi) \\
\log(\mu_i) &= \alpha_{size} + \alpha_j + \beta_{caste} \\
\alpha_j &\sim \text{MVNormal}(0, K(x)) \\
K_{jk} = \eta^2 \text{exp}\left[-\left(\frac{\text{Residence}^2}{2 \times \rho_R^2} + \frac{\text{Native Place}^2}{2 \times \rho_N^2} + \frac{\text{Age}^2}{2 \times \rho_A^2} + \frac{\text{Duration}^2}{2 \times \rho_D^2}\right)\right] &+ \delta_{jk} \times 0.001 \\
\beta_{caste} &= \sigma_{caste} \times z \\
\eta^2 &\sim \text{Normal}(5, 2) \\
\rho_R^2 &\sim \text{Beta}(1, 2) \\
\rho_N^2 &\sim \text{Beta}(1, 2) \\
\rho_A^2 &\sim \text{Beta}(1, 2) \\
\rho_D^2 &\sim \text{Beta}(1, 2) \\
\phi &\sim \text{Normal}(1.5, 3) \\
\alpha_{size} &\sim \text{Normal}(0.5, 1) \\
\sigma_{caste} &\sim \text{Normal}(0.5, 0.5)
\end{aligned}
$$

$$
\begin{aligned}
\text{Entropy} &\sim \text{Truncated Normal}(\mu_i, \sigma)[0,] \\
\mu_i &= \alpha_{entropy} + \alpha_j + \beta_{caste} \\
\alpha_j &\sim \text{MVNormal}(0, K(x)) \\
K_{jk} = \eta^2 \text{exp}\left[-\left(\frac{\text{Residence}^2}{2 \times \rho_R^2} + \frac{\text{Native Place}^2}{2 \times \rho_N^2} + \frac{\text{Age}^2}{2 \times \rho_A^2} + \frac{\text{Duration}^2}{2 \times \rho_D^2}\right)\right] &+ \delta_{jk} \times 0.001 \\
\beta_{caste} &= \sigma_{caste} \times z \\
\eta^2 &\sim \text{Normal}(5, 2) \\
\rho_R^2 &\sim \text{Beta}(1, 2) \\
\rho_N^2 &\sim \text{Beta}(1, 2) \\
\rho_A^2 &\sim \text{Beta}(1, 2) \\
\rho_D^2 &\sim \text{Beta}(1, 2) \\
\sigma &\sim \text{Normal}(0.5, 0.5) \\
\alpha_{entropy} &\sim \text{Normal}(0.5, 1) \\
\sigma_{caste} &\sim \text{Normal}(0.5, 0.5)
\end{aligned}
$$

A.3.2.2 Estimation of Variation

The five statistical models were implemented in the probabilistic programming language Stan 2.18 (Carpenter et al., 2017), using 6000 samples from four chains. Analyses were performed in R (Team, 2019). Data and analyses can be found here: `http:`

//github.com/nhtran93/kolam_signaling. All R-hat values were less than 1.01, and visual inspection of trace plots and rank histograms indicated convergence of all models.

Between-individual variation in entropy (η^2 = 0.00, 90% CI [0.00, 0.00]), density (η^2 = 0.01, 90% CI [0.01, 0.01]), the evenness (η^2 = 0, 90% CI [0, 0]), and in the richness (η^2 = 0.00, 90% CI [0, 0.01]) were estimated with high certainty to be very small and close to zero (see left panel in Figure A.15). The between-artist variability is most pronounced in canvas size ((η^2 = 0.03, 90% CI [0.02, 0.03]), while *kolam* drawings show only small distinct variation between artists in the other structural and information-theoretic properties. Our results further show no evidence that variation in structural and information-theoretic properties of *kolam* drawings covary with the spatial structure, age or practice duration (see Figure A.15).

Prior-posterior plots of all five models show that the priors updated for all parameters except the length scale parameters ρ because there is barely any information to explain individual variation with no individual variation present. We detected very small effects of caste membership on the entropy, density, evenness, and richness, with varying-effect deviations estimated near zero with high certainty (entropy: σ_{caste} = 0.03, 90% CI [0.01, 0.05]; density: σ_{caste} = 0.04, 90% CI [0.01, 0.07]; evenness: σ_{caste} = 0.03, 90% CI [0.01, 0.04]; and richness: σ_{caste} = 0.01, 90% CI [0.00, 0.03] respectively). We detected more pronounced effects of caste membership on canvas size (canvas size: σ_{caste} = 0.09, 90% CI [0.05, 0.14]) as illustrated in Figure A.15.

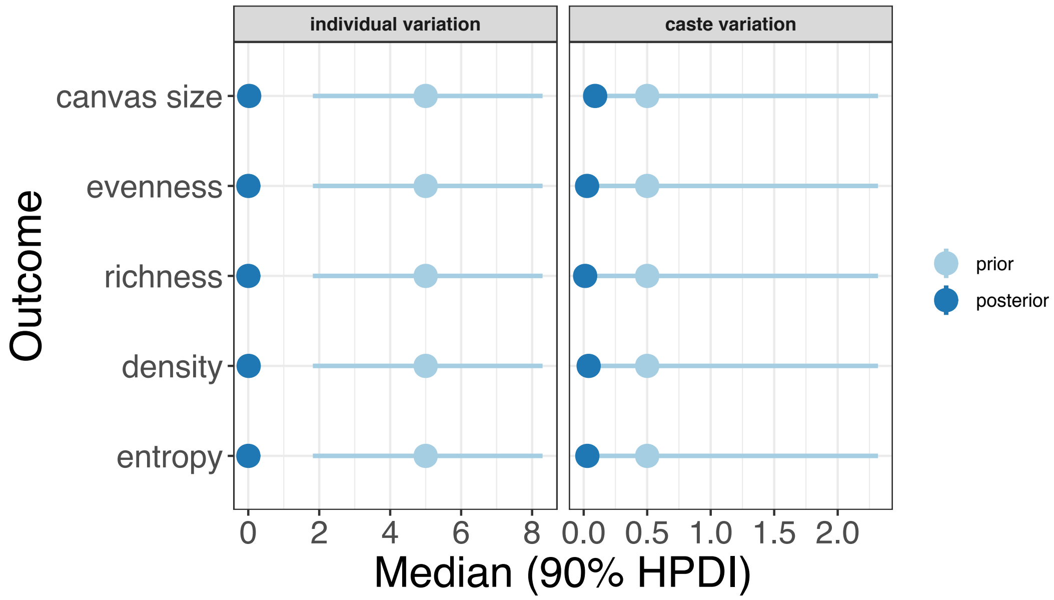

FIGURE A.15: Prior-Posterior Coefficient Plots of Individual variation and Caste Variation. All panels have the same y-axis indicating the five models. The left panel (eta squared) illustrates the estimated individual variation (dark blue) in comparison to the prior (light blue) for each model. The right panel illustrates the estimated population-level standard deviation for the effect of caste (dark blue) in comparison to the prior (light blue) for each model. The 90% Highest Posterior Density Interval (HPDI) was computed for each posterior; however, the interval is very narrow.

Appendix B

Supplementary Information for Chapter 2: "Limited Scope for Group Coordination in Stylistic Variations of *Kolam* Art"

B.1 *Kolam* Data

B.1.0.1 Background Information and Description of Sample and Variables

Between 2007 and 2009, TMW lived in Kodaikanal, Tamil Nadu in India and investigated *kolam* drawings to study human cultural evolution in an artistic domain. This included the development of an expanded gestural lexicon to describe *kolam* drawings and an interactive software for transcribing *kolam* drawings (Waring, 2012b). In spring 2009, TMW and local research assistants collected data according to a snowball sampling procedure on *kolam* drawings from mainly three neighborhoods of Kodaikanal, Tamil Nadu: Anna Nagar, Naidupuram and Munjikal. Kodaikanal is a municipality city in district of Dindigul, Tamil Nadu. According to Census India (2011), Kodaikanal with an area of 21.45 km^2 has a population of 36,501. 48.84% of the population are Hindus, 12.00% are Muslims, 38.69% are Christians and the remaining under 1% follow other religions.

The data set includes interview surveys, which contained demographic details on *kolam*-making practice, questions about *kolam* learning, and spatial location of artists' homes (GPS). A GPS tracker of type Garmin GPSmap 60 CSx was used. Furthermore, a structured sample of *kolam* drawings using pens in notebooks was collected. The survey further contains information on who artists learn from and who they were helping to learn or have taught *kolam*-making. TMW and the local research assistants asked women to share their personal and purchased practice notebooks.

Artists in our data set self-identify with a total of 19 different caste categories. These caste categories are associated with varying privilege and include local and migrant caste groupings. There were on average 10 women in a caste group. Scheduled Castes include Aathi Dravidar, Dhobi, Pariyar, Pallar and Asariyar. Chettiyar, Koundar, Mannadiyar, Mudaliyar, Naidu and Brahmin are Forward Castes. Nambothiri and Iyar are branches of the Brahmin community. All other castes are Backward Castes. We constructed 8 neighborhood clusters with on average 24 women in a neighborhood cluster. Further details on the samples and variables can be found in Tables B.1 and B.2.

