Chapter One

Introduction

1.1 Background of the Study

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 content and programs by providing customized suggestions for meetings, workshops, and networking opportunities based on preferences of the individuals[3].

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[4]. The goal of this project 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 as sentiment analysis, clustering, and predictive modelling, will be 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 experiential design in the events industry, this initiative ultimately aims to establish a new benchmark for proactive, tech-driven event management[4].

In conclusion, the 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.

1.2 Statement of Problem

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.

Studies have shown that machine learning models can analyze attendee's behavior, attendee's involvement and attendee's prediction[8]. Furthermore, research in enhancing attendee's engagement suggests that individual behavioral analysis, preferences and engagement significantly enhance attendee's participation and experience during or after events[9]. Attempting to address individual events attendee's engagement using a step forward machine learning approach that adapts to the availability of features as the event's date approaches, which contributed to the understanding of how machine learning classification changes overtime using demography data and prior attendance record as the features[10]. However, a major limitation in this work is the lack of attendee's behavioral segmentation which corroborates the suggestion from the aforementioned, this study will seek to close the academic gap identified[9].

This study examines attendee's behavioral segmentation into K-clustering technique for identification of attendee's engagement during and or after events. This approach has the potential of enhancing attendee's experience during or after events and serve as a behavioral engagement data for prediction accuracies.

1.3 Aim and Objectives of the Study

The aim of this project is to develop a behavioural analysis model using K-clustering techniques to identify attendees' engagement in events for improved attendees' experiences.

The following are the specific objectives:

1. Collect 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

1.4 Research Questions

The research questions are to:

1. What are the main behavioural engagement elements that enhance attendees' engagement and satisfaction in events?

2. How can data about attendees' behaviour be analysed using k-clustering machine learning approaches to enhance event experiences?

1.5 Significance of the Study

The results of this study could enhance the calibre of attendees' experiences, streamline event management, and create a data-driven framework for engagement and customization at events.

Understanding the tastes and habits of attendees is essential to creating memorable and captivating experiences in a highly competitive events market. Insights into behavioural patterns that impact satisfaction will be given to organizers via this study's model, enabling prompt and tailored adjustments to improve the attendance experience. Event planners may boost satisfaction and promote repeat business by anticipating and addressing attendees' demands, which will enhance their reputation and brand loyalty.

The model can assist event planners in maximizing resource allocation, cutting waste, and streamlining operations by comprehending guest flow, engagement hotspots, and resource demands. In addition to improving the experience of attendees, such efficiency reduces operating expenses, increasing the sustainability and financial viability of events. As a result, this paradigm has wide-ranging effects on events' potential to be sustainable financially and environmentally.

All things considered, this study marks a significant breakthrough in the field of event management by putting forth a proactive, technologically enabled approach to raising operational effectiveness, boosting attendee experiences, and supporting sustainable event design. Its ramifications go beyond events; it provides insights that might be used to other industries that utilize behavioural analysis to optimize the experience.

1.6 Scope of the Study

This scope of this study aims to improve attendees' experiences in event management through the creation and application of a behavioural analysis model utilizing k-clustering technique. The research will specifically concentrate on key behavioural dimensions such as social involvement, emotional reactions, cognitive, and interaction patterns.

1.7 Limitation of the Study

Although the goal of the study is to create a thorough behavioural analysis model, there are a few recognized limitations ranging from concern of data privacy, implementation in real-time,
the human behaviour complexity, data accessibility and quality

1.8 Operational Definition of Terms

Behaviour: The term "behavior" describes the visible behaviors, exchanges, and patterns of participation displayed by participants in both live and virtual events. Digital tools and machine learning approaches can be used to track and evaluate behaviors including session attendance, time spent on event platforms, content interactions, networking activity, and feedback submissions.

Model: The behavioral analysis framework created with k-means clustering and other machine learning techniques is referred to as a model in this study. In order to facilitate real-time customization and decision-making during events, it serves as a computational framework that is intended to recognize, categorize, and divide attendees according to their behavioral data.

Event: Any planned meeting, whether in person or virtually, where attendees congregate for a shared goal—such as conferences, workshops, seminars, or exhibitions—is considered an event. This study primarily focuses on events where data analytics technologies and digital platforms can be used to track and examine attendance behavior.

Attendees: People who sign up for, take part in, and interact with event activities are known as attendees. Within the model, they are the main focus of behavioral analysis, and data collection, segmentation, and event experience customization are based on their interactions.

Event Attendee Engagement: The extent to which attendees actively engage with networking opportunities, event material, and other components, impacting their overall pleasure and experience.

Clustering Algorithm: An unsupervised machine learning method that aids in segmentation and focused engagement by classifying attendees according to comparable behavioural patterns.

Endnotes

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Chapter Two

Literature Review

2.1 Conceptual Review

This chapter examines the diverse perspectives offered by various authors regarding the impact and challenges of behavioural analysis model for enhancing event attendee experiences in events using machine learning techniques.

Conventional method of understanding attendee's engagement is now being re-evaluated by events planners in response to the growing desire for innovative, interactive, and customized experiences which is a promising area for transforming the planning, execution, and assessment of event experiences is behavioural analysis, especially when used with machine learning (ML) techniques[1]. The systematic study of people's behaviours, interactions, and preferences in order to extract valuable insights is known as behavioural analysis. When it comes to event management, behavioural analysis includes a broad range of information, such as social media activity, check-in times, session attendance, participation duration, and immediate polling results. An understanding of these behaviours offers insight into the interests, contentment, and tendency of participants to return for subsequent events[2]. Several studies show the advantages of using attendee behaviour analysis to create more events that are captivating. For example, putting up with behavioural data makes it possible to customize experiences, which increases attendee satisfaction. Similarly, behavioural segmentation plays a strategic role in improving event reactivity. These viewpoints serve as the cornerstone for creating machine learning models that can identify intricate behavioural patterns those conventional methods might miss[3],[4]. Finding pertinent behavioural indicators is the first step in creating a successful behavioural analysis model. These include the regularity of sessions, the use of chat or Q&A features, the amount of time spent in different event zones (both virtual and in-person), and interactions with the material.

Every indication represents a measure of involvement and functions as a feature in the machine learning model[5]. Attendees can be grouped into segments according to behavioural similarities using a model architecture based on unsupervised learning, especially clustering approaches like k-means. Because event participation is dynamic and diverse, this type of clustering excels at identifying latent patterns without the need for programmed labels[6]. Moreover, adaptive learning is made possible by the model's incorporation of instant inputs of data. To ensure ongoing relevance, the model recalibrates clusters when new behaviours appear. The model's output allows for immediate interventions, including delivering tailored messages or modifying session material according to current engagement levels, in addition to providing information for post-event evaluations[7].

