UNIVERSITÉ PARIS, SCIENCES & LETTRES

Arsène Géry

MSc Evolutionary Anthropology

Clustering Religious Traditions: Examinating the Divergent Modes of Religiosity Theory

First year of Master's degree in

Humanités Numériques

June 2024

Acknowledgments

Firstly, I would like to thank my two supervisors who helped me navigate the complexity and richness of this subject. Mr. Chahan Vidal-Gorène, I thank you for helping me broaden my understanding of the methodological approaches employed in this project. I also thank you for your active role and kindness in counselling me throughout the year. Mr. Nicolas Baumard, I thank you for your support in providing me with the necessary reading material and constructive feedback to formulate the original ideas presented in this research project.

***

I also thank all my teachers at Ecole Nationale des Chartes (PSL) for their overall brilliance and availability throughout the year.

***

Last but not least, I would also like to thank my wife, family, and friends who have all lent me their unconditional support, and without whom I would not have had the courage to embark on this journey.

Contents

Abstract

Building upon Harvey Whitehouse's Divergent Modes of Religiosity (DMR) theory, which classifies religious traditions into imagistic and doctrinal modes, this study employs statistical and data visualization techniques on ritual data from the eHRAF world cultures database. The objectives are twofold: to assess the replicability of Whitehouse's categories within a statistical framework, and to uncover hidden patterns within the data, providing a robust quantitative foundation for understanding the relationship between ritual content and societal structure. The results reveal coherent groupings of religious traditions across ritual-level and society-level predictors. The use of visualisation techniques, such as dendrograms and heatmaps, enhances the interpretability of the findings, offering novel insights into the significant differences between clusters of religious traditions. This study contributes to our understanding of the formation and differentiation of religious traditions and lays the necessary groundwork for a more in-depth investigation of cross-cultural religious phenomena.

En s'appuyant sur la théorie des *Divergent Modes of Religiosity* (DMR) de Harvey Whitehouse, qui classe les traditions religieuses en modes imagistique et doctrinal, ce projet de recherche utilise des méthodes statistiques et des techniques de visualisation des données pour explorer les données rituelles de la base de données de *eHRAF world cultures database*. Les objectifs de cette investigation sont doubles : évaluer la reproductibilité des catégories de Whitehouse, et découvrir des méthodes quantitatives robustes pour comprendre la relation entre le contenu rituel et la structure sociétale. Les résultats révèlent des groupements cohérents de traditions religieuses. L'utilisation de techniques de visualisation améliore l'interprétabilité des résultats et permet de comprendre les différences significatives entre les groupements de traditions religieuses. Cette étude contribue à notre compréhension de la formation et de la différenciation des traditions religieuses.

Keywords: Cultural Anthropology, Divergent Modes of Religiosity (DMR), Religious Rituals, Cross-Cultural Analysis, Imagistic and Doctrinal, Statistical Methods, Hierarchical Clustering, Principal Component Analysis (PCA).

Introduction and aim of the research project

Within the domain of human religious practice and experience lies a great diversity of ritual phenomena. Religious rituals are comprised of a collection of ritual actions, or components, and lie at the foundation of all human religious expression, from the historiography of traditional religions (pre-classical religions), to that of large scale modern classical religions strongly influenced by Christianity, Islam, Hinduism, and Buddhism [1]. Since the early 2000s, attempts to understand the ritual differences between traditional religions and classical religions have been undertaken [52]. In 2004, Harvey Whitehouse (Chair of Social Anthropology at the University of Oxford) proposed his Divergent Modes of Religiosity theory (DMR) [54], which posited that religions had a tendency to operate within a spectrum of two distinct modes, the imagistic and the doctrinal. These two modes of religiosity are two distinct ritual conditions under which psychological, cognitive, and social dynamics differ [54]. Through the application of statistical methods and data visualisation techniques on the extensive ritual data collected by Whitehouse and Atkinson [1] from the Probability Sample Files (PSF) within the Human Relations Area Files world cultures database (eHRAF), I propose an exploration of the two modes of religiosity. My investigation has two distinct purposes. The first is to understand whether the categories produced by Whitehouse are replicable using a statistical framework. The second is to further understand and visualise the underlying structure of the data, and to see whether hidden patterns can be revealed. The second step is the main focus of this research project, which aims at laying a solid quantitatively valid foundation for the explanation of the link between the contents of religious rituals and their effects on the structure of the societies that perform them. In short, in building on Whitehouses work, I aim to understand how religious traditions differ from one another, and whether the socio-religious organisation of societies is significantly affected by the religious ritual actions that are performed. In doing so, I wish to elucidate whether the vast cross-cultural expression of human religious phenomena (pertaining to ritual actions) can be mapped effectively. The objective is to set the groundwork for what may become a more in-depth investigation in the years to come. Lastly, to complete this research project, I will hint at potential next steps to further analyse the data, specifically machine learning models that are capable of predicting which ritual actions are most likely to be performed if we are only given knowledge of the socio-religious organisation of a specific society.

Chapter 1

State of the Art

1.1 Cognitive Anthropology and Modes of Religiosity

In the archaeological and anthropological literature, the study of religious behaviour is given a great deal of attention. However, one particular aspect of religiosity that has often been overlooked is the psycho-cognitive dimension of religious practices, and notably, of ritual [53][4]. Cognitive anthropology deals with the psychological mechanisms involved in the performance of religious actions, the acquisition of religious knowledge, and its transmission [6][5][53][59]. Boyer (1993, p.4) explains that "the main point of a cognitive framework is to explain the recurrent properties of religious symbolism by giving a precise answer to the following question: what are the mental representations and processes involved in religious beliefs, discourse and actions? How are these representations acquired and transmitted?". Each religious tradition has its own unique set of ritual practices and features composed of diverse sets of images, symbols, myths, and doctrines governing individual beliefs, morality, and perception of self in society and the cosmos [14][11][50][15][30][47]. These features give insights into the content and context of religious traditions, and reveal the way in which religious knowledge is handled (acquired and transmitted) through cognitive processes such as memory [59]. Cognitive anthropology aims at understanding the organisation and structure of cultural institutions within societies by means of studying the micro-mechanisms of cognition employed in religious behaviour [4][20][2][6][44][45][60][62][26][24]. The psychological dimension of the ritual is therefore of primary importance to the study of cognitive anthropology. This field of study unifies the psychological dimension of religion, and the biological constraints of cognitive processes within particular cultural and environmental contexts [44][45][32][27][48][53][52]. Furthermore, scholars have long argued that religious practice and experience shapes and supports both the social-political institutions and the social order of societies [4][6][19][38][46][47][49][64][55][54].

In all ritual contexts, psychological arousal ("powerful emotions and sensations")[53] is generated through the performance of particular ritual actions [55]. However, some rituals tend to be more arousing than others [54]. The term "high arousal" is used to denote a vast range of potential religious experiences generated by a variety of ritual actions, and should not be understood as sexual arousal [54]. Profound religious experiences, in ritual context, have commonly been referred to as altered states of consciousness (ASCs) and ecstatic states of consciousness (ESCs) [10][9][36][28][65][25]. Religiosity requires the establishment of methods through which a religious experience may be achieved. It can be argued that all religious experiences (ASCs and ESCs) are pre-eminent human psychological conditions that do not take root in any particular culture ; and that they are in essence a "non-historical", or "transcendental" phenomenon [36][10][3][15][29]. The ritual itself acts as the vehicle through which a religious experience is initiated and directed so as to impart a particular religious teaching. ASCs and ESCs are by nature induced by highly arousing ritual actions predominantly observed in the religious life of traditional societies [19]. Rituals that are highly arousing (both euphoric and dysphoric)have a tendency to be less frequently repeated over a specific period of time. Reversely, highly frequent rituals tend to generate low dysphoric arousal and relatively high euphoric arousal. This dichotomy of arousal in human religious practice and experience has led to the formulation of the Divergent Modes of Religiosity theory (DMR) [54][63][64], in which these modalities of religious experience have been termed "imagistic" and "doctrinal" modes of religiosity. The Imagistic mode dates back to the Upper Palaeolithic, and predates the doctrinal mode that tends to define post-agricultural societies in the archaeological record [34][21][54]. The particular class of religious specialists characterising the imagistic and the doctrinal mode of religiosity are the shaman and the priesthood respectively [54][23][25]. The imagistic mode of religiosity is associated with a wide range of highly psychologically arousing ritual actions known to revolve around psychological ordeals, physical ordeals, and the ingestion of psychoactive compounds [36][55][40][16][25][33]. The psychological tendency to which the imagistic mode of religiosity adheres has for trajectory the profound alteration of consciousness [54][64]. The methods employed to alter consciousness in both the imagistic and doctrinal ritual contexts are fundamentally different in that the two generate opposite dynamics of ritual arousal and frequency [60]. The performance of ritual actions triggers the activation of particular cognitive processes in memory required for the retention and transmission of religious knowledge [59][62]. It is proposed that these cognitive micro-mechanisms composing a particular religious ritual affect and shape the landscape of psychological, social, and political dynamics within societies [54].

The cognitive processes involved in the generation, memorization, and transmission of religious concepts are tools accessible to the human psychological repertoire [6]. Out of this cognitive potential arises a vast diversity of religious forms. Since the conceptual generation of religious thought and its transmission originate in the cognitive architecture of the individual, the activation of particular cognitive processes necessarily plays a role in the particular ritual form a religion takes on [4][6][32]. In other words, the transmission of religious knowledge requires the use of memory, and the way in which it is activated yields variation in socio-political dynamics [6][55]. Furthermore, McCauley and Lawson [24] have proposed that the cultural institutions making up a society do not directly affect one another but instead do so through the cognitive micro-mechanisms that mediate human interaction [60]. The way in which religious knowledge is cognitively handled has been proposed to fundamentally shape the handling of socio-political morphology of societies [4][6][19][32][46][62][54]. The dynamics of cognitive integration and transmission of religious knowledge forms the basis for the separation of religious experience and practice into two distinct categories: the imagistic and doctrinal modes of religiosity [54]. According to Harvey Whitehouse [53][55][57][54], the imagistic and doctrinal modes of religiosity represent two distinct ritual conditions under which psychological and socio-political dynamics differ. Figure 1.1 below outlines the crucial psychological and socio-political characteristics of the imagistic-doctrinal modes of religiosity dichotomy [54].

Variable	Doctrinal	Imagistic
Psychological Features		
1. Transmissive frequency	High	Low
2. Level of arousal	Low	High
3. Principal memory system	Semantic schemas and implicit scripts	Episodic/flashbulb memory
4. Ritual meaning	Learned/acquired	Internally generated
5. Techniques of revelation	Rhetoric, logical integration, narrative	Iconicity, multivocality, and multivalence
Sociopolitical Features		
6. Social cohesion	Diffuse	Intense
7. Leadership	Dynamic	Passive/absent
8. Inclusivity/exclusivity	Inclusive	Exclusive
9. Spread	Rapid, efficient	Slow, inefficient
10. Scale	Large scale	Small scale
11. Degree of uniformity	High	Low
12. Structure	Centralized	Noncentralized

Figure 1.1: Contrasting modes of religiosity [54]

Memory has previously been classified into two distinct categories, implicit and explicit [14][55][56]. Implicit memory is activated when performing acquired tasks ; tasks requiring no recollection of their step-by-step performance [54]. For example, it is not required to remember how to speak when engaging in conversation. Instead speech flows with continuity. In short, implicit memory deals with that which is known without having the immediate awareness of knowing [56]. Explicit memory on the other hand deals with consciously accessible knowledge. Unlike implicit memory, explicit memory requires conscious remembrance of events in time and space [4][6]. Because explicit memory has a dimension of time, this enables us to sub-divide it into two distinct types, short-term and long-term [62]. Cognitive procedures or pathways employed for the activation of long and short-term memory are non-identical. Short-term memory allows for the recollection of events or concepts for a limited time, generally amounting to seconds and minutes [54]. Long-term memory on the other hand allows for the conservation of concepts and experiences for hours, years, or an entire lifetime [54]. Long-term memory is additionally sub-divided into episodic and semantic memory. In the religious domain, the activation of these two particular types of memory depends on the way in which religious knowledge is acquired and transmitted [6][5][62][61][53][52][54]. In addition, the existence of a flashbulb memory phenomenon triggered in states of intense religious significance and emotional arousal has been proposed [55][54]. Furthermore, flashbulb memories appear not to degrade over time, but to become more pronounced [55]. Figure 1.2 illustrates the different types of memory and their relationships described above.