TABLE B.1: Descriptive statistics of the sample and variables used in the models.

	Mean	SD	Median	Min	Max	Levels
Age	31.88	10.08	30	15	60	
Duration of Practice	19.46	10.73	18	1	52	
Caste	-	-	-	-	-	19
Nativity	34 Yes, 158 No					2
Residence Distance (in metres)	864.72	686.63	618.42	0	3005.82	

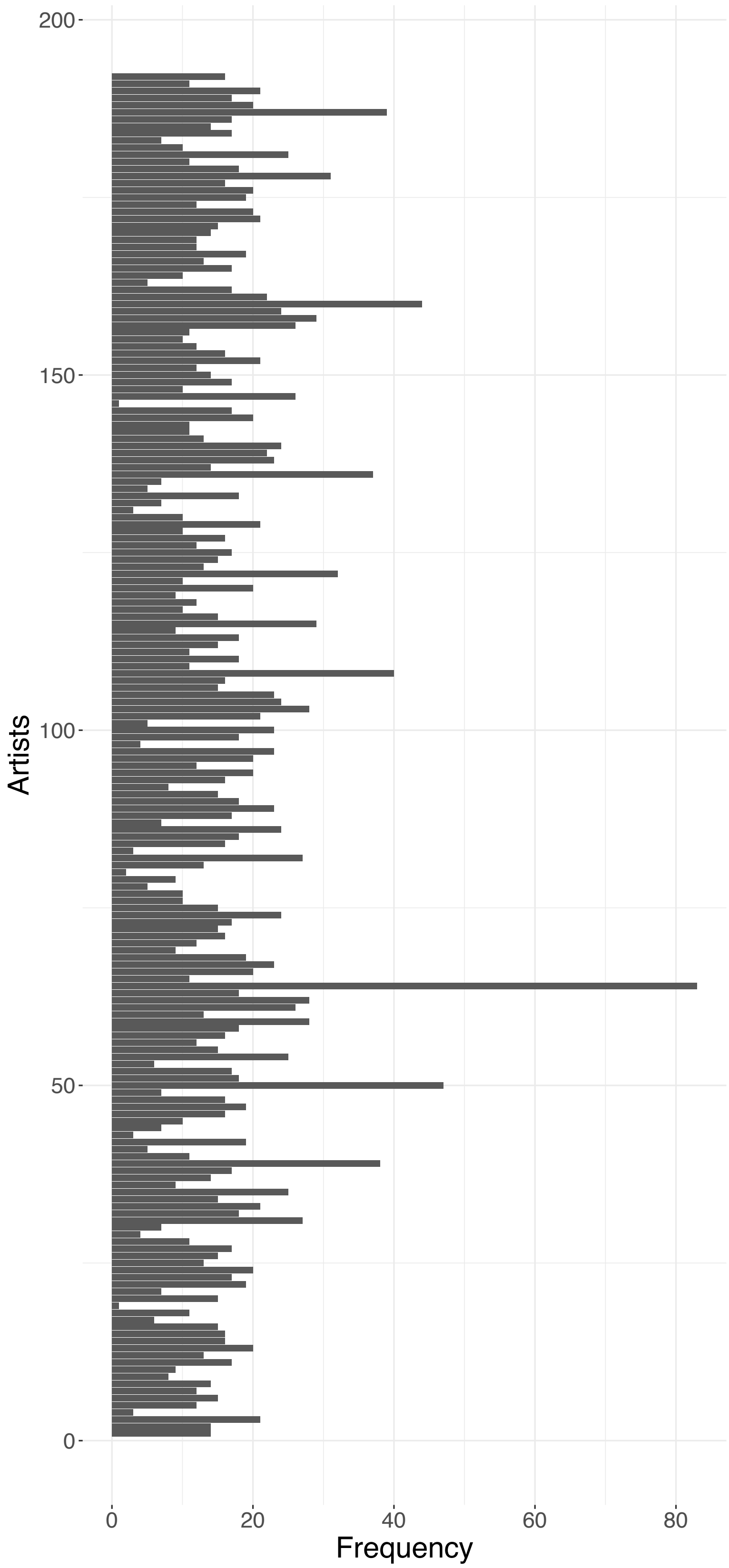

FIGURE B.1: The frequency of *kolam* drawings by artists. Each bar on the y-axis represents one artist. The x-axis shows the number of *kolam* drawings by an artist. Median = 16 and Mean = 16.3 *kolam* drawings per woman.

TABLE B.2: Caste

Caste	Artists
Aathi Dravidar	8
Asariyar	2
Ayyaraka	1
Brahmin	3
Chettiyar	2
Dhobi	39
Iyar	3
Koundar	1
Mannadiyar	2
Mudaliyar	24
Nadar	21
Naidu	34
Naiyakar	4
Nambothiri	1
Pallar	26
Pariyar	1
Thevar	11
Vanniyar	4
Vellalar	5

B.1.0.2 *Kolam* Drawings and the Lexicon of Gestures

The square *kolam* drawings that we are focusing on have the advantage that we can map the drawings on a small identifiable set of gestures suitable for analyses. For this purpose, a lexicon of gestures was developed (Waring, 2012b). We transcribed the *kolam* drawings using the lexicon and subsequently transferred them into a database using the *kolam* R package (Tran, Waring, and Beheim, 2020).

The gestures that constitute a loop and the *kolam* drawings can be categorized into three different geometric spaces with distinct characteristics: orthogonal, diagonal, and transitional (each set of gestures is represented by O, D, T, respectively). Figure B.2 illustrates the three different geometric spaces in distinct colors and all the theoretically possible transitions between gestures and geometric categories. Each of these categories contains four gestures. The orthogonal gestures further contain two special variations (H and P). Every gesture is accessible from itself. Gestures from the same geometric category are transient and fully connected; thus, gestures can transition from or to other gestures of the same geometric category as well as remain in the same gesture (i.e., repeat the same gesture again). Transitions between gestures from different geometric categories are constrained: Diagonal gestures cannot transition to orthogonal gestures and vice versa. Orthogonal and diagonal gestures are only connected to each other via transitional gestures. Thus, transitional gestures can not only transition within their category, but can transition between categories to or from orthogonal and diagonal gestures. Self-loops are possible on the gesture level and the geometric space level. Furthermore, there are three special, decorative gestures that are merely single, stand-alone gestures and cannot be connected to any other gesture.

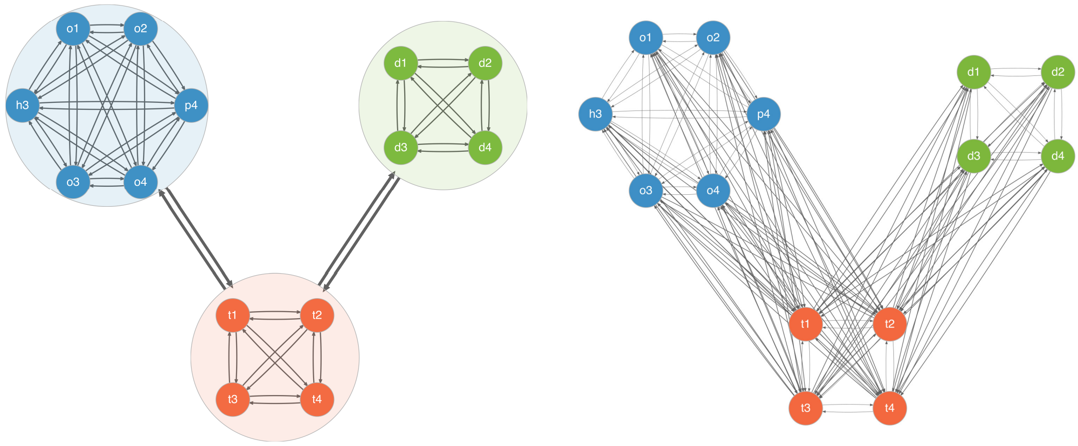

FIGURE B.2: Transitions between orthogonal, diagonal and transitional gestures. Both transition networks depict 14 nodes corresponding to the 14 gestures and three clusters that correspond to the three geometric spaces: orthogonal (blue cluster), diagonal (green cluster), and transitional (orange cluster) spaces. The left transition network emphasizes the conditional probability of switching from a current geometric space to a different one (e.g., transitioning from orthogonal to transitional space) and illustrates that there are no direct transitions between orthogonal and diagonal gestures. The right transition network shows all the possible transitions gesture by gesture. The probability of remaining in the same geometric space or repeatedly using the same gesture is not depicted by a self-loop; however, conceptually, self-loops are possible for all gestures and geometric spaces.

B.2 Statistical Models

The transition count matrix y_i of size 14×14 representing the count of transitions from state (i.e., gesture) j to state (i.e., gesture) k for artist i was used in the statistical models 2 to 5. Four transition count matrices y_i were used in the statistical models 6 and 7 with a transition matrix for transitions between geometric spaces of size 3×3, a transition matrix for transitions within orthogonal space of size 4×4, a transition matrix for transitions within diagonal space of size 4×4 and a transition matrix for transitions within transitional space of size 4×4.

