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Behavioral Analysis Model for Enhancing Attendees Experiences in Events Through K-Clustering Technique

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Abstract
Events management landscape plays an important role in delivering an exceptional attendee experience, from planning to implementation and attendee's engagement which serves as a critical success element for event organizers. Despite the increasing use of technology in event management, there remains a limited understanding of attendees' behavioural engagement in events either during or after for enhanced attendees' experiences. This study seeks to bridge the gap and examine attendees' behavioural segmentation using K-clustering technique for the identification of attendees' engagement during and after events. This research aims to develop a behavioural analysis model using K-clustering techniques to identify attendees' engagement in events for improved attendees' experiences. The quantitative research method was used for this research. The designed and model implementation was developed using Python Programming language. The results showed that the attendees' engagement was clustered into four namely the minimally, multidimensional, highly cognitive and quietly, highly affective and socially engaged. Also, there was no string engagement in terms of the observed age or gender. The elbow performance metrics shows that the four behavioural engagement patterns best represent the data without complexities with the within-cluster sum of squares value of 171820.15 as the inflection point. The silhouette score of 0.37 indicates a decent but not perfect clustering and good enough for the earl-stage attendee segmentation and need further tuning for decision making. The study concludes that event attendees participate more in highly affective and multidimensional segments and that K-clustering technique serve as an important method for understanding both low- and high-involvement of attendees in events

Keywords: Behavioural Analysis, Machine Learning, Events, Behavioural Patterns, K-Clustering

1. Introduction

Examining attendee experiences has changed and improved dramatically as a result of using machine learning (ML) tools in event management. Event planners can now create more customized and captivating events by using machine learning (ML) techniques to obtain a deeper understanding of attendees' preferences, habits, and engagement patterns [1]. A lot of applications that improve the experience of attendees have been made possible by recent developments in artificial intelligence (AI). Chatbots powered by AI, for example, offer immediate support, responding to attendees' questions as quick as possible and raising their level of satisfaction [2]. Furthermore, with personalization through AI, it ensures that attendees interact with major important contents and programs by providing customized suggestions for meetings, workshops, and networking opportunities based on preferences of the individuals [3].

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Providing immediate translation services is made accessible with AI, which eliminates language barriers and increases the accessibility of events for audiences from around the world. During Check-in procedures, it is streamlined with the use of facial recognition technology, which also improves and increases security and reduces time for waiting. Another aspect of AI is predictive analytics, which helps event planners to foresee participant behaviour, narrow-down logistics, and proactively handle possible problems [4].

One notable application of AI is in event Apps. AI helps event planners to develop customized experiences that are tailored to each attendee's interests by analysing large amounts of data. This improves attendance, pleasure, and the success of the event as a whole [5]. The ever-changing field of event management necessitates creative approaches to improve attendees' experiences and guarantee their happiness and involvement. The development of sophisticated data analysis technologies in recent years, particularly machine learning (ML), has created new opportunities for real-time attendance behaviour comprehension and prediction. The goal of this study is to create a thorough behavioural analysis model that uses machine learning methods to evaluate and improve event attendees' experiences.

This methodology may detect behavioural trends and preferences by examining data including guest demographics, preferences, mobility patterns, and engagement metrics. This enables event planners to make tailored, well-informed changes to enhance the attendee journey. Important machine learning techniques, including sentiment analysis, clustering, and predictive modelling, were used to identify trends and predict behavioural reactions, offering insights into the elements that influence attendance happiness [6].

In the event sector, where attendees' expectations are changing quickly, the project tackles the need for data-driven customisation. The Behavioural Analysis Model's real-time feedback features not only improve attendees' overall experience but also give event managers the ability to make quick, strategic decisions that boost participation, maximize resource use, and boost attendee retention [7].

By adding to the expanding corpus of research on the nexus of behavioural analysis, machine learning, and experimental design in the events industry, this initiative ultimately aims to establish a new benchmark for proactive, tech-driven event management.

This underscores the need to use of AI and machine learning in event management provides revolutionary solutions that improve the experiences of attendees while drastically cutting down on the time and work needed by event planners, AI is changing the way that events are planned and carried out by automating.