2.1.1 Events (Virtual and In-person) and Event Management

Different academic disciplines, such as social computing and Topic Detection and Tracking (TDT), have different definitions of "event." Researchers frequently dispute on the exact definition of an event or its characteristics, even within a certain topic. In general, an event on a social media site is anything that takes place at a certain time and location. An event is "an occurrence causing changes in the volume of text data that discusses the associated topic at a specific time,"[8]. According to this definition, the event is defined by the subject and the time, and it is frequently connected to things like people and places. Additionally, an event is defined as something that occurs with a clearly defined beginning and finish[9]. These definitions address a crucial component of an event, which is its essential connection to the temporal dimension.

Since the characteristics of an event are shared by all of these definitions, an event can be described by one or more of the following characteristics: Subject, Time, People, and Place. Put differently, based on information gleaned from social media sources, events can be characterized by four different types of attributes: who (people), where (location), when (time), and what (subject or keywords)[10]. An event is defined as a real-world occurrence that is represented by a shift in the amount of textual data discussing the related subject at a certain time and location.

They range from well-known (international) events like political rallies or professional sporting events to more intimate, local events like neighborhood get-togethers or conferences. Events pertaining to the real world that have an impact outside of a certain location are referred to as global events. On the other hand, local events are those that relate to actual occurrences that have an impact that is limited to a certain area[11]. Both kinds of events pique people's interest; the former are significant global events that everyone should be aware of, while the latter have a more direct impact on our daily lives.

Events serve as an important forum for communication, networking, learning, celebration, and business development. From small-scale seminars to large-scale international displays, they differ greatly in size, intent, and format. Events have changed dramatically in response to the spread of digital technologies and the effects of worldwide emergencies like the COVID-19 pandemic, adopting hybrid and virtual formats in addition to conventional in-person meetings. Professionals must now embrace data-driven, technologically advanced ways to planning and execution as a result of this shift, which has forced a redefining era of event management standards[12]. In-person Events are gatherings that take place in actual places and allow participants to engage with one another in person. They make direct interaction, tactile sensations, and impromptu networking possible, all of which greatly enhance guest pleasure. Events that are held in person give organizers the chance to control environmental cues like lighting, atmosphere, and space arrangement to affect how attendees behave. It takes a lot of resources to manage such events, though, and calls for careful planning, budgeting, crowd control, and problem-solving[13]. Virtual Events utilize digital platforms, these events are held fully online. This includes online product debuts, webinars, virtual conferences, and digital trade shows. Benefits of virtual events include accessibility, cost effectiveness, and a wider worldwide audience. The virtual event experience has been enhanced by technologies such as chatbots powered by AI, virtual reality (VR), and live broadcasting. However, issues like digital fatigue, technical hiccups, fewer networking opportunities, and trouble maintaining audience engagement still exist[14] . The entire process of organizing, planning, carrying out, and assessing events is included in event management. Conventional event management mostly depended on unreliable feedback, manual procedures, and intuition. Data analytics and automation techniques have transformed the field in the modern day. These days, integrated event management software handle tasks like scheduling, content delivery, registration, and feedback gathering[15]. The demand for more in-depth knowledge of attendees' experiences led to the development of behavioural analytics as a key component of event management. Understanding behavioural patterns is essential to providing value and going above and beyond expectations as events get more complicated and audiences get more varied[16]. Organizers can go beyond general measures like headcounts or ticket sales with the help of behavioural analysis. Pain points, popular features, and unmet demands can be found by looking at in-depth attendee interactions. For instance, a virtual event platform may notice that participants frequently leave some sessions midway through, which could lead to an examination of the delivery style or the relevancy of the content[17].

Moreover, adaptive event management is made easier with behavioural insights. The decision to reallocate moderators to popular sessions, send targeted nudges to inactive users, or extend time for conversations where involvement are high are just a few examples of the impromptu decisions that organizers might make. This adaptability raises the event's perceived worth and fosters enduring loyalty.

Essentially, the importance of data-driven tactics has increased as a result of the convergence of virtual and in-person events under a single event management pattern. In addition to facilitating more effective operations, the use of machine learning for behavioural analysis helps to match event design with attendance' complex preferences. It makes it possible to go from reactive to proactive management, where experiences are intelligently modified rather than just observed[18].

2.1.2 The Behavioral Event Modeling Method

In particular, a methodical technique called "Behavioral Event Modeling" was developed for anticipating and forecasting behavior[19]. The goal of behavioral event modeling, or BEM, is to investigate the possible actions that a person might take in a particular circumstance. The model looks at potential follow-up reactions or repercussions that one might encounter as a result of prior conduct[20]. By connecting the behaviors that might arise as a result of each previous activity, the model is able to elicit a variety of possibly connected behaviors, eventually creating a tangible, visual map.

Because of this, the primary goal of BEM is to identify potential occurrences that could result in a "target outcome" or "critical incident". This entails evaluating each of the numerous antecedent events that might have an impact on the "target" event or outcome, as well as any signs or signals that may be present[21]. A predictive model of behavior is eventually created by building upon the significant occurrence, the series of events before the incident, and the indications connected to each event in the sequence[22].

With this information, one might then identify possible places of intervention earlier in the sequence with the aim of changing the course of events to eventually produce a different result. Furthermore, because low-involvement actions and established habits are so common in daily life, it would be particularly illuminating and enlightening to comprehend and forecast them. For instance, a basic event model of a vehicle collision. It might have happened as a result of a number of sequential circumstances, including being late, speeding, or making a phone call while operating a motor vehicle. Other antecedent occurrences, including oversleeping, attempting to fit too much in before departing, or a delayed departure from a previous engagement, may have contributed to the development of these events. One could discover that the time-related events (oversleeping, cramming too much into one day) preceded the distracted-driving events (speeding, taking a shortcut), which eventually caused or culminated in the accident, by using arrows to connect these possible sequences of events.