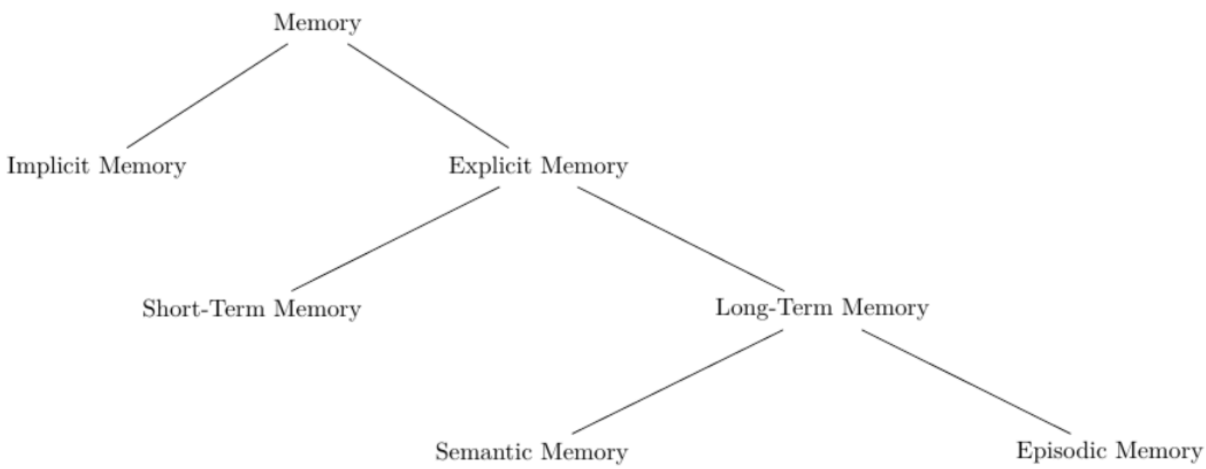

Figure 1.2: Types of memory [54]

Due to a divergence of intensity in experience (arousal) in the two types of religiosity, differences in the cognitive processing of religious information are also expected to arise [6][5][60][55][54]. Whitehouse goes so far as to place the psychology of the imagistic ritual in a distinctive domain of affective, and sensory experiences. In his reporting on the ritual practices of the awan people of Papua New Guinea, Whitehouse remarked, "pervading all these experiences was an awareness of their collective nature, a sense of undergoing something unusual and profoundly significant as a solidary group"[55]. The intensity and character of these experiences provide concrete insight into the reasoning behind much of the socio-political organisation of imagistic societies [4][62]. In 2011, Whitehouse and Atkinson [1] proposed the existence of multiple clusters of ritual features that occur cross-culturally due to the inherent "cognitive constraints on the range of possibilities and functional constraints on how features interact with each other and the broader social system". Examples of these constraints are present in ritual forms that "have been associated with costly signalling [20][44][45], obsessive compulsive disorder and the human hazard precaution system [26], cognitive constraints on memory systems [53], the role ascribed to supernatural agency [32][27], modes of codification and transmission [2][48] and the scale and structure of religious communities [52]". In their 2011 landmark study "The cultural morphospace of ritual form : Examining modes of religiosity cross-culturally", Whitehouse and Atkinson [1] extracted an unbiased, randomly selected dataset from "645 religious rituals from 74 cultures around the globe, as documented in the electronic Human Relations Area Files (eHRAF)", that recorded the "frequency, arousal, and contextual information" [1] (for full details on dataset collection and data preparation, read Whitehouse and Atkinson 2011, p. 52-53). In this study, Whitehouse and Atkinson sought to use a quantitative framework to test the DMR theory, and identify whether ritual actions could cluster together "along frequency and arousal dimensions and to investigate the cultural correlates of variation in ritual form" [1]. In Figure 1.3, I have taken liberty of listing the hypotheses of the 2011 paper so as to clearly outline the main points of the DMR theory.

Main Hypotheses of the DMR Theory
1. Ritual frequency should be negatively correlated with levels of emotional arousal.
2. Ritual frequency should be most strongly negatively correlated with dysphoric (painful or unpleasant), rather than euphoric arousal, because of the effects of pain and trauma on the activation of durable episodic recall (Xygalatas, 2008).
3. The morphospace or ritual frequency vs. arousal should reveal two clusters — high frequency and low arousal vs. low frequency and high arousal.
4. Major world religions (e.g., classical religions and large regional religions) should have higher frequency and lower arousal rituals than small-scale or tribal traditions.
5. Highly arousing rituals should be more prevalent in societies that live in smaller groups.
6. Highly arousing rituals should be more prevalent in less hierarchical societies.
7. Highly arousing rituals should be less prevalent in societies that rely more on agriculture.

Figure 1.3: Hypotheses of the DMR ([1])

Through the application of correlation analysis using Spearman's rank correlation coefficient, the study found a number of significant negative correlations between mean dysphoric and mean euphoric arousal across a set of predictor variables. In addition to correlation analysis, the study made use of the one-way ANOVA regression methods to find significant differences in ritual arousal (both dysphoric and euphoric) between societies. This step was necessary in pursuing the exploration of potential population-level predictors of arousal. Using stepwise regression (hierarchical regression), the study identified ritual-level and society-level predictors of arousal such as frequency of ritual, duration of ritual, influence of classical religion, agricultural intensity, and presence of initiations [1]. Figure 1.4 displays these relationships - their coefficients and significance levels - and were taken directly from the 2011 paper to facilitate the readability and reportability of the results.

Further studies exploring ritual morphology include Kapitány, Kavanagh, and Whitehouses 2020 paper entitled "Ritual morphospace revisited: the form, function and factor

Correlation (Spearman's rho) and p values relating mean dysphoric and euphoric ritual arousal ratings in each culture to the set of candidate cross-cultural predictor variables

Predictor	n	Dysphoric arousal		Euphoric arousal	
		rho	p value	rho	p value
Mean ritual frequency	74	−0.402	<.001***	−0.286	.014*
Community size	53	−0.446	<.001***	−0.196	.259
Local jurisdictional hierarchy	67	−0.031	.804	−0.107	.391
Regional jurisdictional hierarchy	66	−0.182	.143	−0.189	.129
Classical religion	74	−0.230	.048*	−0.264	.023*
Moral high gods	58	−0.260	.049*	−0.042	.753
Moral high gods (binary)	58	−0.294	.025*	−0.259	.233
Agricultural intensity	67	−0.415	<.001***	−0.266	.067
Warfare (Sosis et al. 2007)	55	0.214	.117	0.236	.083
Writing	34	−0.172	.332	0.001	.994

* $p<.05$.
*** $p<.001$.

Results showing significant ritual- and society-level predictors in the stepwise hierarchical regression predicting euphoric ritual arousal

Predictor	Coefficient	t value	p value
Frequency	−1.189	−4.858	<.001***
Frequency^2	0.154	4.759	<.001***
Duration	0.334	7.193	<.001***
Other gatherings	0.303	2.609	.009**
Manipulating this world	0.184	1.968	.049*
Classical religion	−0.182	2.264	.023*

Log likelihood=−881.6.
* $p<.05$.
** $p<.01$.
*** $p<.001$.

Results showing significant ritual- and society-level predictors in the stepwise multi-level linear regression predicting dysphoric ritual arousal

Predictor	Coefficient	t value	p value
Frequency	−0.408	−7.161	<.001***
Duration	0.141	2.254	.024*
Initiations	1.180	6.151	<.001***
Other gatherings	−0.507	−3.513	<.001***
Agricultural intensity	−0.100	−2.392	.017*

Log likelihood=−889.5.
* $p<.05$.
*** $p<.001$.

Figure 1.4: Correlation (Spearman's rho), p-values (left), and stepwise hierarchical regression predicting euphoric ritual arousal (top right) and dysphoric ritual arousal (bottom right) - as outlined in Whitehouse and Atkinson 2011.

structure of ritual practice" [22]. Using unconstrained factor analysis and confirmatory factor analysis, the study found that dysphoric and euphoric ritual arousal factors confirmed theories such the DMR and others that focus specifically on dysphoric arousal and costly signals [41][18].

Chapter 2

Preparing the Data

2.1 Description and origin of the data

The dataset I am using for this research project is the same as the one collected and analysed by Whitehouse and Atkinson [1] in their landmark paper to test the DMR theory. The dataset was extracted from the Probability Sample Files (PSF) within the Human Relations Area Files world cultures database (eHRAF), and was carefully curated to avoid non-independence issues. The dataset was sent to me by Harvey Whitehouse himself on the 5th of October, 2023.

The eHRAF database is a vast repository of anthropological and ethnographic data on past and present cultures, designed as an exploratory platform for cultural researchers. It is organised by cultures, and is updated "by HRAF anthropologists with unique subject identifier codes from the Outline of Cultural Materials (OCM), making it ideal for both exploratory, in-depth cultural research, and cross-cultural comparisons" [8]. The dataset used in this research project consists of an unbiased sampling of 82 randomly selected cultures - representing 81 distinct religions - constituting a sample representative of present societies of all continents of the world. The data itself consist of a wide range of religious ritual descriptions, religious ritual components (in the form of actions), religious ritual cultural characteristics, and information on the features and organisation of religious activities in each culture.

2.2 Structure of the data

The data is structured as rows (or individual ritual occurrences) within 82 unique traditional societies, spanning five continents. Each society has a minimum of one row, or specified coded religious ritual. In this investigation, I have chosen to omit 7 societies as a result of insufficient data in the dataset (composed mostly of missing values). As a result, 75 societies of 84 unique religious affiliations and 645 unique ritual occurrences have been preserved for the data cleaning process. The original dataset consists of 174 variables (continuous, nominal, binary, categorical, and ordinal) for each ritual occurrence. However, I have chosen to select the variables most suited to the questions I wished to address in this investigation. As a result, only 100 of the original 174 variables were conserved for the analysis. I have preserved all 81 binary variables coding the presence and absence ("1" and "0" respectively) of ritual components in a given ritual such as tattooing, vomiting, piercing, superficial wounding, instrument use, throwing of offerings in water, hallucinogenic plant use, smoking, possession, etc. Furthermore, I have chosen to preserve a mix of 19 ordinal, continuous, and categorical variables to act as ritual-level and society-level predictors of clustering differences within the data. All binary variables are displayed in Figure 2.1 and non-ritual component variables are displayed in Figure 2.2 for clarity.

Ritual Components	
Dancing or repetitive rhythmic movement	Fasting
Singing and (repetitive) rhythmic vocalization	Extended athletic feats
Use of percussion instruments	Sleep deprivation
Use of other instruments	Dehydration
Shouting, screaming and other non-rhythmic vocalizations	Long periods of immobility or maintenance of uncomfortable body position
Music and/or dance that evinces excitement	Isolation procedures (solitary confinement, abandonment)
Music and/or dance that evinces sorrow/nostalgia	Threats or actions that evince fear
Music and/or dance that involves large-scale concerted action	Mention of disgust
Marching/ procession/ Proambulation	Humiliation of participants
Loud bangs: firing of guns, fireworks	Dramatic acts evincing displays of emotion from participants
Bowing, kneeling or prostration	Gravitas: awe inspired by sacred persons or objects
Hair cutting or shaving	Gravitas: awe inspired by special site or building
Washing	Ritual associated with group construction work
Participants rubbed or massaged	Large crowd
Sprinkling or blowing of liquids or small particles	Mock conflict
Fumigation, smoke purification	Ceremonial costume/ bodily decorations
Interdiction against use of hands	Use of fire/ embers
Spitting on patient	Sacrifice of animals
Intake of hallucinogenic drugs	Sacrifice of humans
Intake of sedatives	Other offering
Intake of alcohol	Placing or throwing of offerings in water
executive possession	Minature effigies, minature instruments, dolls, other non-life size objects
Trance as performance	Pathogenic possession
Lucid/ vivid dreaming	Speechmaking
Induced by mind-controlling disciplines	Recitation of texts
Stimulants	Naming
Smoking	Blood
Burning of participants	Weapons or firebrands
Significant wound or bleeding	Sexual intercourse
Superficial wound	Narrative or story recounted
Whipping/ beating of participants	Burial of offerings
Piercing	Burning of offerings
Scarification	Confession or begging of forgiveness
Tattooing	Games played in association with ritual
Laceration of sensitive organs	Some participants eat meal together
Circumcision/ removal of uvula	Reference to other shared joyful behavior
Foul or unpleasant sensations, tastes or smells	Restriction on smoking
Vomiting	Restriction on intake of alcohol
Swallowing of undigestable objects (swords, stones)	Restriction on sexual behavior
Patient's body is sucked	Restriction on speaking
Other uncomfortable experiences	

Figure 2.1: Exhaustive list of ritual components.

