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A Cluster Analysis of Challenging Behaviors in Autism Spectrum Disorder

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***Abstract*—We apply cluster analysis to a sample of 2,116 children with Autism Spectrum Disorder in order to identify patterns of challenging behaviors observed in home and center-based clinical settings. The largest study of this type to date, and the first to employ machine learning, our results indicate that while the presence of multiple challenging behaviors is common, in most cases a dominant behavior emerges. Furthermore, the trend is also observed when we train our cluster models on the male and female samples separately. This work provides a basis for future studies to understand the relationship of challenging behavior profiles to learning outcomes, with the ultimate goal of providing personalized therapeutic interventions with maximum efficacy and minimum time and cost.**

I. Introduction

In recent years, an increase in the rate of diagnosis of Autism Spectrum Disorder (ASD) [4] has fueled interest in applications of machine learning to improve the lives of those afflicted. Though the majority of research has focused on diagnosis and genetic modeling, progress has also been made in leveraging machine learning to model social and behavioral aspects of ASD. Autism spectrum disorder is a neurodevelopmental disorder that manifests itself in behaviors typically observed in the early years of life, though diagnosis may be delayed until adulthood. While combinations of ASD symptoms can vary greatly from one individual to another, those diagnosed often display challenging behaviors which can impact safety, learning, social interaction, and adaptive development. As a result, the presence of challenging behaviors can have profound consequences for therapeutic treatment models, such as applied behavior analysis (ABA). Thus, it is important to evaluate the topography and functions maintaining challenging behaviors in order to mitigate the detrimental effects on skill acquisition and quality of life.

The landscape of challenging behaviors in ASD is large and diverse, with some behaviors lacking concrete operational definitions agreed upon by the behavior analysis community. To this end, we restrict the focus of this paper to eight widely-observed and widely-studied behaviors:

- Aggression (hitting, kicking, scratching, etc.)
- Self-injury (head-banging, hand-biting, hitting walls, etc.)
- Disruption (interrupting, yelling, knocking things over, etc.)
- Elopement (wandering, bolting, etc.)
- Stereotypy (hand-flapping, rocking, toe-walking, etc.)
- Tantrums (crying, screaming, defiant behavior, etc.)
- Non-compliance (disobeying directions, whining, etc.)
- Obsession (repeatedly talking about the same topic, perseveration, etc)

It is important to note that the presence of challenging behaviors is not limited to one developmental stage such as early childhood. Indeed, challenging behaviors are present in young children, adolescents, and adults with ASD [16]. Further, no significant relationship between symptom severity and frequency with age has been found [15], which suggests that challenging behaviors persist throughout an individual's life.

While previous work has been undertaken to understand these behaviors and their function, behavioral phenotypes of the autism spectrum remain largely unexplored. This study aims to expand work in this area by providing the first machine learning based study of challenging behaviors using cluster analysis in order to determine common challenging behavior profiles and behavior co-occurrences. We leverage a large clinical dataset consisting of 2,116 geographically dispersed patients with confirmed ASD diagnoses. Our results indicate that while there are indeed common co-occurrences of challenging behaviors, most patients exhibit a dominant behavior that drives their profile.

The remainder of the paper is organized as follows. Section 2 presents an overview of the clinical dataset which forms the basis of our study, including criteria for inclusion and basic demographic statistics for our sample size. Section 3 provides a brief algorithmic overview the machine learning methods employed for analysis. Section 4 presents behavioral patterns identified via our analysis, and discusses how these results can be applied to improve ASD treatment in a clinical setting. Finally, we discuss related work in section 5, followed by conclusions in section 6.