The BEM technique is comparable to other effective predictive modeling approaches in that it examines how one behavior can lead to another and concentrates on basic human tendencies. However, what sets the BEM strategy apart from other predictive modeling tactics is that it employs a technique known as "backwardly modeling" the events that influence decision outcomes, where the ultimate result is the exercise's starting point rather than its end[23]. In this sense, the procedure entails "working backwards" from the result to determine the basic actions that might have preceded it. Instead of starting the study with a specific behavior whose potential outcomes may be more constrained, this method has the advantage of enabling the construction of a wider variety of potential routes that could culminate in a crucial incident. Furthermore, the BEM method to predictive modeling is unique in that it considers a series of events holistically (as opposed to just the end result) and utilizes historical occurrences as factors that influenced a particular behavior or significant event[24]. Therefore, this strategy also makes it possible to develop treatments that might be able to change the final result.

Additionally, the predictive modeling of behavior approach has certain benefits over traditional techniques like focus groups and questionnaires that marketers employ to ascertain how customers reach a specific conclusion[25]. Attendees' final interpretations may therefore not accurately reflect how they came to a specific decision if they are unaware of or unwilling to explain their decision-making process.

Furthermore, although demographic and psychographic information is frequently mentioned as being helpful in gaining understanding of attendees, there are a number of drawbacks to this as well. In particular, gathering this data can be quite expensive, and even then, there may be limitations to how easily the data can be comprehended[26]. Furthermore, psychographic data is usually not objective. Because of these factors, when attendees make low-affect decisions, the constraints of traditional segmentation techniques might not always provide the greatest insights. However, BEM is able to get around these restrictions. Therefore, BEM is a good substitute for traditional segmentation techniques, offering the benefits of speed and affordability.

Another benefit of BEM is that it is simple to use and can be completed by anyone because all that is really needed is an innovative mentality. The ability of BEM to extract insights without the presence of other people is its last benefit[27]. In addition, unlike the gathering of demographic or psychographic data, the procedure does not have to be made public. Consequently, since the BEM technique may also be used to analyze hypothetical circumstances, this approach could be used in a variety of situations that would otherwise be not feasible or morally acceptable to duplicate.

2.1.3 Attendees Behavioural Analysis

The methodical gathering, analysis, and interpretation of information on the choices, behaviours, and preferences of event attendees is known as attendee behavioural analysis. From session attendance and booth visits to click patterns on event applications and social media involvement, it gives event planners detailed insights into how attendees connect with various aspects of an event. Enhancing user experiences, improving event content, and putting adaptive engagement tactics into practice in both the present and the future are all made possible by this data[28]. The understanding that each participant engages with events in a unique way lies at the heart of behavioural analysis. A number of variables, including demographics, time availability, interests, and technical literacy, affect these encounters. For example, younger attendees could prefer interactive Q&A sessions or gamified event features, whereas older professionals might prefer keynote speeches and organized networking opportunities. The goal of behavioural analysis is to identify these patterns in order to guide the planning of strategic events[29]. The length of time a visitor spends in a specific exhibit or session, monitoring an attendee's online activity via applications, websites, or virtual platforms, Participation in live polling, chat conversations, feedback submissions, and social media posts, how participants move through actual events areas or through digital content are among the important behaviour indicators.

These indicators aid in providing a thorough understanding of the factors that influence engagement and disengagement. User interface optimization, better scheduling, and more individualized content distribution are all possible outcomes of such insights.

Behavioural analysis data comes from a variety of sources such as forms for registration, mobile event applications, systems for managing sessions, social media sites, survey tools and feedback, Multi-platform analysis is made possible by integrating different data sources into a single analytical framework, which produces a multifaceted picture of attendance behaviour.

Based on behavioural data, machine learning algorithms, like the K-clustering methodology, can be used to find participants' natural groupings or segments. K-clustering works by assembling related data points into clusters according to predetermined criteria. These attributes could include content preferences, degree of interaction, or frequency of session attendance in the context of events[30]. Providing communications, suggestions, and material that are tailored to each individual, using immediate engagement data to modify sessions or distribute resources, foreseeing future patterns of behaviour to organize more successful events are numerous benefits of using behavioural analysis in event management A key component of contemporary event optimization is the behavioural study of attendees. Organizers may create more memorable and fulfilling experiences by using technology to watch and comprehend how attendees engage with different event components. A level of complexity is added by incorporating machine learning methods such as K-clustering, which allow for large-scale customization and prediction in addition to observation. Behavioural analysis will continue to be a fundamental component of data-driven, user-cantered event design and management as events continue to change.

2.1.4 Machine Learning Techniques in Behavioural Analysis

In behavioural analytics, machine learning (ML) has quickly become a game-changing tool that gives event planners sophisticated tools to mine data, find trends, forecast results, and enhance visitor experiences. ML acts as a link between actionable intelligence and unprocessed behavioural data in the field of event management. When it comes to understanding different levels of involvement and segmenting attendance, unsupervised learning algorithms like k-means clustering are very effective. The main machine learning techniques used in behavioural analysis are examined in this section along with how they enhance event experiences[31].

Computational techniques known as "machine learning" enable systems to learn data and generate predictions or judgments without explicit programming. Three main categories are involved: reinforcement learning, unsupervised learning, and supervised learning. Unsupervised learning approaches, in which the computer discovers latent structures in data without specified labels, are frequently used in behavioural analysis of event attendance[32].

A well-liked unsupervised learning technique for dividing data into k separate clusters is K-means clustering. It can be applied to event management to classify participants according to behavioural characteristics such as regularity of attendance during sessions, conversations with exhibitors, participation in surveys or Q&A, paths for navigation on virtual platforms, time devoted to various event features[33].

Other Machine Learning Methods for Behavioural Analysis include, Random Forests and Decision Trees, Support Vector Machines (SVM), Neural networks and deep learning, Natural Language Processing (NLP). The way that event planners interpret and react to guest behaviour is being completely transformed by machine learning approaches. These methods allow for more individualized, interesting, and successful event experiences through segmentation, prediction, and adaption. K-clustering's strategic integration within this framework supports the project's objectives of improving attendee happiness and providing data-driven insights. The use of machine learning technologies in behavioural analytics will grow more accurate, scalable, and significant as they develop further.

