



From Quarry to Query: Statistical Deconstruction of Mining Heritage Tourism at Barr Conglomerate, India

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Abstract

This research evaluates the viability of mining heritage tourism (MHT) as a strategic pathway for sustainable regional development, using the Barr Conglomerate in Pali, Rajasthan, as a case exemplar. Positioned within the broader discourse on reactivating post-industrial landscapes, the study adopts a mixed-method design that integrates perceptual surveys ($n = 440$) with multivariate tools including Exploratory Factor Analysis (EFA), Principal Component Analysis (PCA), and Discriminant Function Analysis (DFA) to decode stakeholder attitudes and assess spatially differentiated tourism potential. Eight experiential themes emerge from the PCA, encompassing infrastructure adequacy, site distinctiveness, safety perception, interpretive depth, and cultural resonance. While respondents recognize Barr's strong geo-heritage value and visual appeal, persistent deficiencies in accessibility, safety management, and narrative infrastructure constrain its tourism readiness. Findings demonstrate the site's potential to be repositioned through themed geo-trails, multi-sensory interpretive environments, and community-based tourism models. Segment-specific discriminant profiles reveal differing perceptual priorities across tourists, residents, and experts, underscoring the need for tailored branding strategies rooted in geological authenticity, memory landscapes, and living community heritage. Benchmarking against Rajasthan's regional tourism motivations adventure, authenticity, storytelling, and geotourism further highlights the competitive niche Barr can occupy within state-level heritage circuits. The study proposes a scalable, data-driven framework that couples perceptual clustering with participatory planning, offering a replicable model for transforming abandoned extraction sites into culturally rich, economically resilient, and ecologically responsive heritage destinations.

1. Introduction

The shutdown of extractive industries has imposed an enduring imprint on the physical environments and socio-economic characteristics of areas previously influenced by mining [1-4]. These post-industrial landscapes formerly productive but now degraded by mining are increasingly being reimagined as landscapes of cultural memory, ecological restoration, and economic growth [5-6]. The conversion of derelict mines into heritage tourism destinations (HTDs) represents a paradigm shift in societal attitudes toward their industrial heritage not as useless wastelands but as cultural and economic resources

and potentials waiting to be reinvented [6-9]. Globally, mining heritage tourism (MHT) is a dynamic niche within cultural tourism, fostering place-making, community resilience, and sustainable reuse [3, 10]. Leading examples such as the Wieliczka Salt Mine in Poland [11], the Ironbridge Gorge in the UK [12], and the Zollverein Coal Mine in Germany [13] have demonstrated that industrial dereliction and ruins can be transformed into UNESCO-listed heritage sites, learning centers, and economic drivers [14-15]. These sites have leveraged a combination of storytelling, investment in preservation, and



planned tourism development to create value beyond resource extraction [16-18]. In contrast, India's experience is characterized by a chronic underdevelopment of mining heritage assets, with most former mining sites remaining neglected, ecologically polluted, or awaiting formal recognition [19]. Despite India's extensive and diverse history of mineral extraction, systematic recording, preservation, and valorization of such sites are marginal in national tourism and heritage policy discourse [20]. This deficiency is especially evident in states such as Rajasthan, where rich geo-heritage coexists with post-industrial amnesia. One such overlooked site is the Barr Conglomerate in Rajasthan's Pali district [21]. Known for its remarkable sedimentary features and historical significance, the site holds geological, cultural, and educational importance. However, it remains invisible in the tourism sector due to a lack of formal recognition, interpretive facilities, or integrated tourism planning [21]. Additionally, characteristic post-mining features such as uneven terrain, abandoned pits, loose overburden, and unstable slopes continue to affect site safety and visitor mobility, emphasizing the need for structured rehabilitation before tourism development (according to DGMS and IBM guidelines). In this context, the present research positions the Barr Conglomerate as a "potential-in-waiting" landscape one capable of supporting regional development if its heritage value is decoded, interpreted, and communicated through evidence-based strategies.

1.1. From Extraction to Interpretation: Theoretical Imperatives

The transformation from extractive landscapes to HTD is not mere physical reuse—but rather a complex dance among spatial memory, cultural meaning, and political economy [22]. Industrial decline, as argued in *Geographies of Post-Industrial Place* [5], produces more than just infrastructure; it produces contested narratives of labour, loss, and identity. Thus, the valorisation of mining heritage requires a methodologically plural and contextually nuanced approach, which takes into consideration both material heritage and stakeholder perceptions [21, 23]. This is supported by Varriale et al. [14], who suggest that closed mines are studied not just as material heritage but as underground built heritage (UBH) a form which consists of spatial typology, memory systems, and reuse potential [24-26]. The UBH conceptual framework offers a multi-scalar method for

assessing mining landscapes as repositories of history, risk, and opportunity [24-25]. In addition, the Council of Europe and ICOMOS standards highlight integrated conservation and adaptive reuse as primary approaches to post-industrial regeneration [27]. These standards advocate stakeholder-led, sustainable systems that maintain authenticity and integrity principles highly relevant to Barr, where the absence of interpretive identity and narrative coherence limits both its experiential appeal and its tourism-branding potential.

1.2. MHT: Global Trends, Local Voids

Although industrial heritage is gaining international recognition from UNESCO and ERIH (European Route of Industrial Heritage), it remains underrepresented on the World Heritage List, with only about 6% of listed sites belonging to this category [28]. In India, this gap is further widened by bureaucratic fragmentation and the absence of thematic tourism circuits that integrate industrial history, geo-heritage, and cultural narratives [3]. Over recent decades, sustainability discourse has reshaped perspectives on tourism at heritage sites [29-32]. According to Pardo Abad [28], the valuation of industrial heritage must extend beyond aesthetic or emotional appeal to include ecological restoration, socio-economic inclusion, and cultural connectivity [33]. This necessitates new assessment models that reconcile conservation with tourist interaction, particularly in post-industrial areas where environmental damage and livelihood disruptions persist. However, unlike successful international examples that have developed strong interpretive brands, Indian mining landscapes—including Barr—still lack signature stories, symbolic identity cues, or place-based narratives that can form the foundation of a coherent destination image.

1.3. Why Barr Conglomerate?

The Barr Conglomerate offers a special case for such examination. Situated close to Pali a locality already at the periphery of Rajasthan's popular tourism economy the place is abundant in stratified sedimentary records, past mining activities, and residual cultural landscapes [21]. However, in contrast to other Indian geo-heritage sites, Barr does not have a formal designation, interpretive planning, or tourism integration [21]. Its current physical condition marked by erosion gullies, uneven pathways, and limited signage further constrains accessibility and visitor comfort, highlighting a need for structured interventions.

Barr thus provides an ideal testing ground to examine whether perceptual analytics, environmental assessment, and stakeholder modelling can collectively shape sustainable development trajectories and whether its latent geological identity can evolve into a distinctive tourism brand.

1.4. Towards a Statistical Deconstruction of Heritage Potential

Expanding on the findings of Nag [3], who employed mixed methods to evaluate Dhori Mines in Jharkhand, this research extends the analytical depth by statistically deconstructing tourism potential at Barr. A suite of analytical tools exploratory factor analysis (EFA), principal component analysis (PCA), discriminant function analysis (DFA), Kolmogorov Smirnov tests, and canonical territorial mapping is applied to identify latent perceptual dimensions, group-specific variations, and strategic clusters shaping tourism feasibility. These techniques are not merely mathematical enhancements; they reveal concealed structures of perception, classify stakeholders into meaningful groups, and model tourism competitiveness from scratch [34]. For instance, DFA distinguishes between conservation-oriented and experience-oriented visitor types, while PCA condenses multi-dimensional variables into interpretable indices. Such statistical innovation is particularly important in post-industrial contexts like Barr, where tourism planning must integrate safety, branding, community aspirations, and environmental constraints under a coherent decision-making framework.

1.5. Research Objectives and Questions

Against this background, the study examines the following research questions:

- RQ1. What underlying factors organise stakeholder and visitor attitudes regarding the tourism potential of Barr Conglomerate?
- RQ2. How do various stakeholder groups residents, tourists, planners—value site characteristics and development priorities differently?
- RQ3. Can a factor–discriminant modelling framework identify strategic leverage points for heritage tourism (HT) development at post-industrial locations such as Barr?

In the process, this research seeks to contribute to three areas:

- Empirically, by offering a data-driven benchmark for Barr Conglomerate's tourism planning.
- Methodologically, by furthering the use of multivariate methods in HT scholarship.
- Strategically, by providing suggestions for incorporating geo-heritage within larger regional development agendas while aligning with emerging tourism branding principles and place-making constructs.

2. Literature Review

2.1. MHT: Global Narratives and Indian Silence

Growing cross-border appreciation of mining heritage as an important cultural and economic asset has remodelled the trajectories of post-industrial landscapes in Europe, Latin America, and parts of Asia [35-37]. In many cases, derelict mines have been re-described as live cultural attractions—UNESCO sites, eco-museums, geoparks, and educational tourist centres [14-15]. Such reworking shifts pay homage not only to industrial achievements but also to the labour histories, material cultures, and socio-ecological legacies of mining communities [3, 21]. A case in point of this industrial decay transformation into interpretive landscapes through musealization and the practice of local heritage [38-39] is the Floristella-Grottacalda Mining Park in Italy [40] and the Toi Gold Mine in Japan [41]. These are some instances where industrial ruins have become repositories of memory as well as instrumental sources for regeneration at the local level, supporting the narrative that heritage, whether industrial or not, can be a means toward preservation and prosperity [14-15]. Similarly, the European Route of Industrial Heritage (ERIH) has linked over 2,200 sites through a thematic, transboundary framework to promote MHT in multiple countries [20]. There is currently academic consensus with such praxis. Scholars emphasize the need to integrate hard and soft elements—ranging from mining equipment and geology to rituals, workmanship, and in-place identity [3, 25]. Varriale et al. [14] argue that UBH needs to be understood as a conceptual category so that former mine sites can be reconceptualized both as redundant voids and as sophisticated cultural typologies worthy of preservation and reuse [42-44]. This perspective is based on case studies where undervalued landscapes of mining have gained international significance through strategic planning, public support, and interpretive facilities.

In spite of this international trend, India remains surprisingly missing in the conversation about MHT. Although the nation possesses a rich and varied mining heritage—ranging from ancient Deccan's iron and copper to colonial-industrial era's coal and limestone—there is hardly any policy interest in conserving these legacies in tourism dimensions [3]. Even prominent geological features and historical mines hardly ever appear as heritage assets in tourism master plans or cultural policy documents [7, 45]. According to Pardo Abad [28], this exclusion is not only an error of heritage listing but also a loss of economic diversification for resource-dependent or deindustrialising regions. The Barr Conglomerate, as with numerous Indian mining locations, occupies this policy void [21]. It continues to be left out of geo-heritage inventories, mining park projects, or thematic tourist circuits. Such systemic omission is indicative of a general pattern in India where post-extractive landscapes are collectively erased from memory or preserved as liabilities that need ecological remediation rather than as cultural assets that can be capitalised upon through sustainable, community-based tourism development.

2.2. Post-Industrial Competitiveness and Place Rebranding

Post-industrial regions are faced with the twin challenge of economic downturn after the decline of industry and spatial trauma of extraction [46-51]. However, some areas have managed to rebrand by presenting their industrial past as a tale of perseverance and innovation [5]. The process, which is normally referred to as "place rebranding," involves symbolic and infrastructural valuation of derelict industrial spaces into significant destinations, memory, and market value. HT is at the heart of this transformation [52]. As described by Pardo Abad [28], HT enables post-industrial locations to transition from production to consumption economies by reconfiguring themselves in the guise of heritage, which caters to the demands of cultural tourists for experiential depth and local authenticity. Places previously emblematic of pollution and exploitation of labour become re-described as pedagogical landscapes and experiential destinations promoting collective memory and economic rebirth [5, 53]. And yet, competitiveness in this regard is not simply a matter of the number of visitors. As Ravaz et al. [34] insist, post-industrial redevelopment for success needs to take into account the needs of the community, spatial justice, and landscape integrity.

Most case studies identify place attachment, local engagement, and narrative authenticity as more important than infrastructure per se in guaranteeing long-term tourism sustainability [16, 54-59]. Furthermore, competitiveness is multi-faceted, including environmental resilience, interpretive depth, cultural uniqueness, and policy integration [60-64].

China's brownfield redevelopment provides an insightful comparative context. As Wang et al. [65] investigate, urban redevelopment in Beijing's Fatou district shows a hybrid spatial model, in which communist legacies and neoliberal planning approaches come together to create rebranded urban spaces. Fatou's industrial ruins were not destroyed but selectively curated into a post-industrial identity encompassing memory, ecology, and urban liveability [66-67]. This highlights the role of spatial identity construction—using heritage, design, or narrative—at the heart of post-industrial competitiveness. In the context of India, there is hardly ever a discursive extension of competitiveness to post-mining areas [3]. Tourism development continues to be focused on monuments, religious places, or ecotourism, with little inclusion of the industrial-cultural interface [60]. There are no performance measures for mining heritage areas like destination branding, visitor perception index, or stakeholder engagement matrix, making the latter invisible in competitiveness rankings [62-64]. However, as demonstrated by Nag [3] through their research of Dhori Mines, even deteriorated mining landscapes can become assets for tourism when supported by data analysis, participatory governance, and ecologically sensitive design. Their work shows that tourist satisfaction is highly related to interpretive quality and conservation alignment—implying competitiveness for MHT depends on finding a balance between preservation and experiential immersion. The present research, in using a statistical deconstruction framework on Barr Conglomerate, aims to bridge this gap. Utilising factor analysis, PCA, and discriminant mapping, it presents a measurable model to evaluate the site's perceptual and functional competitiveness—thereby providing the foundation for its potential rebranding as a geo-cultural tourism site in Rajasthan's post-industrial geoscape.

2.3. Analytical Approaches in Tourism Studies

Tourism studies, especially in the field of cultural heritage as well as destination

development, have come to involve a broad variety of analytical approaches, each with different epistemological and practical goals [3, 21, 60-62]. Historically, qualitative methods such as narrative research, ethnography, participatory rural appraisal, grounded theory, and phenomenology have played a central role in grasping the subjective, experiential, and cultural aspects of tourism [68]. These approaches continue to be crucial in understanding tourist motivations, heritage stories, and the construction of community identity [69]. Quantitative and mixed-methods research have further enriched the tourist research toolkit with the capacity for modelling, measuring, and predicting tourist phenomena [3, 21]. Of greatest extent of usage is descriptive statistics, regression analysis, cluster analysis, SEM, MCDM, choice experiments, and content analytics [34, 70]. The methods have become the cornerstone of fields such as destination competitiveness, visitor segmentation, site valuation, and policy priorities.

Of these, multivariate statistical methods namely EFA, PCA, and DFA—possess special strengths in working with complex, perceptual-based variables. These techniques are particularly well-suited to latently structured data analysis, detecting inter-group perceptual variance, and dimensionality reduction for more interpretable models [71]. The application of these has been on the rise in tourism research to measure abstract constructs like satisfaction, motivation, image, place attachment, and competitiveness [72-73].

- Factor Analysis (FA) is often used for the extraction of underlying structures from large sets of variables, often applied to visitor perception surveys, destination image scores, or service quality ratings [34].
- PCA serves a similar function, most frequently applied for dimensionality reduction of multiple indicators to compound indices or noise reduction in spatial and perceptual data [74-75].
- DA with canonical and linear forms is particularly applicable to classifying respondents into stakeholder groups based on percept variables, and for forecasting group membership based on tourism behaviour or attitudinal data [28].

These analytical methods are particularly appropriate when analysing tourism in multifaceted, transitioning territory—such as post-mining or post-industrial heritage landscape—where stakeholders often have competing values and expectations. For example, Wang et al. [65]

offered an effective use of such practices in the brownfield redevelopment environments of Beijing, where land-use legacies and future imaginaries typically clashed. Similarly, Nag [8] utilised multivariate methods in the case of Dhori Mines to model the connection between tourist satisfaction and environmental determinants, thereby identifying tourism development design priorities. Despite their methodological firmness and interpretive promise, all these analytical approaches are too underutilised within HT studies of India, particularly for mining and industrial sites.