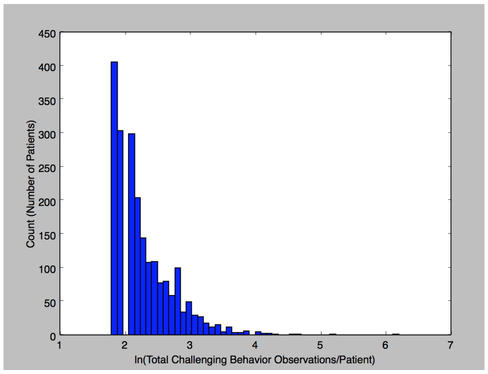

Fig. 1: Distribution of Challenging Behavior Counts

II. Data

To build our unsupervised models of challenging behaviors, we were provided access to the SKILLS™ database. SKILLS™ is a proprietary repository of treatment data maintained by a large national provider of autism treatment services, and contains complete treatment histories for children who are actively enrolled, or have been enrolled, in ABA intervention. As part of ABA services all patients are assigned a behavior intervention plan by a board-certified behavior analyst (BCBA), and behaviors are tracked over time using a combination of mobile applications and web-based software. While the database stores a substantial amount of phenotypic data, for this study we focus on the records of challenging behaviors observed in the course of ABA therapy sessions conducted as part of home and center-based treatment.

Data was stored in Microsoft SQL Server running on a 16-core Intel Xeon processor, 256 GB of RAM, 256GB solid state hard drive and a 8TB spinning-disk hard drive for data storage. Data was extracted using the industry standard Structured Query Language (SQL) in the form of various query statements. The R statistical computing language was used to clean and prepare the data set so that it could be used in the analysis presented here.

Preprocessing resulted in a candidate pool of 4,315 children receiving ABA therapy services from the provider. We then applied filtering criteria to isolate patients that exhibited repeated instances of challenging behavior over time. This criteria produced a sample size of 2,116 participants. Of the 2,116 participants, 82.3% were male and 17.7% were female. Since ASD is known to affect males at approximately 4 times the rate of females, this imbalance is expected. The mean age of the participants was 7.48 years (SD =2.33). Participants in this study resided and received services in the states of Arizona, California, Colorado, Illinois, Louisiana, New York, Texas, and Virginia.

To create the data matrix for our study we aggregated 8-dimensional feature vectors for each patient. These vectors correspond to the number of times each challenging behavior was observed for an individual patient over the course of their therapy. For normalization purposes, each vector element was divided by the total number of observations for the patient, resulting in a probability distribution over challenging behaviors. This is also convenient for visualization, as each challenging behavior vector element is scaled between 0.0 and 1.0, with higher values suggesting higher frequency of the corresponding behavior. After data processing, the end result is a 2116×8 dimensional matrix representing a total of 24,112 instances of challenging behaviors across all patients. The minimum number of observations for a patient is 6, with a corresponding maximum of 492. The mean number of observations is 11.40, with a standard deviation of 13.36. Figure 1 presents a histogram for the total number of challenging behavior observations for our study sample, with a logarithmic transform applied to account for the fact that number of observations spans two orders of magnitude from minimum to maximum.

III. Methods

For this analysis we employ K-means clustering to extract common behavior profiles across the previously defined categories of challenging behaviors. In this section we provide a brief mathematical overview of K-means before presenting the results of our study.

K-means is a simple algorithm that determines cluster membership by identifying cluster centroids [13]. Consider a data matrix, D, of dimension $m \times n$. D can then be represented as a collection of vectors, $D = \{X_1, X_2, ..., X_m\}$. Each vector, X_i, represents a unique data instance, and each vector element, $X_{i,j}$, a specific measurement (attribute) for that point.

K-means clustering takes D as input, as well as the number of clusters to be fit from the data, k. The algorithm then proceeds as follows:

1) Initialize k centroids $C = \{C_1, C_2, ..., C_k\}$ (one for each cluster) with k random data points.
2) For each point, $X_i \in D$, find the closest centroid, C_j, from C based on any appropriate distance metric. Assign X_i to cluster j.
3) For all $C_j \in C$ recalculate
$$C_j = (\sum_i X_i)/P_j$$
for all X_i assigned to cluster j and where P_j is the number of points assigned to cluster j.
4) Go to step 2 and repeat until cluster memberships do not change.