Ritual-Level & Society-Level Variables
Intensity of peak euphoric arousal moment (Average of 3 raters)
Intensity of peak dysphoric arousal (Average of 3 raters)
Euphoric arousal over the course of the ritual for average participant
Dysphoric arousal over the course of the ritual for average participant
Distribution of ritual exegesis
Dominant mode of acquisition of exegesis
Under what circumstances is one recruited to the religious tradition?
Proselytizing individuals
Scale of shared religious ideas and practice perceived by members
How big is the population that considers itself to share a set of identifiable beliefs and practices?
Is tradition mixed?
Perception of religious leaders by laity
Degree of hierarchy in religious roles
Leaders (not necessarily religious) derive moral authority as embodiments of divine or via privileged access to divine
Influence of classical 'world' religions
Has identification with traditional religion ended?
Proportion of population identifying with classical religion
Ritual duration category
Typical frequency of participation for average participant

Figure 2.2: Exhaustive list of ritual-level and society-level components.

In the original dataset provided by Harvey Whitehouse, a description of each ritual occurrence and the source of the ethnographic work which allowed the collection of the data was provided in the original dataset. For the purpose of this investigation, all descriptions of the rituals were stripped from the dataset, but the original document and information on the variable coding method will be provided for the interested reader. Before describing the data cleaning process more extensively, I believe it important to list the 75 societies represented in the data to give an idea of the extensiveness and the richness of the ethnographic data used for this analysis (Figure 2.3).

2.3 Cleaning the data

To prepare my dataset for analysis, I employed a systematic approach to clean the raw data stored in an excel file by using Pythons pandas library. I used the pd.read_excel() function to read the data from the specified file path, storing it in a pandas DataFrame denoted as data. This first step was necessary for all subsequent data cleaning operations. First, I addressed all missing values within the dataset by replacing all instances of NaN values with "0" using the fillna() method. This operation ensured uniformity in handling missing data. Next, I used the replace() method to substitute all occurrences of "-1" with "0". I chose to replace all occurrences of missing or non-collected data (such as "-1") by "0" to ensure uniformity before vectorising my data using cosine distances and subsequent transformation into a similarity matrix. I then proceeded to standardise date-like values present within the dataset by identifying all object data types. By using regular expres-

Society	Religion	Society	Religion
Blackfoot	Blackfoot religion	Somali	Islam
Korea	Buddhism	Korea	Chuntokyo Cult
Korea	Folk religion	Yukut	Shamanistic religion
Yukut	Yakut practice	Santal	Religion of the Santals
Serbs	Serbian Orthodox Church	Tarahumara	Tarahumara religion
Highland Scots	Catholic	Highland Scots	Presbyterian Church
Shulh	Islam	Bororo	Bororo religion
Chuuk	Truk religion	Azande	Azande religion
Akan	Ecstatic Churches	Akan	Anti-witchcraft cults
Akan	Traditional Akan religion	Aymara	Aymara religion
Aymara	Catholic	Tzeltal	Tzeltal religion
Tzeltal	Talking saint cults	Bemba	Bemba religion
Saramaka	Saramaka religion	Taiwan Hokkien	Folk or popular religion
Taiwan Hokkien	Spirit writing cult	Dogon	Dogon religion
Lau Fijians	Lauan religion	Yanoama	Yanoama religion
Klamath	Klamath religion	Kurds	Islam
Kurds	Cult of Angels	Mataco	Mataco religion
Hausa	Bori possession cult	Ifagao	Ifagao religion
Lozi	Lozi religion	Trobriands	Trobriand religion
Trobrianders	Trobriand religion	Toradja	Toraja religion
Tlingit	Tlingit religion	Andamans	Andaman religion
Kanuri	Islam	Bahia Brazilians	Candomble cult
Bahia Brazilians	African cultism	Pawnee	Pawnee religion
Hopi	Hopi religion	Kuna	Kuna religion
Maasai	Maasai religion	Central Thai	Buddhism
Central Thai	Brahman-Animistic	Central Thai	Brahman-Buddhist
Central Thai	Animistic ritual	Central Thai	Buddhist
Khasi	Khasi religion	Iroquois	Iroquois religion
Kogi	Kogi religion	Kapauku	Kapauku religion
Iban	Iban religion	Tukano	Tukano religion
Tiv	Tiv religion	Guarani	Guarani religion
Wolof	Islam	Ojibway	Ojibway religion
Ona	Ona religion	Aranda	Aranda religion
Mbuti	Mbuti religion	Garo	Garo religion
Tikopia	Tikopia religion	Bosnian Muslims	Islam
Croats	Roman Catholic	Garifuna	Roman Catholic
Navajo	Navajo religion	Orokaiva	Orokaiva religion
Orokaiva	Taro cult	Orokaiva	Kekesi cult rites
Tongans	Tongan religion/ custom	Tongans	Christian
Warao	Warao religion	Iran	Islam
Mongor	Lamaism	Mongor	Traditional religion
Igbo	Traditional religion	Igbo	Ayakka Secret Society
Banyoro	Banyoro religion	Banyoro	Mbandwa cult
Mentawaians	Mentawaians religion	Jivaro	Jivaro Religion
Maya	Maya religion	Maya	Catholic
Seminole	Seminole religion	Seminole	Seminole Baptist Church
Palestinians	Islam	San	San religion
Ovimbundu	Ovimbundu religion	Lepcha	Mun religion
Pashtun	Islam	Mongol	Lamaism

Figure 2.3: List of societies and religious traditions analysed.

sions, I replaced these date-like values with "1", seeing as all date-like values had a value of "1" in the original raw dataset. Addressing numerical data, I replaced all occurrences of "," with "." using a lambda function applied element-wise across the entire DataFrame. I also targeted the column titled "Under what circumstances is one recruited to the religious tradition?", after having identified values of "100:00:00" during the data cleaning process. As for the date-like values, I replaced all these values with "1" because these cells had a value of "1" in the original dataset. These formatting adjustments ensured consistency in all numerical representations. In addition to addressing these specific data formatting concerns, I opted to streamline the dataset by removing the column labelled "Details of named religious traditions.". This strategic decision aimed at decluttering the dataset - eliminating all redundant information - and focusing solely on pertinent variables essential for my research objectives. Concluding the data cleaning process, I saved the new, cleaned dataset to a new excel file by using the to_excel() method. To complete the data preparation process, I renamed the "19th Century Yakut practice (Jochelson. Waldemar. 1885-1937 Kumiss festivals of the Yakut and the decoration of Kumiss vessels. 263)" religious tradition name to "19th Century Yakut practice" to ensure visualisation efficiency, and removed the "Society" column from the dataset to avoid object type errors in analysis after grouping the data by "Religious tradition". To improve readability, I have decided to provide the full data preparation code below.

```
import pandas as pd

file_path = '/Users/arsenegery/Desktop/Cleaned_Data_Ritual_M1/Cleaned_Data/
    Updated_Cleaned_HRAF_Rituals_Dataset.xlsx'
data = pd.read_excel(file_path)

# Replace all NaN values with '0'
data_filled = data.fillna(0)
# Replace all occurrences of -1 with 0
data_replaced = data_filled.replace(-1, 0)
# For replacing dates with '1', we first need to identify columns that could
    contain date values
date_columns = data_replaced.select_dtypes(include=['object']).columns
# Replace date-like values detected in these columns with '1'
for col in date_columns:
    data_replaced[col] = data_replaced[col].astype(str).str.replace(r'\d{4}-\d
        {2}-\d{2}', '1', regex=True)
# Replace commas in numerical values with dots
data_replaced = data_replaced.applymap(lambda x: str(x).replace(',', '.') if
    isinstance(x, str) else x)
```

```python
# Check the unique values and their types in my column "Under what
    circumstances is one recruited to the religious tradition?"
column_name = "Under what circumstances is one recruited to the religious
    tradition?"
unique_values = data_replaced[column_name].unique()
# Convert all values in the column to numerical, and handling special cases
data_replaced[column_name] = data_replaced[column_name].replace('1 00:00:00', '
    1').astype(float)
# Removing "Details of named religious traditions" from the dataset
data_replaced.drop(columns=["Details of named religious traditions"], inplace=
    True)

# Copying the cleaned data file to the new specified name
new_filename = '/Users/arsenegery/Desktop/Cleaned_Data_Ritual_M1/Cleaned_Data/
    Cleaned_Data_HN_Master.xlsx'
data_replaced.to_excel(new_filename, index=False)

# Removing the "Society" column from the dataset before grouping rows by "
    Religious tradition"
data = data.drop(columns=['Society'])

# Renaming name of "Religious tradition" to avoid visualisation inefficiency.
specific_value = "19th Century Yakut practice (Jochelson. Waldemar. 1885-1937
    Kumiss festivals of the Yakut and the decoration of Kumiss vessels. 263)"
general_value = "19th Century Yakut practice"
data['Religious tradition'] = data['Religious tradition'].replace(
    specific_value, general_value)
data = data.replace(334, 3.34)
```

Chapter 3

Methodology and Results

3.1 Methodological choices for analysis

Since the objective of this investigation is to understand whether the categories produced by Whitehouse are replicable using a statistical framework, and to further understand and visualise the underlying structure of the data, I have chosen to aggregate all rows in my dataset by religious tradition using median values, and to represent these unique religious traditions as cosine distance vectors before transforming them into a cosine similarity matrix. I chose a cosine similarity matrix rather than a euclidean similarity matrix due to the relative unimportance of the magnitude in the data. Being more interested in the direction rather than the magnitude of the vectors, cosine distances were a more suitable choice, especially given the high-dimensional nature of my dataset. The output similarity matrix was then used for Principal Component Analysis (PCA). Below is a sample of the code for clarity in understanding the method used to prepare the data for analysis.

```
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.decomposition import PCA
import numpy as np

# Aggregating the data by 'Religious tradition' using the median
data_aggregated = data.groupby('Religious tradition').median()

# Computing my cosine similarity matrix from the aggregated data
cosine_sim_matrix = cosine_similarity(data_aggregated)
# Converting the cosine similarity matrix into a DataFrame for better
    readability
cosine_sim_df = pd.DataFrame(cosine_sim_matrix, index=data_aggregated.index,
    columns=data_aggregated.index)

# Initialize PCA with 6 principal components
```

```
pca = PCA(n_components=6)
# Fit PCA on my cosine similarity matrix
pca.fit(cosine_sim_matrix)

# Calculating the individual explained variance
individual_explained_variance = pca.explained_variance_ratio_
# Calculating the cumulative explained variance
cumulative_explained_variance = np.cumsum(individual_explained_variance)
```

This process was used for several reasons. Firstly, the dataset I was working with was inherently high-dimensional, with 100 ritual components, ritual-level, and society-level variables and 646 unique rituals, for a total of 64 500 data points. By utilising a similarity matrix, I aimed to address the dimensionality issue while preserving the information captured within the similarities among data points. Through applying PCA on the similarity matrix, I sought to distil the essential features of the dataset while mitigating the complexity associated with high-dimensional raw data, and uncover the latent patterns and associations among data points. This approach allowed me to delve deeper into the intrinsic connections between data points and extract valuable insights that might have been obscured within the raw data. Furthermore, I recognized the potential for noise within the similarity matrix, stemming from various sources such as measurement errors or irrelevant features. To address this challenge, I relied on PCA's ability to reduce and filter out the noise to extract the dominant patterns within the similarity structure. This step was crucial in ensuring the robustness and reliability of my analyses, particularly in the context of this large and complex dataset where noise can significantly impact the results. In addition to addressing dimensionality and noise concerns, the use of the similarity matrix for PCA conferred non-negligible computational advantages. Given the high dimensionality of the original data, performing PCA directly on raw data would have been more computationally intensive and potentially impractical (in this case, this computational efficiency is not easily apparent because of the relatively small dataset). That being said, I chose to run PCA on a similarity matrix so as to choose the most efficient computational outcome in the hope of analysing my dataset within reasonable timeframes. Secondly, the interpretability of the results was a key consideration in my decision-making process. I recognized that principal components derived from a similarity matrix might offer more straightforward interpretations compared to those obtained from raw data. By capturing relationships and similarities between data points, the principal components derived from the similarity matrix would provide insights into the underlying structure of the dataset that are intuitively understandable.