2.4. Gap Statement: Scarcity of Statistically Intensive Studies on Mining Heritage in India

A rigorous examination of Indian scholarship on tourism identifies an interesting absence of statistically rigorous research into industrial heritage mining as a potential niche for tourism. Whereas international scholarship has adopted industrial HT as an area of academic inquiry—ranging from geo-heritage valuation studies, typologies of visitors, ecological influence modelling, and planning and destination—Indian scholarship remains dominated by religious tourism, ecotourism, or architectural heritage [3, 28]. Current mining site analyses in India are typically fragmented, qualitative, or policy-oriented, and usually ignore perceptual analytics or stakeholder modelling. There might be environmental assessments (e.g., EIAs), but socio-cultural and perceptual aspects of reuse after mining are hardly mapped quantitatively. This leaves a severe knowledge gap: there is no statistically based framework for assessing the tourism potential of India's mining landscapes, nor for informing their conversion into sustainable HTD. This gap is also augmented by the lack of canonical statistical methods—such as PCA, DFA, or normality testing—within HT policy reports or regional planning documents. In the absence of these tools, the construction of MHT in India is speculative, reactive, and without a strategic, data-driven basis. This research aims to fill this gap through an in-depth, statistical breakdown of stakeholder attitudes and site competitiveness in the Barr Conglomerate. By using a stringent suite of multivariate methods, this research stands as one of the first quantitative modelling studies in India of MHT preparedness, with methodological contributions and actionable recommendations for policymakers, planners, and community stakeholders.

3. Study Area: Barr Conglomerate, Pali District, Rajasthan

3.1. Geological and Mining Profile

The Barr Conglomerate within the Pali district of Rajasthan is a major stratigraphic unit of the Vindhyan Supergroup that is defined by coarse-grained sedimentary rock exposures. The geological composition mainly consists of quartz pebbles cemented in a siliceous matrix, which is indicative of ancient fluvial depositional facies, implying tectonically controlled sedimentation of Proterozoic-Paleoproterozoic age [21]. This region has been considered not just for the mineral deposits it bears but also for the geological uniqueness that it presents, which provides a singular window into India's paleogeographic and tectonic history. The history of mineral extraction in this site arises from the small- to medium-scale mining activities that took advantage of its stone materials and aggregates to be used locally for construction and industry. Though not a metalliferous mining area, the geoheritage significance of Barr is its intact lithostratigraphic outcrops, fossil-yielding potential, and unique conglomeratic fabric—features that make it a prospective geo-tourism site as well as an educational heritage walk candidate [21]. Land degradation resulting from post-mining and absence of reclamation activities, on the other hand, has led to erosion, vegetation loss, and safety issues—characteristics of India's abandoned extraction landscapes [3, 20].

3.2. Historical Use and Post-Closure Dynamics

The mining operation at Barr Conglomerate is traced to the mid-20th century, when Pali and the surrounding areas' infrastructure and development requirements were met by local quarries [21]. The extraction processes were inadequately regulated, with primitive equipment and casual systems of labour, and little regard for ecological protections or post-use planning. After the end of official mining activities, the site entered a phase of functional abandonment, repeating larger post-industrial trends found throughout rural India [8, 16]. In contrast to some areas which have been invested in as adaptive reuse of industrial sites, Barr saw no institutional interest in either reclamation or heritage transformation. As a result, the site has continued to be ecologically vulnerable and socially under-exploited, even though it is geoculturally significant and located near developing urban agglomerations [5, 21]. Post-closure, the site welcomed sporadic visits from geologists,

conservationists of heritage and local youth groups, but without formal protection or structured interpretation. This highlights the gap between decommissioning of mines and reintegration of heritage, an issue common in most post-extraction areas in India, where frameworks for transition are non-existent [28].

3.3. Socio-Cultural Context

The Barr site is located within a culturally rich and historically dense area of Rajasthan, marked by an assemblage of Marwari cultural practices, folk epistemological traditions, and rural-urban interaction spaces [21]. Local communities—agricultural families, artisans, and seasonal workers—have historically had a subsistence-level engagement with the earth, perceiving the erstwhile mining site as an economic livelihood source as well as, increasingly, as a spatial memory of loss and change. As noted by Nag and Mishra [8, 16], the site's cosmopolitan body of visitors now comprises tourists, geologists, historians, teachers, and local families, hinting at a possible reconceptualisation of Barr as a multi-purpose cultural landscape from an extractive emptiness. The locally associated communities have a moderate level of historical consciousness regarding the site, but no capacity or institutional backing to launch tourism activities. Interaction is generally ad hoc and sometimes seasonal, associated with academic field trips or district-level displays [8]. Additionally, there is a gap in alignment between customary knowledge guardians and formal institutions of heritage, making it important that participatory models prioritise community voices in Barr's possible repositioning as a heritage tourist node.

3.4. Current Status: Accessibility, Infrastructure, and Community Interfaces

Infrastructure-wise, Barr Conglomerate does not have the minimal tourist facilities like signage, interpretation centres, sanitation, or guided access [21]. There are partially paved access roads, which allow the site to be accessed by private cars but not public transport, except perhaps during monsoon seasons. Field observations further revealed that mobility across the site is constrained by uneven walking paths, the absence of directional signage, and limited public transport linkages, creating practical barriers that directly affect visitor comfort and navigation. Although there is better mobile connectivity, there is no formal safety protocol for visitors and no monitoring mechanism in place to

deter vandalism and site deterioration. In spite of these limitations, the site is spatially well-placed—sited close to pre-existing urban settlements and within range of cultural circuits linking Jodhpur, Ranakpur, and Mount Abu. Such a geographical advantage opens the door to future integration into regional heritage routes, provided infrastructure and narrative investment are in place. Barr is also confronted with the usual problems of post-industrial heritage sites: illegal use of land, uncertainty of zoning, and random dumping of waste, all of which diminish its perceived worth. Yet recent academic and institutional interest—like the AI-congregated HT study of Nag and Mishra [8, 16, 21]—indicates increasing awareness of the site's transdisciplinary uses. Their research demonstrates the potential of applying digital technologies, participatory governance, and principles of sustainability at Barr as a replicable model for data-based HT in post-extractive Indian landscapes. In short, the Barr Conglomerate presents a treasure trove of geological uniqueness, cultural significance, and development value. However, in the absence of planned interventions, the site faces the danger of further declining into obsolescence. This research lays the foundations for the site's natural worth and modern-day issues to evaluate its tourism potential, utilising robust statistical modelling—designed to place Barr as a model for India's future mining heritage initiative.

4. Methodology

4.1. Research Design

This research employs a quantitatively driven mixed-methods approach, combining statistical analysis with contextual interpretation to evaluate the tourism potential of the Barr Conglomerate site. The rationale is based on the awareness that HT development, especially in post-industrial environments, requires empirical confirmation as well as socio-cultural understanding. Quantitative methods are thus employed to identify perceptual patterns, group differentials, and measures of competitiveness, while qualitative inferences situate these statistical observations within the wider context of heritage valorisation and sustainable development. Primary data were obtained using a guided perceptual questionnaire completed by 440 respondents, comprising domestic and overseas tourists (n=217), residents (n=163), and planning or heritage specialists (n=60). Given the comparatively smaller representation of planners and heritage specialists, a slight influence on the precision of DFA

classification outcomes is expected, although the cross-validation procedure minimizes this effect. The sample size was statistically calculated using Cochran's formula with the estimated population figures of the area, a confidence level of 95%, and a margin of error of 5%. The stratified sampling approach ensured proper representation in the main stakeholder categories. The survey instrument comprised 46 perceptual variables (see Table 1 in the Appendix), measured using a five-point Likert scale (ranging from 1 = Strongly Disagree to 5 = Strongly Agree), designed to capture respondents' evaluations of various site-related dimensions, including infrastructure adequacy, cultural significance, interpretive quality, visitor engagement, conservation awareness, and tourism potential. Aside from these closed-ended questions, the survey contained socio-demographic queries (age, gender, education, occupation, place of origin, and frequency of visits to the site) along with open-ended questions requesting qualitative responses about the site's current status, perceived challenges, and suggestions for improvement. These quantitative data were supplemented through observational comments during site visits, casual interviews with local stakeholders, and a review of relevant heritage management reports and planning documents. This multi-source approach enabled contextual interpretation of the statistical outcomes to ensure the results were grounded in the lived experiences of the site and its community.

4.2. Statistical Toolkit Overview

Data analysis moved in three interconnected phases: EFA to effect dimensionality reduction, test of distribution to check normality, and DFA to segment and classify stakeholders. All the analyses were performed on SPSS Version 16.0, and findings were interpreted using both statistical requirements and their implications for tourism development at the location.

4.2.1. Exploratory Factor Analysis (EFA)

To determine the underlying latent constructs of the 46 perceptual variables, EFA with principal component extraction was employed. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were used before factor extraction to test whether the data were suitable. A KMO greater than 0.70 and a significant Bartlett's test ($p < 0.05$) validated the use of EFA for the data. PCA was employed for extracting components with eigenvalues greater

than one according to the Kaiser criterion. The scree plot was utilised in order to observe the break point in eigenvalues, which guided the number of retained components. The cumulative percentage of total variance explained by the retained components was examined to gauge model stability. For increasing the interpretability of the obtained factors, a Varimax orthogonal rotation was performed. The rotated component matrix and the transformation matrix were examined to establish the coherence and autonomy of factor loadings. The resultant components indicated dominant perceptual dimensions like cultural interpretation, visitor involvement, conservation awareness, environmental responsiveness, and infrastructure preparedness.

4.2.2. Distribution and Normality Testing

After factor extraction, the normality of the variables was checked in order to ascertain the appropriateness of using parametric multivariate methods. Kolmogorov–Smirnov Z test was applied to compare the distributional properties of all Likert-scaled variables. Variables with p-values ≤ 0.05 were identified as non-normal in distribution. Theoretical fits were further tested with normal, uniform, Poisson, and exponential models. Visual diagnostic plots like probability-probability (PP) plots and detrended PP plots were also created. These plots allowed for the detection of departures from the anticipated normal distribution and for the identification of concerns like skewness and kurtosis that might affect the validity of conclusions drawn. A lack of normality in a portion of variables notwithstanding, robustness in the overall sample and incorporation of cross-validation in later phases guaranteed validity in applied techniques. The findings of this phase guided the confidence with which discriminant functions could be generated from the data.

4.2.3. Discriminant Function Analysis (DFA)

To classify respondents based on their perceptual profiles and identify variables that significantly differentiate stakeholder groups, canonical DFA was conducted. The analysis began with the Test of Equality of Group Means, which identified variables that differed significantly among the three stakeholder groups: tourists, residents, and planners. Only variables with p-values < 0.05 were retained as predictors. Homogeneity of variance-covariance matrices was tested using Box's M test. Although Box's M is sensitive to sample size, interpretation was

tempered by comparing group sizes and the proportion of variance in the pooled within-groups covariance matrix. Canonical discriminant functions were then derived to transform the high-dimensional perceptual data into a smaller number of linear combinations that best distinguished between groups. Eigenvalues indicated the proportion of variance explained by each function, while Wilks' Lambda tested the overall significance of these functions. Standardized canonical coefficients provided insight into the relative importance of each predictor variable within the functions, and the structure matrix displayed correlations between original variables and the canonical functions, aiding interpretability. Group centroids were calculated to represent the mean scores of each group on the canonical functions. These centroids were plotted to visualize perceptual distances and overlaps among groups. A territorial map was created using the first two canonical functions, allowing spatial interpretation of group segmentation and perceptual alignment. The classification accuracy was evaluated by comparing the percentage of correctly classified cases to the proportional chance criterion. Cross-validation using the leave-one-out method ensured the generalizability of the classification results. Ultimately, the DFA facilitated categorizing respondents into five perceptual types, providing targeted insights for tourism strategies and stakeholder-specific recommendations.

Overall, this multi-method statistical approach enabled a strong and rich deconstruction of tourism attitudes around the Barr Conglomerate location. Through the incorporation of dimensionality reduction, distribution diagnostics, and classification of stakeholders, the research offered a robust evidence base for the formulation of context-attuned and data-driven HT initiatives.

5. Results and Analysis

5.1. Descriptive Summary

A total of 440 valid questionnaires were gathered from the survey using a structured questionnaire to measure the perceptions of stakeholders towards MHT at the Barr Conglomerate location in Pali District, Rajasthan. The sample of respondents was stratified along five general categories of key stakeholders to obtain broad coverage: tourists (n = 230), residents (n = 188), site managers and tourism planners (n = 12), research and academic professionals (n = 6), and policy-level decision makers (n = 4). Such multi-perspectivity was essential in detecting nuanced

opinions on heritage worth, infrastructural preparedness, and participatory governance. Demographically, the findings were in a relatively balanced gender split (51.8% male, 48.2% female) and an emphasis on the 25–45 age group, indicating a mobile, youthful, and active demographic. Education levels were relatively high, with more than 68% of respondents graduating or postgraduates, indicating the attractiveness of the Barr Conglomerate to educated and culturally aware travellers.

The initial findings of stakeholders' perceptions presented a positive image. Most of the respondents reported favourable perceptions of the site's uniqueness and its touristic appeal. The average scores of 46 perceptual statements ranged from 3.27 to 4.31 on a five-point Likert scale, with particularly strong agreement for questions related to geological interest, visual scenic beauty, and the educational significance of the site. Respondents also overwhelmingly agreed that natural terrain and the visual distinctiveness of the site offer a distinctive foundation for tourism development. More than 70% of visitors and professionals showed keen interest in guided geo-trails, interpretive signage, and heritage experiences based on storytelling. These results indicate an underlying demand for experiential and knowledge-based tourism paradigms, particularly from non-local stakeholders. Nevertheless, some issues were consistently mentioned by groups. Safety, limited amenities, poor signage, and poor access to sites were mentioned as being key deterrents—especially by tourists and residents. These infrastructural shortfalls are seen to limit first-time visit behaviour as well as repeat tourism behaviour, highlighting the need for investment in core services, interpretive infrastructure, and risk management systems. Notably, locals, though less supportive of top-down tourism branding overall, strongly favoured mechanisms for community-led engagement. These were represented by functions such as local guides, cultural performers, food vendors, and artisan producers. Such attitudes are

consistent with international best practices in post-industrial tourism development, where locally-based, inclusive economic systems are increasingly recognised as core to the provision of social sustainability and equitable benefit-sharing [3, 5].

Overall, the descriptive analysis (see Table 2 in the Appendix) shows that the Barr Conglomerate has great latent tourism potential, supported by its geological uniqueness, interpretive significance, and cultural appeal. Simultaneously, the results identify critical challenges across infrastructure, stakeholder congruity, and institutional integration. The alignment mismatch of stakeholder priorities—between demand for formalised experiences and imperative for grassroots-based participation—indicates the need for a hybrid, multi-scalar site development approach. These initial findings lay the groundwork for the following multivariate analyses, which explore more deeply the latent perceptual patterns and group-specific predictors. This transition in analysis is essential to create targeted intervention strategies, align community desires with visitor intentions, and inform regionally integrated tourism planning.

5.2. Factor Analysis and PCA Findings

To answer the question of what latent dimensions are present behind stakeholder attitudes towards MHT at the Barr Conglomerate site, a PCA with varimax rotation was used on the 46 Likert-scale variables (see Tables 4, 5, 6, 7 and 8 in the Appendix). Analytically, the process commenced with an initial assessment of sampling adequacy. The Kaiser-Meyer-Olkin (KMO) measure was 0.804, which indicated meritorious adequacy and verified that the dataset was good for reducing the dimension. The Bartlett's Test of Sphericity yielded a significant Chi-square statistic ($\chi^2 = 33,480$, $df = 1035$, $p < 0.001$), confirming the factorability of the correlation matrix, validating the factorability of the correlation matrix (Refer to Table 3).

Table 1. KMO and Bartlett's Test of Sphericity (Source: Author)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.804	
Bartlett's Test of Sphericity	Approx. Chi-Square	3.348E4
	df	1035
	Sig.	.000

5.2.1. Extraction and Variance Explained

PCA yielded eight factors with eigenvalues of 1.0 or higher in the initial extraction, which collectively explained 83.43% of the variance. The scree plot provided a clear point of inflexion at the eighth factor, which further justified the retention factor decision using Kaiser's criterion and the Cattell scree test (Refer to Figure 1).

- Component 1: This component accounted for 18.11% of the variance and measured concepts associated with tourist infrastructure, access to services, signage, and access to facilities. It contained items like hotel proximity, tourist facilities, and perceived cleanliness of the site. These perceptual indicators aligned closely with field observations, where access pathways were noted to be discontinuous, trails showed signs of erosion, and drainage channels were irregular, collectively reinforcing why respondents rated infrastructure gaps as a key concern.
- Component 2: Contributing 17.95% of the variance, this factor focused on visitor safety, residents' perception of security, and facility in navigation, highlighting physical and emotional comfort both for residents and tourists.
- Component 3: Explaining 10.18% of the variance, this factor clustered perceptions of the site's uniqueness, geological and historical interpretation, and quality of interaction with locals, capturing the site's experiential value and educational opportunities. These interpretive and narrative features strongly resonate with branding pillars such as “Geological

Authenticity,” reflecting how visitors anchor meaning in the site’s deep-time geological narratives and scientific distinctiveness.

- Component 4: Accounting for 9.17% of the total variance, this factor emphasized place identity, cultural symbolism, authenticity of stories, and emotional attachment to the site—particularly among residents. These emotional-symbolic attributes align with branding constructs like “Memory Landscapes” and “Living Community Heritage,” underscoring how cultural resonance and local identity influence Barr’s long-term destination image.