Once the cluster membership has stabilized, cluster structure may be visualized, with the centroid of each cluster serving as a representative description of data points captured by that group.

While k-means provides an algorithmically straightforward way for identifying grouping, the substantial challenge is determining the number of clusters, k, to be modeled. In absence of domain information to suggest the correct parameter setting, several mechanisms exist for statistically determining the most likely k, including nonparametric statistical techniques. Here we rely on determining k by finding the value that gives the most drastic reduction in intra-cluster sum of squared distances.

TABLE I: Frequency of Challenging Behaviors

Behavior	Frequency
aggression	51.61%
stereotypy	50.47%
tantrums	49.29%
noncompliance	49.01%
selfinjurious	22.02%
elopement	21.17%
disruption	14.74%
obsessive	5.77%

IV. RESULTS

To begin our analysis, we first explore the prevalence of challenging behaviors among our sample of 2,116 patients. Table 1 presents the percentage of the sample population that exhibits each behavior. The data indicates that of the eight behaviors, the most common are aggression, stereotypy, tantrums, and noncompliance, all of which are present in approximately 50% of the sample. This is in agreement with previous surveys of the challenging behavior landscape [5], and gives credibility to the representativeness of the data considered here.

Before diving into the cluster analysis, it is useful to not only understand the frequency of individual challenging behaviors, but also the relative frequency of pairs of challenging behaviors. Table 2 presents the prevalence of all pairs of challenging behaviors observed in our sample population. Not surprisingly, the most common pairs of challenging behaviors are drawn from the Cartesian product of the most prevalent single behaviors in table 1. However, we also observe substantial co-occurrence of elopement with these behaviors as well. These simple statistics suggest that the overall challenging behavior profiles of our sample are likely to contain a mix of challenging behaviors.

As a first step in our K-means cluster analysis, we first determined the value of k that best explained the latent structure in the data. This was achieved by varying k from 1 to 20, and then selecting the value of k that corresponded to a plateau in intra-cluster sum of squared distances. This technique is colloquially referred to as the "elbow method" in the machine learning community [19]. For our data set, this approach identified a total of seven clusters, and so we use this value of k for the final analysis.

Figure 2 depicts the centroids of the seven clusters extracted by K-means. Each cluster is well-represented by patients from the sample, with each cluster containing the following number of data points:

- Cluster 1: 211 patients
- Cluster 2: 265 patients
- Cluster 3: 494 patients
- Cluster 4: 233 patients
- Cluster 5: 243 patients
- Cluster 6: 155 patients
- Cluster 7: 515 patients

From the figure one is immediately struck by the fact that most clusters are defined by a single dominant challenging behavior, though obsessive behavior is not a significant component of any group. When multiple challenging behaviors are present, such as in cluster 5 and 6, we see that the relative strengths of challenging behaviors, other than the dominant behavior, are all small. The sole exception is cluster 7, which shows similar levels of aggression, noncompliance, tantrums, stereotypy, and elopement. This aligns well with our analysis of challenging behavior pairs, and would indicate that if a patient exhibits diversity in challenging behaviors, it is most likely to come from these areas.

TABLE II: Frequency of Challenging Behavior Pairs

Behavior Pair		Frequency
stereotypy	noncompliance	49.57%
tantrums	noncompliance	47.21%
noncompliance	aggression	46.50%
stereotypy	tantrums	44.85%
tantrums	aggression	43.81%
stereotypy	aggression	42.82%
elopement	noncompliance	26.65%
elopement	aggression	24.24%
elopement	tantrums	24.05%
aggression	selfinjurious	23.16%
elopement	stereotypy	22.64%
stereotypy	selfinjurious	20.84%
tantrums	selfinjurious	20.13%
noncompliance	selfinjurious	19.28%
disruption	aggression	16.07%
disruption	noncompliance	14.93%
disruption	stereotypy	13.00%
disruption	tantrums	12.62%
stereotypy	obsessive	10.59%
noncompliance	obsessive	9.83%
elopement	selfinjurious	9.40%
tantrums	obsessive	9.22%
disruption	elopement	8.22%
obsessive	aggression	8.03%
disruption	selfinjurious	7.14%
elopement	obsessive	4.35%
obsessive	selfinjurious	3.26%
disruption	obsessive	2.74%