The aim of this research is to develop a behavioural analysis model using K-clustering techniques to identify attendees' engagement in events for improved attendees’ experiences. The specific objectives are:

1. Design a behavioural analysis model for identifying attendee engagement form behavioural data;
2. Develop the model using k-clustering for segmentation of attendee engagement;
3. Evaluate the performance of the model using selected metrics

This paper is organised as follows after the introduction. Section 2 provides the related works from existing body of knowledge. Section 3 highlights the methodology employed in conducting the research, section 4 explains the results and discussion and the last section draws out the conclusion.

2. Related works

Over the past ten years, developments in data analytics, artificial intelligence, and digital interaction platforms have greatly changed the idea of behavioural analysis in the context of event management. Attendee engagement, event customization, and the use of machine learning techniques for descriptive and predictive analytics have all been the subject of several studies. The construction of a behavioural analytic model for improving event attendee experiences is informed and supported by the thorough evaluation of current research, publications, and methodology shown in this section [5].

With the move toward virtual and hybrid forms, there has been an increase in interest in the use of behavioural analytics in event management. Event planners can gain a more accurate understanding of attendees' choices and levels of involvement by analysing their behaviour in real time. Their research demonstrated how behavioural data, such as dwell time, clickstream logs, and feedback forms, may be leveraged to create better event experiences [8].

The information gathered from event platforms can offer profound insights into the reasons behind attendance, how attendees navigate, and what they desire to see. They evaluated user journeys using descriptive analytics techniques and came to the conclusion that behavioural segmentation can greatly enhance information retention and event pleasure [9].

The use of machine learning in behaviour analysis, namely in clustering and classification models, has been emphasized in a number of research. Marketing, healthcare, and education are just a few of the industries that have made extensive use of K-means clustering, an unsupervised learning technique, for audience segmentation). The use of k-means clustering in the context of events to divide up attendees of a virtual conference according to their feedback answers and interaction levels. The study showed how data-driven segmentation produced useful insights that enhanced engagement and content delivery [10]. Other approaches to machine learning have also been investigated. The use of decision tree classifiers, for example, to forecast attendee satisfaction based on past behavioural data, such as the amount of time spent in a session, the number of networking interactions, and poll participation. Their model produced interpretable guidelines for enhancing future event formats and had an accuracy rate of over 80% [11].

Neural networks were also employed to examine the emotional content of social media posts about events. Their sentiment analysis model helped organizers plan sessions more effectively by correlating speaker performance and session topics with emotional emotions [12]. One of the main goals of behavioural analysis models is event personalization. The experience economy states that individualized encounters have a greater impact and are more memorable. This is corroborated by research which found that employing behavioural data to personalize virtual events in real time raised attendee satisfaction by 23% [13].

A framework for personalized event content recommendation utilizing k-means clustering and collaborative filtering was presented. Based on peer similarity and user behaviour, their algorithm recommended pertinent sessions and networking groups. A tech summit case study's findings showed a notable rise in user retention and favourable comments [14]. The opportunities for gathering real time behavioural data have increased due to developments in wearable technology and Internet of Things technologies. Wearable sensors could record biological information like heart rate and movement, which are linked to emotional engagement, according to event studies. By integrating them into event apps, organizers were able to track attendees' levels of excitement, boredom, or stress, which allowed them to make last-minute content changes [15].

In a more recent study, it was investigated the use of RFID tags and Bluetooth beacons for tracking attendees in major shows. They were able to determine which areas of the event space were more engaging and why by examining mobility patterns, session lengths, and interaction hotspots. This enhanced crowd control and venue layout planning [16].

The restricted scope and retroactive nature of traditional attendee feedback mechanisms, which are usually dependent on post-event questionnaires, have drawn criticism. It was pointed out that surveys frequently have poor response rates and skewed responses, making it difficult to capture sentiments and micro-level behaviours in real time. Behavioural data, on the other hand, provides an impartial, ongoing, and thorough image of attendees' involvement.

In a hybrid educational conference, research contrasted behaviour-based and survey-based engagement methods. Their findings demonstrated that, with a correlation coefficient of 0.78 as opposed to 0.45 for surveys, behaviour-based models were noticeably more effective at forecasting satisfaction [17].

Despite the popularity of k-means, academics have looked into different clustering methods such as Gaussian Mixture Models, DBSCAN, and hierarchical clustering. The effectiveness of several clustering algorithms in dividing individuals into groups according to their web surfing habits was compared in a study. They discovered that k-means provided superior interpretability and computational efficiency, making it appropriate for real-time event settings, even if DBSCAN performed better at handling noise [18].