B.2.1 Model 1: Null Model

In the null model, we did not model the effect of duration of practice and assumed no variation between individuals and castes on the transition count matrices.

$$\begin{aligned} y_{ij} &\sim \text{Multinomial}(\pi_j) \\ \pi_j &\sim \text{Dirichlet}(\underbrace{1, ..., 1}_{14}) \end{aligned} \tag{B.1}$$

B.2.2 Model 2: Fixed Individual Variation Model

In the fixed individual variation model, we only modeled the individual variation in the transitions from j to k, but the extent to which the individual variation influences the transition probabilities to k is fixed across the rows j of the transition matrix y_i as well as individuals.

$$\begin{aligned} y_{ij} &\sim \text{Multinomial}(\pi_{ij}) \\ \pi_{ij} &= \text{softmax}(\theta_{ij}) \\ \theta_{ijk} &= \mu_{jk} + \sigma \times z_{ijk} \\ \mu_{jk} &\sim \mathcal{N}(0, 1) \\ \text{z}_{\text{ijk}} &\sim \mathcal{N}(0, 1) \\ \sigma &\sim \text{Gamma}(2, 5) \end{aligned} \tag{B.2}$$

B.2.3 Model 3: Full Individual Variation Model

In the full individual variation model, we allowed the individual variation to vary across the rows j of the transition matrix y_i.

$$\begin{aligned} y_{ij} &\sim \text{Multinomial}(\pi_{ij}) \\ \pi_{ij} &= \text{softmax}(\theta_{ij}) \\ \theta_{ijk} &= \mu_{jk} + \sigma_j \times z_{ijk} \\ \mu_{jk} &\sim \mathcal{N}(0, 1) \\ \text{z}_{ijk} &\sim \mathcal{N}(0, 1) \\ \sigma_j &\sim \text{Gamma}(2, 5) \end{aligned} \tag{B.3}$$

B.2.4 Model 4: Fixed Variation Model with Predictors

The fixed variation model with predictors extends the previous model with duration of practice as a predictor and caste variation fixed across the rows j of the transition matrix y_i.

$$
\begin{aligned}
y_{ij} &\sim \text{Multinomial}(\pi_{ij}) \\
\pi_{ij} &= \text{softmax}(\theta_{ij}) \\
\theta_{ijk} = \mu_{jk} + \beta_{jk} \times \text{duration}_i + \sigma_{\text{ind}} \times z_{ijk} &+ \sigma_{\text{caste}} \times z_{cjk} \\
\mu_{jk} &\sim \mathcal{N}(0,1) \\
z_{ijk} &\sim \mathcal{N}(0,1) \\
z_{cjk} &\sim \mathcal{N}(0,1) \\
\sigma_{\text{ind}} &\sim \text{Gamma}(2,5) \\
\sigma_{\text{caste}} &\sim \text{Gamma}(2,5) \\
\beta_{jk} &\sim \mathcal{N}(0,1)
\end{aligned}
\tag{B.4}
$$

B.2.5 Model 5: Full Individual Variation Model with Predictors

In the full variation model, we allowed the individual variation to vary across the rows j of the transition matrix y_i and extended the previous model with duration of practice as a predictor and caste variation further allowed to vary across the rows j of the transition matrix y_i.

$$
\begin{aligned}
y_{ij} &\sim \text{Multinomial}(\pi_{ij}) \\
\pi_{ij} &= \text{softmax}(\theta_{ij}) \\
\theta_{ijk} = \mu_{jk} + \beta_{jk} \times \text{duration}_i + \sigma_{\text{ind}_j} \times z_{ijk} &+ \sigma_{\text{caste}_j} \times z_{cjk} \\
\mu_{jk} &\sim \mathcal{N}(0,1) \\
z_{ijk} &\sim \mathcal{N}(0,1) \\
z_{cjk} &\sim \mathcal{N}(0,1) \\
\sigma_{\text{ind}_j} &\sim \text{Gamma}(2,5) \\
\sigma_{\text{caste}_j} &\sim \text{Gamma}(2,5) \\
\beta_{jk} &\sim \mathcal{N}(0,1)
\end{aligned}
\tag{B.5}
$$

B.2.6 Model 6: Conditional Transition Model with Main Predictors

For each of the four matrices $m = \{\text{geometric spaces, orthogonal, diagonal, transitional}\}$, the model includes predictor of duration, and includes individual variation that itself varies across the rows of the matrices, as well as the caste variation that also varies across the rows of the matrices.

$$
\begin{aligned}
y^{\mathrm{m}}_{ij} &\sim \text{Multinomial}(\pi^{\mathrm{m}}_{ij}) \\
\pi^{\mathrm{m}}_{ij} &= \text{softmax}(\theta^{\mathrm{m}}_{ij}) \\
\theta^{\mathrm{m}}_{ijk} = \mu^{\mathrm{m}}_{jk} + \beta^{\mathrm{m}}_{jk} \times \text{duration}_i + \sigma^{\mathrm{m}}_{\text{ind}_j} \times \mathrm{z}^{\mathrm{m}}_{\text{ind}_{ijk}} &+ \sigma^{\mathrm{m}}_{\text{caste}_j} \times \mathrm{z}^{\mathrm{m}}_{\text{caste}_{cjk}} \\
\mu^{\mathrm{m}}_{jk} &\sim \mathcal{N}(0,1) \\
\mathrm{z}^{\mathrm{m}}_{\text{ind}_{ijk}} &\sim \mathcal{N}(0,1) \\
\mathrm{z}^{\mathrm{m}}_{\text{caste}_{cjk}} &\sim \mathcal{N}(0,1) \\
\sigma^{\mathrm{m}}_{\text{ind}_j} &\sim \text{Gamma}(2,5) \\
\sigma^{\mathrm{m}}_{\text{caste}_j} &\sim \text{Gamma}(2,5) \\
\beta^{\mathrm{m}}_{jk} &\sim \mathcal{N}(0,1)
\end{aligned}
\tag{B.6}
$$

B.2.7 Model 7 - Full Model: Conditional Transition Model with All Predictors

This is our full model and best-performing model according to leave-one-out cross validation presented in the main text.

For each of the four matrices $m = \{\text{geometric spaces, orthogonal, diagonal, transitional}\}$, the model includes predictors of duration and migration (i.e., nativity), and includes individual variation that itself varies across the rows of the matrices, as well as the caste and neighborhood variations that also vary across the rows of the matrices.

$$
\begin{aligned}
y^{\text{m}}_{ij} &\sim \text{Multinomial}(\pi^{\text{m}}_{ij}) \\
\pi^{\text{m}}_{ij} &= \text{softmax}(\theta^{\text{m}}_{ij}) \\
\theta^{\text{m}}_{ijk} &= \mu^{\text{m}}_{jk} + \beta^{\text{m}}_{\text{duration}_{jk}} \times \text{duration}_i + \beta^{\text{m}}_{\text{native}_{jk}} \times \text{native}_i \\
&\quad + \sigma^{\text{m}}_{\text{ind}_j} \times \text{z}^{\text{m}}_{\text{ind}_{ijk}} + \sigma^{\text{m}}_{\text{caste}_j} \times \text{z}^{\text{m}}_{\text{caste}_{cjk}} + \sigma^{\text{m}}_{\text{residence}_j} \times \text{z}^{\text{m}}_{\text{residence}_{rjk}} \\
\mu^{\text{m}}_{jk} &\sim \mathcal{N}(0,1) \\
\text{z}^{\text{m}}_{\text{ind}_{ijk}} &\sim \mathcal{N}(0,1) \\
\text{z}^{\text{m}}_{\text{caste}_{cjk}} &\sim \mathcal{N}(0,1) \\
\text{z}^{\text{m}}_{\text{residence}_{rjk}} &\sim \mathcal{N}(0,1) \\
\sigma^{\text{m}}_{\text{ind}_j} &\sim \text{Gamma}(2,5) \\
\sigma^{\text{m}}_{\text{caste}_j} &\sim \text{Gamma}(2,5) \\
\sigma^{\text{m}}_{\text{residence}_j} &\sim \text{Gamma}(2,5) \\
\beta^{\text{m}}_{\text{duration}_{jk}} &\sim \mathcal{N}(0,1) \\
\beta^{\text{m}}_{\text{native}_{jk}} &\sim \mathcal{N}(0,1)
\end{aligned}
\tag{B.7}
$$

B.3 Model Comparison

Table B.3: Pseudo-Bayesian Model Averaging Weights with Bayesian bootstrap

	weights
Null Model	0.00
Fixed Individual Variation Model	0.00
Full Individual Variation Model	0.00
Fixed Variation Model with predictors	0.00
Full Individual Variation Model with predictors	0.00
Conditional Transition Model with main predictors	0.21
Full Model: Conditional Transition Model with all predictors	0.79

Table B.4: Stacking weights of predictive distributions

	weights
Null Model	0.26
Fixed Individual Variation Model	0.01
Full Individual Variation Model	0.01
Fixed Variation Model with predictors	0.01
Full Individual Variation Model with predictors	0.00
Conditional Transition Model with main predictors	0.27
Full Model: Conditional Transition Model with all predictors	0.44

B.4 Full Model (Model 7) Results

B.4.1 Visual MCMC Diagnostics

All $\widehat{R}$ values were less than 1.01, and visual inspection of trace plots, rank histograms and pairs plots indicated convergence of all models. We have added the trace plots of the estimated parameters for the transition matrix across geometric spaces to illustrate that our model converged. However, since our model estimates many parameters and multiple transition matrices, we refrain from plotting over 100 traceplots. Our open repository provides the data and code to fit all of the Bayesian transition models in order to reproduce our results and further contains code to produce trace, rank histogram and autocorrelation plots.