After analyzing clusters of behaviors for the entire sample, we repeated the analysis separately on the male and female sample populations. In each case eight clusters were identified as best explaining the latent structure of the data. The results for the male and female groups are displayed in figures 3 and 4, respectively. As with the clusters fit on the entire population, the male population exhibits clusters that are all dominated by a single challenging behavior. This is also largely the case with the female population, though clusters 1 and 3 stand out as exceptions. The almost equal presence of elopement/tantrums and noncompliance/stereotypy are not present in the male profiles, and suggest there are gender differences in challenging behaviors on the spectrum that should be taken into account for treatment.

While the existence of challenging behavior clusters is interesting in its own right, this result has practical application for intervention. Specifically, behavior intervention plans from each group can be examined, and the plans that have demonstrated the most efficacy historically can be assigned to other members in the cluster as a starting point for treatment. In this way, the BCBA assigned to the case need not start from scratch to formulate a behavior intervention plan, but rather from a template that has worked well for other patients with a similar challenging behavior profile. This can build on

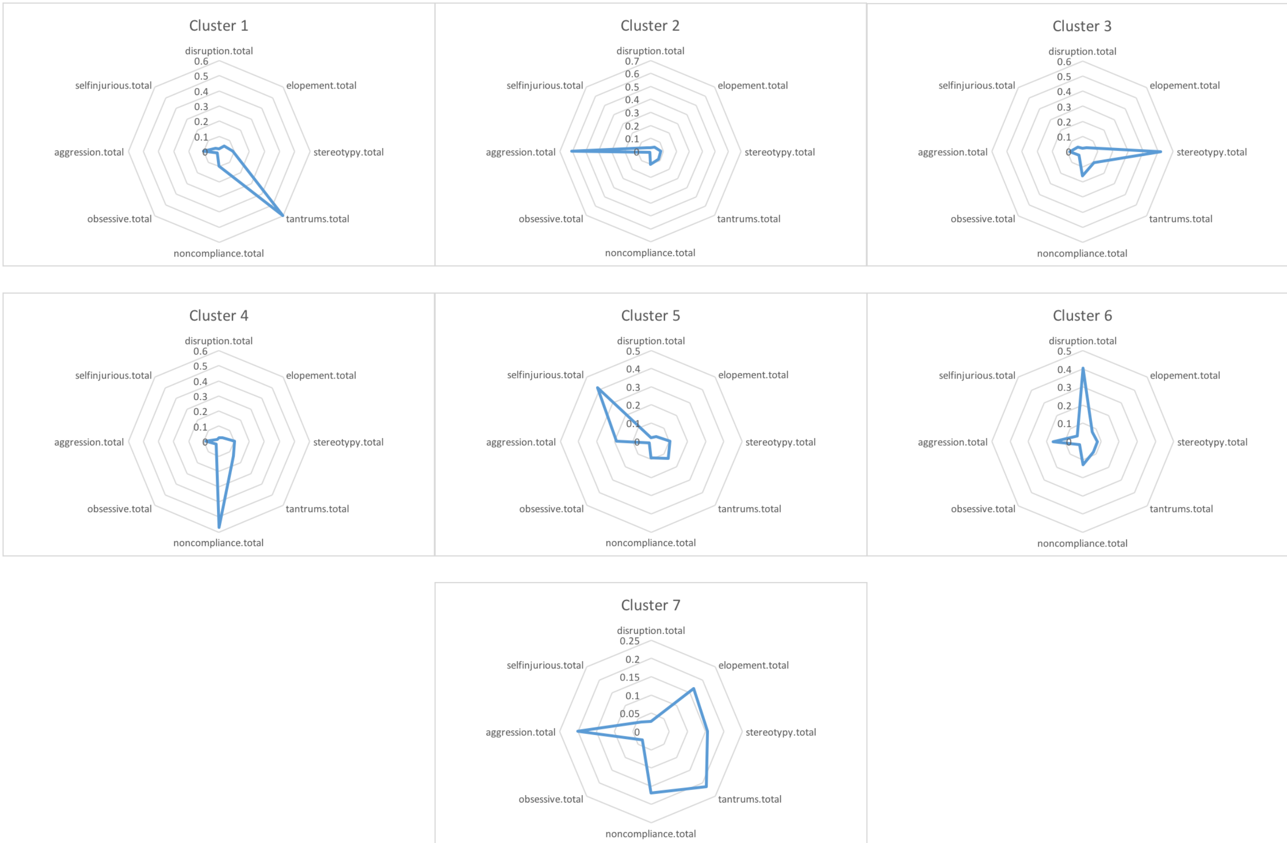

Fig. 2: Clusters of Challenging Behaviors Learned by K-means

previous work that demonstrates the importance of intensive, targeted intervention in ASD treatment [2], [1], [9].

V. Related Work

The study of challenging behaviors in the broader realm of psychiatric disorders has been a broadly explored research topic. Emerson et al crafted a composition of current findings related to the assessment and treatment of challenging behavior. They combined research across disciplines to further the assessment of challenging behaviors caused by learning disabilities including nature, epidemiology, causes and potential treatment outcomes. In particular, they explored contributions to the understanding of the relationship between challenging behavior and psychiatric disorder [3]. In our study we focus specifically on individuals with ASD and the trends of challenging behaviors within this set.