In a similar vein, it was examined fuzzy c-means and k-means clustering in an online learning environment. More distinct clusters were produced with K-means, making them simpler to understand and act upon. When actionable insights are a top concern in event behavioural modelling, this encourages the usage of k-clustering [19]. Models of behavioural analysis have been effectively used in related fields like health, education, and e-commerce, offering insightful methodological information. For instance, clustering was employed in e-commerce to divide up their clientele and customize their marketing tactics. Their method is comparable to event personalization tactics, which supports the usefulness of comparable models [20]. Behavioural modelling has been applied in education to monitor student participation in online courses. A clustering approach that recognized learning patterns and forecasted dropout risks was created. These approaches can be modified to identify attendees who are not participating or to suggest re-engagement tactics for events.

3. Methodology

The methodology involves the different approaches, tools and algorithm used in achieving the stated objectives of this research.
Figure 1 shows the process of methodology for the cluster development using the K-clustering algorithm which consist of six main components namely; data collection stage, data pre-processing stage, clustering stage, evaluation stage and comparative analysis stage.

3.1 Data Collection

The dataset captured attendees emotional, cognitive, behavioural, social dimension of engagement alongside the event satisfaction as a supplemental data and engagement with resources, as this served as a database for event attendees' dataset and was obtained from Kaggle, with the link: https://doi.org/10.34740/kaggle/dsv/11942740, This data was the original data that needed to be cleaned before supplying it to the model. The datasets consist of a total number of 9973 rows and have 19 columns with 16 columns representing behavioural engagement data alongside the event satisfaction and engagement with resources during and after the event.

The first three columns captured the age range, gender and the event status whether online or on-site. Column 4 to 6 captured the emotional attendee's engagement, column 7 to 9 captured the cognitive attendee's engagement, column 10 – 12 captured the behavioural attendee's engagement, column 13 – 15 captured the social engagement, column 16-17 captured the attendee's event satisfaction, and lastly the column 18 – 19 captured the attendee's engagement with the event resources during and after the event.

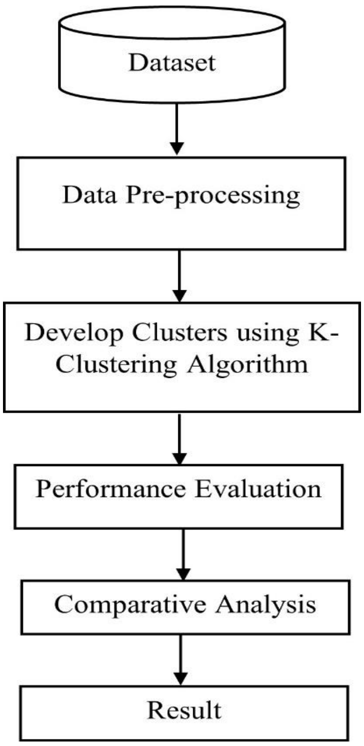

Figure 1: Methodology Process Flow (Researcher's Model, 2025)

Table 1 displays the dataset as it captures into six categories that are used to described the records.

Table 1: Behavioural Data Dimensions

S/N	Dimension	Descriptions
1	Emotional	This dimension captures the event attendees' interest, and emotional connection to the events.
2	Cognitive	This dimension captures the event attendee's mental involvement in the event.
3	Behavioural	This dimension captures the event attendees' participation and interaction with event activities.
4	Social	This dimension evaluates the event attendees' interaction and networking activities.
5	Event Satisfaction	This dimension indicates the event attendees' satisfaction
6	Resource Engagement	This dimension focus on event attendees' engagement with the event materials both during and after events.

3.2 *Behavioural Analysis Model Development*

This model is a way of identifying attendee engagement from the pre-processed behavioural data.

Figure 2 indicates the proposed behavioural analysis model which consisted of four components, namely the input stage which is the data collection stage where the behavioural data are supplied into the model based on the engagement patterns. Followed by the data storage stage where the dataset is stored for processing, also the model components which comprises of the clustering and labelling components, this contained the python code for k-means clustering model to assign cluster labels to each attendee. Lastly is the output stage which displays the clustering labels accordingly.