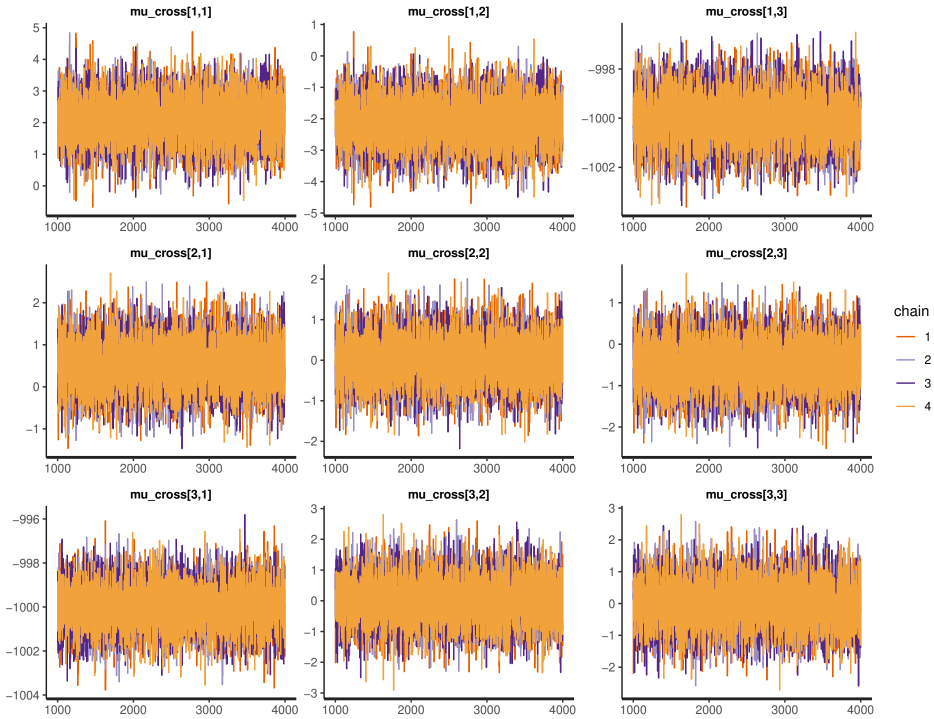

FIGURE B.3: Traceplot of the population-level mean transition matrix of transitioning between geometric spaces showing mixing across chains and convergence.

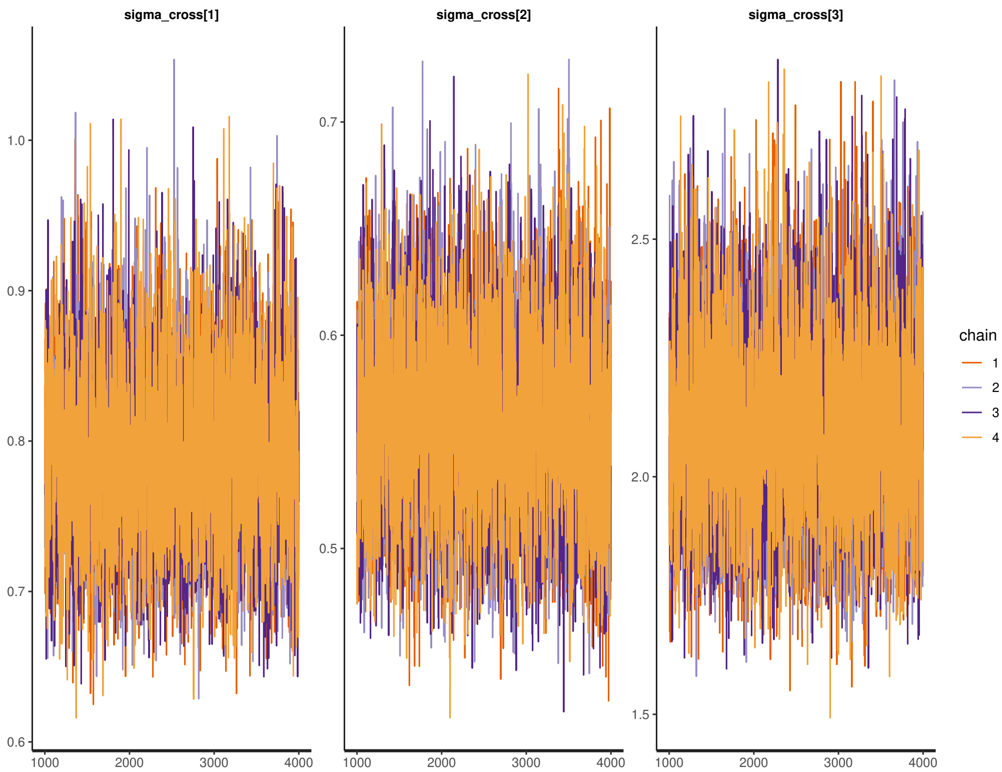

FIGURE B.4: Traceplot of the individual variation in the transition matrix of transitioning between geometric spaces showing mixing across chains and convergence.

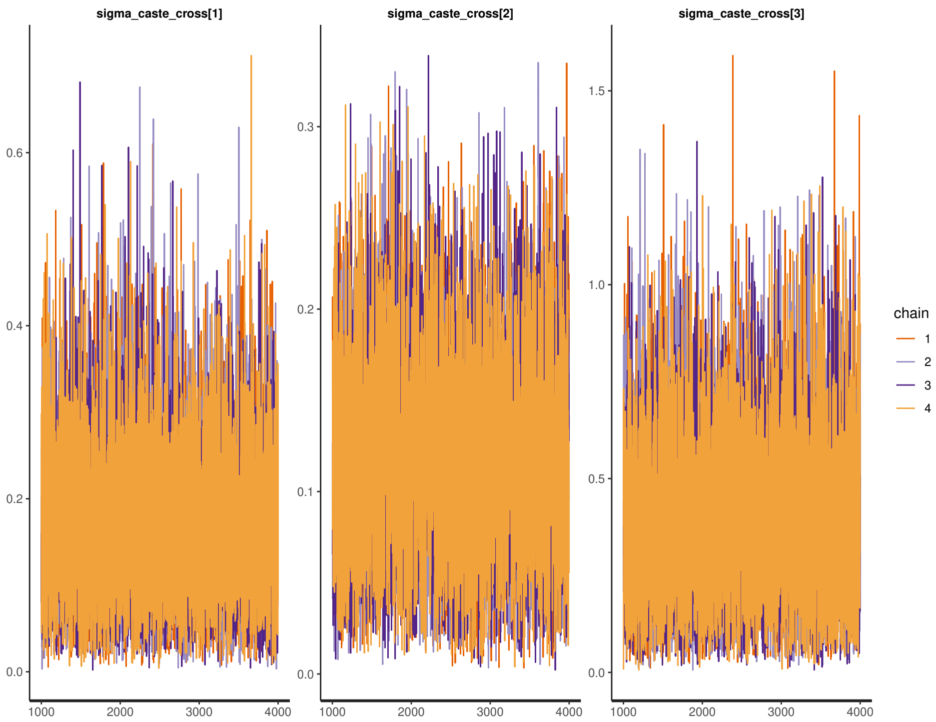

Figure B.5: Traceplot of the caste variation in the transition matrix of transitioning between geometric spaces showing mixing across chains and convergence.

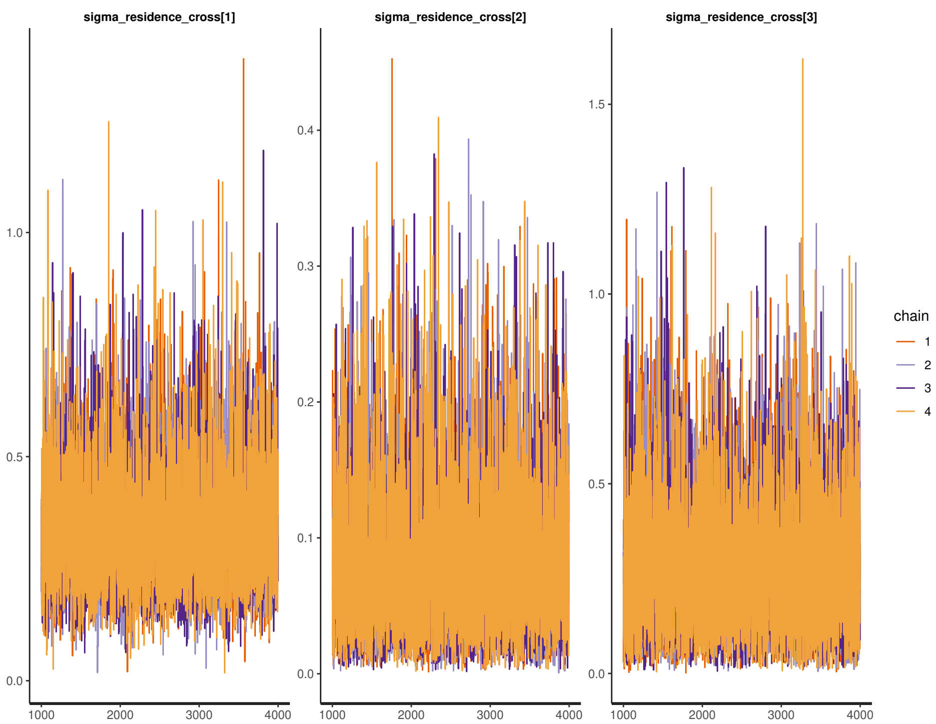

Figure B.6: Traceplot of the neighborhood variation in the transition matrix of transitioning between geometric spaces showing mixing across chains and convergence.