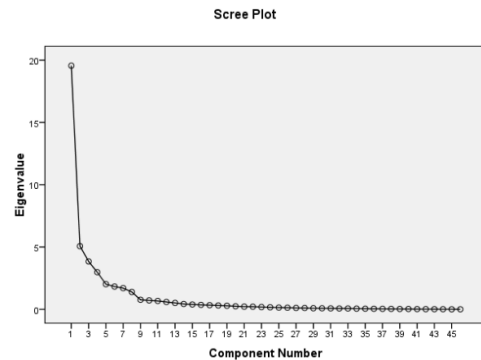


Figure 1. Scree Plot Showing Eigenvalue Drop (Source: Author)

Other component extractions (Components 5 to 8) together explained an additional 27.2% of the variance and comprised themes such as commercial services, transportation connectivity, participation in interpretation activities, and intensities of tourist engagement (Refer to Table 9).

Table 2. Extracted PCA Component Themes and Interpretations (Source: Author)

Component	Variance (%)	Theme Name	Interpretive Focus	Key Variables
Component 1	18.11%	Tourism Infrastructure & Facility Access	Reflects tourist perceptions of physical amenities, accommodation proximity, signage, cleanliness, and availability of facilities.	A1, A2, A5, A24, A27, A45
Component 2	17.95%	Safety, Navigation, & Comfort	Captures perceptions of safety, spatial legibility, and emotional comfort among tourists and residents regarding the site environment.	A6, A10, A11, A36, A40
Component 3	10.18%	Experiential & Interpretive Value	Measures geo-heritage distinctiveness, educational signage, geological narratives, and engagement with local culture and people.	A8, A12, A13, A20, A22, A26
Component 4	9.17%	Place Identity & Cultural Resonance	Represents attachment to the site, symbolism, authenticity, place meaning, and emotional association—particularly among local stakeholders.	A14, A15, A16, A19, A28, A34
Component 5	8.15%	Commercial & Service Participation	Evaluates respondent perspectives on commercial tourism services, employment opportunities, and participation in tourism-related businesses.	A17, A23, A25, A33
Component 6	7.80%	Transport & Connectivity Satisfaction	Focuses on transportation access, adequacy of routes, and satisfaction with mobility across and around the site.	A18, A21, A29, A41, A44
Component 7	6.08%	Interpretation Activities & Local Role	Highlights interpretive participation, guiding, storytelling, and local involvement in site communication and tourist education.	A3, A7, A30, A31, A32
Component 8	5.99%	Engagement Intensity & Affective Response	Reflects subjective engagement levels, interest intensity, emotional connection, and perceived tourism relevance.	A4, A9, A35, A37, A38, A42, A43, A46

5.2.2. Factor Structure Interpretation

The rotated factor loadings facilitated more unambiguous thematic interpretation and justified the multidimensional perceptual space for MHT (see Tables 5, 6, 7 and 8 in the Appendix). A number of the variables reflected cross-loadings, pointing to their applicability across numerous components—a reflection of the interrelatedness among physical infrastructure, interpretive depth, and community involvement. The PCA verified that the tourism value proposition of Barr Conglomerate is not seen as a single product, but as a composite of tangible and intangible components. Statistical differentiation of these themes allows more precise development of intervention design. As an illustration, infrastructure upgrade (Component 1) should be developed concurrently with plans for upgrading interpretation and interaction (Components 3 and 4), so that there is both functional use and experiential richness. The alignment of Components 3 and 4 with identifiable branding pillars (“Geological Authenticity,” “Memory Landscapes,” and “Living Community Heritage”) further clarifies how these perceptual dimensions can be translated into a coherent brand identity for Barr strengthening its conceptual positioning within HT markets. Lastly, factor analysis not only affirms the multidimensionality of perceptions but also offers an empirical basis to segment stakeholder concerns, rank planning inputs, and direct targeted HT policy interventions at the site.

5.3. Distribution Patterns and Normality Assessment

Before performing classification-based multivariate analyses, it was necessary to analyse the distribution patterns of the 46 Likert-scale variables employed to quantify stakeholder perceptions at the Barr Conglomerate location. This analysis served a dual purpose: firstly, to test whether the assumption of multivariate normality was satisfied for methods like DFA; and secondly, to investigate whether underlying perceptual variables showed signs of clustering or skewness patterns that might provide interpretive guidance.

5.3.1. Normality Testing using Kolmogorov–Smirnov Z

One-sample Kolmogorov–Smirnov Z (K-S Z) test was used to test goodness-of-fit for four models of distributions: normal, uniform, Poisson, and exponential. In all 46 variables, the K-S Z statistics were statistically significant ($p < 0.001$), decisively

rejecting the null hypothesis of normality (see Table 10 in the Appendix). This finding was also supported by the PP plots and detrended PP plots (see Figure 3 in the Appendix), which showed considerable deviation from the anticipated normal curve, especially at the extremes. Whereas some variables (e.g., A4, A9, A14) came close to quasi-normal patterns, most exhibited positive skew, indicative of a general tendency for respondents to rate site characteristics positively—consistent with previous descriptive statistics. Variables like A24 (amenity adequacy) and A33 (commercial integration) exhibited greater variability and kurtosis, indicating polarising perspectives within the sample.

5.3.2. Comparison across Distributions

When compared against uniform, Poisson, and exponential reference distributions:

- The uniform distribution exhibited moderate fit for subjective satisfaction variables (e.g., A10, A23), but significantly failed the K-S test for high-engagement items.
- The Poisson distribution, appropriate for fitting count-like or rare-events data, fitted poorly for all of the perceptual constructs, ensuring that such a model was not suitable for the 5-point ordinal design.
- The exponential distribution, applied for modelling decreasing perceptions (such as satisfaction decline), exhibited partial fit in items such as A36 and A45, but not consistently across the dataset.

These results as a whole reconfirmed the non-parametric character of the data and supported the application of multivariate methods resistant to distributional errors, like canonical DFA (used in Section 5.4). They also gave insight into stakeholder heterogeneity—implying that although there is converging agreement on the potential for the site, there is divergence within perceptions of quality, safety, and site-specific participation. The distributional analysis is not only used for statistical validation purposes; it also forms the basis of interpretive segmentation in order to discern diverse stakeholder motivations. The absence of normality and the existence of multimodal patterns indicate differentiated user expectations, as shall be analysed in the discriminating function results that follow.

5.4. Discriminant Function Analysis and Classification Results

In order to further examine differences across stakeholder groups in perceptions of MHT at Barr Conglomerate, a canonical discriminant analysis (CDA) was performed based on the 46 Likert-scale perceptual variables as discriminating variables and stakeholder type (Tourists, Residents, Planners, Researchers, Policy Makers) as the grouping variable. The goal was to determine which underlying perceptual dimensions did the best job of distinguishing between the five stakeholder groups and to assess the accuracy of the classification of these groupings.

5.4.1. Group Differences and Test of Equality of Means

The Wilks' Lambda equality of group means test was statistically significant for most perceptual items across stakeholder groups ($p < 0.001$ for 43 out of 46 variables) (see Tables 11 and 12 in the Appendix). Items with the lowest Lambda scores were A17 (commercial services participation), A36 (perception of public safety), and A45 (transport satisfaction), suggesting these variables had the greatest discriminatory capability. This corroborates descriptive findings that residents and tourists, respectively, exhibited differing responses in the domains of infrastructure, security, and tourism services.

5.4.2. Validity of Discriminant Functions

The Box's M Test for equality of covariance matrices was significant and indicated that the equal covariance matrices in groups assumption does not hold (see Table 21 in the Appendix). Still, due to the solid sample size and multivariate character of the data, CDA was still considered fitting since the method is rather forgiving with such violations when applied for exploratory classification purposes. Four canonical discriminant functions were retained, jointly accounting for 100% of group membership variance. The first function alone contributed 81.5%, followed by 15.5%, 2.0%, and 1.0% in the following functions, respectively. The canonical correlations for Functions 1 and 2 were impressively high (Function 1: 0.995; Function 2: 0.974), attesting to the excellent discriminatory power of the model (see Tables 13, 14 and 15 in the Appendix).

5.4.3. Interpreting the Functions

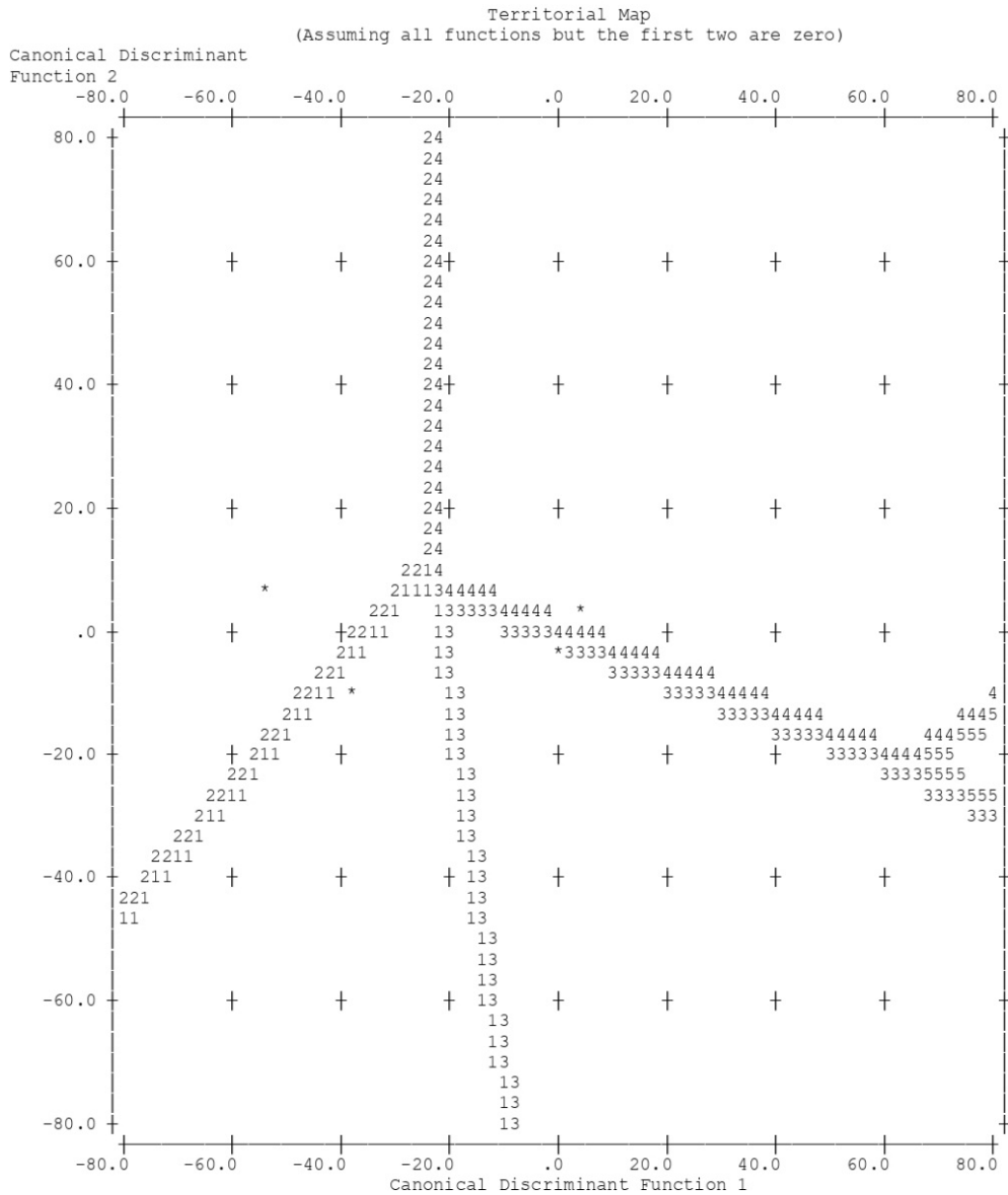
- Function 1 mainly differentiates residents from professionals and tourists. Strong positive loadings were noted on items such as community participation, employment potential (A17, A23), and dissatisfaction with services (A24, A45). This indicates the socio-economic prism through which residents evaluate tourism.
- Function 2 differentiated researchers and planners from other groups by their positive assessment of educational signage, site distinctiveness, and conservation value (A5, A8, A20). These groups had a stronger focus on interpretation, educational relevance, and site integrity.
- Functions 3 and 4, although explaining minor variance, captured subtleties in how policy stakeholders view commercial viability and administrative feasibility—an observation gleaned from variables like A33 (commercial product integration) and A40 (governance satisfaction) (see Tables 16 and 17 in Appendix).

5.4.4. Classification Accuracy

The matrix of classification revealed a hit rate of more than 92%, with the highest accuracy found in the correct classification of tourists and residents. While planning and research groups with smaller numbers also achieved acceptable classification levels, this indicates clear perceptual identities. Policy-makers were the most dispersed, likely due to their cross-cutting roles and dual stakeholder functions (see Tables 18 and 19 in the Appendix). These findings affirm that stakeholder perceptions are not homogeneous but vary according to lived experience, professional status, and site proximity. The high success in classification and robust canonical relationships highlight the need for differentiated tourism policies that are sensitive to unique stakeholder priorities ranging from infrastructure provision and public engagement to educational use and policy framing.

5.5. Territorial Mapping and Group Perception Visualisation

In an effort to spatially depict the perceptual differences noted using DFA, a territorial mapping strategy was implemented. By graphing the functions at group centroids in two-dimensional canonical space (Function 1 vs. Function 2), a perceptual map was created to visually identify how stakeholder groups group along their aggregate reactions to tourism development at the Barr Conglomerate location (Refer to Figure 2).



Symbols used in territorial map

Symbol	Group	Label
1	1	
2	2	
3	3	
4	4	
5	5	

* Indicates a group centroid

Figure 2. Territorial Map of Stakeholder Group Centroids – Function 1 vs. Function 2 Axes (Source: Author)

5.5.1. Spatial Clustering of Stakeholder Groups

The territorial map indicated five clusters that were quite different from the stakeholder types,

also supporting the statistical results of the canonical DFA.

- Tourists were positioned comparatively mid-way on Function 1 and negative on Function 2, displaying a perception mix focused on physical

infrastructure (A1–A10), experiential quality (A18, A21), and place aesthetics (A5, A8). Though generally positive about the destination's tourism appeal, tourists were particularly anxious about shortcomings in physical access, signage, and safety.

- Residents exhibited high positive loading along Function 1 and marginal on Function 2, which indicated strong emphasis on people's participation (A17, A23), worry over infrastructure (A24, A36), and local anticipation of tourism. The perceptual centroid of their answers largely overlapped with economic livelihood issues and bottom-up rather than top-down preference for tourism.
- Researchers and Planners developed a joint cluster positive on Function 2, and negative on Function 1, suggesting an academic and policy-styled orientation. Their positioning on variables such as site uniqueness (A20), conservation value (A12), and interpret potential (A10) gave precedence to intangible longer-term benefits over shorter-term tourism economics.

- Policy Makers, although fewer in number, also had a dispersed location in the canonical space, expressing unlike internal views and a compounded perception influenced by institutional constraints and strategic considerations. Their diversity of perception also warrants the use of systematic stakeholder dialogue in decision-making.

5.5.2. Group-Specific Priority Themes

The perceptual map was overlaid with the dominant interpretive themes established in prior factor analysis (see Table 20):

1. Tourism Infrastructure and Amenities – locals and tourists group highly under this theme.
2. Safety and Public Environment – locals dominate this perception cluster.
3. Cultural Engagement and Site Interpretation – researchers and planners cluster with this theme.
4. Place Identity and Uniqueness – all groups are positively associated, but stress differs.

Table 3. Cross-tabulation of Perceptual Themes and Group Priorities (Source: Author)

Perceptual Theme	Tourists	Residents	Planners	Researchers	Policy Makers
1. Tourism Infrastructure & Amenities	High priority – demand for signage, trails, toilets, info centres	High priority – highlight lack of connectivity, demand for improved services	Moderate – acknowledge need, but less urgent	Low – focus elsewhere	Mixed – some prioritise it for investment appeal
2. Safety & Public Environment	Moderate concern – linked to travel comfort	High concern – related to everyday use, gender safety, night-time mobility	Low – addressed via broader planning	Low – often overlooked	Low to Moderate – part of governance, but not urgent
3. Cultural Engagement & Interpretation	Moderate – interest in storytelling formats, cultural shows	High – strong interest in being involved in interpretive services	High – stress interpretive zones, signage	Very High – see site as “living archive”	Moderate – support depends on visibility gains
4. Place Identity & Site Uniqueness	High – fascinated by geo-heritage and aesthetic appeal	Moderate – attach identity but want livelihood focus	High – rebranding importance noted	High uniqueness is the key research draw	Moderate – site image tied to regional branding

5.5.3. Implications for Site Zoning and Experience Design

Territorial visualisation not only verifies perceptual variation but also yields practical spatial implications. For example:

- Tourist-oriented areas must focus on interpretive paths, visual vantages, and guided tours to meet Function 1 requirements.
- Resident-oriented areas can be centred on entry nodes that provide community-based services like food stalls, craft kiosks, and oral narration.
- Researcher and planner areas can make use of designed geoscientific signage, conservation paths, and documentation stations to accommodate continued study and monitoring.