Figure 3 shows how each objective of this study is implemented as a system process representing the model learning architecture. The architecture explains the workflow and architecture of how the K-Means clustering machine learning model learns from behavioural engagement data in detecting and classifying the level of engagement among attendees during events.

The process begins with the attendee event engagement data that comprises of age range, the gender, and status of event, followed by the emotional engagement, cognitive engagement, behavioural engagement, social engagement, satisfaction on events, and engagement during and after the event, these served as the input variables that the model will learn from. Followed the data pre-processing phase, which prepares the raw dataset for machine learning, and include the Likert scale mapping for converting the text data into numerical values.

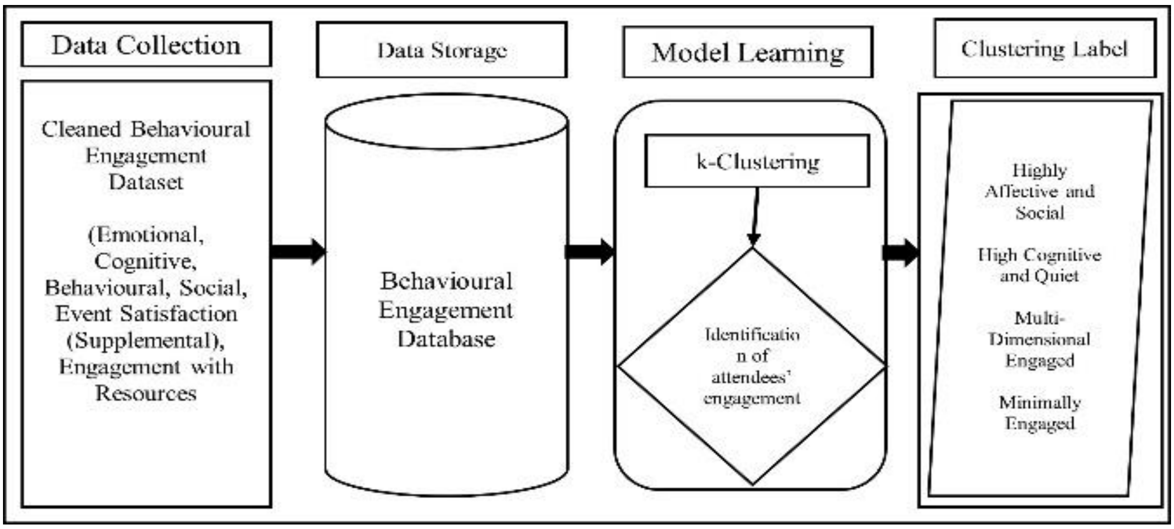

Figure 2: Proposed Behavioural Analysis Model for Attendee Engagement Identification

The variables were encoded categorically specifying the appropriate numerical value for each variable according to the equivalent value. Filling up the missing values were handled to have a complete instance of responses, with the aim of ensuring the dataset is fully numeric and clean for clustering.

The feature selection phase was used in removing the irrelevant columns while retaining only the useful numeric columns with Likert scores and encoded demographic variables as this will create the final variable dataset that the model can learn from. The model was trained by applying K-clustering with the specified number of clusters and in this case, it is four (4), as the K-Means algorithm identifies the patterns in the data, assigns each attendee to a cluster ranging from 0 to 3, learn centroids that represent the average attendee per cluster, this discovered the natural groupings of attendees based on their behavioural engagement.

The cluster assignment phase labelled each attendee with a cluster number and as this numerical label identifies the engagement group that the attendee belongs to. The visualization and evaluation phase used the principal component analysis (PCA) was used in visualizing the clusters, while the heatmaps was used in seeing the average Likert scores according to their cluster. The elbow method and the Silhouette score was used in evaluating the quality of the model, understand and validate the result of the clustering. The engagement labelling map each cluster into four labels based on the observed behavioural patterns in the cluster centroids and finally the trained model can be saved and reuse for another new data and the clustered dataset can be exported for reporting.

4. Result and discussion

The model was implemented by applying K-means clustering for the grouping of the attendees based on their behavioural engagement and characterised by their behavioural patterns into four cluster labels as shown in Table 2.