2.1.5 Personalising Events with Behavioural Insights

The practice of customizing an event experience to each attendee's unique requirements, tastes, and behaviors is known as event personalization. Personalization has emerged as a crucial component of improving the overall experience of attendees in today's digital and data-driven environment. Event planners can learn what attendees value, how they interact with event components, and how to adjust these components to accommodate individual or group preferences by using behavioral insights obtained from data analytics and machine learning models[34]. A generic, one-size-fits-all experience is not what guests of today expect. Throughout their event journey, they look for memorable, pertinent, and meaningful interactions. For event planners, personalized experiences result in higher levels of engagement, pleasure, and brand recall as well as better ROI. Because attendees are more likely to engage with information and activities that mirror their interests and habits, personalized event experiences can boost attendance by up to 45%[35]. Data-driven understandings of how people or groups behave in particular situations are known as behavioral insights. These insights are taken from a variety of sources in event management such as information about ticketing and registration, clickstream data and website navigation, attendance at sessions and dwell time, sentiment analysis and social media interaction, tracking a location with beacons, poll results and feedback questionnaires. These statistics can be analyzed using machine learning techniques to find trends and forecast preferences. In order to help organizers tailor material and services for each segment, clustering algorithms such as K-Means, for example, can group participants based on behavioral similarities[36].Recommendation systems that are driven by collaborative or content-based filtering can produce customized agendas or session ideas for each participant based on prior sessions attended, subjects of interest, or click patterns[37]. Attendee data can be used to personalize emails, app notifications, or SMS reminders, increasing open and response rates. An attendee with an interest in technological advancements, for instance, might be notified of forthcoming robotics or artificial intelligence workshops. Attendees can get directions or schedules that are tailored to their preferences and reduce conflicts between their interests. Attendees can be directed to exhibits or programs they are likely to appreciate via indoor positioning systems (IPS)[38]. Immediate personalization is made possible by behavioral tracking through wearables or smartphone apps. For example, lighting, music, or booth participation can be changed according to the demographics or past behavior of attendees in the vicinity. Behavior insights can help create gamified experiences that are tailored to each person's preferences, including giving points for visiting particular booths or engaging in particular activities[39]. Post-event engagement can also be tailored, and surveys can be modified according to sessions attended or interactions had, which boosts response rates and makes them more pertinent[40]. Artificial Intelligence facilitates content adaptation and predictive modeling, Internet of Things devices like smart badges, RFID wristbands, and beacons collect immediate behavioral data, Natural Language Processing examines textual feedback or social media posts to tailor responses or content and Big Data platforms manage vast amounts of diverse data for analysis and personalization delivery[41].

2.1.6 Privacy Issues in Behavioural Data gathering

Privacy issues have become a major worry as event planners use behavioral analysis more and more to improve the experience of attendees. In terms of consent, transparency, data protection, and abuse, the collection, storage, and use of behavioral data such as location tracking, session attendance, device engagement, and sentiment analysis presents moral and legal dilemmas. Maintaining trust, adhering to legal obligations, and guaranteeing the moral use of technology in event management all depend on addressing privacy problems[42]. Any information that documents people's movements, preferences, and behaviors is referred to as behavioral data. This information could consist of clickstreams on applications or websites for events, history of session participation, interactions on social media, facial recognition or biometric information, location monitoring using beacons, data from surveys and feedback. Although this data is useful for engagement and personalization, it is frequently gathered in bulk and passively, which raises questions regarding people's awareness and control over the use of their data[43]. Informed consent is one of the fundamental tenets of ethical data collecting. Participants need to be made fully aware of what information is being gathered, how it will be applied, with whom it will be shared, how much time it will be kept. Event planners need to steer clear of vague or too complicated terminology when creating data policies. approval systems should also include explicit opt-in and opt-out options instead of default settings that presume user approval.

Whenever feasible, behavioral data should be anonymized to reduce privacy issues. Before analysis, personally identifying information (PII) including names, email addresses, and device IDs must be eliminated. But sometimes, especially when paired with other information, even anonymized data might be re-identified using advanced analytics—a danger known as re-identification[44]. Strong data security procedures must so be implemented, such as encryption in storage and transmission, protocols for secure authentication, limitations on access control and frequent incident response plans and security audits[45]. Beyond merely adhering to the law, behavioral data collecting has ethical ramifications. If attendees believe that data collecting is opaque or is being utilized for objectives other than event enhancement like targeted advertising or third-party sales they may feel monitored or coerced. This impression may damage confidence and deter people from attending upcoming events. To establish trust, using a privacy by design strategy in which the system architecture incorporates data protection, communicating value exchange outlining the advantages of data collection for the attendee and providing dashboards and other data control tools so that participants may manage their data preferences[46]. In the end, event planners need to find a balance between protecting participants' privacy and using behavioral insights for personalization. Aggressive data use or excessive personalization may come out as intrusive. The secret is to only gather the information required to improve the experience of attendees, to ensure that this information is handled ethically, and to give people authority over their data.

2.1.7 Evaluation Metrics for Event Management Machine Learning Models

In order to better analyze and forecast the behavior of event attendees, optimize event logistics, improve user experiences, and facilitate decision-making, machine learning models have become indispensable tools. However, assessing these models using the right performance indicators is crucial to their efficacy. Selecting the appropriate metrics for classification, clustering, and regression tasks is crucial in the event management setting, as data can be both structured such as ticket sales, registration records and unstructured such as social media posts, location data. The main assessment metrics utilized in machine learning systems for event management are examined in this section[3]. In event management, classification challenges frequently entail forecasting discrete outcomes, such whether a guest will arrive, leave, or use a certain service.

The most widely used statistic is accuracy, which is just the proportion of accurate forecasts. It measures how accurate the classifier's predictions are overall. It is computed by dividing the total number of instances in the dataset by the number of accurately predicted instances including true positives and true negatives. Although accuracy gives a broad sense of how accurate the model is, it may not be appropriate for datasets that are imbalanced, meaning that one class is substantially more prevalent than the other. For example, a classifier that consistently predicts a class that comprises 95% of the data will still achieve a high accuracy of 95%, but it may not be practical[47].

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + F} \qquad \text{………………}eqn.\ 1$$

The percentage of favorable forecasts that came true is known as precision. It is computed as the sum of true positives and false positives (forecasted as positive but actually negative) divided by the number of genuine positive predictions (instances accurately predicted as positive). In situations like fraud detection or medical diagnosis, where the cost of false positives is large, precision is especially important. A high precision means that the classifier has a high probability of being right when it predicts a favorable result.

$$\text{Precision} = \frac{\text{TP}}{\text{TP + FP}} \qquad \text{…………………eqn. 2}$$

The F1 score is a metric that provides a fair assessment of a model's performance by combining precision and recall into a single value. It is particularly helpful in cases where the distribution of classes is unbalanced and accounts for both false positives and false negatives. The F1 score is calculated by taking the harmonic mean of recall and precision.

$$\text{F1} = 2 * \frac{\text{Precision* Recall}}{\text{Precision + Recall}} \qquad \text{…………………..eqn. 3}$$

Better overall performance is indicated by a higher F1 score, which goes from 0 to 1. Because the F1 score accounts for both false positives and false negatives, it can be used in scenarios where accuracy and recall are equally important and both metrics should be given equal weight. Evaluation measures called ROC (Receiver Operating Characteristic) and AUC (Area Under the ROC Curve) are used in binary classification to gauge a model's performance across various threshold settings.