These geographically situated observations highlight the ability of data-driven participatory planning to unlock the potential in mining heritage sites, facilitating personalised visitor experience and tourism process ownership by communities.

6. Discussion

The outcomes of the multivariate statistical analysis, most notably the factor structures and group-wise discriminant results, provide strong evidence of both the latent tourism potential of the Barr Conglomerate site and varied perceptual priorities among different stakeholder categories. Synthesising the evidence, a few major dimensions emerge as crucial for transforming the site from a

slumbering post-industrial landscape into an active geo-HTD.

6.1. Synthesis of Statistical Findings with Tourism Potential

The identification of eight main components accounting for more than 83% of the variance highlights the multidimensionality of stakeholder attitudes towards MHT. Four primary perceptual themes—tourism facilities and services, security and public amenities, cultural interaction and interpretation, and place identity and character serve as essential foundations for developing tourism destinations. Tourists and educational stakeholders exhibited similar congruence regarding the aesthetic and educational value of the site, reinforcing its uniqueness and the appeal of geological stories. Locals emphasized service quality, accessibility, and income opportunities, indicating readiness for participatory tourism models. The DFA also statistically significantly demonstrated perceptual variation between groups (Wilks' Lambda = 0.000, $p < 0.001$), indicating that tourism planning must adopt a segmented, stakeholder-responsive approach rather than a blanket strategy. Notably, the discriminant function classification accuracy exceeded 90%, confirming the model's predictive capacity and supporting the empirical validity of these perceptual dimensions. The mapping of these dimensions across stakeholder groups (see Table 20) further illuminates zones of synergy and dissonance—particularly regarding infrastructure needs and heritage conceptualization. Comparable transformations, such as the Zollverein Coal Mine Industrial Complex in Germany and the Wieliczka Salt Mine in Poland [8, 16, 21], demonstrate that derelict extraction landscapes can be successfully repositioned through integrated interpretation, infrastructural upgrades, and community participation—underscoring the feasibility of similar interventions at Barr. However, unlike these global exemplars, which possess clearly articulated interpretive identities, curated signature narratives, and well-defined unique selling propositions rooted in industrial memory and geo-interpretation, Barr currently lacks a cohesive brand story or an anchored interpretive framework highlighting the necessity of developing a distinctive narrative identity to guide its long-term positioning. Such a narrative may draw upon themes like “Proterozoic Time Journeys,” “Stone-as-Story,” or “Quarry Lives,” each capable of framing geological chronology, quarrying heritage, and community

memory within an integrated interpretive arc. From a place-making perspective, these thematic anchors can be reinforced by identity cues such as Marwari folk associations with land, intangible cultural practices linked to stone-working traditions, and symbolic assets embedded in community memory. These elements serve as the socio-cultural scaffolding through which visitors construct meaning and attachment, ensuring that Barr's evolving brand is rooted in both geological authenticity and lived cultural resonance.

6.2. Implications for Experience Design

With high loadings on variables related to educational value, visual setting, and interactivity, one of the strongest implications is the need for themed geo-trails and multi-lingual interpretation centres. Over 70% of visitors and scholars expressed a preference for guided heritage walks, storytelling-led site navigation, and interactive signage—indicating potential for a layered visitor experience based on science and culture. Such experience design must go beyond static exhibits to include immersive learning modules, QR-coded geo-points, augmented reality overlays, and local guide networks. These elements can transform the site from a passive historic location into an active “geo-learning environment,” appealing to both domestic tourists and international geotourism enthusiasts. For policymakers and planners, this also offers a model for integrating conservation education, citizen science, and live interpretation modes into heritage renewal—thereby enhancing long-term sustainability alongside increased place attachment. Similar interpretive trail models in repurposed mining landscapes—such as the geotrails at Cornwall's mining districts in the UK—illustrate how narrative-driven design can anchor visitor engagement and improve on-site learning [8, 16, 21]. Applying such approaches to Barr will require identifying its own signature themes—whether rooted in its Proterozoic geological history, quarrying legacy, or community narratives to craft a distinctive branding language that reflects the interpretive coherence seen in international success stories. Practically, this could include thematic circuits such as “Strata Stories Trail” (interpreting sedimentary layering and pebble compositions), “Quarry Workscapes Walk” (showcasing extraction practices and tools), or “Living Landscapes Loop” (connecting ecological regeneration with community memory), along with immersive experiences like soundscapes of quarry

labour, tactile rock galleries, or augmented-reality reconstructions of paleo-environments.

6.3. Tourism Readiness Gaps

In spite of the latent attraction, the statistical results and open-ended comments come together on a number of key readiness gaps. Safety infrastructure—such as lighting, patrolling, and gender-sensitive planning—lies low, particularly in areas outside the core area. The community and visitors identified a lack of wayfinding and limited interpretive signage as large deterrents to extended site use. These gaps align with low loadings on confidence and accessibility factors, especially among first-time users. In addition, narrative coherence—how the mining past, cultural present, and tourism future of the site are interpreted—remains disjointed. Without a compelling story that puts the geological, historical, and community aspects together, the potential for memorable and repeat visitation is lost. This lack of narrative cohesion was strongly underscored by researchers and planners who explained that without an obvious interpretive thread, the site is likely to be viewed as "just another quarry" instead of a heritage-rich destination. The experiential and emotional variables (A14–A20), which relate to place attachment, symbolic meaning, authenticity, and affective resonance, further underscore these shortcomings; in tourism psychology, such variables are central to destination image formation and the shaping of visitor expectations. Their relatively weaker performance at Barr indicates an underdeveloped identity framework, suggesting that visitors are unable to construct a coherent mental image of the site or anticipate a distinctive experiential offering—thereby weakening emotional engagement and long-term memorability. Summarily, while Barr Conglomerate has a strong case for MHT, its metamorphosis will require conscious investment in safety infrastructure, interpretive architecture, and co-creation with stakeholders. The quantitative results not only shed light on perceptual priorities but also provide actionable points of entry for formulating spatially responsive, community-focused, and experientially rich tourism interventions.

6.4. Segmentation Strategy

The canonical DFA provided robust statistical support for a segmented stakeholder approach, with substantial group-wise perceptual variations and high classification rates (over 90%).

Discriminant profiles are not only statistically significant but also actionable. They enable the customization of interventions based on the differing preferences, expectations, and sensitivities of various user groups: tourists, residents, planners, academics, and policymakers. For example, visitors prioritized interpretive depth and security above all—demanding targeted investment in trail security, narrative infrastructure, and multi-language signage. Locals, however, were more concerned with access to economic opportunities, local entrepreneurial incubation, and quality services. Measures for this group should include skill development initiatives, vendor facilitation spaces, and community-managed facilities. Planners and researchers, who showed the greatest agreement on geo-education and conservation priorities, can be strategically involved in the co-design of educational modules and site zoning frameworks. Meanwhile, policy-level players, though few, expressed concerns about narrative clarity and regional integration—highlighting the importance of coupling site development with district- and state-level tourism roadmaps. These differentiated perceptual profiles also translate into segment-specific branding strategies: tourists are most responsive to branding pillars centered on "Geological Authenticity" and experiential depth; residents align more closely with "Living Community Heritage," where livelihood, pride, and cultural continuity shape the brand narrative; and experts or planners gravitate toward "Memory Landscapes," emphasizing scientific credibility, conservation value, and heritage stewardship. Such differentiated branding anchors allow Barr to maintain a coherent overall identity while tailoring its narrative resonance to the expectations of each stakeholder segment. By projecting group-specific perceptual weights (through canonical structure matrices and function centroids), the site management agency can prioritize interventions based on evidence-driven perceptual clusters—selecting developments that are not merely need-sensitive but also resource-efficient.

6.5. Model Transferability

The methodology employed in this research—combining EFA, PCA, and DFA within a mixed-methods design demonstrates strong transferability to other post-industrial heritage destinations in India. Mining sites, abandoned mills, and disused industrial belts in the states of Jharkhand, Odisha, Chhattisgarh, and regions of Maharashtra all share

these same developmental challenges: cultural emptiness, environmental degradation, and stakeholder mistrust. With the model capable of:

- Revealing underlying perceptual themes among 46 Likert variables,
- Statistically distinguish between stakeholder groups with high accuracy,
- Diagnose thematic potential and readiness gaps through factor loadings, and
- Provide a scalable model for policy targeting and experience design.

It provides a replicable and adaptable toolkit for heritage managers, tourist boards, and local government authorities wishing to transform industrial scars into socio-economic and cultural assets. Significantly, this model does not dictate a prescriptive route but reacts to site-specific perceptual, infrastructural, and socio-political conditions, which makes it highly suited for application in India's extremely variegated post-industrial landscape. Coupled with satellite analytics, participatory mapping, and regional economic indicators, the model could become a complete HT forecasting system. The Barr Conglomerate study, therefore, provides not merely site-specific analysis but also a proof of concept for India's wider industrial heritage revalorization agenda synthesising history, economy, and society in an integrated statistical-analytical matrix.

7. Strategic and Policy Implications

The empirical data generated through this research culminate in strategic and policy-level recommendations with direct relevance for repositioning the Barr Conglomerate site on Rajasthan's evolving heritage and tourism map. The data not only highlight the hidden tourism potential of the site but also emphasize strategic operational gaps and perceptual misalignments among stakeholders. Only through an integrative approach that combines geo-heritage value with inclusive development and evidence-based planning can these insights be translated into actionable strategies. The first implication is the formal inclusion of the Barr Conglomerate in Rajasthan's geo-HT model. The state has gained widespread recognition for its palaces, forts, and sacred circuits, yet its remarkable geological formations remain underutilized in tourism policy. The Barr site, with its rock exposures and historic quarrying features, offers an attractive opportunity to diversify the local tourism portfolio through the

development of a geo-heritage circuit. This would not only elevate Barr's profile on state and national tourism platforms but also align with broader objectives of geological conservation and public geoscience education. Formal institutional backing from the tourism department, geological societies, and heritage commissions would be necessary to legitimize this inclusion and ensure the site is integrated into official promotional campaigns, signage plans, and tourist routes. A related practical consideration is that the site's post-mining degradation characterized by uneven terrain, abandoned pits, unstable quarry faces, and loose debris directly impacts visitor safety and route planning. Addressing slope stabilization, controlled access, and hazard mitigation at the early stages of tourism development is essential. Benchmarking these developments against Rajasthan's dominant tourist motivations—adventure-oriented mobility, authenticity-driven heritage exploration, storytelling-rich cultural routes, and emerging geotourism interests—indicates that Barr's competitiveness will depend on how effectively its geological authenticity and community-linked narratives can be aligned with the experiential profiles that currently drive regional circuits such as Jodhpur–Osian, Ranakpur–Kumbhalgarh, and the Udaipur heritage belt. A second key aspect is local community involvement in shaping and maintaining the site's tourism growth. The DFA revealed differing perceptual patterns: tourists prioritize safety, signage, and quality of experience, whereas residents focus on employment opportunities, recognition, and regulation of site-related activities. This disparity necessitates a community involvement approach that is not tokenistic but structurally integrated into the tourism model. Locals have expressed interest in becoming guides, food vendors, crafts producers, and caretakers. They should be supported through training schemes, micro-enterprise facilitation, and inclusion in decision-making structures. Participatory models of this kind align with international trends toward community-based HT, emphasizing local benefit-sharing and long-term custodianship.

The statistical precision used in this research, especially through EFA and discriminant function modelling, lends credibility to the design of data-driven tactics that transcend anecdotal planning. Site distinctiveness, cultural relevance, accessibility, and interpretive simplicity were important variables that influenced visitor satisfaction and return intentions. Decision-makers

and managers of a location can use this information to inform spatial investment decisions i.e., where to locate interpretation centres, how to stage upgrades to infrastructure, and which segments of visitors to target through marketing campaigns. Furthermore, knowledge of latent perception structures makes possible the development of tailored experience design components, such as themed geo-trails, augmented reality experiences, or mobile-guided narrative applications that directly address recognised visitor interests. A major issue is the bridging of infrastructural and experiential gaps that were repeatedly identified in all stakeholder groups. Safety issues, inadequate public facilities, and lack of narrative framing coherence were pervasive deterrents. These safety-related concerns further intersect with regulatory obligations; therefore, the proposed transition of Barr into a HT site must operate within the guidance of DGMS safety codes, IBM mine-closure norms, and Rajasthan's post-mining land rehabilitation provisions to ensure that tourism infrastructure complies with nationally recognised standards for site stability, risk mitigation, and responsible reuse. These deficits highlight the necessity for PPPs where private companies can be encouraged to invest in interpretative infrastructure, technology rollout, and service excellence improvement while public agencies maintain control over ecological and cultural protection [76]. Academia, in disciplines like geology, architecture, and tourism, should be integrated as knowledge partners to guarantee interventions are scientifically rigorous and culturally acceptable. Eventually, the development of Barr Conglomerate into a sustainable tourism site requires an integrated approach that brings together cultural, economic, and ecological sustainability. Culturally, the location must preserve and honour the oral histories, traditions, and social affiliations that are encoded in its landscape. Economically, tourism development will need to produce sustainable livelihoods for host communities and small-scale entrepreneurship. Ecologically, all physical interventions will need to follow principles of low-impact development with stringent guidelines for visitor flow management, site conservation, and climatic sensitivity [77]. Strengthening the tourism-branding interface is equally vital; therefore, recommendations must also emphasise interpretive design strategies such as co-created narrative themes, geo-heritage storytelling modules, and digital immersion tools that communicate Barr's geological character and memory landscapes across multiple visitor

segments. In practical terms, several interventions can be sequenced: immediate-term actions include basic signage installation, trail demarcation, hazard fencing, and foundational community training [78-80]; whereas medium-term planning should focus on developing interpretation centres, phased infrastructure upgrades, zoning frameworks, and digital trail integration requiring coordinated institutional investment [81-82]. The intersection of these three axes will guarantee that the Barr Conglomerate will not only be revived as HTD but also serve as an exemplary model for sustainable redevelopment of post-industrial sites everywhere in India.

8. Conclusions

MHT is an important and prospective field of research in the debate over regional development sustainability, particularly relevant for the case of post-industrial environments. This study demonstrated that when these locations are analysed with statistically intensive methodologies, namely multivariate analytics, their intrinsic potential for tourism reactivation and cultural regeneration can be empirically found and strategically formulated. Using an integration of EFA, PCA, and DFA, the research constructed a dense perceptual map of stakeholder expectations and experience and ultimately created a grounded, data-driven model for tourism development at the Barr Conglomerate site in Pali, Rajasthan. The findings reiterated that Barr Constellation is not only an industrial extraction residue but also a multi-scalar, multi-faceted space where regional identity, community memory, and natural history meet. The eight perceptual elements emphasised driving experiences—ranging from tourism infrastructure, interpretive quality, and cultural significance through safety, accessibility, and site uniqueness. Notably, the interviewees identified the site's great visual and geological features as a platform for education tourism, geo-trail-led, and theme interpretation. However, such opportunities are tempered by a general lack of basic facilities, safety amenities, and coordination among stakeholders. Locals expressed a deep wish to become involved in tourism-driven economic models in the form of guiding work, vending, or craft production employment, while policy and professional stakeholders welcomed the site for its potential to be integrated into Rajasthan's larger geo-heritage narrative.

Despite this overlap of interest, research further revealed perceptual fragmentation in stakeholder

groups and the need for coordinated narrative stewardship, place branding, and participatory planning instruments. Without deliberate investments in infrastructure, interpretation, and local capacity building, the Barr Conglomerate is likely to be a value-enclave possessing symbolic capital but functionally disconnected from the core tourism economy. This research not only diagnoses the present health of the Barr Conglomerate but also provides a replicable methodological blueprint for other Indian post-industrial settings. The application of DFA to stakeholder profile categorisation and intervention avenue ranking provides a scalable model that can be used in diverse cultural and environmental settings. It bridges the methodological gap commonly found in Indian HT research, with qualitative description dominating but unsubstantiated by empirical evidence. Moreover, the integration of spatial cognition, perceptual information, and multivariate modelling offers a forward-looking model for local authorities, planners, and private developers seeking to diversify the tourism economy while preserving cultural and ecological authenticity. More generally, this work argues that post-industrial landscapes, often relegated to the fringes of heritage thinking, need to be refashioned as positive agents of regional development. Through a judicious combination of narrative planning, policy support, and local mobilisation, these environments can be seen anew as living heritage centres—rooted in their geologic pasts but pointing towards expansive, experiential futures. MHT, if properly interpreted and utilised cautiously, thus has the capacity not only to recall industrial pasts, but to revive communities, rehabilitate lost geographies, and re-envision India's trajectory of development in terms of cultural sustainability.