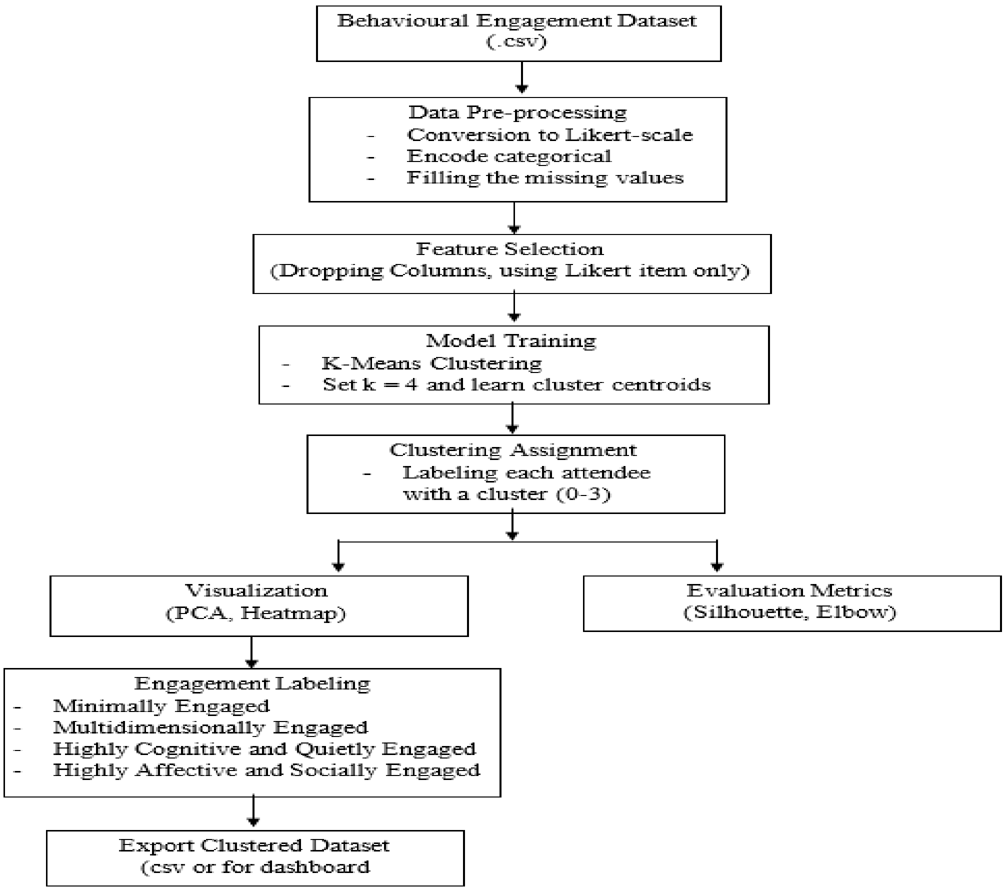

Figure 3: Model Learning Architecture

Table 2: Grouping of the attendees based on their behavioural engagement

Cluster	Cluster Type	Cluster Count	Interpretation
0	Minimally Engaged	3332	Involved in the event but not emotionally or mentally engaged
1	Multidimensional Engaged	2270	Fully involved and were engaged in cognitive, behaviour, and affective
2	Highly Cognitive and Quietly Engaged	2194	Socially or emotionally involved and were intellectually engaged
3	Highly Affective and Socially Engaged	2177	Fully involved and emotionally, actively, and socially engaged

Table 2 shows that 3332 attendees' behavioural patterns are minimally engaged, 2270 attendees were multidimensional engaged, 2194 were highly cognitive and quietly engaged, and 2177 attendees were highly affective and socially engaged. For better understanding of the distribution and separate ability of the clusters, the principal section analysis was applied as shown in Figure 4.3.

This indicated how attendees were clustered based on the event engagement behavioural pattern, as the x-axis, the principal component 1, explains the highest variance in event engagement behavioural pattern which indicates the dominant engagement while the y-axis, the principal component 2 explains the next highest variance, which is linked to the other aspect of attendees' engagement within the cognitive and social behavioural pattern. The attendee's engagement cluster was visualized in heatmap as shown in Figure 4 as this assisted in understanding how each cluster responded across different event-related characteristics, the red portion of the heatmap indicates a stronger engagement while the blue portion indicate a weaker engagement. It was observed that motivation and participation were strong for highly affective and multidimensional clusters and very weak for minimally engaged. Also, that the cognitive engagement was very high for cognitive, quiet and multidimensional engagement and moderate for others.