Following the application of PCA, I chose to further the analysis by employing hierarchical clustering using the ward linkage method on the PCA results. I had first thought of using the k-means clustering method ; an effective clustering technique to uncover distinct clusters within the dataset based on their inherent similarities. However, hierarchical clustering, contrary to the k-means approach, does not require specifying the number of clusters and is more suited for dealing with non-euclidean distances. Hierarchical clustering is also useful because it allows for intuitive visualisation of the data in the form of dendrograms. Visualising my clusters as dendrograms rather than clusters of points also has another key advantage in that it ultimately allows me to manually set a cutoff distance in the branching. A cutoff distance of 5 within the linkage corresponds to a very broad grouping of religious traditions (producing 2 clusters). On the other hand, a cutoff of 1 corresponds to a highly granular grouping of religious traditions in the data (producing 18 clusters). Using this method, I was easily able to tune the granularity of the clustering for subsequent statistical testing. Ive outlined the code for clarity in understanding the method used to prepare the data for analysis. However, manually setting the cutoff distance can be quite subjective. Therefore, I used the Elbow method to find the optimal number of clusters, and calculated silhouette scores for each cluster formation configuration (see Figure 2.4). Based on these results, I was able to identify the optimal number of clusters to include in PCA and further analysis (3 or 4 clusters).

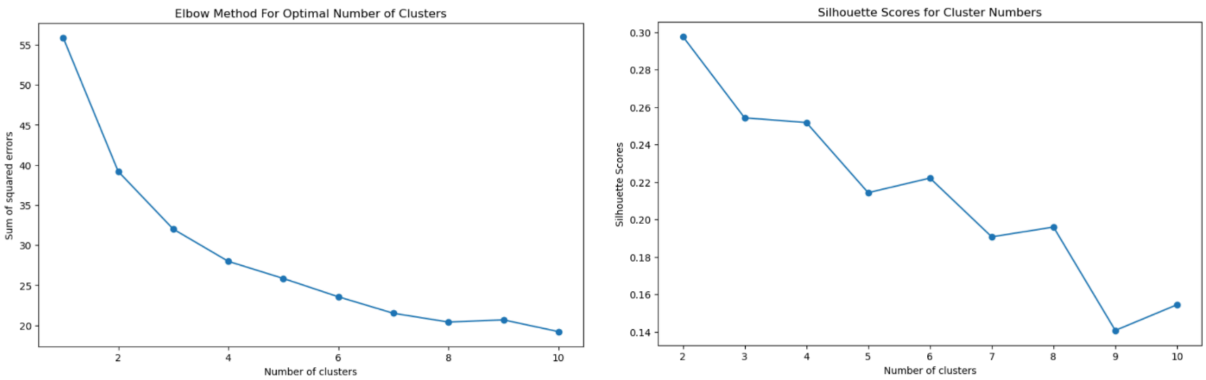

Figure 3.1: Elbow method and silhouette score results.

```
from scipy.cluster.hierarchy import dendrogram, linkage
from scipy.cluster.hierarchy import fcluster

# Transforming data using the selected number of PCA components
pca_transformed = pca.transform(cosine_sim_matrix)

# Performing hierarchical clustering using the 'ward' linkage method
linked = linkage(pca_transformed, method='ward')
# Setting cutoff distance
cutoff_distance = 3
```

```
# Assigning cluster labels based on chosen cutoff distance
cluster_labels = fcluster(linked, cutoff_distance, criterion='distance')
# Appendding the cluster labels
data_aggregated['Cluster'] = cluster_labels
# Checking how many clusters were formed from the cutoff
unique_clusters = np.unique(cluster_labels)
print("Number of clusters formed:", unique_clusters.size)

# Adding cluster labels to the labels in the dendrogram
labels_with_clusters = [f"{label} (Cluster {cluster})" for label, cluster in
    zip(data_aggregated.index, cluster_labels)]
```

Next, I chose to conduct a one-way analysis of variance (ANOVA) on the resulting clusters and all ritual and society-level predictor variables (e.g. "Degree of hierarchy in religious roles" and "Influence of classical 'world' religions"). I chose this method because ANOVA is a robust statistical technique that compares the variation between multiple groups, making it suitable for exploring differences in the target variables across the distinct clusters identified via hierarchical clustering. However, understanding whether there are global significant differences between clusters with regards to ritual-level and society-level predictor variables is not sufficient. What I am truly interested in is understanding how each pair of clusters differ from one another, and how much they differ. To reveal the underlying significant differences between pairs of clusters, I used a Tukey Honestly Significant Difference test (Tukey-HSD) to extract the significance values (p-adj values) for each pair of clusters along all predictor variables. To visualise these differences between clusters, I chose to create a heatmap of cluster pair p-values for each predictor variable. To recapitulate the methodological processes involved in setting up this project, Ive created the following rudimentary visualisation in the form of a flowchart (Figure 3.2).

3.2 Results

The analyses chosen for this research project yielded interesting and encouraging results. Firstly the cosine similarity matrix transformation (sample in Figure 3.3) allowed the formation of analysis appropriate components. As a rule of thumb, a cumulative explained variance of 70% or above is recommended, so I analysed the cumulative explained variance of the PCA output. After analysis, the sum of the explained variance of the first 3 components were sufficient (76%) to conduct further analysis (see Figure 3.4). However, in my wish to capture as much of the variance in the data as possible before applying hierarchical clustering using the ward linkage method, I opted to include the first 6 principal components (94% of cumulative variance explained) in all subsequent testing (with

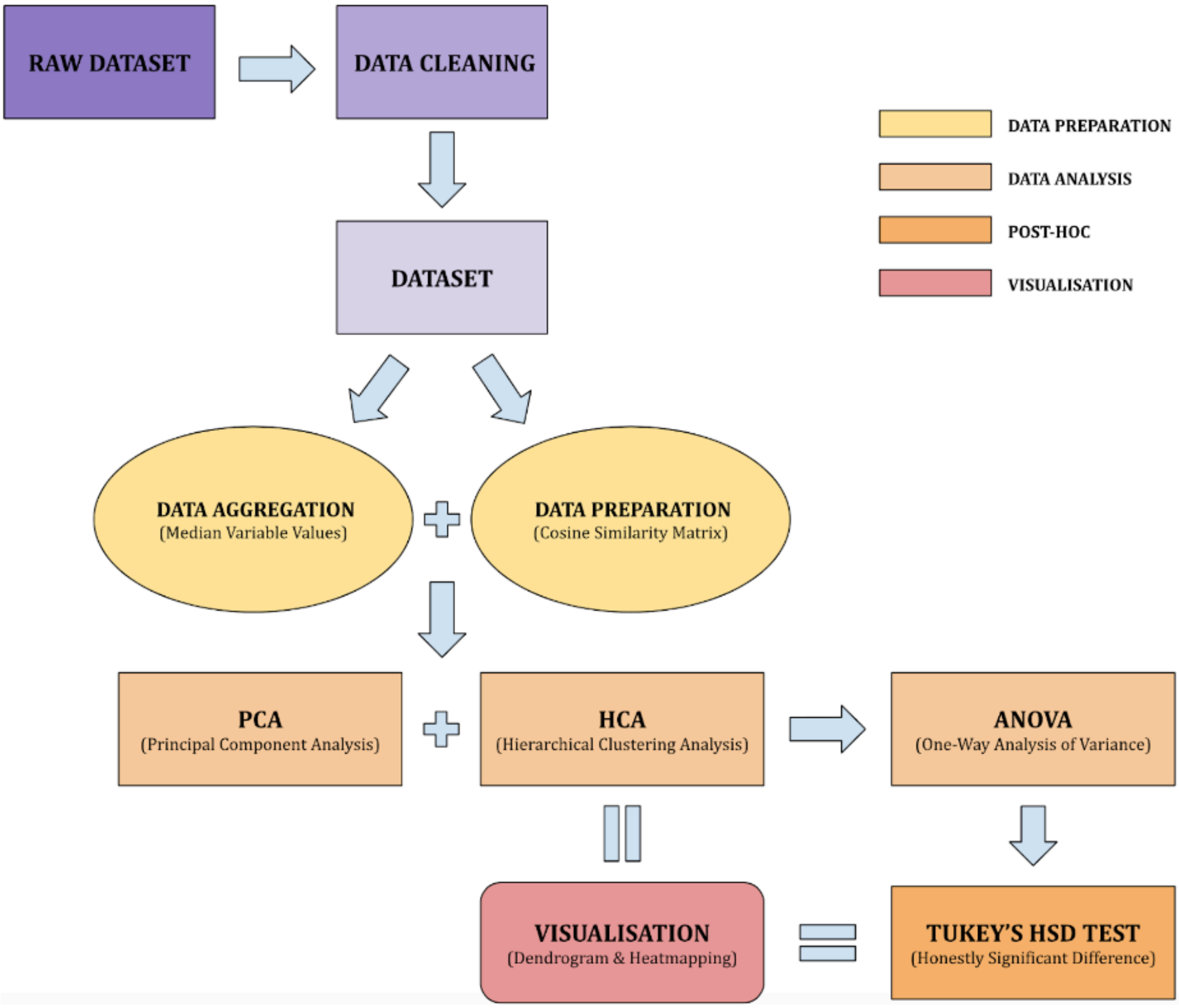

Figure 3.2: Recapitulation of the processes for the realisation of this project.

99% of cumulative variance explained at 9 components).

Religious tradition	19th Century Yakut practice	African cultism	Andaman religion	Animistic ritual	Anti-witchcraft shrine-related cults	Aranda religion	Ayakka Secret Society	Aymara religion	Azande religion	Banyoro religion
Religious tradition										
19th Century Yakut practice	1.000000	0.706414	0.827012	0.823161	0.652490	0.645412	0.779138	0.869447	0.818781	0.767421
African cultism	0.706414	1.000000	0.843062	0.748726	0.835323	0.659779	0.780811	0.749717	0.803400	0.734765
Andaman religion	0.827012	0.843062	1.000000	0.812754	0.771226	0.844572	0.862573	0.803659	0.887946	0.739944
Animistic ritual	0.823161	0.748726	0.812754	1.000000	0.782000	0.715042	0.896619	0.861673	0.848868	0.916308
Anti-witchcraft shrine-related cults	0.652490	0.835323	0.771226	0.782000	1.000000	0.601581	0.858713	0.655353	0.760942	0.787334
Aranda religion	0.645412	0.659779	0.844572	0.715042	0.601581	1.000000	0.743321	0.697072	0.795976	0.672857
Ayakka Secret Society	0.779138	0.780811	0.862573	0.896619	0.858713	0.743321	1.000000	0.763440	0.867832	0.862836
Aymara religion	0.869447	0.749717	0.803659	0.861673	0.655353	0.697072	0.763440	1.000000	0.896185	0.847238
Azande religion	0.818781	0.803400	0.887946	0.848868	0.760942	0.795976	0.867832	0.896185	1.000000	0.836250
Banyoro religion	0.767421	0.734765	0.739944	0.916308	0.787334	0.672857	0.862836	0.847238	0.836250	1.000000

Figure 3.3: Sample of the religious traditions cosine similarity matrix produced.

PCA loadings of the 84 grouped religious traditions yielded insights across six principal components (summary statistics Figure 3.5, and PCA loadings sample Figure 3.6). The mean loadings for most components are negative, with PC1 at -0.0737, PC2 at -0.0646, PC3 at -0.0020, and PC4 at -0.0455, while PC5 and PC6 are slightly positive at 0.0080 and 0.0031, respectively. Standard deviations indicate significant variability, especially in PC3 (0.1097) and PC5 (0.1095), suggesting that these components capture the most variation. The range of loadings is widest for PC3 and PC5, which further highlights their importance. Religious traditions with the highest loadings are the "Church of Scotland (Presbyterian)" for PC1 (0.1477), "Lozi religion" for PC2 (0.1687), "Folk or popular religion" for PC3 (0.2630), "Mbuti religion" for PC4 (0.1225), "Tlingit religion" for PC5 (0.3503), and "Kuna religion" for PC6 (0.2646). Conversely, the lowest loadings are seen in the Maasai religion for PC1 (-0.2159), Cult of Angels for PC2 (-0.2606), Christian tradition for PC3 (-0.2563), Serbian Orthodox Church for PC4 (-0.2644), Folk Religion for PC5 (-0.2513), and Jivaro Religion for PC6 (-0.2307).