2.1.8 Comparing Architectural framework and system development for behavioral analysis model in events

Strong architectural frameworks and system development methodologies are necessary for the design and development of successful behavioral analysis models, particularly those that make use of machine learning techniques like k-clustering[48]. These systems must provide multivariate behavioral inputs, immediate data streams, and dynamic feedback loops for event management in order to customize the experiences of attendees[49]. Modularity, scalability, interoperability, and instant processing capabilities are considered, which critically evaluates current architectural frameworks and development approaches pertinent to the creation of such behavioral models.

A widely used models in behavior driven systems is layered or tiered architecture. When it comes to event management, this framework usually includes handling gathering of raw behavioral data such as check ins, clickstreams, device motions, and session engagement[50]. Preprocessing, feature extraction, and normalization are implemented by the data processing layer. Hierarchical clustering, DBSCAN, and K-means are executed with the ML analysis layer. Dashboards or recommendation engines with insights for event planners are provided by the presentation layer. Because of its scalability and modularity, microservices architecture is becoming more and more popular for contemporary, instant event systems. Data ingestion, processing, clustering, and feedback are all separate services that are frequently orchestrated with Kubernetes and containerized with Docker[51]. Its benefits include; instantaneous computation that is scalable, scaling or updating individual services that is simple, facilitation of continuous deployment and integration (CI/CD).

The timeliness of data processing must be considered in system development techniques, particularly during events where attendees participation fluctuates quickly. These systems process attendee data as it is created using frameworks such as spark streaming, apache kafka, or flink[52]. It enables immediate customization such as delivering nudges or changing session ideas but its disadvantage is that it needs a significant investment in infrastructure and error tolerance measure.

Effective storage systems are necessary for managing behavioral data from multiple sources, relational databases for structured attendee data, such as PostgreSQL, NoSQL databases for semi-structured or unstructured data, such as chat logs, social media feeds, and MongoDB, time-series databases for time-stamped engagement signals, such as InfluxDB and a hybrid architecture that uses a polyglot persistence model guarantees the best query performance for many kinds of data[53]. A hybrid architecture that uses a polyglot persistence model guarantees the best query performance for many kinds of data.

Integrating ML capabilities into the system's lifetime is crucial for behavioral models. Standardized machine learning pipelines include[54]; modules for data normalization and cleaning, feature engineering (such as the length of an encounter or return visits), model training (e.g., segmentation using k-means clustering), evaluation of the Model (using DBI, Silhouette Score, etc.), layer of deployment (using embedded SDKs or RESTful APIs)

Models for behavioral analysis need to comply with the GDPR and NDPR[55]. Important architectural elements to guarantee this consist of; modules for data anonymization, systems for controlling access (like OAuth 2.0), audit records and monitoring of consent[56]. For decentralized data processing in behavioral systems, federated learning and privacy-preserving clustering algorithms[57].

Decentralizing behavioral analysis in events is possible because to recent advancements in edge computing and federated learning. Edge computing lowers latency by enabling local data processing (e.g., wearable sensors) prior to transmission to the cloud. Federated Learning preserves user privacy while facilitating cooperative ML model training across dispersed data sources. For hybrid and decentralized events where data comes from several user settings, both paradigms work well[58].

Choosing architectural frameworks that strike a compromise between scalability, instant capabilities, modularity, and privacy is essential for developing behavioral analytic systems for event management. Microservices provide greater flexibility and scalability than traditional layered systems, especially when handling massive amounts of dynamic behavioral data, even though the latter are simpler to deploy. It is crucial to integrate powerful machine learning pipelines, flexible data storage, and streaming analytics. In order to stay ethical and sustainable, future models must also incorporate privacy-by-design principles and make use of newly developed decentralized frameworks.

2.2 Methodological Review

A novel approach was developed for forecasting individual event attendance by leveraging machine learning techniques, specifically employing a 'step-forward' modeling strategy. The methodology chosen in this study is anchored on fundamental econometric principles, enhanced by contemporary machine learning frameworks, and carefully intended to optimize predictive accuracy in behavioral outcomes such as event attendance[59].

A quantitative predictive modeling study design was employed by the authors. Their dataset included 300,000 event-day observations and transaction-level tickets data from a major Australian sports league, which included a longitudinal panel of more than 17,000 members. Variables including individual demographics, ticket buying patterns, past attendance records, weather, opponent team statistics, and event-specific context were all included in this extensive dataset. Notably, the integrity of the analysis was guaranteed by pre-processing and cleaning the data to eliminate null values and inconsistencies.

Additionally, data were normalized and, if required, encoded to meet the specifications of machine learning models. The "step-forward" strategy, a variant of the conventional forward selection method frequently employed in econometrics, constitutes the main methodological contribution. This approach iteratively increases the prediction power of the model by methodically adding variables in small amounts. Its incorporation into a machine learning (ML) pipeline is novel in this case, as the researchers used multiple ML algorithms to examine variable combinations at each iteration. Among the main machine learning models used are the logistics regression, random forest classier, gradient boosting machine, support vector machine.

To find the most efficient and accurate feature set, each model was evaluated using several subsets of variables. To evaluate the models' performance, the authors used a strict evaluation approach. They employed: 10-fold cross validation to make sure that certain data subsets weren't overfit to the models performance. Area under the receiver operating characteristics curve showing the trade-off between true positive and false positive rates as the main performance indicator. F1-score, accuracy, precision and recall are further metrics for a thorough evaluation of categorization performance. The capacity of random forest and GBM to model intricate non-linear interactions in the attendance data was demonstrated by their greatest AUC scores among all tested models. Because feature importance analysis is crucial for behavioral prediction tasks, the authors gave it a lot of attention. variables like previous frequency of attendance, collective performance, time and place of the match, weather circumstances as well as the availability of promos were discovered to be reliable indicators of attendance.