Although no studies could be found that used machine learning to analyze challenging behaviors, the work in [17] aggregated and statistically analyzed data from 22 studies conducted over the 30 years leading up to 2003. Their findings emphasized the scarcity of methodologically robust studies when it comes to the research of challenging behaviors. They detail the lack of data that would allow for investigation into incidence, prevalence and chronicity of challenging behavior in people with intellectual disabilities.

Outside of the study of challenging behaviors, there have been several other applications of machine learning in the ASD domain. For example, [7], [21] demonstrate the feasibility of machine learning to reduce the number of diagnostics that need to be administered to converge on an ASD diagnosis. The work in [11] and [10] leverages artificial neural networks to model the relationship between treatment intensity and outcomes in ASD. Liu et al built a support vector machine based affective model in order to improve computer based ASD intervention tools, allowing them to monitor and gage an individual's progress, adjusting therapy accordingly [12]. Mieanner et al trained a random forest classifier to use words and phrases found in evaluations to classify case status in Autism Developmental Disability Monitoring [14]. Finally, in the realm of unsupervised machine learning, [18], [8], [6] leverage cluster models to learn phenotypic patterns across the autism spectrum. Unlike our analysis however, clusters are based on broad diagnostic instruments and sensory processing characteristics, respectively. The work in [20] extends this by considering the relationship of sensory processing disorders to anxiety, though with a small sample size of 57 children.

VI. Conclusion

Here we have presented the first machine learning based analysis of challenging behaviors in a large population sample of 2,116 patients. Using K-means clustering, we are able to identify meaningful behavior profiles, which indicate that in most clusters a dominant single challenging behavior is