The social engagement was the highest in highly affective and social and very low in highly cognitive and quiet, while for satisfaction, it was a top for multidimensional engagement and highly affective and low for minimally engaged. For the post-event actions, the multidimensional engagement had a higher value than others especially for the minimally engaged. In relation to the demographics, the gender, age, and event status have relatively the similar features, and there were no strong engagement differences in terms of the observed age or gender.

Three performance evaluation metrics were used in assessing the effectiveness and quality of the clustering, the elbow method was used in determining the optimal number of clusters using the within-cluster sum of squares to indicate how tightly grouped the clusters are. From figure 5 the elbow point is where the rate of the within-cluster sum of squares decreases and slowly insignificant, the most noticeable elbow is around 4, which align with the within-cluster sum of squares value of 171820.15 as the inflection point where it drops sharply and the slopes flattens showing a minimal additional improvement. So, the optimal number of clusters is 4, which minimizes the within-cluster sum of squares effectively, avoiding overfitting with too much clusters and matches the heatmap label engagement clusters. This shows that the four behavioural engagement patterns best represent the data without complexities.

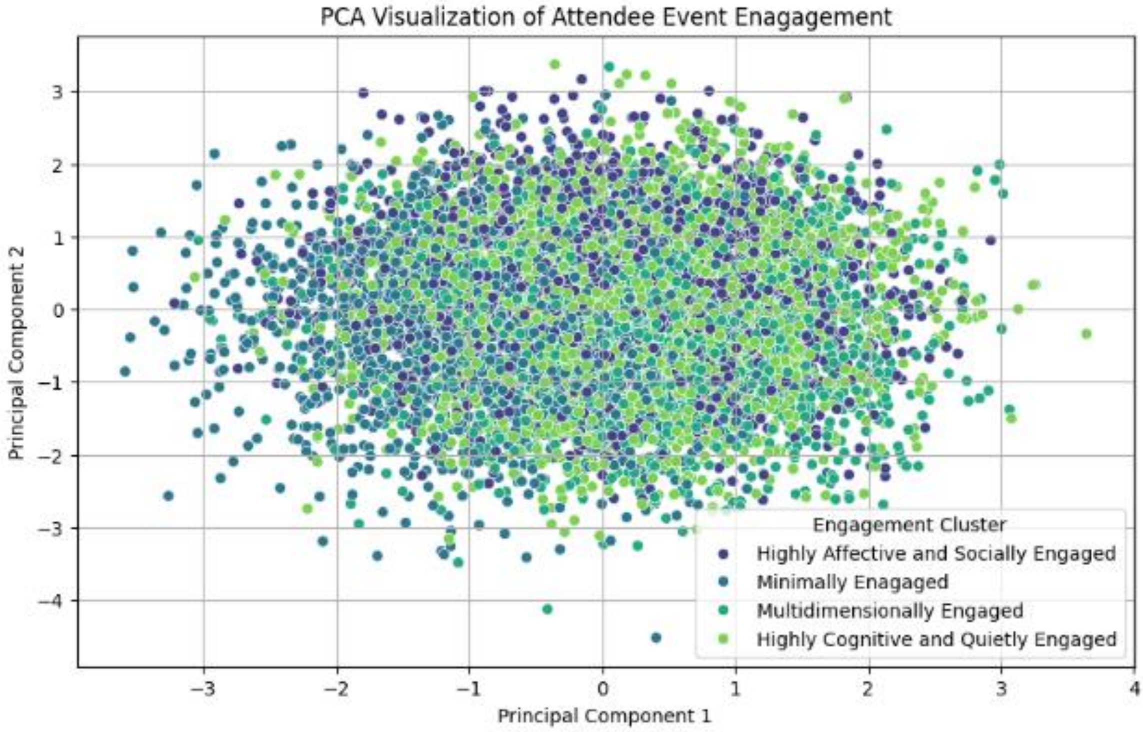

Figure 4: PCA Visualization of Attendee Event Engagement

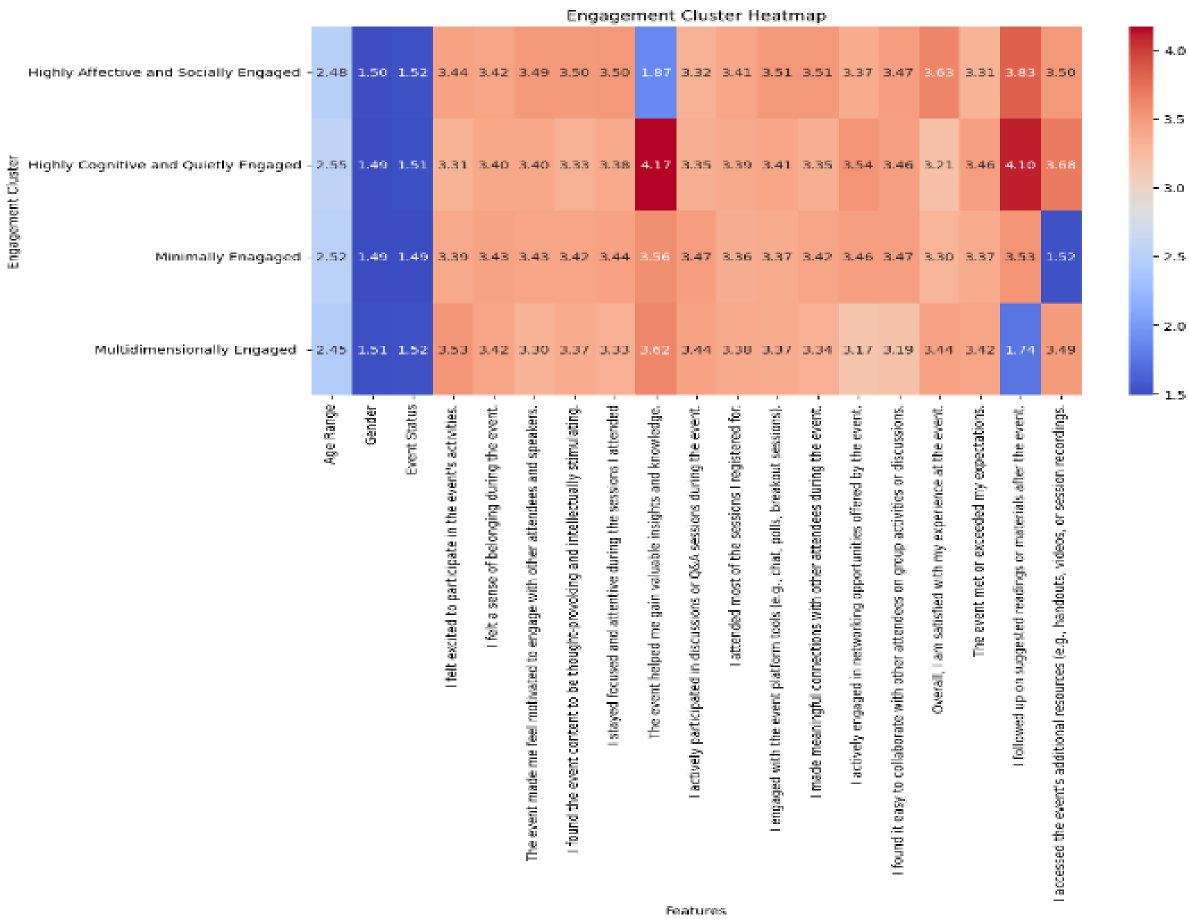

Figure 5: Engagement Cluster Heatmap

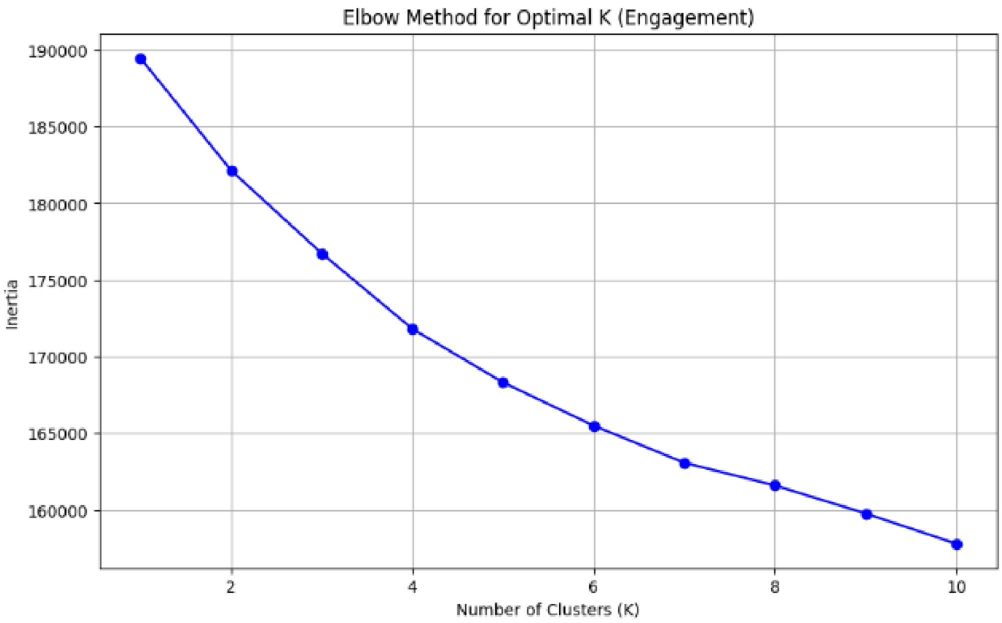

Figure 6: Elbow Method for Optimal K (Engagement)

Also, the Silhouette score was used in evaluating the performance of the behavioural pattern and to assess the quality of the clustering by measuring how similar a data point is to its own cluster compared to other clusters. The score was 0.37 and it indicates a decent but not perfect clustering, showing there are some structures in the data and that most data points are closer to their own cluster than to others but some overlap between the clusters still exists and the separation is not very strong. So, the 0.377 shows that the cluster is the weak to moderate and good enough for the early-stage attendee segmentation and need further tuning for decision making.