Hierarchical clustering analysis of the principal components at a cutoff distance of 3 yielded 3 distinct groups of religious traditions (Figure 3.7). Corroborating the PCA results, high loadings for institutionalised religions (e.g. "Roman Catholic", "Serbian Orthodox Church", "Islam", "Buddhism", Church of Scotland (Presbyterian)", etc.) contrast with low loadings for indigenous traditions (e.g. "Maasai religion"). This separation is evident in the clustering where institutionalised religions all group within a distinct cluster - cluster 1. As demonstrated in the loading data, traditions with high PC2 loadings (e.g. "Lozi religion"), high PC3 loadings (e.g. "Folk or popular religion"), and high PC4 loadings (e.g. "Mbuti religion") are distributed across clusters, indicating that these components

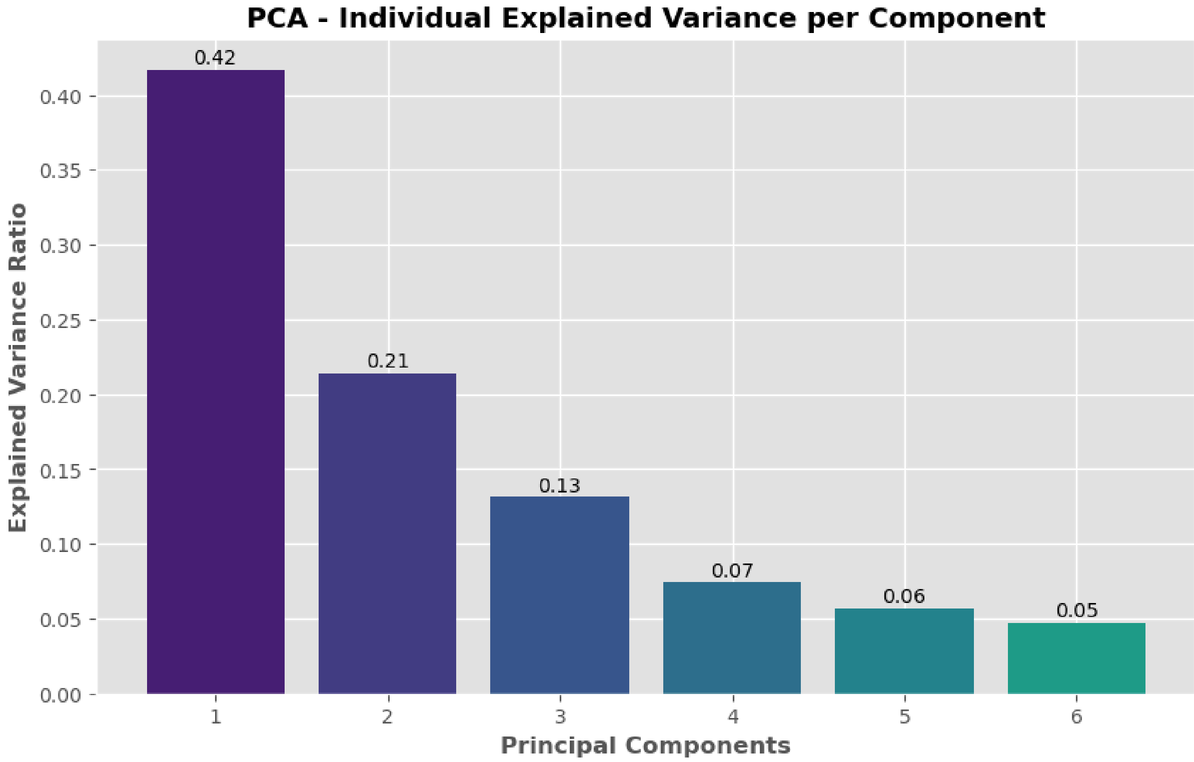

Figure 3.4: Detail of individual explained variance for each component after PCA.

	PC1	PC2	PC3	PC4	PC5	PC6
count	84.000000	84.000000	84.000000	84.000000	84.000000	84.000000
mean	-0.073713	-0.064585	-0.001990	-0.045523	0.007991	0.003126
std	0.080927	0.088469	0.109746	0.099754	0.109470	0.109719
min	-0.215929	-0.260623	-0.256341	-0.264448	-0.251260	-0.230697
25%	-0.130721	-0.123663	-0.079926	-0.132877	-0.067631	-0.061767
50%	-0.087904	-0.073145	-0.001236	-0.031336	0.001576	0.004020
75%	-0.031398	-0.004720	0.074665	0.026580	0.063422	0.061694
max	0.147730	0.168696	0.262981	0.122465	0.350254	0.264624

Figure 3.5: Summary statistics for each principal component.

Religious tradition	PC1	PC2	PC3	PC4	PC5	PC6
Church of Scotland (Presbyterian)	0.1477299207	-0.1829074256	-0.01455116995	-0.2019100004	0.03106411388	-0.01970791906
Cult of Angels	0.1208185525	-0.260623047	-0.0802048052	-0.03023278367	0.07859417522	-0.05486513106
Buddhism	0.1123232524	-0.166441881	-0.04640156972	-0.1733763667	0.04179347326	-0.00166358453
Serbian Orthodox Church	0.09432159232	-0.1049297025	-0.00193140718	-0.264447541	-0.01942129255	-0.02136281775
Chuntokyo Cult	0.07664686644	-0.2024812102	-0.2219638381	-0.03447174326	-0.1406570995	0.1819144904
Roman Catholic	0.07660173749	-0.1527310416	0.0369834631	-0.1427550852	0.2304639207	0.09936333258
Catholic	0.07420023276	-0.1507634073	-0.1067221855	-0.1822108462	0.00016823307	-0.00091222226
Islam	0.05324926382	-0.2264074987	-0.00478221845	-0.04272689115	0.08809153972	0.00701760735
Lamaism	0.05101887266	-0.1254129642	0.1956536427	-0.1545366201	-0.1385537428	0.04630810192
Christian	0.0458075516	-0.1908380256	-0.2563409859	0.013747135	0.1728375528	-0.06191970348
Traditional religion	0.04373924306	-0.09347527352	0.1777654164	-0.2090684919	-0.1928172971	-0.00951020196
Bori possession cult	0.03190842715	-0.06401927391	0.1713981189	-0.2224968422	-0.02217088354	-0.05840831657
Lauan religion	0.0174808099	-0.08827660953	0.03607953615	-0.2107276393	-0.00480942403	0.1126112496
Navajo religion	-0.01450639768	-0.1015540422	-0.1009085696	-0.05728653749	0.1969739873	0.04394094171
Kogi religion	-0.020943202	-0.2384622232	0.07540110509	0.09007714765	-0.1643261892	-0.0375160741
Pawnee religion	-0.0218263455	-0.07281666903	0.1538217553	-0.08497821762	0.1332836652	0.1900610258
Tlingit religion	-0.02896391379	-0.0169610182	0.07442012637	-0.1366875773	0.3502537827	0.04516934546
Kekesi cult rites	-0.02951223526	0.05222056603	-0.09932049032	-0.2476747636	-0.04280914886	-0.1489139627
Tongan religion	-0.03060585279	-0.1246443981	-0.1407011413	-0.01647688227	0.2162262213	0.05266351412
Traditional Akan religion	-0.03099954224	-0.1236552544	0.2405626515	0.00193718511	0.00861889869	0.1454490968
Mun religion	-0.03123392991	-0.2140293584	0.00858817127	0.07525665102	-0.1168234128	0.04078714606
Brahman-Animistic	-0.03145307327	-0.2040457549	0.01197519123	0.1003951207	0.00466124029	-0.1412082501
Maya religion	-0.03191183071	-0.1265088619	-0.1299034743	-0.06444423826	0.03460690276	0.05566449235
Folk Religion	-0.03246656828	-0.1122034004	-0.2256507031	-0.06524379023	-0.2512600834	0.09929472979

Figure 3.6: Sample of principal component loadings per religious tradition.

capture variability within and between clusters. With high loadings scores in PC5, the "Tlingit religion" was grouped within cluster 2, which includes similar traditional small-scale religions. This suggests that PC5 significantly contributes to the distinction of this cluster. In PC6, high loadings for "Kuna religion" also place it within cluster 2, which further reinforces the pattern of indigenous and animistic traditions clustering together. The religious tradition grouping distinction between cluster 1 and cluster 2 and 3 are relatively intuitive. However, the reasons behind the split of clusters 2 and 3 is more opaque. As expressed through the components obtained through PCA (41% variance), PC1 has all the traits of cluster 1, where all classical religions ("doctrinal mode") are grouped together. Inversely, PC2, PC3, and PC4, with low loadings scores for classical religions and a cumulative explained variance of 40%, represent traditional religions ("imagistic mode").

PC5 and PC6 account for smaller variance values in the model (11%), but these share a mix of low negative, low positive, and neutral loadings for both traditional religious and classical religions. These principal components represent the section of the modes of religiosity spectrum where doctrinal and imagistic modes share common ritual-level and society-level characteristics like high peak arousal moments [39]. To understand the global ritual-level and society-level significant differences between clusters, I performed ANOVA

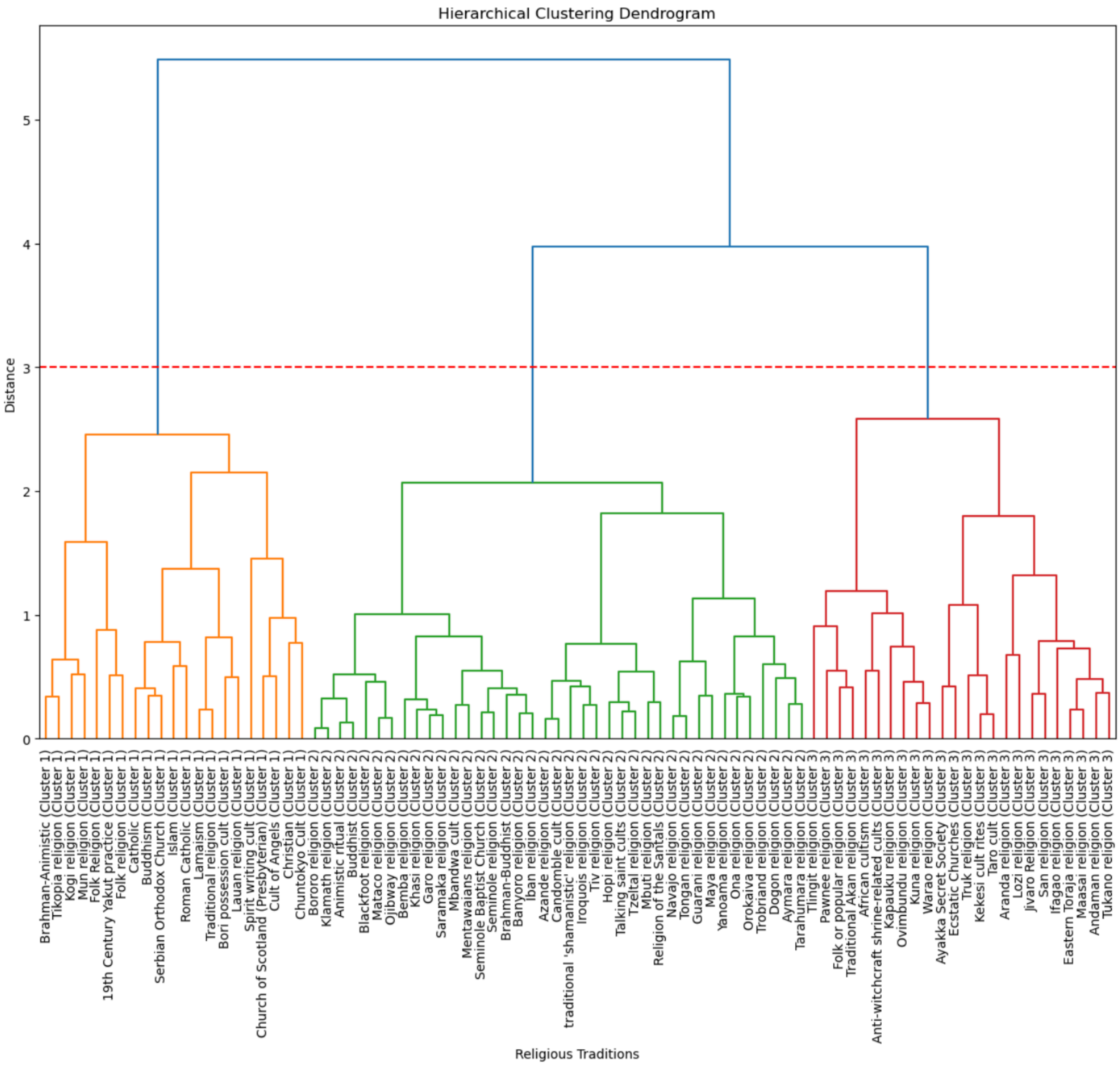

Figure 3.7: Dendrogram of the hierarchical clustering analysis at cutoff distance of 3.

across a set of predictor variables. The results on the ANOVA include F-statistics and p-values for each predictor variable, which indicate the significance of differences between clusters (Figure 3.8).