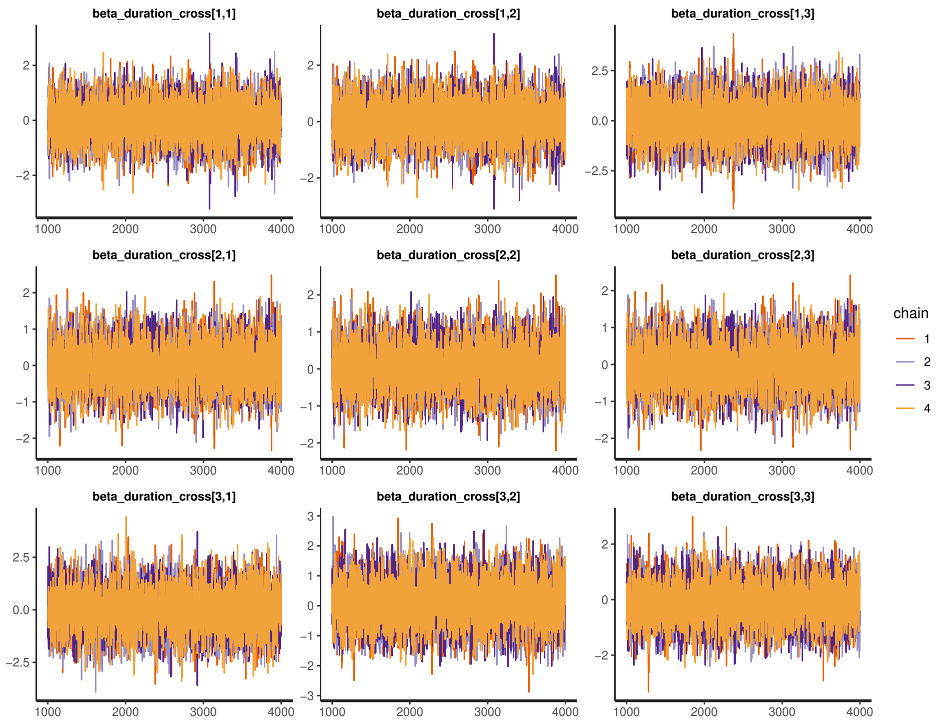

FIGURE B.7: Traceplot of the effect of the duration of practice in the transition matrix of transitioning between geometric spaces showing mixing across chains and convergence.

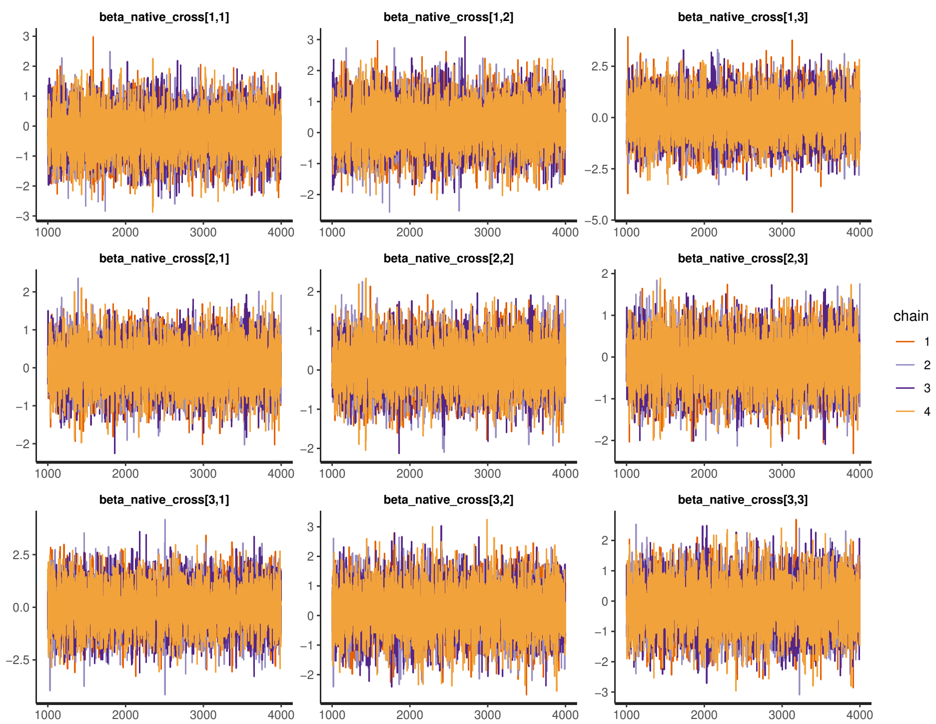

FIGURE B.8: Traceplot of the effect of the migration history (nativity) in the transition matrix of transitioning between geometric spaces showing mixing across chains and convergence.

B.4.2 Population-level Results

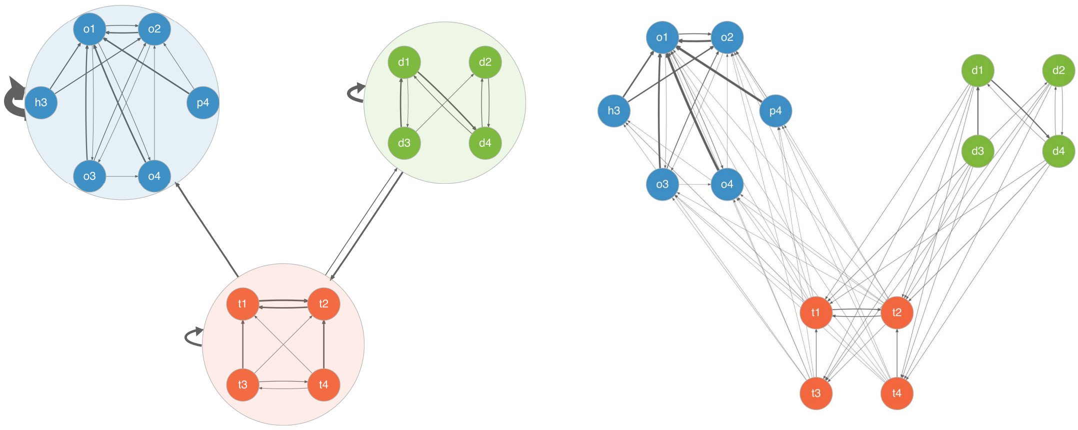

FIGURE B.9: Estimated population-level transitions between gestures. The left state transition diagram emphasises the probability of transitioning between orthogonal, diagonal, and transitional gestures. The right state transition diagram illustrates all transitions between gestures within the same geometric space and between different geometric spaces. The width of the edges reflects the probability of transition, whereby a wider or bolder edge implies an increased probability of transition. The colours represent the three different geometric categories. The self-loops for each gesture are not depicted. Self-loops for the geometric categories on the right transition network are not depicted.

The ability to describe *kolam* art as a Markovian system further allows us to compute the stationary distribution after a sufficiently long time. The stationary distribution or the state distribution of the system at equilibrium describes the proportion of time that the Markov chain (sequence of gestures) is in any given state (i.e., gesture within a geometric space). The stationary distribution π can be found using the transition matrix T and by setting an initial distribution for π (π is a row vector of probabilities over the state space S), so that $\pi = \pi$T.

On the population-level, our results illustrate that although artists are unconstrained in their patterns or stylistic variation in *kolam* drawings, and they can freely transition back and forth between geometric spaces, artists have evident preferences and biases towards certain gestures and geometric spaces. As seen in Figure B.9, *kolam* patterns that arise in orthogonal geometric space are predicted to stay in orthogonal geometric space with a probability of 0.985 and transitioning to a different geometric space to access a greater diversity of gestures hardly occurs (probability of 0.015). Therefore, when an artist draws *kolam* patterns in orthogonal space, they are unlikely to transition between different geometric spaces and only draw patterns with different gestures within the orthogonal space. However, if artists draw *kolam* patterns in diagonal or transitional space, they tend to use a diverse set of gestures that span across multiple different geometric spaces. Considering that transitioning away from orthogonal space hardly occurs and concomitantly transitioning into orthogonal space occurs relatively frequently, the probability of orthogonal gestures at equilibrium is very high with 0.96. Thus, *kolam* artworks predominantly arise and remain in orthogonal space. Conversely, *kolam* patterns with gestures from transitional and diagonal space are very rare (0.03 and 0.01 respectively). Viewed at the population-level, our results show that transitions within geometric spaces are not equal, but there are evident biases for certain transitions. For instance, in orthogonal space, there are no transitions between *h3* and *o4* or *p4* and *o3*, and in diagonal space there are no transitions between *d1* and *d2*.