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Appendix

Table 4. Survey Variables (A1–A46) and Justification for MHT Assessment at Barr Conglomerate (Source: Author)

Variable Code	Variable Label	Justification
A1	Proximity to Tourist Attractions	Indicates ease of access to key sites, critical for tourism infrastructure assessment.
A2	Visibility of Signage	Reflects clarity of navigation and interpretive infrastructure on-site.
A3	Availability of Local Guides	Assesses availability of human resources for interpretation and personalized engagement.
A4	Cleanliness of the Site	Indicates hygiene standards and visual appeal of the site, impacting visitor satisfaction.
A5	Perceived Uniqueness of the Site	Captures the distinctiveness of the site, fundamental for branding and experiential value.
A6	Wayfinding Clarity	Tests the spatial orientation experience of visitors and ease of movement across the site.
A7	Quality of Infrastructure	Broad indicator of the physical environment including trails, shelters, lighting, etc.
A8	Geological Features Visibility	Represents aesthetic and educational visibility of the site's unique geomorphology.
A9	Accessibility for Elderly and Disabled	Reflects inclusivity and universal design consideration at the site.
A10	Interpretation Material Satisfaction	Measures effectiveness of signage, boards, or brochures in conveying heritage significance.
A11	Sense of Security	Captures emotional comfort and safety perceptions by visitors and locals.
A12	Conservation Value Recognition	Evaluates public recognition of the site's ecological and historical preservation importance.
A13	Quality of Historical Narratives	Tests depth and appeal of storytelling at the site (guides, signage, interpretation panels).
A14	Symbolic Value of the Site	Assesses cultural or identity-related meaning attached by the local population.
A15	Cultural Identity Association	Measures how closely individuals relate the site to their community's heritage or culture.
A16	Emotional Attachment to the Site	Captures subjective place bonding, critical in long-term stewardship and local support.
A17	Participation in Commercial Tourism Services	Tests existing engagement of locals in tourism as vendors, hosts, or service providers.
A18	Satisfaction with Transport Routes	Assesses quality, reach, and comfort of public/private transport options.
A19	Awareness of Site's Historical Background	Reflects basic site literacy and prior knowledge among stakeholders.
A20	Site's Geological Distinctiveness	Measures recognition of geodiversity and educational value.
A21	Visitor Comfort and Spatial Perception	Tests perceived legibility, seating, shade, and other comfort provisions.
A22	Availability of On-site Information	Measures presence and accessibility of orientation material, maps, and signboards.
A23	Willingness to Participate in Tourism	Reflects community interest in future involvement as stakeholders.
A24	Adequacy of Amenities	Measures perceptions of restrooms, water stations, sitting areas, etc.
A25	Purchase of Local Products	Indicates tourist interaction with local economy—handicrafts, souvenirs, etc.
A26	Use of Interpretation Facilities	Tests actual utilization of interpretive services offered at the site.
A27	Access to Nearby Restaurants/Cafes	Measures satisfaction with surrounding food services and hospitality support.
A28	Connectivity to Nearby Attractions	Reflects degree of integration into regional tourism circuits.
A29	Availability of Parking Spaces	Indicates adequacy of vehicular accommodation infrastructure.
A30	Perceived Overcrowding	Captures experience of congestion, which affects satisfaction and sustainability.
A31	Quality of Trails and Pathways	Assesses trail maintenance, route diversity, and physical safety.
A32	Storytelling Quality	Evaluates the richness and relevance of the stories presented during visits.
A33	Integration of Local Commercial Products	Measures how embedded local vendors and products are within the site experience.
A34	Cultural Festivals and Event Engagement	Reflects linkages to cultural programming and seasonal tourist attraction.
A35	Perceived Management Quality	Measures confidence in site oversight and maintenance.
A36	Satisfaction with Public Safety	Captures broader civic infrastructure's influence on tourism perception.
A37	Satisfaction with Interpretation Sessions	Evaluates formal guiding, tours, or talks delivered at the site.
A38	Engagement with Interactive Displays	Tests modern interpretive formats (e.g., AR/VR, tactile exhibits, demos).
A39	Availability of Emergency Services	Reflects preparedness and safety assurance for crisis scenarios.
A40	Governance Satisfaction	Measures perceived transparency, efficiency, and participation in decision-making.
A41	Satisfaction with Staff Behaviour	Captures frontline engagement and tourist service quality.
A42	Aesthetic Appeal of the Landscape	Evaluates natural beauty and visual coherence—key to mining heritage site rebranding.
A43	Cultural Representation in Displays	Tests inclusion and relevance of local culture in exhibitions.
A44	Perceived Inclusiveness of Development	Reflects whether tourism benefits appear to be equitably distributed.
A45	Satisfaction with Transport Services	Assesses perceived quality, frequency, and reliability of available transport options.
A46	Overall Satisfaction with Site Experience	A holistic variable summarizing general approval of the visit or site conditions.

Table 5. Descriptive Statistics of the 46 Variables (Source: Author)

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
A1	440	1.00	5.00	4.1727	.93145
A2	440	1.00	5.00	3.7023	1.00341
A3	440	1.00	5.00	4.0205	.78832
A4	440	2.00	4.00	3.6477	.49691
A5	440	3.00	5.00	3.8250	.68755
A6	440	1.00	5.00	3.9659	.94071
A7	440	2.00	5.00	4.1909	.83211
A8	440	3.00	5.00	4.3114	.79912
A9	440	3.00	5.00	3.9659	.56570
A10	440	1.00	5.00	3.4614	.89969
A11	440	2.00	5.00	3.7341	.83474
A12	440	2.00	5.00	4.0659	.86054
A13	440	1.00	5.00	3.7432	.58059
A14	440	1.00	5.00	3.7818	1.51158
A15	440	2.00	5.00	4.2727	.76850
A16	440	2.00	5.00	3.8795	.69593
A17	440	1.00	5.00	3.3773	.60252
A18	440	2.00	5.00	3.8205	.72824
A19	440	1.00	5.00	4.0295	.96713
A20	440	2.00	5.00	4.0250	.87320
A21	440	1.00	5.00	3.7182	.94140
A22	440	3.00	5.00	4.1864	.82213
A23	440	1.00	5.00	3.7409	.78201
A24	440	1.00	5.00	3.2682	1.19638
A25	440	1.00	5.00	3.5727	.83717
A26	440	1.00	5.00	4.0591	.99939
A27	440	2.00	5.00	4.1591	.74989
A28	440	3.00	5.00	3.9818	.62202
A29	440	1.00	5.00	3.4705	.90508
A30	440	1.00	5.00	3.6705	.87384
A31	440	1.00	5.00	3.9818	.86155
A32	440	1.00	5.00	3.7841	.62683
A33	440	1.00	5.00	3.7841	1.47453
A34	440	1.00	5.00	4.2182	.81144
A35	440	2.00	5.00	3.9091	.71808
A36	440	1.00	5.00	3.4455	.66252
A37	440	2.00	5.00	3.9114	.59524
A38	440	1.00	5.00	3.4773	1.01220
A39	440	2.00	5.00	3.7750	.85740
A40	440	1.00	5.00	4.0136	.87214
A41	440	1.00	5.00	3.7386	.60924
A42	440	1.00	5.00	3.7818	1.45944
A43	440	2.00	5.00	4.2182	.77114
A44	440	2.00	5.00	3.8955	.69687
A45	440	1.00	5.00	3.3977	.65683
A46	440	1.00	5.00	3.4091	.61560
Valid N (listwise)	440				

Table 6. Communalities Table – Extraction Summary (Source: Author)

	Communalities	
	Initial	Extraction
A1	1.000	.849
A2	1.000	.796
A3	1.000	.834
A4	1.000	.716
A5	1.000	.857
A6	1.000	.793
A7	1.000	.842
A8	1.000	.866
A9	1.000	.893
A10	1.000	.907
A11	1.000	.876
A12	1.000	.886
A13	1.000	.925
A14	1.000	.934
A15	1.000	.915
A16	1.000	.909
A17	1.000	.921
A18	1.000	.893
A19	1.000	.820
A20	1.000	.845
A21	1.000	.852
A22	1.000	.848
A23	1.000	.770
A24	1.000	.782
A25	1.000	.813
A26	1.000	.642
A27	1.000	.727
A28	1.000	.768
A29	1.000	.777
A30	1.000	.699
A31	1.000	.748
A32	1.000	.888
A33	1.000	.912
A34	1.000	.816
A35	1.000	.826
A36	1.000	.894
A37	1.000	.787
A38	1.000	.685
A39	1.000	.843
A40	1.000	.733
A41	1.000	.847
A42	1.000	.919
A43	1.000	.875
A44	1.000	.872
A45	1.000	.839
A46	1.000	.940

Extraction Method: Principal Component Analysis.

Table 7. Total Variance Explained with Eigenvalues (Source: Author)

Component	Total Variance Explained								
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	19.553	42.506	42.506	19.553	42.506	42.506	8.331	18.111	18.111
2	5.070	11.021	53.528	5.070	11.021	53.528	8.259	17.954	36.065
3	3.841	8.351	61.878	3.841	8.351	61.878	4.683	10.180	46.245
4	2.979	6.476	68.354	2.979	6.476	68.354	4.221	9.175	55.420
5	2.018	4.387	72.741	2.018	4.387	72.741	3.746	8.145	63.565
6	1.827	3.972	76.713	1.827	3.972	76.713	3.587	7.799	71.364
7	1.700	3.696	80.409	1.700	3.696	80.409	2.796	6.078	77.442
8	1.392	3.026	83.435	1.392	3.026	83.435	2.757	5.994	83.435
9	.768	1.669	85.104						
10	.715	1.555	86.659						
11	.673	1.464	88.123						
12	.589	1.281	89.404						
13	.516	1.121	90.525						
14	.431	.938	91.463						
15	.391	.851	92.314						
16	.359	.780	93.093						
17	.334	.726	93.820						
18	.310	.673	94.493						
19	.287	.624	95.117						
20	.247	.538	95.655						
21	.217	.473	96.128						
22	.211	.459	96.586						
23	.184	.399	96.986						
24	.165	.360	97.345						
25	.141	.307	97.652						
26	.132	.287	97.939						
27	.113	.246	98.185						
28	.106	.230	98.415						
29	.087	.189	98.604						
30	.083	.181	98.785						
31	.076	.166	98.951						
32	.069	.150	99.100						
33	.067	.145	99.245						
34	.055	.119	99.365						
35	.050	.109	99.473						
36	.046	.100	99.573						
37	.039	.086	99.659						
38	.035	.076	99.735						
39	.030	.066	99.801						
40	.026	.056	99.857						
41	.019	.041	99.898						
42	.015	.033	99.931						
43	.013	.028	99.959						
44	.009	.020	99.978						
45	.006	.014	99.992						
46	.004	.008	100.000						

Extraction Method: Principal Component Analysis.

Table 8. Unrotated Component Matrix (Source: Author)

Component Matrix ^a								
	Component							
	1	2	3	4	5	6	7	8
A1	-.163	-.474	.424	.438	.349	.050	.075	.311
A2	.430	.563	.007	.013	.178	.109	-.481	.137
A3	.728	.252	-.152	.122	-.162	.141	-.393	.038
A4	.797	.021	.171	-.175	.111	.065	.022	.054
A5	.774	.266	-.248	-.204	-.082	-.229	-.157	-.002
A6	.677	-.296	-.368	-.208	.141	-.121	-.133	-.129
A7	.843	-.169	.016	-.055	-.248	-.040	-.039	-.188
A8	.790	-.250	-.128	.043	-.134	-.070	-.286	.236
A9	.524	.148	.454	.520	.050	-.078	-.275	-.188
A10	.358	.646	.443	-.226	.265	.038	.189	.087
A11	.704	-.391	.040	-.146	.431	.057	.022	-.123
A12	.874	-.131	-.144	-.188	.099	.069	-.061	-.175
A13	.663	-.021	.305	-.098	-.283	.537	.117	.011
A14	.827	.071	.189	.152	-.079	-.363	.200	.086
A15	.857	-.171	.155	.000	-.327	-.122	.065	-.024
A16	.696	-.414	-.306	.303	.160	.065	.142	.136
A17	.367	.647	-.483	.326	.009	.082	.146	-.025
A18	.793	.172	-.359	-.135	-.094	.009	-.214	-.180
A19	.866	-.131	-.138	-.058	-.080	-.116	-.009	.100
A20	.822	-.083	-.256	-.137	.012	-.183	.108	.180
A21	.590	.319	.030	-.392	.115	-.235	.252	.339
A22	.872	-.048	.188	-.099	.029	-.032	.069	.185
A23	.682	.125	-.167	-.327	-.109	-.115	-.339	.118
A24	.260	.659	.145	-.496	-.031	-.075	-.040	-.074
A25	.518	-.070	-.023	-.098	.153	.326	-.366	.516
A26	.721	-.152	-.204	.005	.145	-.038	-.089	.165
A27	.409	.157	.494	.406	-.033	.053	-.233	.262
A28	.460	.139	.416	.486	.091	-.063	-.273	-.204
A29	.321	.584	.427	-.199	.289	.036	.157	.045
A30	.579	-.313	.055	-.114	.438	.115	-.009	-.210
A31	.771	-.136	-.063	-.162	.102	.129	-.047	-.276
A32	.592	-.006	.269	-.042	-.279	.592	.187	-.012
A33	.806	.068	.207	.212	-.097	-.338	.214	.043
A34	.769	-.168	.197	.004	-.359	-.118	.098	-.077
A35	.652	-.363	-.279	.329	.118	.131	.204	.103
A36	.327	.607	-.440	.412	.049	.161	.160	-.029
A37	.443	.114	.437	.471	.103	-.115	-.204	-.315
A38	.316	.529	.377	-.183	.297	.009	.200	-.029
A39	.659	-.322	.050	-.146	.482	.065	.063	-.200
A40	.752	-.119	-.090	-.162	.141	.081	.041	-.301
A41	.594	-.038	.258	-.100	-.326	.533	.160	-.011
A42	.812	.063	.196	.194	-.097	-.332	.238	.058
A43	.797	-.192	.188	.005	-.364	-.126	.121	-.073
A44	.670	-.400	-.327	.294	.125	.073	.181	.123
A45	.332	.564	-.510	.324	.044	.105	.167	-.067
A46	.348	.616	-.517	.361	.038	.115	.160	-.028

Extraction Method: Principal Component Analysis.
a. 8 components extracted.

Table 9. Rotated Component Matrix (Varimax) (Source: Author)

	Rotated Component Matrix ^a							
	Component							
	1	2	3	4	5	6	7	8
A1	-.063	.044	-.329	-.127	.267	-.057	.055	-.801
A2	-.043	.078	.332	.384	.354	-.002	.569	.285
A3	.291	.231	.380	.005	.337	.255	.496	.356
A4	.418	.495	.030	.347	.148	.294	.246	.077
A5	.525	.345	.303	.210	.049	-.008	.305	.481
A6	.350	.724	.072	-.139	-.071	-.044	.195	.277
A7	.591	.468	.039	-.054	.216	.351	.079	.305
A8	.571	.410	.045	-.189	.159	.149	.521	.122
A9	.252	.128	.097	.115	.878	.110	.084	-.029
A10	.100	.018	.136	.909	.162	.148	.066	.016
A11	.236	.869	-.113	.106	.105	.110	.108	-.082
A12	.385	.733	.133	.079	.088	.245	.185	.273
A13	.268	.242	.014	.175	.133	.848	.159	.042
A14	.822	.263	.157	.253	.301	.077	.047	-.025
A15	.759	.334	-.018	.004	.225	.375	.092	.165
A16	.441	.632	.287	-.293	.040	.127	.198	-.300
A17	.121	.010	.926	.150	.062	.011	.068	.134
A18	.357	.481	.384	.028	.091	.155	.268	.531
A19	.646	.495	.149	.011	.058	.172	.284	.148
A20	.656	.509	.217	.085	-.118	.055	.272	.103
A21	.539	.203	.129	.622	-.233	-.008	.239	.073
A22	.609	.450	.018	.292	.150	.285	.291	-.013
A23	.409	.314	.075	.145	.005	.059	.491	.483
A24	.085	-.068	.100	.695	-.034	.064	.083	.516
A25	.094	.306	.014	.082	.018	.239	.799	-.089
A26	.419	.539	.176	-.014	.049	.046	.374	.011
A27	.261	-.102	.015	.184	.622	.216	.364	-.221
A28	.182	.139	.091	.108	.827	.077	.067	-.027
A29	.058	.047	.110	.843	.183	.117	.044	.008
A30	.089	.795	-.086	.111	.150	.111	.047	-.051
A31	.274	.695	.086	.076	.143	.287	.080	.259
A32	.206	.209	.079	.147	.107	.868	.093	-.011
A33	.800	.244	.174	.223	.345	.104	.000	-.043
A34	.715	.272	-.051	-.002	.229	.386	.005	.164
A35	.402	.572	.324	-.274	.041	.199	.132	-.314
A36	.051	.013	.926	.117	.114	.053	.050	.034
A37	.191	.174	.064	.118	.833	.054	-.070	-.009
A38	.065	.099	.121	.786	.167	.092	-.039	.012
A39	.169	.867	-.075	.168	.119	.091	.026	-.072
A40	.289	.709	.121	.107	.103	.238	7.384E-5	.232
A41	.251	.201	.024	.124	.075	.842	.100	.049
A42	.811	.252	.177	.230	.315	.113	.000	-.051
A43	.748	.295	-.048	-.012	.217	.394	-.001	.153
A44	.440	.603	.306	-.301	.004	.144	.161	-.289
A45	.076	.067	.898	.094	.034	.007	.022	.106
A46	.086	.034	.951	.111	.052	.011	.060	.092

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 9 iterations.