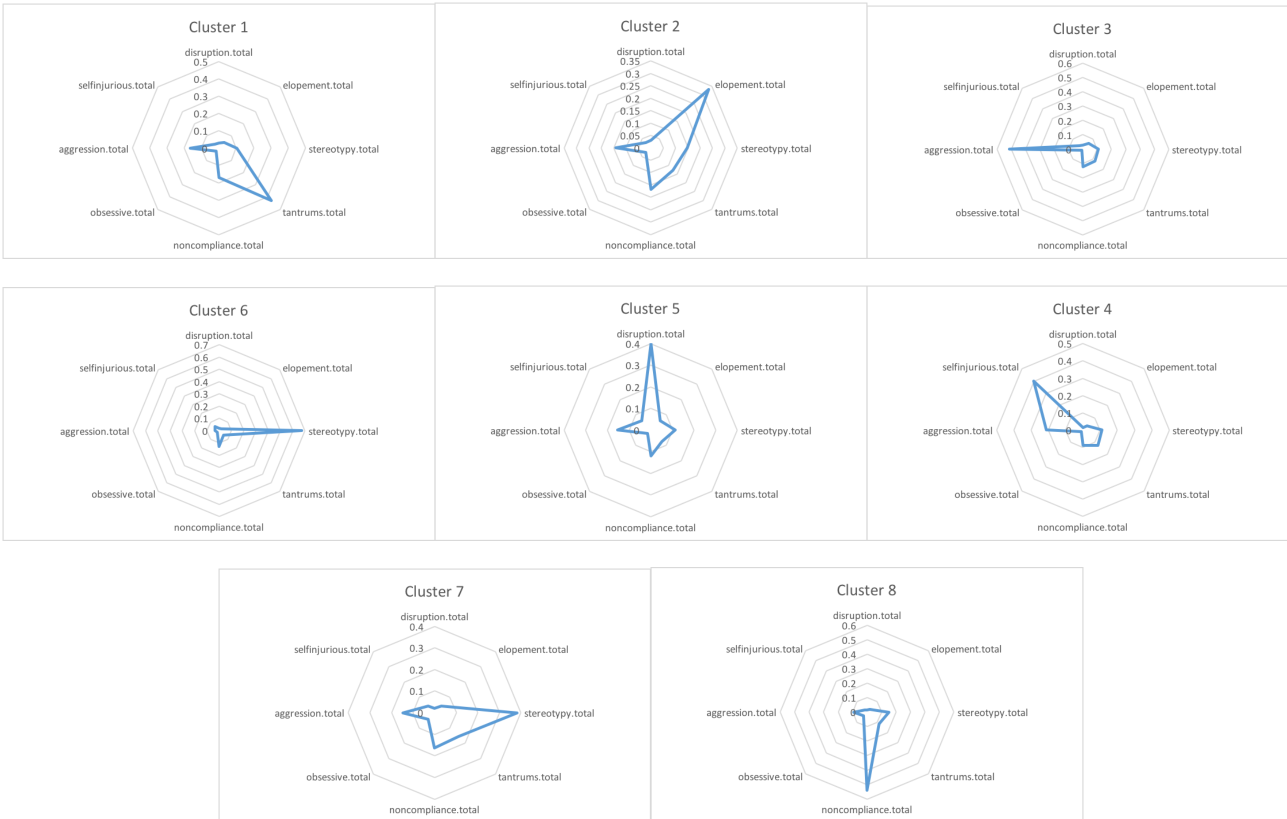

Fig. 3: Clusters of Male Challenging Behaviors Learned by K-means

present. Additionally, we identified some potential differences in challenging behavior profiles across male and female populations. This study lays the foundation for future work in challenging behavior analysis, with the most obvious direction being to model how treatment intensity, learning objective mastery, and stimulus response are correlated within each defined challenging behavior cluster. This, in turn, may provide a basis for individualized treatment, with the ultimate goal of higher efficacy at lower cost.

It is important to emphasize that the study presented here focuses only on the presence of challenging behaviors, and not the function of those behaviors. Function-based treatment has been shown to be among the most effective interventions for challenging behavior, and so a natural way to augment our work would be to integrate functional components within our cluster profiles. This is not without its challenges, however, as identifying the environmental variables and consequences maintaining behaviors is complex. Such factors vary significantly across individuals and even within individuals over contexts and/or time. Nevertheless, we intend to expand our current work in challenging behaviors to include a functional component.