The researchers were able to determine the marginal value of each extra variable by iteratively and step-by-step selecting these features, which improved the interpretability of the model. In order to investigate the customer experience of using chatbots in business settings, a quantitative research methodology was used. Their methodological approach was based on the collection of empirical data using structured survey instruments, which were intended to evaluate various aspects of the customer's interaction with chatbot technology. The methodology is methodical and in line with best practices in digital user experience research, specifically in the areas of perceived value, usability, satisfaction, and trust[60].

The researchers were able to measure client views and experiences since the study used a descriptive quantitative methodology. In order to uncover important factors that influence consumer satisfaction when using chatbot services, this method made it easier to statistically understand user responses. Because the design was cross-sectional and collected data at a single moment in time, it is appropriate for exploratory research into new technologies such as chatbots. Purposive sampling, a non-probability sampling technique that targets individuals who meet specific criteria in this case, prior chatbot usage—was used to recruit participants. The sample consisted of respondents who had prior experience interacting with chatbots. Though the abstract does not explicitly state the sample size, the authors clarify that the data were collected through online questionnaires, which is a cost-effective and scalable method for reaching tech-savvy participants.

The questionnaire was created based on previously validated constructs in the field of customer experience and digital communication, and it was distributed via digital channels to ensure accessibility and reach. Likert-scale items (probably 5-point or 7-point), which are frequently used in user experience research due to their effectiveness in capturing subjective perceptions, were used to measure each of the independent and dependent variables in the questionnaire: overall customer experience; ease of use, usefulness, perceived enjoyment, and trust in chatbots; and the authors cited pertinent literature to ensure construct validity and relevance, drawing from prior models in customer relationship management and human-computer interaction.

Partial Least Squares Structural Equation Modeling (PLS-SEM), a statistical technique especially well-suited for exploratory research with intricate inter-variable connections and relatively small sample sizes, was employed for data analysis. This was done using PLS-SEM: Examine the measuring model (construct validity and reliability), Examine the structural model (path analysis and hypothesis testing), Assess the direction and strength of the correlations between the variables.

The authors were able to evaluate the mediating or moderating effects of many elements affecting customer experience in addition to their direct effects thanks to this technique. In order to guarantee the integrity of their measurements, the authors carried out thorough reliability and validity assessments, such as: Discriminant Validity using the Fornell-Larcker Criterion to make sure each construct was unique from the others; Convergent validity confirmed by Average Variance Extracted (AVE); Internal consistency checked by Cronbach's Alpha and Composite Reliability; and robustness of their instrument supported by the credibility of their findings.

The study put forth a number of hypotheses that linked the dependent variable (consumer experience) to the independent variables (e.g., enjoyment, simplicity of use). According to the PLS-SEM results, perceived utility and enjoyment significantly improved customer experience, whereas trust and usability had less of an influence than anticipated. This complex result gave strategic recommendations a data-driven basis. In order to empirically explore the connections between event experience dimensions and behavioral outcomes including satisfaction, image perception, and behavioral intents, a quantitative study approach based on positivist philosophy was used.

The 2019 Napoli Summer Universiade, a major sporting event, served as the study's focal point and gave data collecting and analysis a practical setting[61]. The authors synthesized previous models, especially the Pine and Gilmore experience economy model, and modified them into five essential dimensions pertinent to the sports event context: eustress (specific to sporting events), entertainment, escapism, and education. These dimensions were treated as latent constructs for structural modeling. The methodology was founded on a multidimensional conceptualization of event experience, drawing from the experiential marketing literature. Targeting participants at the sporting mega-event, a convenience sampling strategy was employed. Although generalizability is limited by this non-probabilistic approach, it works well for exploratory modeling in an event-specific and time-constrained environment.

During the event, a structured, self-administered questionnaire was given out. Among the instruments were; measurement items for every aspect of the experience (tailored to the sports context using previously validated measures), metrics for behavioral goals, destination perception, and event satisfaction. 758 useable replies made up the final sample, which satisfied the criteria for multivariate statistical methods like structural equation modeling (SEM). Seven-point Likert scales, with endpoints ranging from strongly disagree to strongly agree, were used to measure the survey items. Multi-item measures that were modified from previous research and revalidated for the sports context were used to measure the constructs.

To guarantee clarity and contextual appropriateness, the instrument was pilot tested with a small group of attendees and subjected to face validity checks with specialists. The purpose of exploratory factor analysis (EFA) is to evaluate the experience dimensions' underlying factor structure. By taking this step, the survey items were guaranteed to load correctly onto the anticipated structure. Confirmatory Factor Analysis (CFA) confirms the measurement model using AMOS. The following important indicators were utilized to confirm model fit: Chi-square (χ^2), RMSEA or root mean square error of approximation, Index of Comparative Fit (CFI), Index of Tucker-Lewis (TLI). Structural Equation Modeling (SEM) was utilized to test the proposed connections between the three outcome variables (behavioral intents, destination image, and satisfaction) and the five experience dimensions. SEM made it possible to include latent variables and estimate several dependent connections at once. Internal consistency was evaluated using composite reliability (CR) and Cronbach's alpha, convergent validity was assessed using average variance extracted (AVE), to verify discriminant validity, the Fornell-Larcker criterion was applied. The technique utilized gives a thorough and empirically informed approach to interpreting event experiences in the context of sports mega-events.

By combining well-validated instruments, robust statistical modeling, and context-specific adjustments (e.g., inclusion of eustress), the study gives a good framework for analyzing how event experiences transfer into behavioral intentions. Notwithstanding certain sampling and generalizability issues, the study's results are supported by the methodological rigor, which also offers a reproducible model for upcoming behavioral research on events. A thorough methodological evaluation was carried out in this journal paper, Machine learning for cognitive behavioral analysis: datasets, methodologies, paradigms, and research goals. The paper, which was published in Brain Informatics, provides a thorough examination of machine learning (ML) applications in cognitive behavioral analysis. Classifying datasets, classifying machine learning approaches, discussing analytical paradigms, and suggesting future research paths are the main components of the authors' methodological approach. For behavioral analysis in event management environments, this methodological paradigm offers insightful information that may be modified[62].

The first step in the study is to classify the different kinds of datasets that are used in cognitive behavioral analysis. These datasets consist of textual, multimodal, physiological, audio, and video data. In their analysis of the sources, data gathering techniques, and data features, it was emphasized the significance of data modality in choosing the right machine learning algorithms. Understanding how various data types can affect the results of behavioral analysis requires this classification. Reviewing and classifying machine learning algorithms utilized in behavioral analysis constituted a substantial portion of the process. The authors distinguished between reinforcement learning, supervised learning, and unsupervised learning. The function of supervised learning algorithms, including neural networks, decision trees, and support vector machines (SVM), in classification and regression problems was examined.