Table 10. Component Transformation Matrix (Source: Author)

Component	Component Transformation Matrix							
	1	2	3	4	5	6	7	8
1	.603	.570	.224	.171	.237	.297	.259	.144
2	-.119	-.409	.562	.625	.130	-.055	.056	.300
3	.059	-.206	-.596	.452	.507	.270	-.111	-.231
4	.055	-.177	.447	-.402	.605	-.064	-.075	-.479
5	-.404	.568	.046	.380	.071	-.452	.071	-.392
6	-.555	.119	.169	-.046	-.078	.765	.188	-.142
7	.287	.009	.218	.241	-.433	.199	-.623	-.445
8	.248	-.313	-.031	.104	-.326	-.052	.696	-.486

Extraction Method: Principal Component Analysis.
 Rotation Method: Varimax with Kaiser Normalization.

Table 11. Kolmogorov–Smirnov Z Test Summary for All Distributions (Source: Author)

N	Normal		Most Extreme Differences		Kolmogoro v-Smirnov	Asymp. Sig. (2-
	Mean	Std.	Negativ	Positiv		
440	4.1727	.93145	-.263	.187	5.513	.000
440	3.7023	1.0034	.292	.292	6.127	.000
440	4.0205	.78832	-.269	.238	5.647	.000
440	3.6477	.49691	.418	.247	8.760	.000
440	3.8250	.68755	.262	.236	5.492	.000
440	3.9659	.94071	.228	.151	4.784	.000
440	4.1909	.83211	.285	.174	5.969	.000
440	4.3114	.79912	.328	.194	6.887	.000
440	3.9659	.56570	.347	.333	7.274	.000
440	3.4614	.89969	.278	.278	5.827	.000
440	3.7341	.83474	.235	.235	4.938	.000
440	4.0659	.86054	.248	.195	5.192	.000
440	3.7432	.58059	.423	.302	8.876	.000
440	3.7818	1.5115	.276	.210	5.794	.000
440	4.2727	.76850	.287	.180	6.022	.000
440	3.8795	.69593	.296	.261	6.209	.000
440	3.3773	.60252	.321	.321	6.728	.000
440	3.8205	.72824	.263	.230	5.523	.000
440	4.0295	.96713	.231	.158	4.845	.000
440	4.0250	.87320	.247	.221	5.191	.000
440	3.7182	.94140	.231	.178	4.852	.000
440	4.1864	.82213	.287	.187	6.011	.000
440	3.7409	.78201	.251	.251	5.265	.000
440	3.2682	1.1963	.176	.176	3.689	.000
440	3.5727	.83717	.325	.232	6.810	.000
440	4.0591	.99939	.274	.173	5.758	.000
440	4.1591	.74989	.235	.218	4.926	.000
440	3.9818	.62202	.309	.304	6.490	.000
440	3.4705	.90508	.273	.273	5.735	.000
440	3.6705	.87384	.226	.226	4.746	.000
440	3.9818	.86155	.213	.196	4.472	.000
440	3.7841	.62683	.389	.299	8.166	.000
440	3.7841	1.4745	.263	.205	5.525	.000
440	4.2182	.81144	.271	.168	5.684	.000
440	3.9091	.71808	.280	.252	5.872	.000
440	3.4455	.66252	.299	.299	6.279	.000
440	3.9114	.59524	.348	.311	7.296	.000
440	3.4773	1.0122	.236	.236	4.949	.000
440	3.7750	.85740	.235	.235	4.933	.000
440	4.0136	.87214	.226	.191	4.730	.000
440	3.7386	.60924	.421	.304	8.822	.000
440	3.7818	1.4594	.255	.202	5.346	.000
440	4.2182	.77114	.265	.191	5.561	.000
440	3.8955	.69687	.296	.263	6.209	.000
440	3.3977	.65683	.307	.307	6.442	.000
440	3.4091	.61560	.306	.306	6.417	.000

a. Test distribution is Normal.

Expo Mean	N	Asymp. Sig. (2-	Kolmogorov v-Smirnov	Most Extreme Differences			Kolmogorov v-Smirnov	Most Extreme Differences		
				Negativ	Positiv	Absolut		Negativ	Positiv	Absolut
4.172	440	.000	5.085	-.237	-.242	.242	12.300	-.586	.016	.586
3.702	440	.000	5.073	-.242	.170	.242	9.582	-.457	.034	.457
4.020	440	.000	4.598	-.219	.218	.219	11.108	-.530	.016	.530
3.647	440	.000	6.350	-.285	.303	.303	13.778	-.657	.009	.657
3.825	440	.000	5.556	-.265	.188	.265	7.103	-.164	.339	.339
3.965	440	.000	4.396	-.170	.210	.210	9.725	-.464	.009	.464
4.190	440	.000	5.147	-.202	.245	.245	9.439	-.450	.009	.450
3.965	440	.000	5.563	-.196	.265	.265	10.965	-.523	.211	.523
3.461	440	.000	4.688	-.224	.137	.224	7.485	-.323	.357	.357
3.734	440	.000	4.914	-.234	.175	.234	8.295	-.395	.093	.395
4.065	440	.000	4.725	-.210	.225	.225	6.039	-.288	.129	.288
3.743	440	.000	6.164	-.251	.294	.294	8.104	-.386	.018	.386
3.781	440	.000	3.813	-.158	.182	.182	10.536	-.502	.223	.502
4.272	440	.000	5.429	-.205	.259	.259	10.202	-.486	.186	.486
3.879	440	.000	4.995	-.238	.196	.238	10.266	-.489	.009	.489
3.377	440	.000	6.456	-.308	.243	.308	8.263	-.394	.163	.394
3.820	440	.000	5.190	-.247	.187	.247	9.725	-.464	.241	.464
4.029	440	.000	4.604	-.171	.220	.220	6.976	-.333	.161	.333
4.025	440	.000	4.632	-.221	.219	.221	10.345	-.493	.009	.493
3.718	440	.000	4.588	-.219	.173	.219	7.961	-.380	.014	.380
4.186	440	.000	5.131	-.212	.245	.245	9.153	-.436	.045	.436
3.740	440	.000	5.653	-.269	.176	.269	9.392	-.448	.261	.448
3.268	440	.000	2.455	-.117	.113	.117	10.297	-.491	.068	.491
3.572	440	.000	4.523	-.203	.216	.216	4.291	-.205	.070	.205
4.059	440	.000	4.702	-.166	.224	.224	8.295	-.395	.177	.395
4.159	440	.000	5.039	-.209	.240	.240	9.392	-.448	.009	.448
3.981	440	.000	5.051	-.241	.212	.241	9.789	-.467	.007	.467
3.470	440	.000	4.557	-.217	.139	.217	6.627	-.298	.316	.316
3.670	440	.000	4.567	-.218	.166	.218	8.200	-.391	.089	.391
3.981	440	.000	4.526	-.216	.212	.216	9.964	-.475	.002	.475
3.784	440	.000	5.520	-.244	.263	.263	10.583	-.505	.184	.505
4.218	440	.000	3.820	-.152	.182	.182	9.821	-.468	.173	.468
3.909	440	.000	5.241	-.192	.250	.250	11.537	-.550	.002	.550
3.445	440	.000	4.899	-.234	.201	.234	8.311	-.396	.136	.396
3.911	440	.000	6.181	-.295	.223	.295	9.725	-.464	.209	.464
3.477	440	.000	5.130	-.245	.224	.245	9.551	-.455	.204	.455
3.775	440	.000	4.244	-.202	.139	.202	7.914	-.377	.059	.377
4.013	440	.000	4.820	-.230	.181	.230	6.086	-.290	.097	.290
3.738	440	.000	4.552	-.213	.217	.217	10.011	-.477	.005	.477
3.781	440	.000	6.098	-.247	.291	.291	10.583	-.505	.220	.505
4.218	440	.000	3.813	-.152	.182	.182	9.582	-.457	.170	.457
3.895	440	.000	5.241	-.199	.250	.250	9.932	-.473	.009	.473
3.397	440	.000	4.943	-.236	.199	.236	8.454	-.403	.156	.403
3.409	440	.000	6.182	-.295	.224	.295	9.535	-.455	.218	.455
	440	.000	6.327	-.302	.244	.302	9.725	-.464	.236	.464

a. Test distribution is Uniform.

b. Test distribution is Poisson.

Kolmogorov v-Smirnov	Most Extreme Differences		
	Nezativ	Positiv	Absolut
9.501	-.453	.302	.453
10.742	-.512	.259	.512
10.696	-.510	.288	.510
11.569	-.552	.334	.552
11.402	-.544	.271	.544
9.606	-.458	.283	.458
10.533	-.502	.303	.502
10.516	-.501	.314	.501
11.131	-.531	.283	.531
9.966	-.475	.236	.475
10.630	-.507	.262	.507
10.565	-.504	.292	.504
10.993	-.524	.316	.524
7.387	-.352	.267	.352
10.391	-.495	.310	.495
10.914	-.520	.276	.520
11.585	-.552	.297	.552
11.030	-.526	.270	.526
9.249	-.441	.289	.441
10.735	-.512	.289	.512
10.280	-.490	.261	.490
10.731	-.512	.303	.512
11.379	-.542	.263	.542
8.648	-.412	.217	.412
9.725	-.464	.254	.464
9.624	-.459	.292	.459
10.636	-.507	.301	.507
11.102	-.529	.285	.529
9.851	-.470	.237	.470
10.187	-.486	.256	.486
10.577	-.504	.285	.504
10.911	-.520	.282	.520
7.574	-.361	.267	.361
10.294	-.491	.306	.491
10.858	-.518	.278	.518
11.432	-.545	.272	.545
11.092	-.529	.279	.529
9.550	-.455	.237	.455
10.595	-.505	.266	.505
10.566	-.504	.288	.504
10.906	-.520	.313	.520
7.721	-.368	.267	.368
10.485	-.500	.306	.500
10.884	-.519	.277	.519
11.348	-.541	.276	.541
11.513	-.549	.296	.549

Asymp.
Sig. (2-

c. Test Distribution is Exponential.

Table 12. Tests of Equality of Group Means – Wilks’ Lambda and F-statistics (Source: Author)

	Tests of Equality of Group Means				
	Wilks' Lambda	F	df1	df2	Sig.
A1	.804	26.438	4	435	.000
A2	.706	45.254	4	435	.000
A3	.711	44.275	4	435	.000
A4	.952	5.474	4	435	.000
A5	.714	43.505	4	435	.000
A6	.959	4.609	4	435	.001
A7	.963	4.167	4	435	.003
A8	.915	10.130	4	435	.000
A9	.860	17.718	4	435	.000
A10	.873	15.873	4	435	.000
A11	.940	6.936	4	435	.000
A12	.949	5.802	4	435	.000
A13	.978	2.407	4	435	.049
A14	.836	21.276	4	435	.000
A15	.963	4.179	4	435	.002
A16	.868	16.528	4	435	.000
A17	.116	825.579	4	435	.000
A18	.735	39.164	4	435	.000
A19	.914	10.183	4	435	.000
A20	.858	18.021	4	435	.000
A21	.859	17.799	4	435	.000
A22	.919	9.550	4	435	.000
A23	.807	25.929	4	435	.000
A24	.837	21.175	4	435	.000
A25	.921	9.306	4	435	.000
A26	.796	27.928	4	435	.000
A27	.911	10.616	4	435	.000
A28	.899	12.173	4	435	.000
A29	.914	10.224	4	435	.000
A30	.970	3.338	4	435	.010
A31	.971	3.193	4	435	.013
A32	.974	2.895	4	435	.022
A33	.846	19.803	4	435	.000
A34	.990	1.088	4	435	.362
A35	.875	15.476	4	435	.000
A36	.159	576.997	4	435	.000
A37	.879	15.006	4	435	.000
A38	.909	10.935	4	435	.000
A39	.951	5.616	4	435	.000

Tests of Equality of Group Means					
	Wilks' Lambda	F	df1	df2	Sig.
A40	.965	3.996	4	435	.003
A41	.980	2.181	4	435	.070
A42	.839	20.862	4	435	.000
A43	.987	1.396	4	435	.235
A44	.871	16.107	4	435	.000
A45	.218	390.705	4	435	.000

Table 13. Box's Test of Equality of Covariance Matrices (Source: Author)

Log Determinants			
A46	Rank	Log Determinant	
1	. ^a	. ^b	
2	. ^c	. ^b	
3	28	. ^d	
4	39	. ^d	
5	. ^c	. ^b	
Pooled within-groups		45	-103.857

The ranks and natural logarithms of determinants printed are those of the group covariance matrices.

a. Rank < 4

b. Too few cases to be non-singular

c. Rank < 12

d. Singular

e. Rank < 6

Table 14. Summary of Canonical Discriminant Functions – Eigenvalues and Canonical Correlations (Source: Author)

Function	Eigenvalues			Canonical Correlation
	Eigenvalue	% of Variance	Cumulative %	
1	97.573 ^a	81.5	81.5	.995
2	18.606 ^a	15.5	97.0	.974
3	2.345 ^a	2.0	99.0	.837
4	1.254 ^a	1.0	100.0	.746

a. First 4 canonical discriminant functions were used in the analysis.

Table 15. Wilks' Lambda for Canonical Functions – Chi-square and Significance (Source: Author)

Test of Function(s)	Wilks' Lambda			
	Wilks' Lambda	Chi-square	df	Sig.
1 through 4	.000	3969.036	180	.000
2 through 4	.007	2068.448	132	.000
3 through 4	.133	836.449	86	.000
4	.444	336.530	42	.000

Table 16. Standardized Canonical Discriminant Function Coefficients (Source: Author)

	Standardized Canonical Discriminant Function Coefficients			
	Function			
	1	2	3	4
A1	.574	.207	.906	1.096
A2	2.036	-.292	-.735	.552
A3	-.461	-.109	.060	-.475
A4	-7.022	1.324	.154	-1.726
A5	9.551	-3.121	-2.000	.014
A6	1.544	-.974	.159	-.316
A7	5.424	-2.777	.131	-1.588
A8	4.540	-1.012	.578	.672
A9	-6.064	1.258	-.022	-1.013
A10	7.022	-1.813	-.046	1.119
A11	5.160	-2.450	-.215	-1.344
A12	-7.332	3.576	2.138	1.009
A13	2.207	-2.453	-1.661	-.418
A14	-4.854	.606	-1.272	1.125
A15	.700	1.147	3.072	2.367
A16	1.278	2.819	.373	2.396
A17	1.394	.280	.709	-.327
A18	2.565	.423	-.602	2.049
A19	-1.631	-.800	.102	-1.607
A20	-4.424	1.443	-1.728	-.934
A21	1.150	-.167	-.284	-.365
A22	-.037	.262	.261	.231
A23	-8.741	3.225	.764	.421
A24	-6.351	2.069	1.602	.386
A25	-2.055	.469	.965	-.033
A26	3.708	-1.296	-1.881	-.295
A27	1.154	-.126	-.976	.395
A28	-.271	.005	.049	-.073
A29	-.107	-.027	.495	-.070
A30	-.173	.060	-.038	-.101
A31	.097	-.452	.155	.393
A32	.308	1.235	-.623	.080
A33	-.287	-.113	.170	.042
A34	.098	.509	-.040	-.556
A35	-.419	-2.131	.742	-.012
A36	.246	.718	-.061	-.116
A37	-.108	.348	.161	-.392
A38	-.072	-.135	-.116	.173
A39	.331	-.025	-.083	.136
A40	-.072	-.047	.065	-.152
A41	-.011	.465	.046	-.218
A42	.703	1.217	.083	-.843
A43	-.309	-.992	-.188	.581
A44	.060	-.263	.033	-.531
A45	.156	.289	-.026	.055

Table 17. Structure Matrix – Variable Correlations with Canonical Functions (Source: Author)

	Structure Matrix			
	Function			
	1	2	3	4
A17	.179	.486*	.051	-.218
A36	.147	.409*	.039	-.265
A45	.122	.335*	.038	-.193
A2	.012	.139*	-.098	.116
A3	.022	.134*	-.067	.097
A18	.033	.114*	-.064	-.054
A42	-.001	.098*	-.077	-.007
A14	.000	.096*	-.092	.066
A33	-.001	.095*	-.075	-.007
A24	-.012	.094*	-.075	-.035
A9	-.016	.085*	-.009	-.053
A28	-.013	.071*	.021	-.034
A29	-.002	.067*	-.061	-.021
A12	.015	.041*	.024	-.003
A34	.000	.023*	.000	.016
A5	.012	.133	-.156*	.031
A26	.044	.012	-.146*	.099
A21	.011	.076	-.125*	.079
A20	.012	.082	-.101*	.049
A10	.000	.081	-.095*	-.030
A35	.033	.027	.091*	.017
A44	.034	.028	.089*	.041
A19	.021	.043	-.085*	-.002
A38	.000	.067	-.080*	-.024
A4	.000	.044	-.079*	-.016
A7	.005	.038	.061*	.021
A13	.002	.027	-.059*	.005
A32	.004	.031	-.048*	-.042
A31	.011	.024	.044*	-.036
A1	-.009	-.099	.070	.180*
A8	.017	.027	-.074	.178*
A27	.000	.047	-.101	.159*
A25	-.001	.043	-.099	.149*
A37	-.018	.068	.016	-.122*
A23	-.009	.101	-.101	.115*
A15	.002	.037	-.027	.094*
A16	.034	.031	.076	.091*
A22	-.005	.063	-.032	.084*
A30	.009	-.021	.061	-.066*
A11	.015	-.037	.064	-.066*
A39	.016	-.028	.055	-.057*
A41	.002	.025	-.043	-.052*
A40	.012	.027	.044	-.051*
A6	.018	.013	-.049	-.049*
A43	.000	.024	-.005	.039*

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
 Variables ordered by absolute size of correlation within function.