B.4.3 Estimated Population-level Transition Matrices

TABLE B.5: Estimated Posterior Transition Matrix within Orthogonal Space

	o1	o2	o3	o4	h3	p4
o1	0.41	0.30	0.10	0.18	0.01	0.00
o2	0.68	0.16	0.11	0.05	0.01	0.00
o3	0.61	0.28	0.03	0.08	0.00	0.00
o4	0.84	0.09	0.06	0.00	0.00	0.00
h3	0.53	0.46	0.00	0.01	0.00	0.00
p4	0.82	0.15	0.02	0.00	0.00	0.00

TABLE B.6: Estimated Posterior Transition Matrix within Diagonal Space

	d1	d2	d3	d4
d1	0.08	0.05	0.09	0.78
d2	0.03	0.69	0.01	0.27
d3	0.76	0.15	0.05	0.04
d4	0.25	0.27	0.00	0.47

TABLE B.7: Estimated Posterior Transition Matrix within Transitional Space

	t1	t2	t3	t4
t1	0.03	0.95	0.02	0.01
t2	0.81	0.18	0.00	0.01
t3	0.63	0.10	0.04	0.22
t4	0.08	0.76	0.11	0.05

B.4.4 Estimated Effects of Migration and Duration of Practice

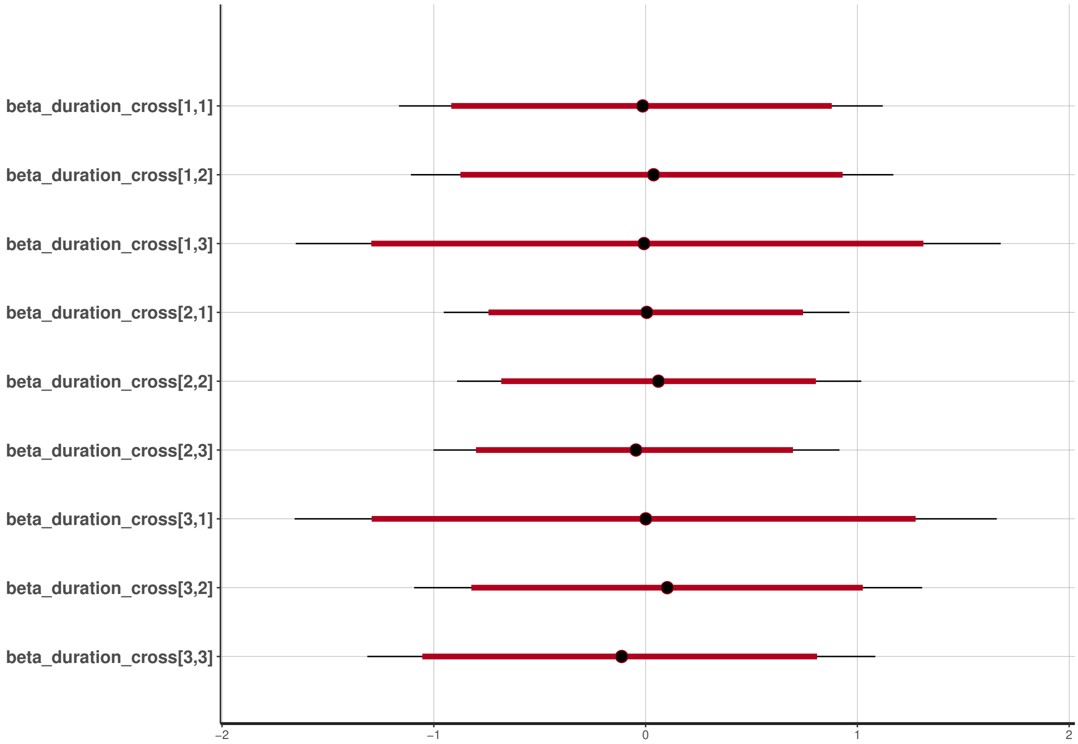

FIGURE B.10: Estimated coefficients of the duration of practice on the transition matrix across geometric spaces. On the x-axis, the red interval shows the 90% HPDI interval and the black interval shows the 80% HPDI interval around the posterior mean.

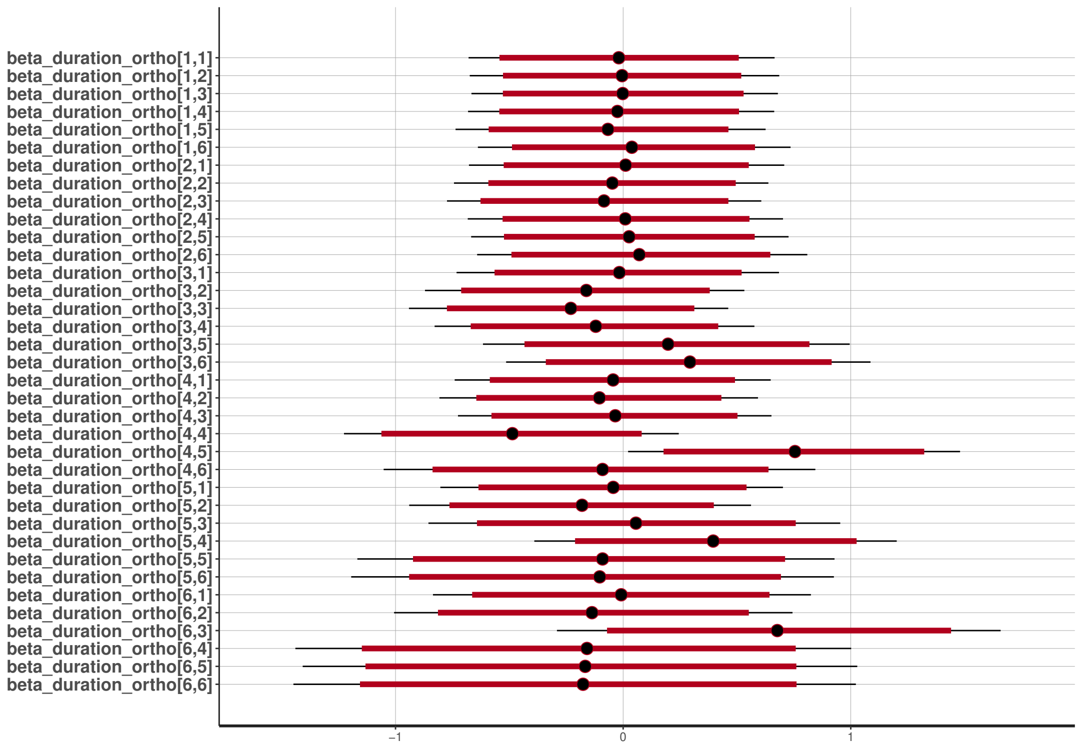

FIGURE B.11: Estimated coefficients of the duration of practice on the transition matrix within orthogonal space. On the x-axis, the red interval shows the 90% HPDI interval and the black interval shows the 80% HPDI interval around the posterior mean.

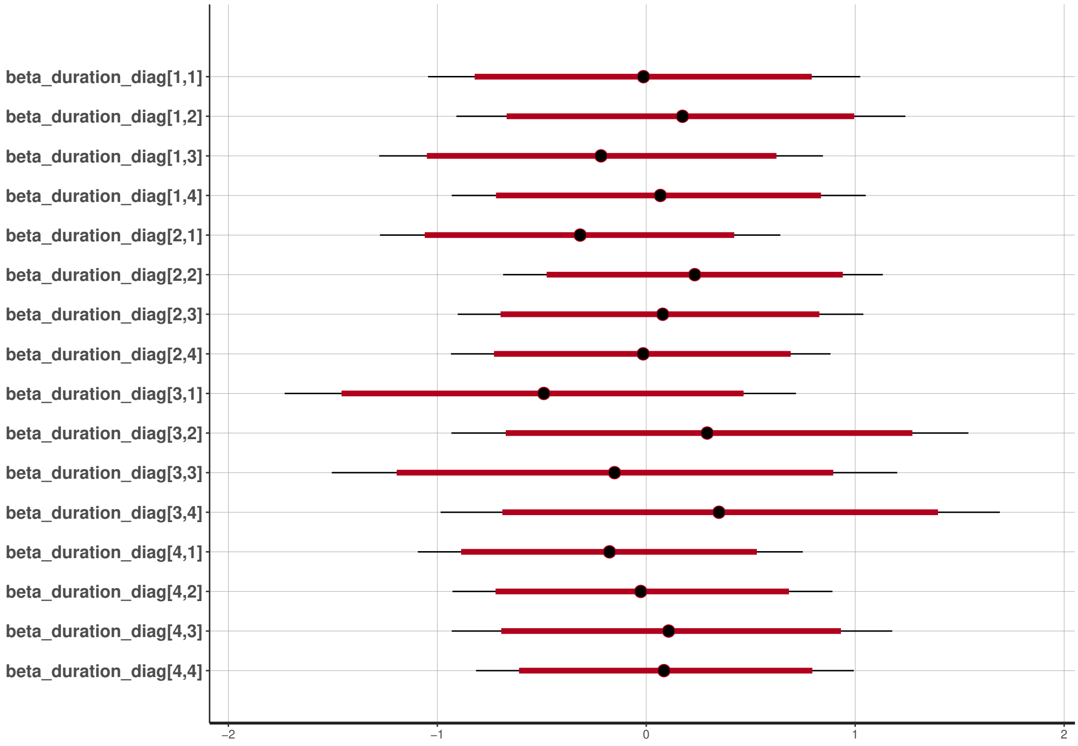

FIGURE B.12: estimated coefficients of the duration of practice on the transition matrix within diagonal space. On the x-axis, the red interval shows the 90% HPDI interval and the black interval shows the 80% HPDI interval around the posterior mean.