The capacity of unsupervised techniques such as DBSCAN and k-means clustering to reveal latent behavioral patterns was assessed. Although less prevalent in the literature currently in publication, reinforcement learning has been examined for its potential to explain sequential and adaptive behavior patterns. In addition to listing algorithms, the study evaluated their suitability based on interpretability, scalability, and computing efficiency. A paradigm-based classification of ML models was chosen, classifying them into classical ML, deep learning (DL), and hybrid techniques. Traditional ML covers decision trees and SVMs, while DL encompasses CNNs, RNNs, and LSTMs. Hybrid models integrate several strategies to capitalize on each one's unique advantages. The authors emphasized the trade-offs between accuracy, speed, and complexity and critically examined the benefits and drawbacks of each paradigm. Their methodology also featured preprocessing techniques such as normalization, feature selection, and dimensionality reduction, emphasizing the significance of preparing raw behavioral data for successful analysis.

A discussion of the evaluation measures used to gauge the performance of ML models was included in the technique review. These include of clustering-specific measures like the Davies-Bouldin index and silhouette score, as well as accuracy, precision, recall, F1-score, and ROC-AUC. Context-aware metric selection is essential, particularly in behavioral areas where interpretability and practical applicability are critical.

2.3 Review of 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[63].

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[64].

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[65]. 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[66]. 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%[67]. 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[68].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%[69]. 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[70]. 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[71].

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[72].

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[73]. 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[74].

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[75]. 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[76]. 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[77].

2.4 Summary of Gaps in Reviewed Literature

There are still gaps unique to event management situations despite a wealth of research on behavioural modelling and machine learning. Inadequate integration of multi-modal data sources, such as integrating social media, app usage, and sensor data, insufficient immediate adaptive behavioural modelling to customize dynamic events, small to medium-sized events are underrepresented in behavioural research, inadequate qualitative feedback cross-validation of behavioural clusters are gaps in event management.

By applying a k-clustering-based behavioural analysis model designed especially for event contexts, this study aims to close some of these gaps by processing real-time data and providing useful segmentation insights. Immediate behavioral cues, such as app interactions and live social media activity, are not included in some models, which mostly depends on static and historical data (such as demographics and past attendance). In dynamic event contexts, this restricts the prediction power.

Contextual factors (such as weather and event timing) and psychological motivators (such as enthusiasm and peer pressure) that are known to influence attendance behavior are not taken into consideration by the model. The model may not extend well to other event types because it was only used for one kind of event (sport vs. music festivals, for example). The study does not remark on how personal data is ethically generated or the privacy implications of employing behavioral patterns for prediction, especially in conformity with data protection legislation like the NDPR or GDPR.

Although useful for comprehending digital user experience, the study did not relate behavioral data from chatbot interactions to physical or hybrid event environments. Cognitive-behavioral signals that could improve chatbot responsiveness, like tone detection, sentiment analysis, and stress indicators, are not integrated in this research. Generic interaction channels are provided by the analyzed chatbot.

An opportunity to connect machine learning algorithms that tailor user journeys according to past behavioral interactions has been lost as previous studies did not analyze how user data obtained by chatbots is protected or if users are appropriately informed or agreed, which is critical in behavioral data management. Self-reported data and questionnaires, which may be skewed or lacking, are the study's main sources of data. It excludes objective behavioral data gathered by smart technology, such as dwell time, spatial mobility, and biometric feedback.

Machine learning is not integrated to examine trends or forecast behavioral outcomes based on event experience characteristics. Pre-event anticipation such as ticket purchase behavior and social media discussion and post-event reflection such as reviews, feedback, and sharing are crucial for a full-cycle behavioral study, but they are largely ignored in favor of during-event experiences. Previous reports acknowledge behavioral responses, but it doesn't address how data protection laws should be followed while recording such activities, especially during major public gatherings. The review of existing literatures highlights the lack of diverse, real-world datasets, particularly from underrepresented regions like Nigeria, which hinders generalizability. Many cognitive-behavioral datasets involve sensitive information, but the review does not explore how privacy, consent, and ethical collection practices are enforced or guided by global or local data regulations. This research finds challenges in integrating multiple data types e.g., voice, facial expressions, gestures, a gap crucial to fully understanding complex attendee behaviors in live event settings.

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Chapter Three

Methodology

3.1 Research Approach

This chapter presents the details of the behavioural analysis model for enhancing attendees' experiences in events using k-clustering techniques. It explains the various approaches, tools, and algorithms that will be used in achieving the objectives of this research.

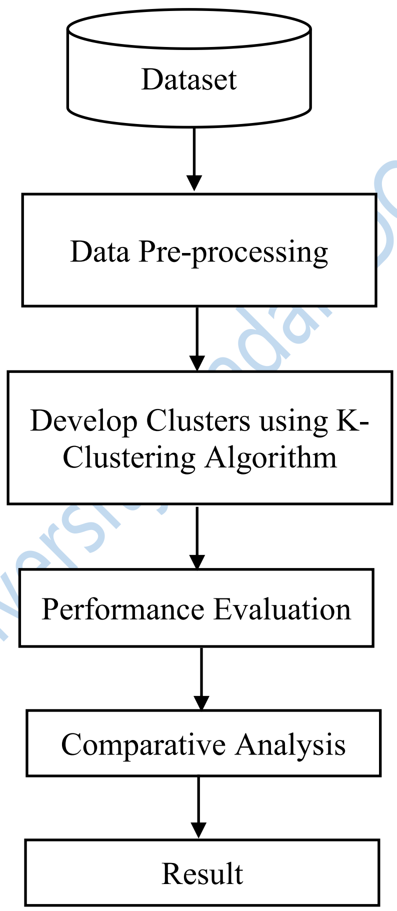


Figure 3.1 Methodology Process Flow (Researcher's Model, 2025)

Figure 3.1 shows the process of the methodology for the cluster development using the K-Clustering algorithm from section 3.1 to 3.4 which consist of six components namely: data collection stage, data pre-processing stage, clustering stage, evaluation stage, comparative analysis stage.