*. Largest absolute correlation between each variable and any discriminant function

Table 18. Canonical Centroid Showing Group Clusters (Source: Author)

Canonical Discriminant Function Coefficients				
	Function			
	1	2	3	4
A1	.684	.247	1.079	1.306
A2	2.403	-.345	-.868	.651
A3	-.690	-.163	.090	-.711
A4	-14.416	2.718	.317	-3.544
A5	16.362	-5.346	-3.426	.023
A6	1.668	-1.052	.171	-.341
A7	6.612	-3.385	.160	-1.936
A8	5.913	-1.318	.752	.875
A9	-11.508	2.388	-.042	-1.922
A10	8.316	-2.147	-.055	1.326
A11	6.346	-3.014	-.265	-1.653
A12	-8.705	4.245	2.538	1.198
A13	3.826	-4.252	-2.880	-.724
A14	-3.495	.436	-.916	.810
A15	.924	1.514	4.054	3.124
A16	1.962	4.328	.573	3.679
A17	6.751	1.353	3.432	-1.584
A18	4.089	.675	-.960	3.266
A19	-1.755	-.861	.109	-1.730
A20	-5.445	1.776	-2.127	-1.150
A21	1.312	-.190	-.323	-.417
A22	-.047	.331	.329	.291
A23	-12.383	4.568	1.083	.596
A24	-5.776	1.882	1.457	.351
A25	-2.545	.581	1.196	-.041
A26	4.141	-1.447	-2.100	-.329
A27	1.605	-.175	-1.357	.550
A28	-.457	.009	.083	-.123
A29	-.124	-.031	.570	-.080
A30	-.200	.069	-.044	-.116
A31	.114	-.530	.182	.460
A32	.495	1.988	-1.003	.128
A33	-.211	-.083	.125	.031
A34	.121	.628	-.049	-.685
A35	-.620	-3.158	1.099	-.017
A36	.927	2.708	-.230	-.437
A37	-.193	.620	.288	-.699
A38	-.074	-.140	-.120	.178
A39	.394	-.030	-.098	.162
A40	-.083	-.055	.075	-.176
A41	-.018	.767	.077	-.359
A42	.524	.907	.062	-.628
A43	-.402	-1.288	-.244	.755
A44	.092	-.403	.051	-.813
A45	.507	.938	-.084	.178
(Constant)	-28.478	-20.780	-10.348	-.968
Unstandardized coefficients				
Functions at Group Centroids				
A46	Function			
	1	2	3	4
1	-37.467	-9.812	-13.761	-3.058
2	-53.636	5.984	2.899	.582
3	.593	-3.880	.429	.119
4	3.372	4.457	-.524	.173
5	3.837	3.674	3.362	-9.086
Unstandardized canonical discriminant functions evaluated at group means				

Table 19. Classification Results and Hit Ratio by Group (Source: Author)

Prior Probabilities for Groups			
A46	Prior	Cases Used in Analysis	
		Unweighted	Weighted
1	.200	4	4.000
2	.200	12	12.000
3	.200	230	230.000
4	.200	188	188.000
5	.200	6	6.000
Total	1.000	440	440.000

Table 20. Classification Function Coefficients – Raw and Standardized (Source: Author)

Classification Function Coefficients					
	A46				
	1	2	3	4	5
A1	45.315	60.886	92.282	95.282	87.510
A2	-62.469	-118.871	16.708	21.373	13.357
A3	47.838	55.338	19.614	16.215	22.951
A4	205.798	474.193	-333.499	-351.392	-326.177
A5	-174.046	-580.027	368.444	372.610	370.871
A6	-47.592	-89.569	11.005	6.686	12.109
A7	-133.161	-297.911	94.526	84.419	108.692
A8	-85.708	-186.419	144.997	149.772	148.375
A9	248.091	464.172	-182.437	-194.573	-184.162
A10	-162.301	-326.771	144.925	150.258	143.319
A11	-128.474	-289.123	86.191	78.865	98.448
A12	150.440	404.881	-115.861	-107.015	-115.612
A13	-73.531	-253.159	3.690	-18.420	-17.803
A14	-30.564	20.532	-171.432	-176.592	-189.615
A15	-7.070	80.826	104.522	116.014	102.087
A16	12.629	72.214	132.784	173.970	139.659
A17	-58.351	-94.712	250.274	276.963	307.038
A18	-.262	-59.823	156.138	174.221	141.619
A19	18.619	28.932	-57.243	-69.495	-53.199
A20	103.419	179.892	-127.114	-125.469	-127.011
A21	79.764	48.643	122.647	124.992	128.352
A22	30.360	42.891	36.138	38.471	36.773
A23	141.738	434.307	-285.211	-282.541	-293.187
A24	85.905	234.558	-100.974	-102.705	-104.454
A25	-16.465	53.635	-93.063	-96.438	-93.052
A26	-36.627	-162.623	81.554	82.981	80.927
A27	-23.221	-72.547	19.310	23.635	14.154
A28	8.200	16.661	-8.366	-9.646	-8.402
A29	2.220	12.936	5.161	4.015	6.938
A30	3.182	6.361	-5.025	-4.972	-4.211
A31	-7.983	-13.500	-2.745	-6.999	-10.086
A32	22.748	29.892	39.557	58.467	52.053
A33	.055	4.352	-6.576	-7.967	-7.801
A34	5.299	9.953	10.756	16.339	22.058
A35	-29.156	-50.763	-55.948	-85.046	-78.431
A36	27.154	49.522	73.836	99.189	100.650
A37	13.630	28.805	11.816	16.136	23.148
A38	1.706	-.648	-3.086	-4.333	-6.373
A39	-4.691	-12.586	9.257	10.206	8.527
A40	2.857	3.943	-.128	-.901	1.027
A41	20.725	33.090	24.538	30.788	33.805
A42	-.920	3.682	23.267	32.187	37.773
A43	-7.222	-22.396	-31.225	-42.808	-49.923
A44	-6.736	-16.712	-7.481	-10.678	-2.591
A45	-1.140	4.739	23.076	32.398	29.919
(Constant)	-492.641	-1.148E3	-1.008E3	-1.259E3	-1.332E3

Fisher's linear discriminant functions

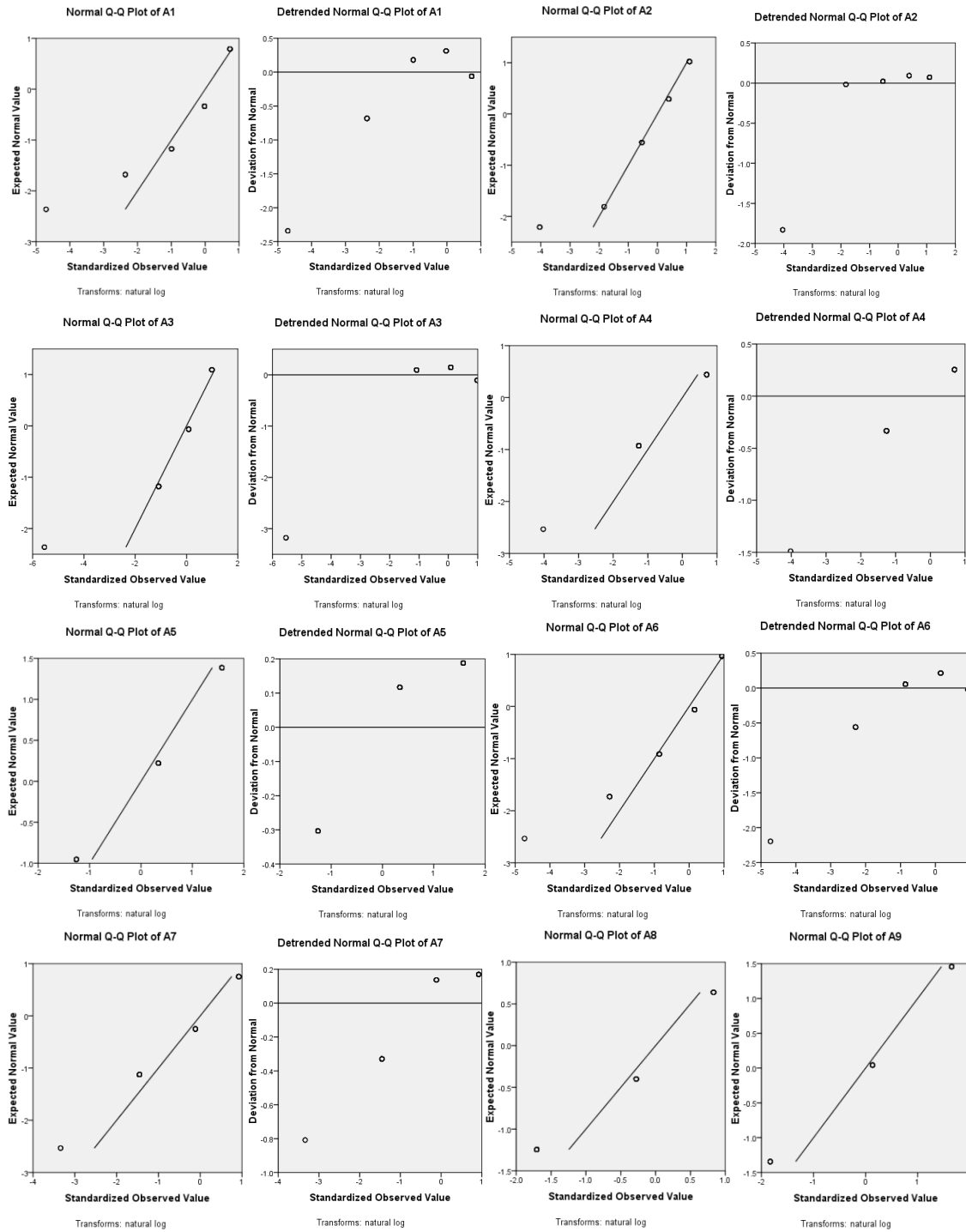
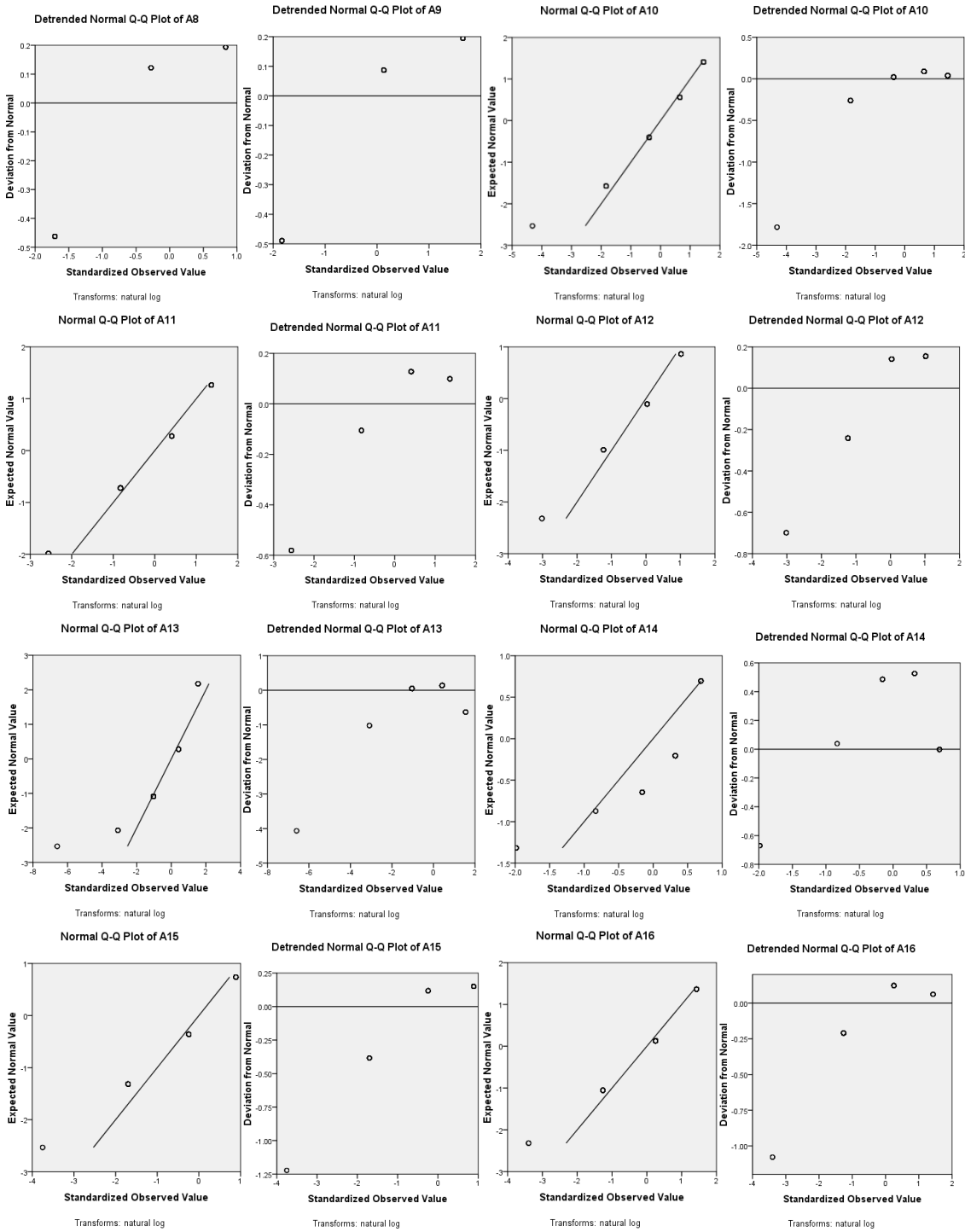
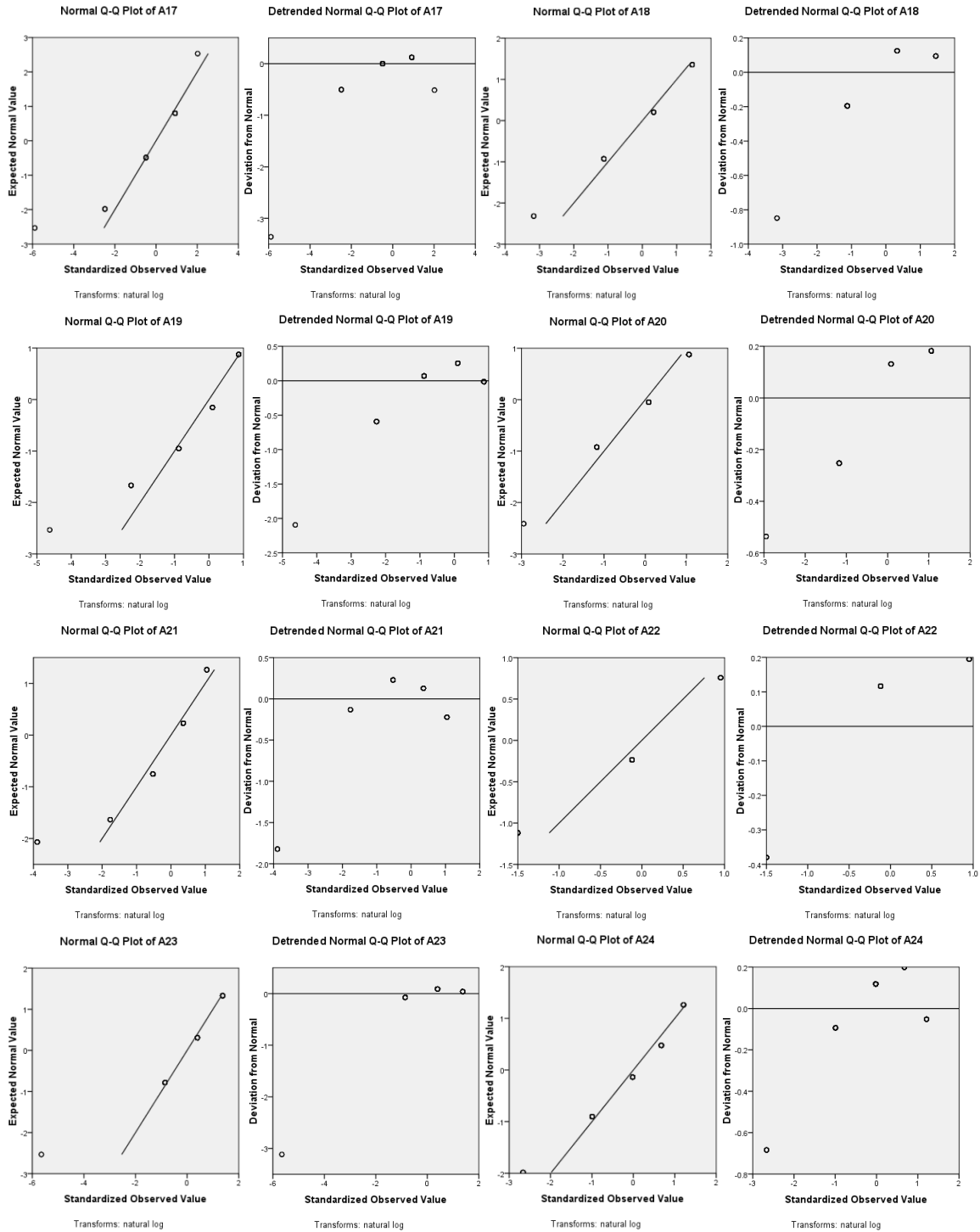