Ritual-Level & Society-Level Predictor Variables	F-statistic	p-value
Euphoric arousal over the course of the ritual for average participant	13.02	<.0001
Scale of shared religious ideas and practice perceived by members	14.31	<.0001
Degree of hierarchy in religious roles	15.34	<.0001
Influence of classical 'world' religions	21.9	<.0001
Intensity of peak dysphoric arousal (Average of 3 raters)	10.5	0.0001
Proportion of population identifying with classical religion	9.61	0.0002
Size of population that shares identifiable beliefs and practices	8.71	0.0004
Intensity of peak euphoric arousal moment (Average of 3 raters)	8.27	0.0005
Dysphoric arousal over the course of the ritual for average participant	7.97	0.0007
Typical frequency of participation for average participant	8.03	0.0007
Under what circumstances is one recruited to the religious tradition?	5.07	0.0084
Speechmaking	4.48	0.0143
Proselytizing individuals	3.82	0.0259
Perception of religious leaders by laity	3.46	0.036
Ritual duration category	2.52	0.0866
Is tradition mixed?	2.19	0.1188
Has identification with traditional religion ended?	0.95	0.3893
Leaders derive moral authority as embodiments of divine	0.91	0.4076
Distribution of ritual exegesis	0.35	0.7074
Dominant mode of acquisition of exegesis	0.25	0.7775

Figure 3.8: ANOVA results across ritual-level and society-level predictor variables.

Variables with substantial F-statistics and low p-values include the intensity of peak euphoric and dysphoric arousal, reported euphoric and dysphoric arousal over course of the ritual, recruitment circumstances, proselytising individuals, the scale of shared religious ideas, the population size sharing these beliefs, the perception of religious leaders, the degree of hierarchical roles, the influence of classical 'world' religions, and participation frequency. These variables greatly contribute to the differentiation of clusters. Non-significant predictors include the distribution and acquisition mode of exegesis, mixed traditions, divine authority of leaders, end of traditional religion identification, and ritual duration. The results corroborate the DMR theory, in that variations in emotional arousal, both euphoric and dysphoric, accurately predict the separation of religious traditions into different groups. Interestingly, the results also allow us to build upon DMR theory, because they shed light into the multitude of ritual-level and society-level factors contributing to distinguishing religious traditions into quantifiable categories. These factors allow us to formulate a relatively effective mapping of how religion is created and deployed in the human world. It allows us to bring to light a quantitatively valid way of understanding the spectrum of human religious phenomena at the ritual-level (collection of actions performed), at the population-level (scale of religious tradition), at the society-level (structure of religious hierarchies), and at the synergetic-level (influence and interaction between different religious traditions). Although these categories exist, they are not written in stone since the methodological approach employed in the preparation of the data and in the choice of analyses naturally leads to variations in categorisation.

To further elucidate the significant differences between each cluster pair across the predictor variables, I ran a Tukeys-HSD test and created a heatmap of p-adj values of cluster pairs for each variable (Figure 3.9).

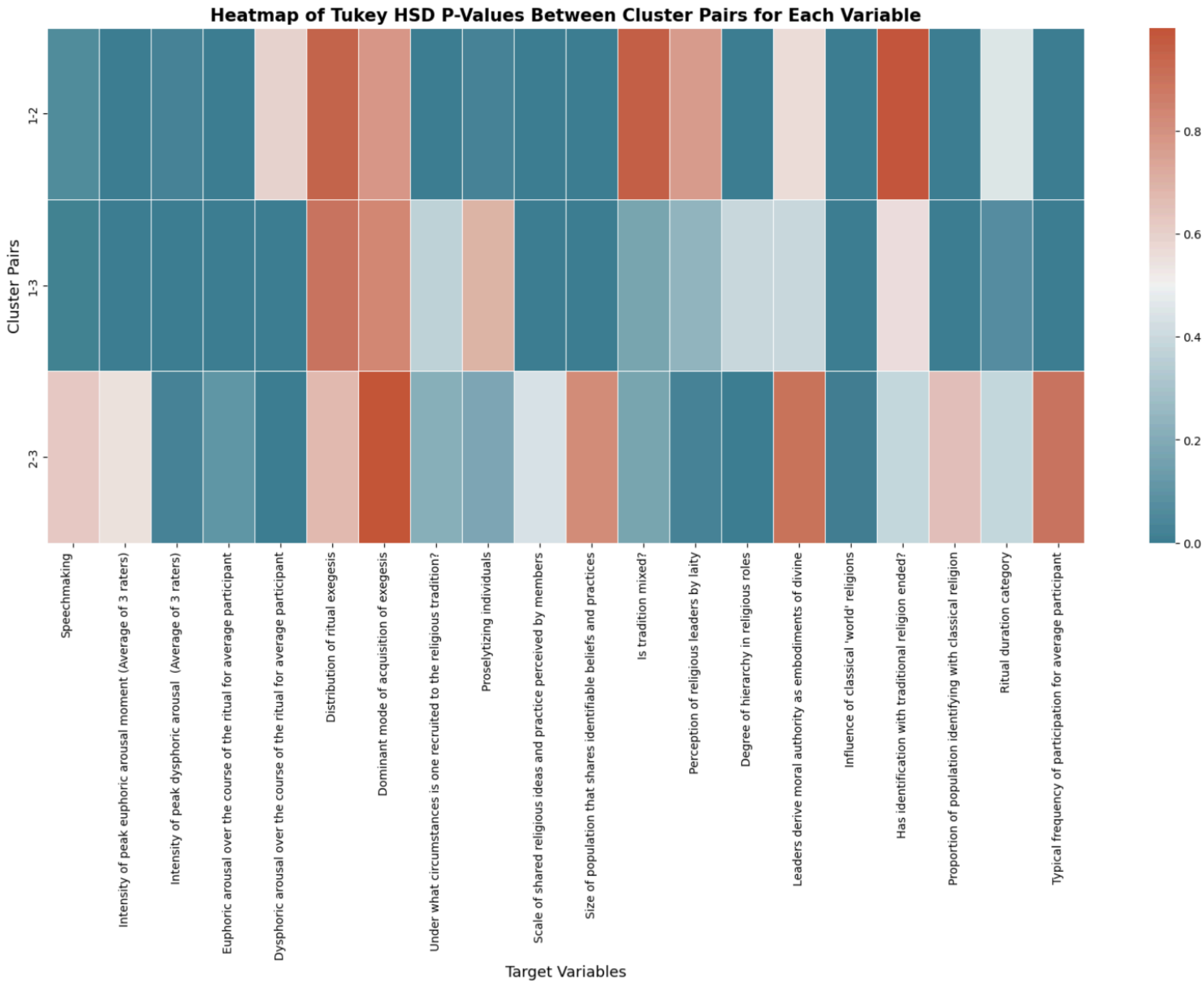

Figure 3.9: Heatmap of cluster pair p-adj values across predictor variables (3 clusters).

The heatmap gives further insights into cluster differences. Notably, it has allowed us to determine that more differences exist between cluster 1 and 2 and between cluster 1 and 3 than there are differences between clusters 2 and 3. This means that the clusters 2 and 3 could benefit from more granular clustering to better identify more subtle differences between groups of religious traditions. We can also observe that there are significant differences in emotional arousal, both euphoric and dysphoric, between groups 2 and 3. However, the peak intensity of the euphoric arousal moment is not significantly different between clusters 2 and 3. This means that higher values of average emotional arousal for the duration of the ritual, and peak dysphoric arousal moment are expected in cluster 3 than in cluster 2. The degree of religious hierarchy in group 2 and also is also expected to be much greater than in group 3. Therefore, there seems to be a direct inverse relationship between average emotional arousal and the degree of hierarchy between clusters. Other notable interactions exist, but will be discussed at length in my masters 2 research project. Before concluding on this preliminary round of results, it is also interesting to note that by decreasing the cutoff distance in the hierarchical clustering analysis (e.g 1.8), we are able to increase the number of clusters, leading to a more granular distinction of religious traditions. However, increasing the complexity of clustering decreases our ability to straightforwardly interpret what distinguishes groups (Figure 3.10). Due to space and time constraints, Ive decided to delve into more granular clusterization and heatmap results (Figure 3.11) in my masters 2 research project.

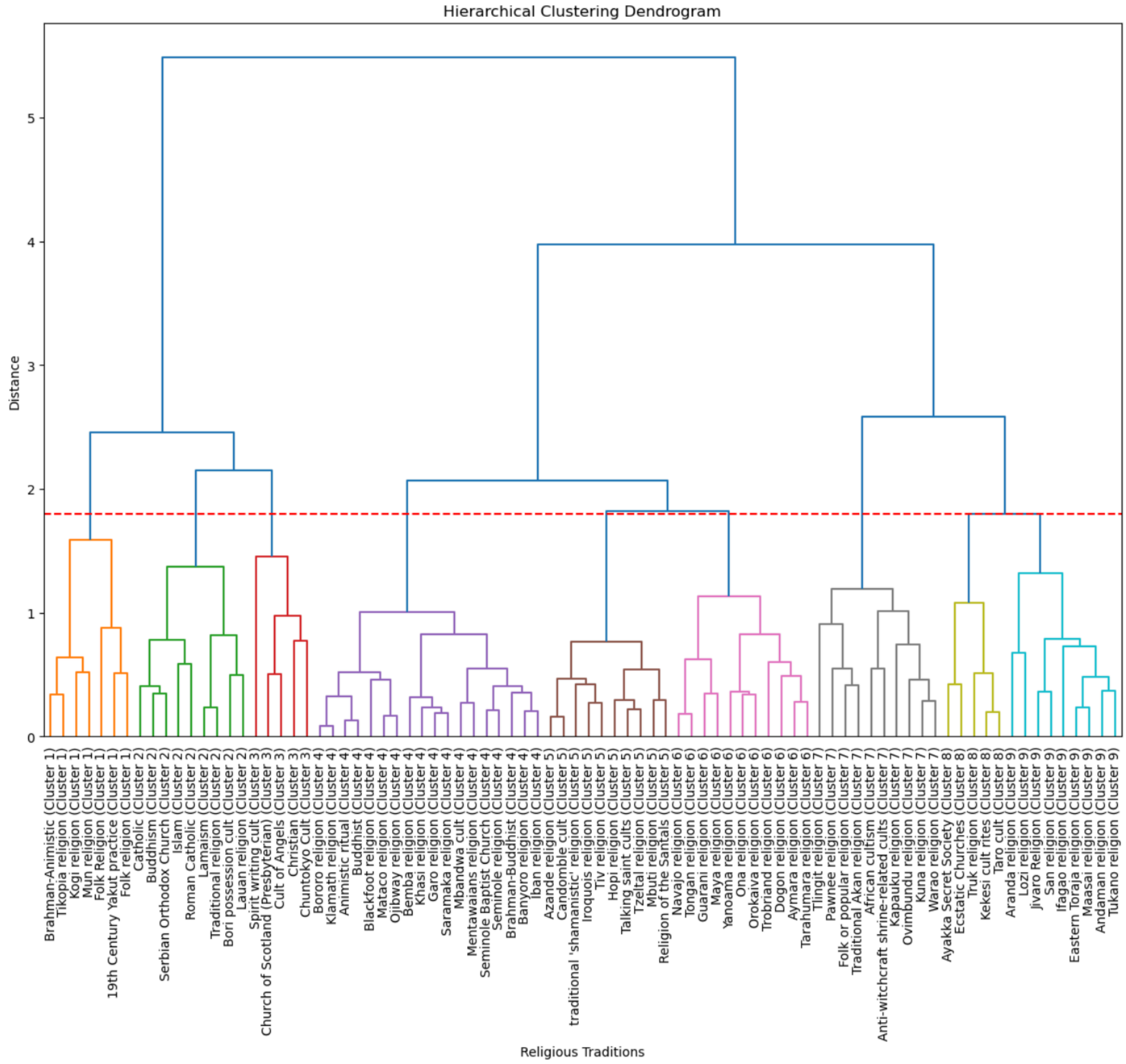

Figure 3.10: Hierarchical clustering dendrogram at a cutoff distance of 1.8 (9 clusters).