The research was performed on behavioural analysis model for enhancing events attendees' experiences. Research on the algorithms such as K-Means clustering, was evaluated for attendees' segmentation. From the research, K-Means clustering was chosen as most suitable for conducting the attendee's segmentation. The visualization showed that some attendees shared mixed behavioural patterns, which is common in human behavioural details. There are clearer behavioural differences as the highly affective and socially engaged alongside minimally engaged are more concentrated in various principal component areas. The multidimensional engaged with the highly cognitive and quietly engaged are more diffused, indicating that these behavioural patterns may overlap in some behaviours.

The behavioural personalities of the attendees shows that some are motivated, engaged, participated and connected socially, others are intellectually engaged without high social interaction, some did not connect deeply and did not follow up or engaged in the post-event materials, while some engaged emotionally, socially and cognitively. Attendees had high level of engagement particularly in actively participating in interactive segments of the events.

With these findings, event planners can gain a more accurate understanding of attendees' choices and levels of involvement by analysing their behaviour in real time. The information gathered from event platforms can offer profound insights into the reasons behind attendance, how attendees navigate, and what they desire to see. The evaluated user journeys using descriptive analytics techniques and came to the conclusion that behavioural segmentation can greatly enhance information retention and event pleasure which aligns with the review of literature. The result shows how data-driven segmentation produced useful insights that enhanced engagement and content delivery.