As a discipline, it is encouraging to see that ASD research, like so many other fields, is becoming data-driven. Ultimately, however, this field lacks an Internet-scale, public repository of longitudinal data that could serve as a baseline for more exploratory research in big data. Until then, it is imperative that machine learning researchers partner directly with ASD treatment providers to ensure that data, where available, is leveraged to make informed decisions about treatment. The work in this paper represents a modest contribution toward that goal.

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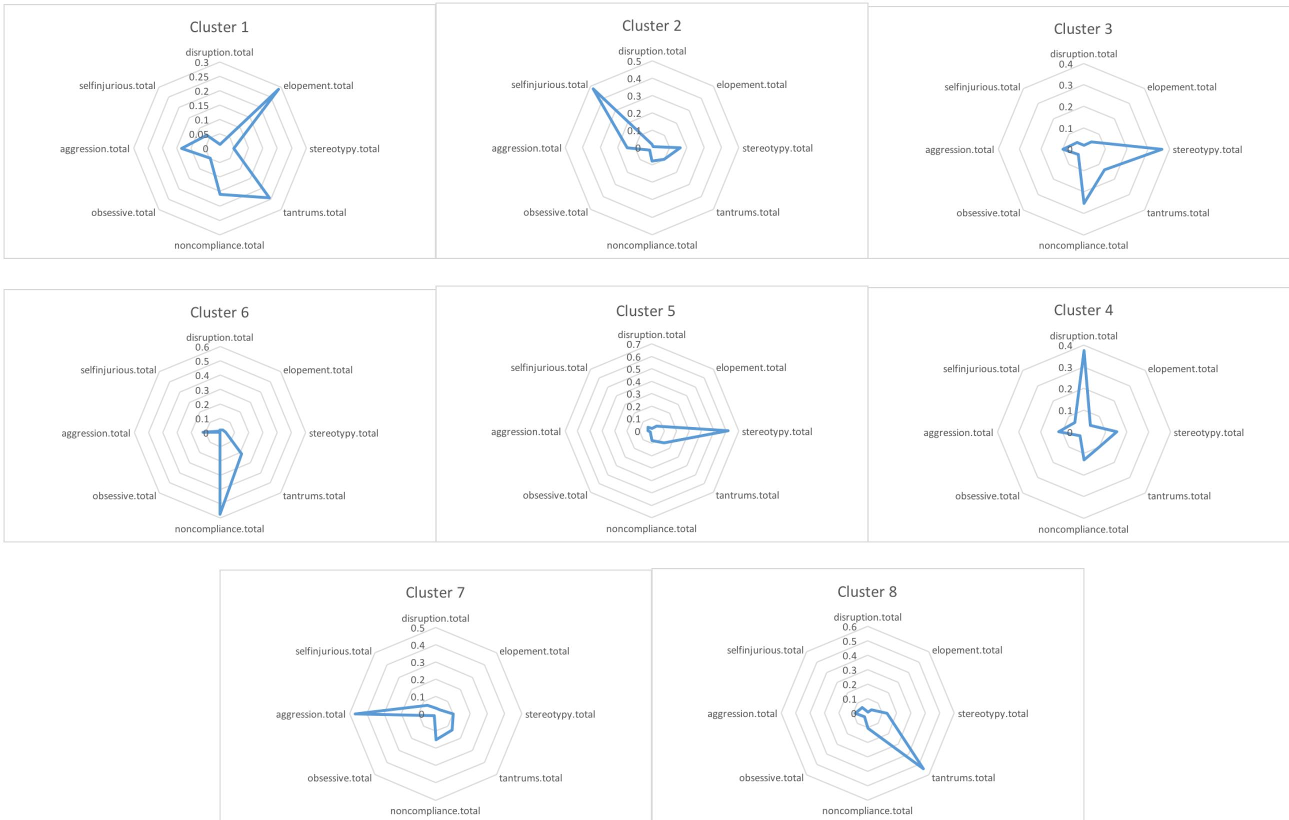

Fig. 4: Clusters of Female Challenging Behaviors Learned by K-means

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