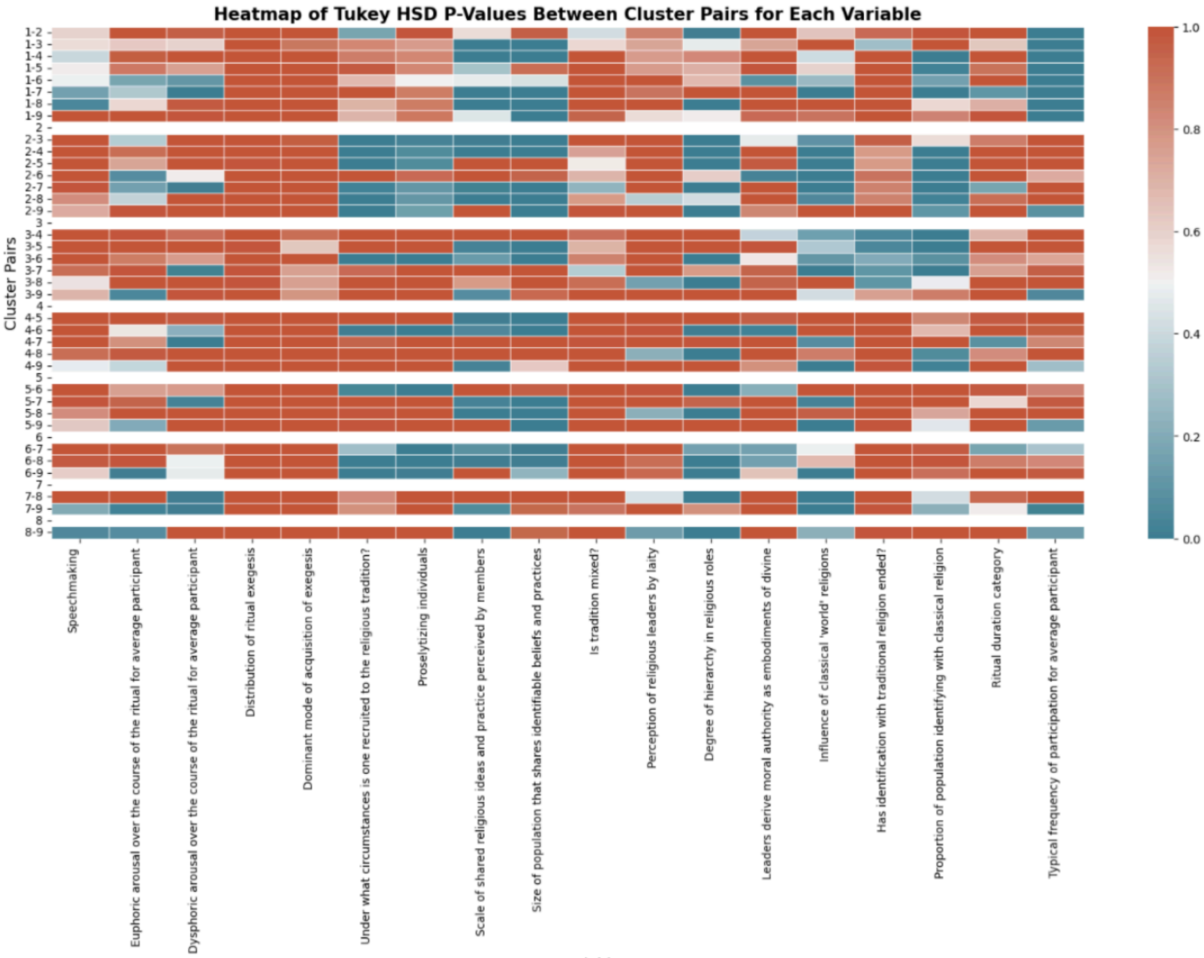

Figure 3.11: Heatmap of cluster pair p-adj values across predictor variables (9 clusters).

Chapter 4

Further analysis

4.1 Machine learning algorithms

To expand on the results thus far identified in this research project, the use of specific machine learning algorithms could be of great utility for predicting which ritual actions are most likely to be performed if we are only given knowledge of the socio-religious organisation of a specific society. In addition, machine learning models could further help in identifying which predictor variables are most important in determining the overall shape of religious clusters. With this in mind, two distinct approaches could be explored, each with a specific set of advantages and disadvantages : supervised learning, and unsupervised learning [13].

Supervised learning uses labelled data to train models, which makes it ideal for predicting known outcomes like cluster membership or predicting the presence of specific ritual components when the degree in hierarchical roles is high or low in various religious traditions [12]. For example, algorithms like "Random Forests" [43][35] and "Gradient Boosting" [7] handle high-dimensional data and model complex interactions between variables. Random forests reduce modelling errors such as overfitting. On the other hand, gradient boosting builds a sequential series of decision trees (weak learners) to improve prediction performance. By and large, these methods could be extremely useful to identify which factors are most influential (importance scoring of each variable) in distinguishing different religious traditions and ritual components. Another method which could be helpful is "Support Vector Machines" (SVM), which is used for classification tasks. This technique could help me construct precise classifications of my clusters [17][66]. Contrary to supervised learning, unsupervised learning identifies patterns within the data without the use of labelled outcomes. Unsupervised learning is therefore highly efficient at exploring data unconstrained. A common algorithm like "Density-Based Spatial Clustering of Applications with Noise", or DBSCAN, does not need a predefined number of clusters and can identify smaller, more densely packed clusters to uncover subtle differences in my religious traditions groupings [31][37][42].

Which machine learning methods are to be incorporated into my masters 2 research project remains to be decided, but I would ideally like to incorporate a supervised method and an unsupervised method so as to test both approaches. Combining both approaches will help me gain further insight into the religious traditions clustering and will test approaches which have never been tested in the context of DMR theory, nor in the context of research into the evolution and structure of religions. Using both approaches in a single study would provide complementary results, and help me identify the best path forward in my efforts to plan and execute further research inquiries.

Conclusion

In this short, but hopefully comprehensive research project, I aimed to build upon the foundational work of Whitehouse [54] and Whitehouse and Atkinson [1] by furthering our understanding of DMR theory. I aimed not only to replicate their findings but also to extend them through the use of advanced statistical methods and visualisation techniques. One of the primary contributions of my work is the detailed mention of the entire data cleaning and preparation process using Pythons pandas library. This ensured a high level of data consistency and addressed the importance of providing more transparency in the data handling of complex cross-cultural research, which is often altogether lacking from research papers.

The use of a cosine similarity matrix, PCA, and hierarchical clustering analysis (ward linkage method) distinguishes my methodological approach from Whitehouse and Atkinsons 2011 paper [1]. I was notably able to manage the high-dimensionality of my dataset effectively, which revealed underlying groupings of religious traditions. By capturing the directionality of data points rather than their magnitude, the cosine similarity approach provided a more coherent representation of the relationships between different religious traditions. The principal components explained a substantial portion of the variance (94%), and hierarchical clustering with the ward linkage method offered an intuitive way to group religious traditions. The method's ability to visualise clusters through dendrograms and adjust the granularity of clustering without presetting the number of clusters proved efficient (although it is important to note that the dendrograms do not imply any phylogenic relationships). I was able to show how different traditions relate to one another across the spectrum of doctrinal and imagistic modes, something that binary classifications of ritual-level and society-level data alone could not achieve. To my knowledge, the approach of setting cut-off distances to produce different levels of granularity in groups of religious traditions is completely novel in the study of religious morphology. Through statistical validation using one-way ANOVA and Tukey's HSD tests, I compared clusters across various predictor variables, and identified significant differences in the factors driving distinctions between religious tradition groups. This provided empirical support for the DMR theory, and goes beyond the initial findings by expanding the theoretical framework to incorporate a broader range of predictor variables. Lastly, the use of heatmaps to visualise Tukeys HSD p-adj values was another key contribution of my research. These tools allowed for an intuitive comparison of pairwise differences between clusters. This enabled a novel way of viewing the strength of the significant differences between clusters across a vast range of ritual-level and society-level predictor variables. Visualisation is an important aspect of data analysis, which makes the results accessible and more interpretable. Unfortunately, advanced visualisation is oftentimes missing from journal articles, so much of the time spent on this research project was dedicated to producing explicit and intuitive visual representations of the findings rather than to write out the statistical results in numerical form.

To conclude, I believe this research project brings a fresh perspective to the study of the formation of religious traditions, and provides insights into the cultural mechanisms that differentiate them. By building on the work of Whitehouse and Atkinson [1], I aspire to continue exploring the dataset using machine learning models and to publish my findings in the near future.

Bibliography

[1] Quentin D. Atkinson and Harvey Whitehouse. "The cultural morphospace of ritual form: Examining modes of religiosity cross-culturally". In: *Evolution and Human Behavior* 32.1 (Jan. 1, 2011), pp. 50–62. DOI: 10.1016/j.evolhumbehav.2010.09.002. URL: https://www.sciencedirect.com/science/article/pii/S1090513810001029.

[2] Fredrik Barth. "The Guru and the Conjurer: Transactions in Knowledge and the Shaping of Culture in Southeast Asia and Melanesia". In: *Man* 25.4 (1990). Publisher: [Wiley, Royal Anthropological Institute of Great Britain and Ireland], pp. 640–653. DOI: 10.2307/2803658. URL: https://www.jstor.org/stable/2803658.

[3] Maurice Bloch. "Why Religion Is Nothing Special but Is Central". In: *Philosophical Transactions: Biological Sciences* 363.1499 (2008). Publisher: The Royal Society, pp. 2055–2061. URL: https://www.jstor.org/stable/20208610.

[4] Pascal Boyer. *Cognitive aspects of religious symbolism*. CUP Archive, 1993.

[5] Pascal Boyer. *Religion explained: The evolutionary origins of religious thought*. Hachette UK, 2007.

[6] Pascal Boyer. *The naturalness of religious ideas: A cognitive theory of religion*. Univ of California Press, 2023.

[7] Peter Bühlmann. "Boosting for High-Dimensional Linear Models". In: *The Annals of Statistics* 34.2 (2006). Publisher: Institute of Mathematical Statistics, pp. 559–583. URL: https://www.jstor.org/stable/25463430.

[8] *eHRAF World Cultures*. URL: https://ehrafworldcultures.yale.edu/.

[9] Mircea Eliade. *Shamanism: Archaic techniques of ecstasy*. Princeton University Press, 2024.

[10] Mircea Eliade. *The sacred and the profane: The nature of religion*. Vol. 81. Houghton Mifflin Harcourt, 1959.

[11] Roland Fischer. "A cartography of the ecstatic and meditative states". In: *Leonardo* 6.1 (1973), pp. 59–66.

[12] Hongjuan Gao, Guohua Geng, and Wen Yang. "Sex Determination of 3D Skull Based on a Novel Unsupervised Learning Method". In: *Computational and mathematical methods in medicine* 2018 (2018). In collab. with Reinoud Maex. Place: United States Publisher: Hindawi, pp. 4567267–10. DOI: 10.1155/2018/4567267.

[13] Matthew S. Goldberg et al. *Machine Learning Approach*. Institute for Defense Analyses, 2018, pp. 29–32. URL: https://www.jstor.org/stable/resrep22894.7.

[14] P. Graf and D. L. Schacter. "Implicit and explicit memory for new associations in normal and amnesic subjects". In: *Journal of Experimental Psychology. Learning, Memory, and Cognition* 11.3 (July 1985), pp. 501–518. DOI: 10.1037//0278-7393.11.3.501.

[15] R. R. Griffiths et al. "Psilocybin can occasion mystical-type experiences having substantial and sustained personal meaning and spiritual significance". In: *Psychopharmacology* 187.3 (Aug. 2006), 268–283, discussion 284–292. DOI: 10.1007/s00213-006-0457-5.

[16] Joseph Havens. "A Working Paper: Memo on the Religious Implications of the Consciousness-Changing Drugs (LSD, Mescalin, Psilocybin)". In: *Journal for the Scientific Study of Religion* 3.2 (1964). Publisher: [Society for the Scientific Study of Religion, Wiley], pp. 216–226. DOI: 10.2307/1384511. URL: https://www.jstor.org/stable/1384511.

[17] Joseph T. Hefner and Stephen D. Ousley. "Statistical Classification Methods for Estimating Ancestry Using Morphoscopic Traits". In: *Journal of forensic sciences* 59.4 (2014). Place: United States Publisher: Blackwell Publishing Ltd, pp. 883–890. DOI: 10.1111/1556-4029.12421. URL: https://api.istex.fr/ark:/67375/WNG-G188Q31P-T/fulltext.pdf.

[18] Joseph Henrich. "The evolution of costly displays, cooperation and religion: credibility enhancing displays and their implications for cultural evolution". In: *Evolution and Human Behavior* 30.4 (July 1, 2009), pp. 244–260. DOI: 10.1016/j.evolhumbehav.2009.03.005. URL: https://www.sciencedirect.com/science/article/pii/S1090513809000245.

[19] Lawrence Hirschfeld. *Mapping the Mind: Domain Specificity in Cognition and Culture*. Apr. 29, 1994. DOI: 10.1017/CBO9780511752902.009.

[20] William Irons. "Religion as a hard-to-fake sign of commitment". In: *Evolution and the capacity for commitment* 292309 (2001).

[21] P. J. John E. Pfeiffer. "The creative explosion. An inquiry into the origins of art and religion." In: *Antiquity* 58.223 (July 1984), pp. 136–137. DOI: 10.1017/S0003598X00051619. URL: https://www.cambridge.org/core/journals/antiquity/article/john-e-pfeiffer-the-creative-explosion-an-inquiry-into-the-

origins-of-art-and-religion-new-york-harper-row-1982-270-pp-16-colour-pls-80-intext-illustrations-1850/455539F9FF0156BBAE461DCAB7583122.