One of the main goals of behavioural analysis models which this result has shown is event personalization. The results showed that individual encounters have a greater impact and are more memorable on attendees which corroborates with one of the objectives of this research. The current research findings and interpretation inform event planners on decision when organizing an event on patterns or segments of event toward effective engagement and attendees' satisfaction.

5.0 Conclusion

In the digital era, event participants' pleasure indicates how effective the event was, making a lasting impression on them and influencing their likelihood of attending again. This study examined attendees' views and behavioral patterns regarding their event experiences using a data-driven methodology. Four themes emerged from the discussion of the findings: minimally engaged, multidimensional engaged, highly affective and socially engaged, and highly cognitive and quietly engaged.

Analyzing the behavior of event attendees via the data on the heatmap, it was discovered that motivation and participation for highly affective and multidimensional cluster was strong and very weak for minimally engaged. The cognitive engagement was very high for cognitive, quiet and multidimensional engaged and moderate for others. Social engagement was highest in highly affective and socially engaged and very low in highly cognitive and quiet. For satisfaction, it was high for multidimensional and highly affective and low for minimally engaged.

Event attendees participate more in highly affective and multidimensional segments as well as for cognitive and quiet segments and social engagement participation in affective and socially engaged segments and satisfaction is high for multidimensional segments as well. Summarily, K-clustering technique serves as an important method for understanding both low- and high-involvement of attendees in events

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