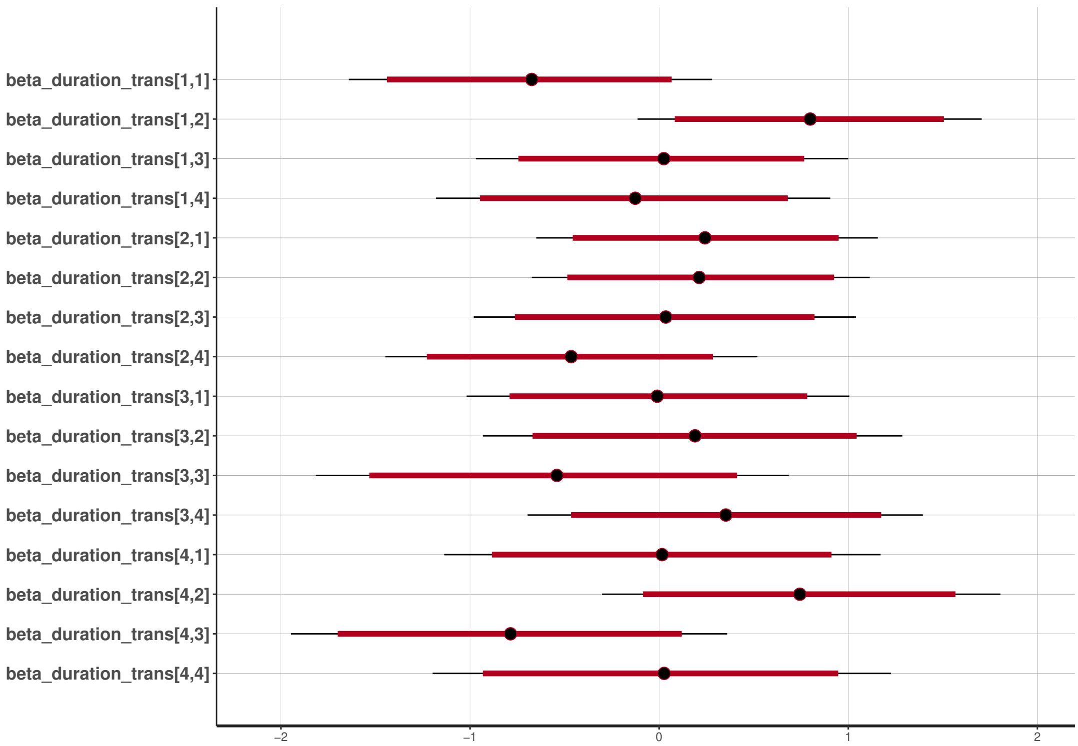

FIGURE B.13: estimated coefficients of the duration of practice on the transition matrix within transitional space. On the x-axis, the red interval shows the 90% HPDI interval and the black interval shows the 80% HPDI interval around the posterior mean.

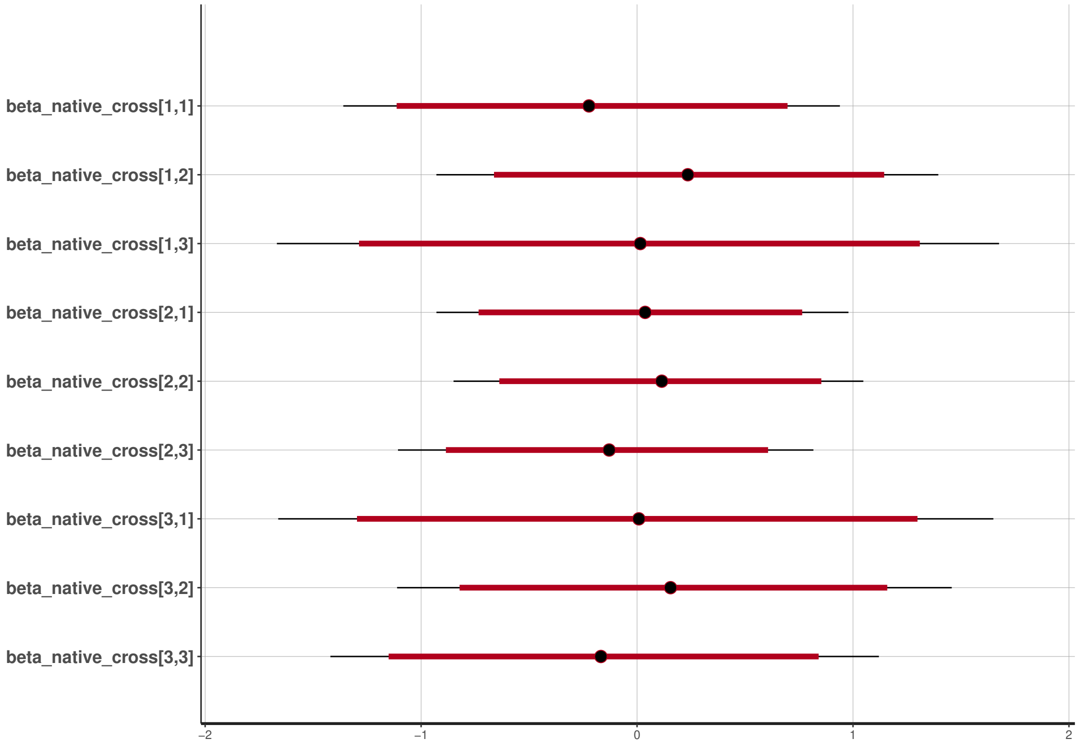

FIGURE B.14: Estimated coefficients of the migration history (nativity) on the transition matrix across geometric spaces. On the x-axis, the red interval shows the 90% HPDI interval and the black interval shows the 80% HPDI interval around the posterior mean.

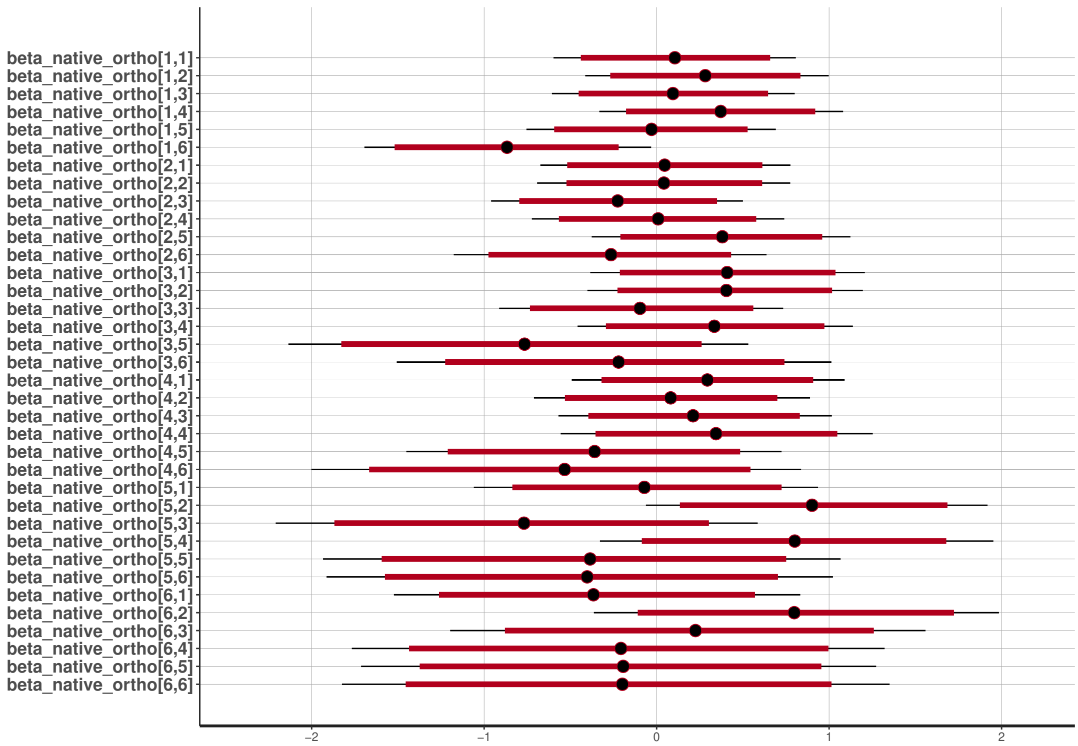

FIGURE B.15: Estimated coefficients of the migration history (nativity) on the transition matrix within orthogonal space. On the x-axis, the red interval shows the 90% HPDI interval and the black interval shows the 80% HPDI interval around the posterior mean.