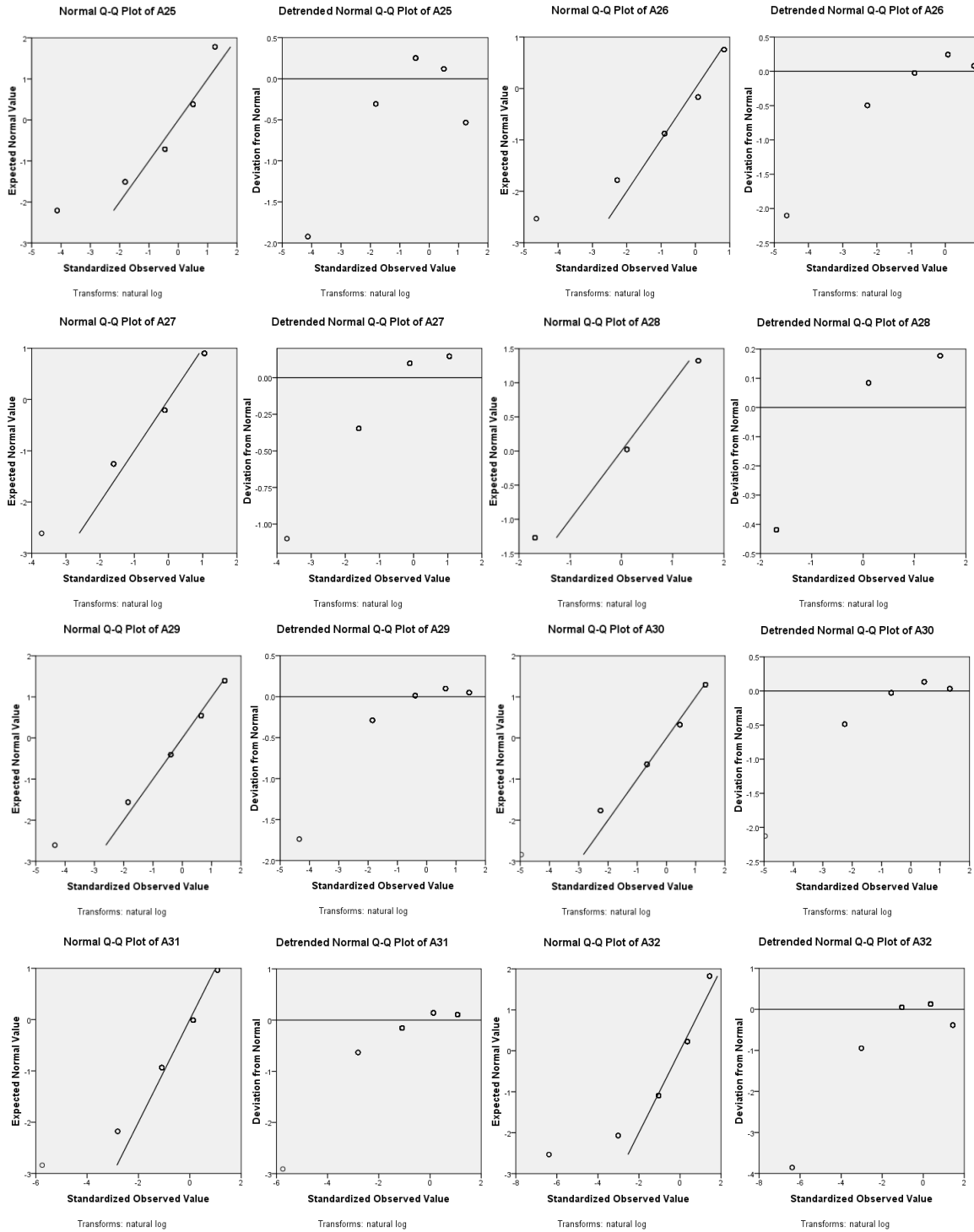
Figure 3. PP Plot and Detrended PP Plot for Select Variables (Source: Author)



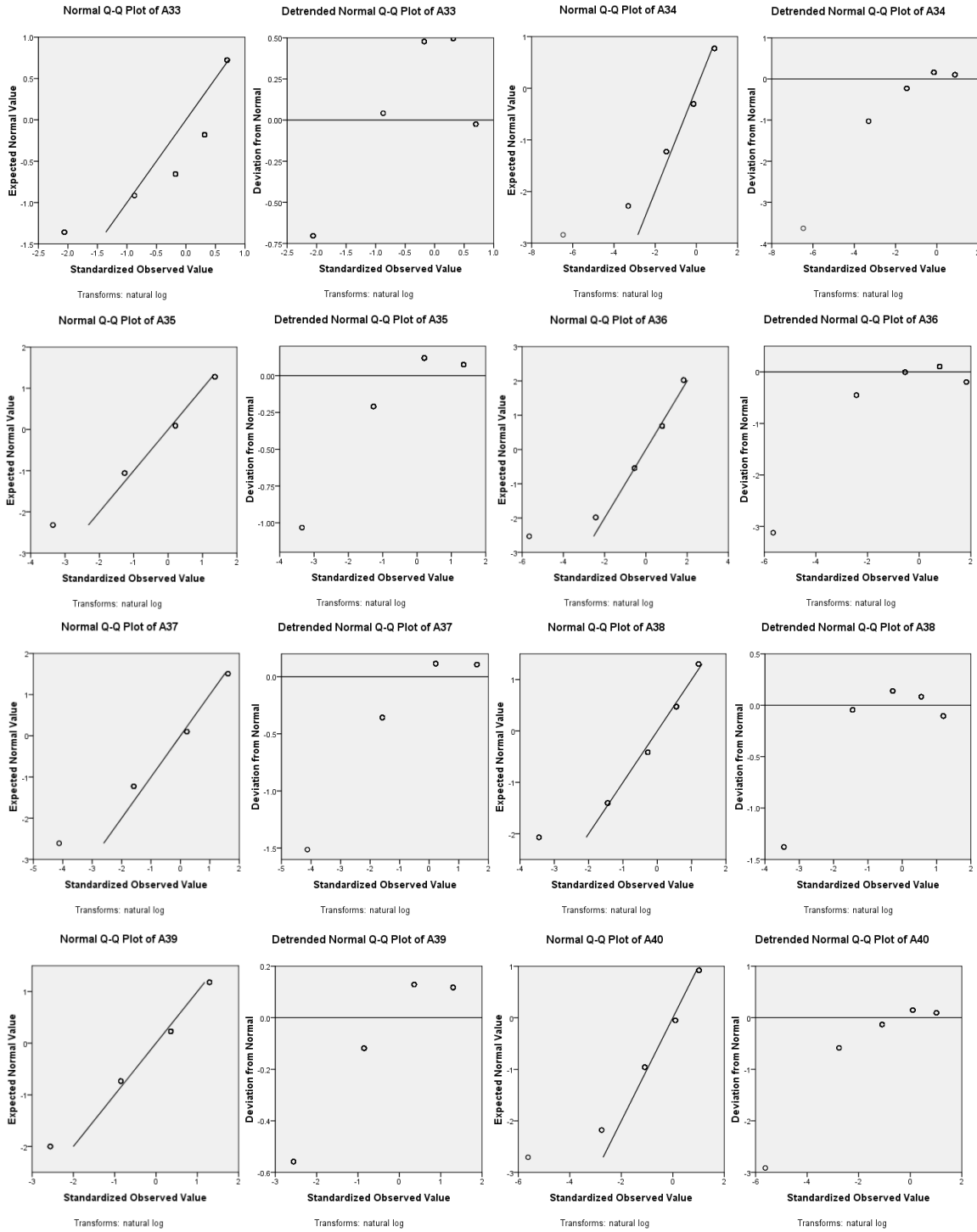
Continous of Figure 3. PP Plot and Detrended PP Plot for Select Variables (Source: Author)



Continuation of Figure 3. PP Plot and Detrended PP Plot for Select Variables (Source: Author)



Continous of Figure 3. PP Plot and Detrended PP Plot for Select Variables (Source: Author)



Continuation of Figure 3. PP Plot and Detrended PP Plot for Select Variables (Source: Author)

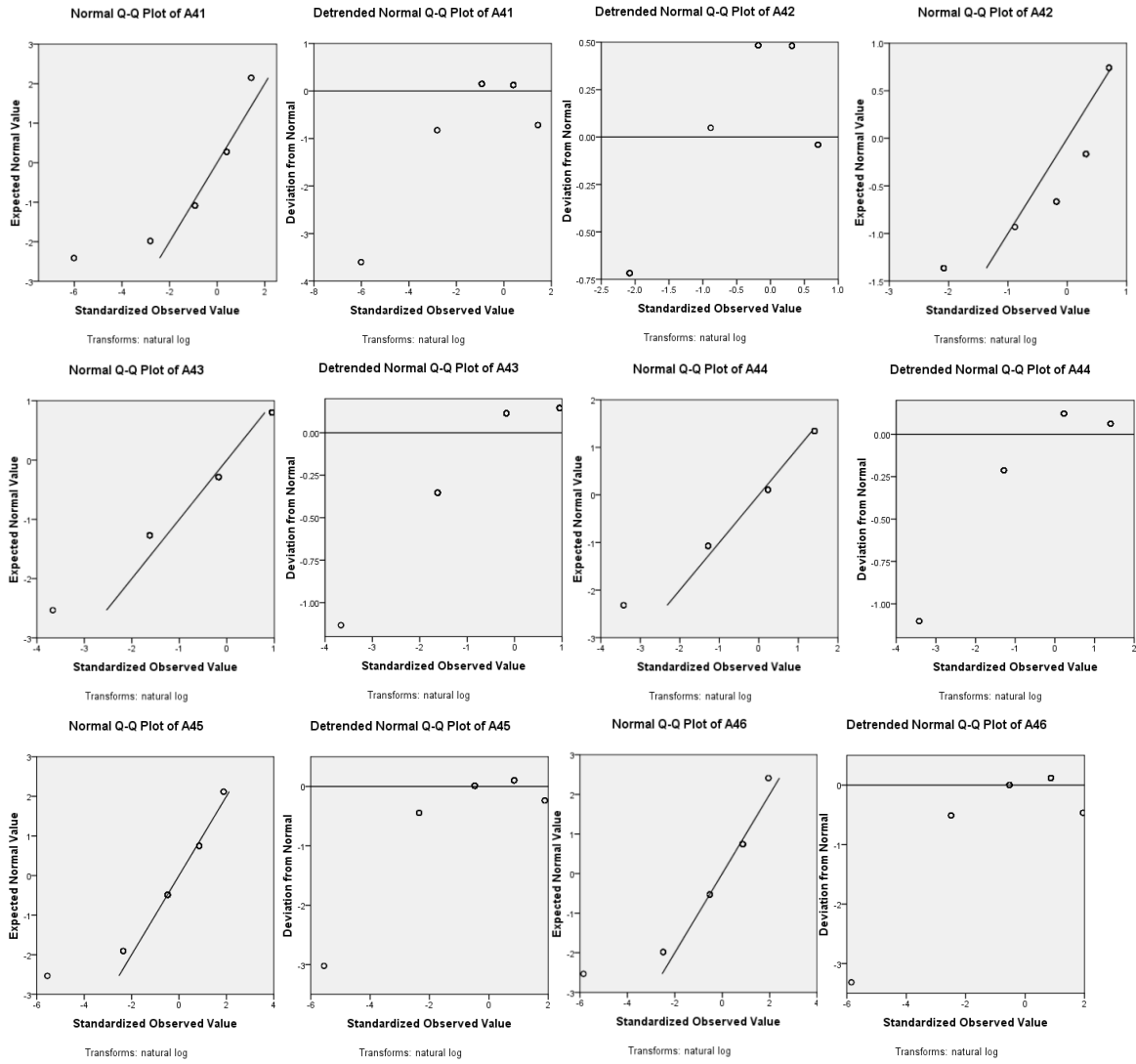


Figure 3. PP Plot and Detrended PP Plot for Select Variables (Source: Author)



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انجمن مهندسی معدن ایران

از معدن سنگ تا پرسی و جو: ساختار شکنی آماری گردشگری میراث معدنی در کنگلومرای بار، هند

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چکیده

این تحقیق قابلیت گردشگری میراث معدنی (MHT) را به عنوان یک مسیر استراتژیک برای توسعه پایدار منطقه ای، با استفاده از کنگلومرای بار در پالی، راجستان، به عنوان نمونه مورد ارزیابی قرار می دهد. این مطالعه که در گفتمان گسترده تر در مورد فعال سازی مجدد مناظر پسا صنعتی قرار دارد، یک طرح ترکیبی را اتخاذ می کند که بررسی های ادراکی ($n=440$) را با ابزارهای چند متغیره از جمله تحلیل عاملی اکتشافی (EFA)، تجزیه و تحلیل مؤلفه اصلی (PCA) و ارزیابی عملکرد متمایز (DFA) ادغام می کند. پتانسیل گردشگری متمایز فضایی هشت موضوع تجربی از PCA بیرون می آید که شامل کفایت زیرساخت، متمایز بودن سایت، درک ایمنی، عمق تفسیری و طنین فرهنگی است. در حالی که پاسخ دهندگان ارزش میراث جغرافیایی و جذابیت بصری قوی بار را می شناسند، کمبودهای مداوم در دسترسی، مدیریت ایمنی و زیرساخت های روایت، آمادگی گردشگری آن را محدود می کند. یافته ها پتانسیل سایت را برای تغییر موقعیت از طریق مسیرهای جغرافیایی موضوعی، محیط های تفسیری چندحسی و مدل های گردشگری مبتنی بر جامعه نشان می دهند. نمایه های متمایز بخش خاص اولویت های ادراکی متفاوتی را در بین گردشگران، ساکنان و کارشناسان نشان می دهند، که بر نیاز به استراتژی های برندسازی مناسب که ریشه در اصالت زمین شناسی، چشم اندازهای حافظه و میراث جامعه زنده دارند، تأکید می کند. مقایسه با انگیزه های گردشگری منطقه ای راجستان، ماجراجویی، اصالت، داستان سرایی و ژئوتوریسم، جایگاه رقابتی را که Barr می تواند در مدارهای میراثی در سطح ایالت اشغال کند، بیشتر نشان می دهد. این مطالعه چارچوبی مقیاس پذیر و مبتنی بر داده را پیشنهاد می کند که خوشه بندی ادراکی را با برنامه ریزی مشارکتی زوج ها ارائه می کند، و مدلی تکرار پذیر برای تبدیل مکان های استخراج متروکه به مقصدهای میراث فرهنگی غنی، از نظر اقتصادی انعطاف پذیر و سازگار با محیط زیست ارائه می دهد.

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