[22] Rohan Kapitány, Christopher Kavanagh, and Harvey Whitehouse. "Ritual morphospace revisited: the form, function and factor structure of ritual practice". In: *Philosophical Transactions: Biological Sciences* 375.1805 (2020). Publisher: Royal Society, pp. 1–10. URL: https://www.jstor.org/stable/26991561.

[23] Cecelia F. Klein et al. "The Role of Shamanism in Mesoamerican Art: A Reassessment". In: *Current Anthropology* 43.3 (2002). Publisher: [The University of Chicago Press, Wenner-Gren Foundation for Anthropological Research], pp. 383–419. DOI: 10.1086/339529. URL: https://www.jstor.org/stable/10.1086/339529.

[24] E. Thomas Lawson and Robert N. McCauley. *Rethinking religion: Connecting cognition and culture*. Rethinking religion: Connecting cognition and culture. Pages: ix, 194. New York, NY, US: Cambridge University Press, 1990. ix, 194.

[25] Ioan Myrddin Lewis. *Ecstatic religion : a study of shamanism and spirit possession*. Third ed. Country: GB 22 cm. Bibliogr. p. 185-194. Index. London: Routledge, 2003. 200 pp.

[26] Pierre Lienard and Pascal Boyer. "Whence Cultural Rituals? A Cultural Selection Model of Ritualized Behavior". In: *American Anthropologist* 108 (Dec. 1, 2006). DOI: 10.1525/aa.2006.108.4.814.

[27] Roland Littlewood. "McCauley, Robert N., and E. Thomas Lawson: Bringing Ritual to Mind. Psychological Foundations of Cultural Forms". In: *Anthropos* 100.2 (2005), pp. 622–623. DOI: 10.5771/0257-9774-2005-2-622.

[28] Ralph G. Locke and Edward F. Kelly. "A Preliminary Model for the Cross-Cultural Analysis of Altered States of Consciousness". In: *Ethos* 13.1 (1985). Publisher: [American Anthropological Association, Wiley], pp. 3–55. URL: https://www.jstor.org/stable/640008.

[29] Arnold M. Ludwig. "Altered states of consciousness". In: *Archives of General Psychiatry* 15.3 (1966). Place: US Publisher: American Medical Association, pp. 225–234. DOI: 10.1001/archpsyc.1966.01730150001001.

[30] David Lukoff, Robert Zanger, and Francis Lu. "Transpersonal psychology research review: Psychoactive substances and transpersonal states." In: *Journal of Transpersonal Psychology* (Jan. 1, 1990), pp. 107–148.

[31] Jasmin Malki et al. "Cluster analyses of association of weather, daily factors and emergent medical conditions". In: *Collegium antropologicum* 37.1 (2013). Place: Croatia, pp. 189–194.

[32] Robert N. McCauley and E. Thomas Lawson. *Bringing Ritual to Mind: Psychological Foundations of Cultural Forms*. 1st ed. Pages: xiiixiii. Cambridge: University Press, 2002. DOI: 10.1017/CBO9780511606410.

[33] M. D. Merlin. "Archaeological Evidence for the Tradition of Psychoactive Plant Use in the Old World". In: *Economic Botany* 57.3 (2003). Publisher: New York Botanical Garden Press, pp. 295–323. URL: https://www.jstor.org/stable/4256701.

[34] S. J. Mithen. "From Ohalo to Çatalhöyük: the development of religiosity during the early prehistory of Western Asia, 20,000-7000 BC". In: ed. by H. Whitehouse and L. H. Martin. Walnut Creek CA: AltaMira Press, 2004, pp. 17–43. URL: https://centaur.reading.ac.uk/3840/.

[35] David Muchlinski et al. "Comparing Random Forest with Logistic Regression for Predicting Class-Imbalanced Civil War Onset Data". In: *Political Analysis* 24.1 (2016). Publisher: [Oxford University Press, Society for Political Methodology], pp. 87–103. URL: https://www.jstor.org/stable/24573207.

[36] Douglass Price-Williams and Dureen J. Hughes. "Shamanism and Altered States of Consciousness". In: *Anthropology of Consciousness* 5.2 (1994), pp. 1–15. DOI: 10.1525/ac.1994.5.2.1.

[37] Marco Ramazzotti, Paolo Massimo Buscema, and Giulia Massini. "Landscape Archaeology and Artificial Intelligence: the Neural Hypersurface of the Mesopotamian Urban Revolution". In: *CyberResearch on the Ancient Near East and Neighboring Regions*. Ed. by Vanessa Bigot Juloux, Amy Rebecca Gansell, and Alessandro di Ludovico. Case Studies on Archaeological Data, Objects, Texts, and Digital Archiving. Brill, 2018, pp. 60–82. URL: https://www.jstor.org/stable/10.1163/j.ctv4v349g.11.

[38] Roy A. Rappaport. *Ritual and Religion in the Making of Humanity*. Cambridge Studies in Social and Cultural Anthropology. Cambridge: Cambridge University Press, 1999. DOI: 10.1017/CBO9780511814686. URL: https://www.cambridge.org/core/books/ritual-and-religion-in-the-making-of-humanity/99F1AE57E9E2ACFD4019ED9A6DA38036.

[39] Naomi Irit Richman. "What does it feel like to be post-secular? Ritual expressions of religious affects in contemporary renewal movements". In: *International Journal of Philosophy and Theology* 79.3 (May 27, 2018), pp. 295–310. DOI: 10.1080/21692327.2018.1434011. URL: https://doi.org/10.1080/21692327.2018.1434011.

[40] Marlene Dobkin de Rios et al. "The Influence of Psychotropic Flora and Fauna on Maya Religion [and Comments and Reply]". In: *Current Anthropology* 15.2 (June 1974). Publisher: The University of Chicago Press, pp. 147–164. DOI: 10.1086/201452. URL: https://www.journals.uchicago.edu/doi/abs/10.1086/201452.

[41] Uffe Schjoedt et al. "Cognitive resource depletion in religious interactions". In: *Religion, Brain & Behavior* 3.1 (Feb. 1, 2013), pp. 39–55. DOI: 10.1080/2153599X.2012.736714. URL: https://doi.org/10.1080/2153599X.2012.736714.

[42] Friedhelm Schwenker and Edmondo Trentin. *Partially Supervised Learning: First IAPR TC3 Workshop, PSL 2011, Ulm, Germany, September 15-16, 2011, Revised Selected Papers*. In collab. with Friedhelm Schwenker and Edmondo Trentin. 1st ed. Vol. 7081. LNCS sublibrary. SL 7, Artificial intelligence. Netherlands: Springer Nature, 2012.

[43] Tao Shi and Steve Horvath. "Unsupervised Learning with Random Forest Predictors". In: *Journal of Computational and Graphical Statistics* 15.1 (2006). Publisher: [American Statistical Association, Taylor & Francis, Ltd., Institute of Mathematical Statistics, Interface Foundation of America], pp. 118–138. URL: https://www.jstor.org/stable/27594168.

[44] Richard Sosis and Candace Alcorta. "Signaling, solidarity, and the sacred: The evolution of religious behavior". In: *Evolutionary Anthropology: Issues, News, and Reviews: Issues, News, and Reviews* 12.6 (2003), pp. 264–274.

[45] Richard Sosis, Howard C Kress, and James S Boster. "Scars for war: Evaluating alternative signaling explanations for cross-cultural variance in ritual costs". In: *Evolution and human behavior* 28.4 (2007), pp. 234–247.

[46] Dan Sperber. *Explaining Culture: A Naturalistic Approach*. Wiley, Nov. 6, 1996. 188 pp.

[47] Dan Sperber and Lawrence A. Hirschfeld. "The cognitive foundations of cultural stability and diversity". In: *Trends in Cognitive Sciences* 8.1 (Jan. 1, 2004), pp. 40–46. DOI: 10.1016/j.tics.2003.11.002. URL: https://www.sciencedirect.com/science/article/pii/S1364661303003140.

[48] Victor Turner. *Dramas, Fields, and Metaphors: Symbolic Action in Human Society*. Cornell University Press, 1974. URL: https://www.jstor.org/stable/10.7591/j.ctv75d7df.

[49] Victor Turner, Roger Abrahams, and Alfred Harris. *The Ritual Process: Structure and Anti-Structure*. New York: Routledge, Dec. 31, 1995. 232 pp. DOI: 10.4324/9781315134666.

[50] Roger Walsh and Charles S Grob. *Higher wisdom: Eminent elders explore the continuing impact of psychedelics*. State University of New York Press, 2005.

[51] H. Whitehouse. *Theorizing religions past*. Accepted Manuscript. AltaMira Press, 2004. URL: https://ora.ox.ac.uk/objects/uuid:f60a5714-0f43-496d-92ba-b4cbe823ecb4.

[52] Harvey Whitehouse. *Arguments and icons: divergent modes of religiosity / Harvey Whitehouse*. Oxford: University Press, 2000.

[53] Harvey Whitehouse. "Memorable Religions: Transmission, Codification and Change in Divergent Melanesian Contexts". In: *Man* 27.4 (1992). Publisher: [Wiley, Royal Anthropological Institute of Great Britain and Ireland], pp. 777–797. DOI: 10.2307/2804174. URL: https://www.jstor.org/stable/2804174.

[54] Harvey Whitehouse. *Modes of religiosity: A cognitive theory of religious transmission*. Rowman Altamira, 2004.

[55] Harvey Whitehouse. "Modes of Religiosity: Towards a Cognitive Explanation of the Sociopolitical Dynamics of Religion". In: *Method & Theory in the Study of Religion* 14.3 (2002). Publisher: Brill, pp. 293–315. URL: https://www.jstor.org/stable/23550000.

[56] Harvey Whitehouse. "Religious reflexivity and transmissive frequency". In: *Social Anthropology* 10.1 (Feb. 2002), pp. 91–103. DOI: 10.1017/S0964028202000071.

[57] Harvey Whitehouse. "Rites of Terror: Emotion, Metaphor and Memory in Melanesian Initiation Cults". In: *The Journal of the Royal Anthropological Institute* 2.4 (1996). Publisher: [Wiley, Royal Anthropological Institute of Great Britain and Ireland], pp. 703–715. DOI: 10.2307/3034304. URL: https://www.jstor.org/stable/3034304.

[58] Harvey Whitehouse. "The Cognitive Foundations of Religiosity". In: Jan. 1, 2005.

[59] Harvey Whitehouse. "Transmissive Frequency, Ritual, and Exegesis". In: *Journal of Cognition and Culture* 1.2 (2001). Publisher: Brill Academic Publishers, pp. 167–181. DOI: 10.1163/156853701316931399.

[60] Harvey Whitehouse and James Laidlaw. *Religion, Anthropology, and Cognitive Science*. Carolina Academic Press, 2007. 316 pp.

[61] Harvey Whitehouse and James Laidlaw. *Ritual and Memory: Toward a Comparative Anthropology of Religion*. Rowman Altamira, 2004. 236 pp.

[62] Harvey Whitehouse, Emma Stewart, and Rebekah Richert. "Memory and Analogical Thinking in High-Arousal Rituals". In: Jan. 1, 2005.

[63] Harvey Whitehouse et al. "Modes of Religiosity and the Evolution of Social Complexity at Çatalhöyük". In: *Religion at Work in a Neolithic Society: Vital Matters*. Ed. by Ian Hodder. Cambridge: Cambridge University Press, 2014, pp. 134–156. DOI: 10.1017/CBO9781107239043.008. URL: https://www.cambridge.org/core/books/religion-at-work-in-a-neolithic-society/modes-of-religiosity-and-the-evolution-of-social-complexity-at-catalhoyuk/6328A5C9CA3D9ECC52770C6A20166E71.

[64] Harvey Whitehouse et al. "The role for simulations in theory construction for the social sciences: case studies concerning Divergent Modes of Religiosity". In: *Religion, Brain & Behavior* 2.3 (Oct. 1, 2012), pp. 182–201. DOI: 10.1080/2153599X.2012.691033. URL: https://doi.org/10.1080/2153599X.2012.691033.

[65] Clark Wissler. *The American Indian: An Introduction to the Anthropology of the New World*. Oxford University Press, 1922. 546 pp.

[66] Imam Yuadi et al. "Digital forensics for skulls classification in physical anthropology collection management". In: *Computers, materials & continua* 68.3 (2021). Place: Henderson Publisher: Tech Science Press, pp. 3979–3995. DOI: 10.32604/cmc.2021.015417.

List of Figures