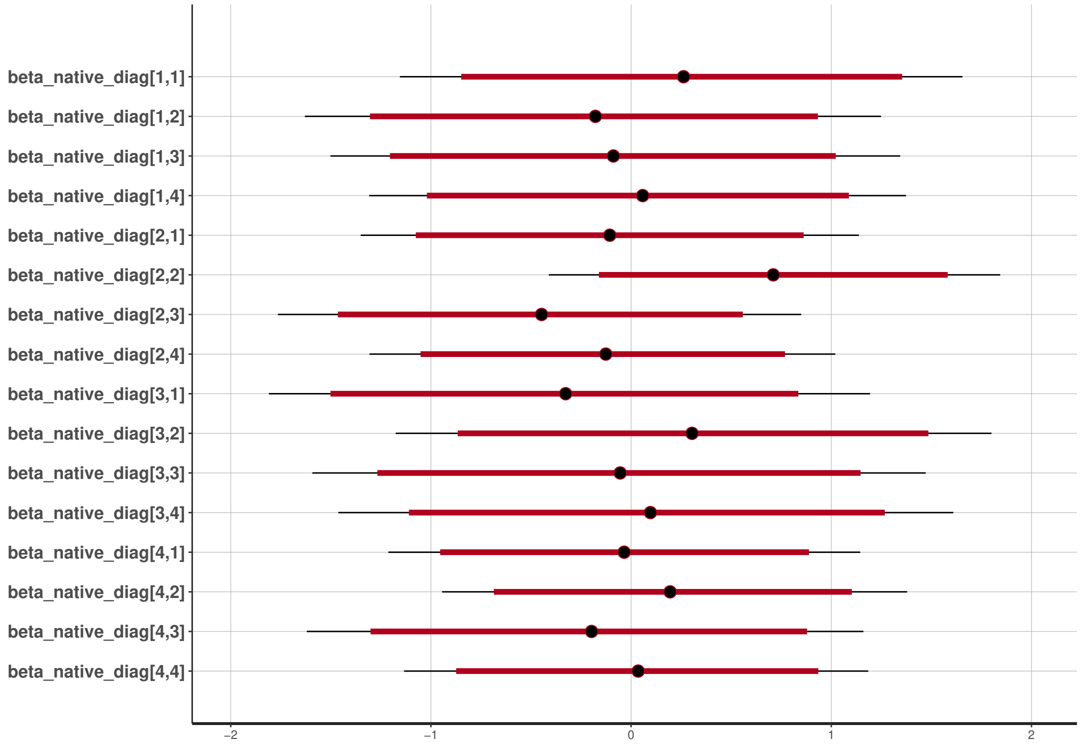

FIGURE B.16: Estimated coefficients of the migration history (nativity) on the transition matrix within diagonal space. On the x-axis, the red interval shows the 90% HPDI interval and the black interval shows the 80% HPDI interval around the posterior mean.

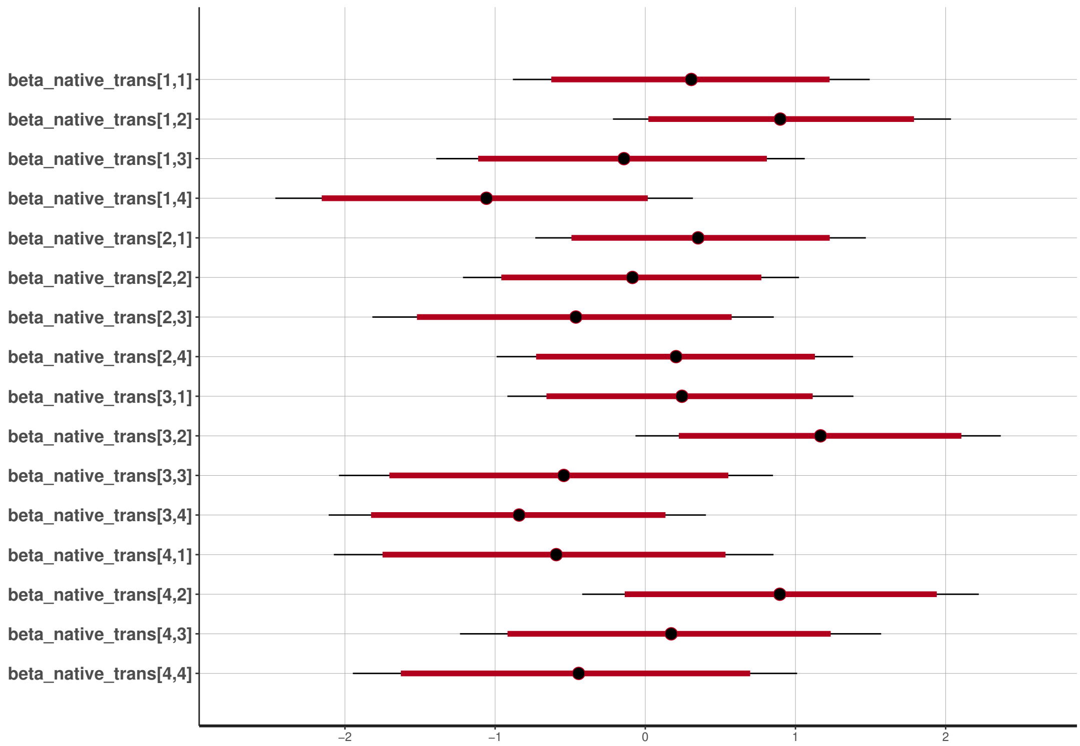

FIGURE B.17: Estimated coefficients of the migration history (nativity) on the transition matrix within transitional space. On the x-axis, the red interval shows the 90% HPDI interval and the black interval shows the 80% HPDI interval around the posterior mean.

B.4.5 Equilibrium State Vectors

Over time Markov chains automatically find their equilibrium distribution. The equilibrium is the position where there is no more change in the distributions.

B.4.5.1 Population-level

TABLE B.8: Equilibrium State Vector for the Between Geometric Space Transitions

orthogonal	transitional	diagonal
0.96	0.03	0.01

TABLE B.9: Equilibrium State Vector for the Within Orthogonal Space Transitions

o1	o2	o3	o4	h3	p4
0.54	0.24	0.09	0.12	0.01	0.00

TABLE B.10: Equilibrium State Vector for the Within Diagonal Space Transitions

d1	d2	d3	d4
0.15	0.41	0.02	0.42

TABLE B.11: Equilibrium State Vector for the Within Transitional Space Transitions

t1	t2	t3	t4
0.45	0.53	0.01	0.01

B.4.5.2 Caste

TABLE B.12: Equilibrium State Vector for the Between Geometric Space Transitions by Caste

Caste	orthogonal	transitional	diagonal
1	0.961	0.026	0.012
2	0.964	0.026	0.010
3	0.960	0.029	0.011
4	0.960	0.029	0.011
5	0.959	0.030	0.011
6	0.960	0.030	0.010
7	0.963	0.027	0.010
8	0.961	0.029	0.010
9	0.959	0.030	0.011
10	0.969	0.022	0.008
11	0.959	0.030	0.011
12	0.960	0.029	0.012
13	0.956	0.032	0.011
14	0.959	0.030	0.011
15	0.959	0.031	0.010
16	0.956	0.032	0.012
17	0.958	0.030	0.012
18	0.959	0.031	0.011
19	0.960	0.028	0.012

B.4.5.3 Neighborhood

TABLE B.13: Equilibrium State Vector for the Between Geometric Space Transitions by Neighborhood

Neighborhood	orthogonal	transitional	diagonal
1	0.939	0.044	0.017
2	0.962	0.027	0.011
3	0.950	0.037	0.012
4	0.979	0.015	0.006
5	0.959	0.029	0.012
6	0.967	0.025	0.009
7	0.967	0.024	0.009
8	0.967	0.024	0.009

B.4.5.4 Native

TABLE B.14: Equilibrium State Vector for the Between Geometric Space Transitions by Nativity

Nativity	orthogonal	transitional	diagonal
native	0.961	0.029	0.011
non-native	0.943	0.044	0.012

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Selbstständigkeitserklärung

Hiermit erkläre ich, dass ich die vorliegende Arbeit mit dem Titel "Information Complexity in Material Culture" selbständig und nur unter Verwendung der angegebenen Hilfsmittel angefertigt habe.

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- Multi-core simulation-based calibration, design analysis, Bayesian modeling of cross-sectional behavioral data coupled with DAGs for causal inference.
- Distill complex results into simple and clear visualizations.
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HTTPS://GITHUB.COM/NHTRAN93/KOLAM_SIGNALING *2021*

Systematic Parameter Reviews in Cognitive Modeling *Published Article*
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- Entwicklung der Datentranskription
- Überprüfung der Datentranskription
- Entwicklung der Datenverarbeitungssoftware und Analysen
- Verarbeitung und Analyse der Daten
- Visualisierung der Daten
- Schreiben der Publikation

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Titel: **Limited scope for group coordination in stylistic variations of *kolam* art**
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