3.2 Requirements Specification

The technical and functional specification required in the implementation of the behavioural analysis model for enhancing attendees' experiences in events through K-clustering technique which include the design description and specification, programming techniques, procedure identification, system requirements, supported hardware details, input and output processing details. The system used a procedural programming methodology with support from object-oriented components using Python Programming classes in modelling data and clustering. The software requirements for the programming language are Python 3.13.5 with the support of libraries such as Pandas, NumPy, Scikit-Learn, Matplotlib, Seaborn, StandardScaler. The programming language is for scripting, Pandas is for data manipulation, NumPy is for numerical operations, Scikit-Learn is for clustering, preprocessing, and evaluation. The Matplotlib and Seaborn is for visualizations and the StandardScaler is for data scaling. The operating system is the windows 11 operating system and the use of the Jupyter notebook as the development environment.

The hardware requirement comprises of the Intel Corei5 processor with 16G RAM, and storage of 1Terabyte disk space, the GPU is not required as the model used are CPU-efficient. The input processing reads data in comma separated values (.csv) file based on the data gathered, the output processing comprises of the generation of the labelled clusters with the addition of engagement level interpretation followed by the visual outputs in heatmaps, scatter plots, elbow, and silhouette score, the final clustered dataset is exported as comma separated values (.csv) file and the trained model saved as a pickle (.pkl) file for future use.

3.2 System Design

The methodology concept demands the use of the agile and waterfall project methodology. The agile method comprises cyclic and collective method in which projects undergo series of cycles throughout the period of the project task. This is observed from the research methodology process flow that the dataset will be run through the k-clustering algorithm for attendee's engagement as shown in figure 3.1, also the dataset will also be applied on the algorithms using the 70:30 splitting percentage. Afterward, this research will undergo the waterfall method after each cluster has been achieved in validating the model based on the results.

3.4 Research Methods

The quantitative research methods would be used for this research and this will be achieved using the Python programming language, which is due to its simplicity, extensive library support.

3.4.1 Data Collection

The attendee's behavioural dataset generation was acquired through the use of online capturing tool that will be designed within the scope of this study. The dataset was generated through the use of a google form for capturing all the attendee's behavioural data as reviewed from literature and tailored based on the identified different dimensions of engagement for clarity and specific variables. To achieve this, the convenient sampling method was used for the survey, while ensuring the privacy of data without any harm whatsoever, the population of the study are attendees in any events either online or on-site. 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. Table 3.1 displays the dataset as it captures into six categories that are used to described the records.

Table 3.2: 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.

3.4.2 Design of a Behavioural Analysis Model

To achieve the first objective, extensive literature review was conducted on the existing body of knowledge which assisted in highlighting the behavioural data in identifying the attendee engagement as the main determinant in the segmentation of attendee engagement that guided the design of the post-event surveys for data collection and model. The designed and proposed model was designed using Numpy, Scikit-learn and pickle module of Python Programming language, this model is a way of identifying attendee engagement from the pre-processed behavioural data.

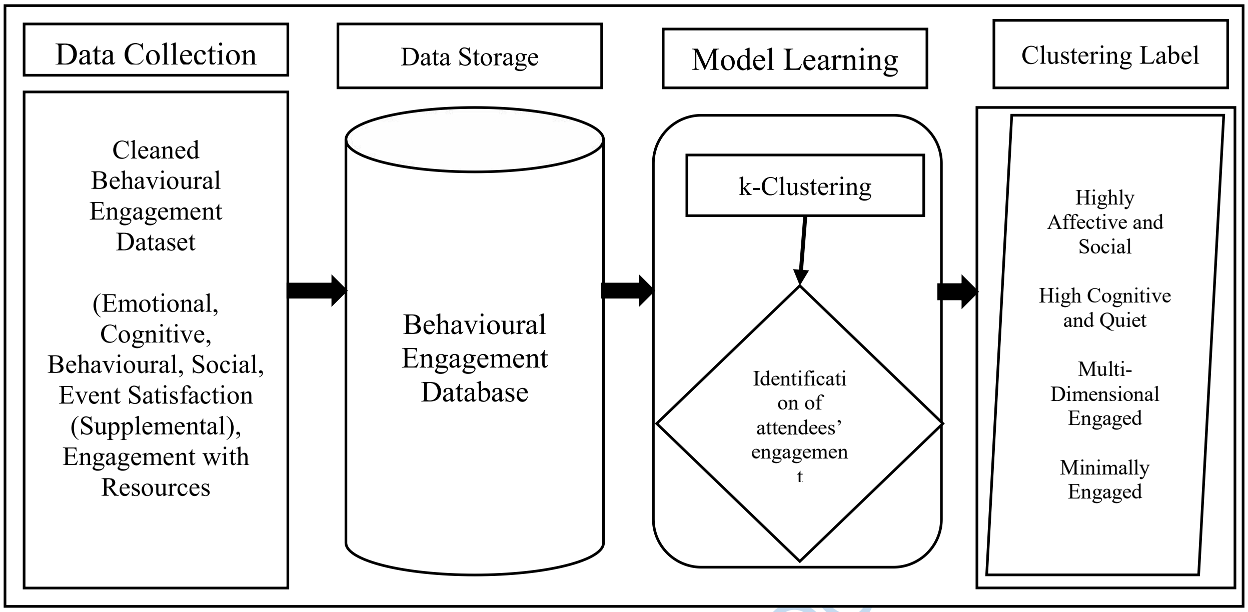


Figure 3.3: Proposed Behavioural Analysis Model for Attendee Engagement Identification

Figure 3.3 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.

3.4.3 K-Clustering for Segmentation of Attendee Engagement

To achieve this objective, the k-clustering model was implemented and the first process is the pre-processing of data, which is to check for missing values and inconsistent entries, in which the missing values were replaced by computing the mean to fill in the missing values and inconsistent entries. The categorical variables was encoded by converting the Likert scale into numerical form for analysis, and this was done using one-hot encoding by turning each category into numbers. This was followed by the scaling of the data; was done using the standardization to rescale all variables so that they have a mean of 0 and standard deviation of 1. After which the data was transformed for the final clean behavioural dataset and stored for training.

3.4.4 Model Evaluation Metrics

To achieve this objective, the model was evaluated to ensure the clusters truly reflected the engagement patterns using three selected metrics namely the silhouette score for cluster cohesion and separation, the parity score to indicate the agreement with the survey labels, and lastly using the principal component analysis plot to understand how the data and clusters for the projection of the attendee clusters.

3.4.5 Systematic Approach to Model Learning

As shown in Figure 3.4, this 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. The variables were encoded categorically specifying the appropriate numerical value for each variable according to

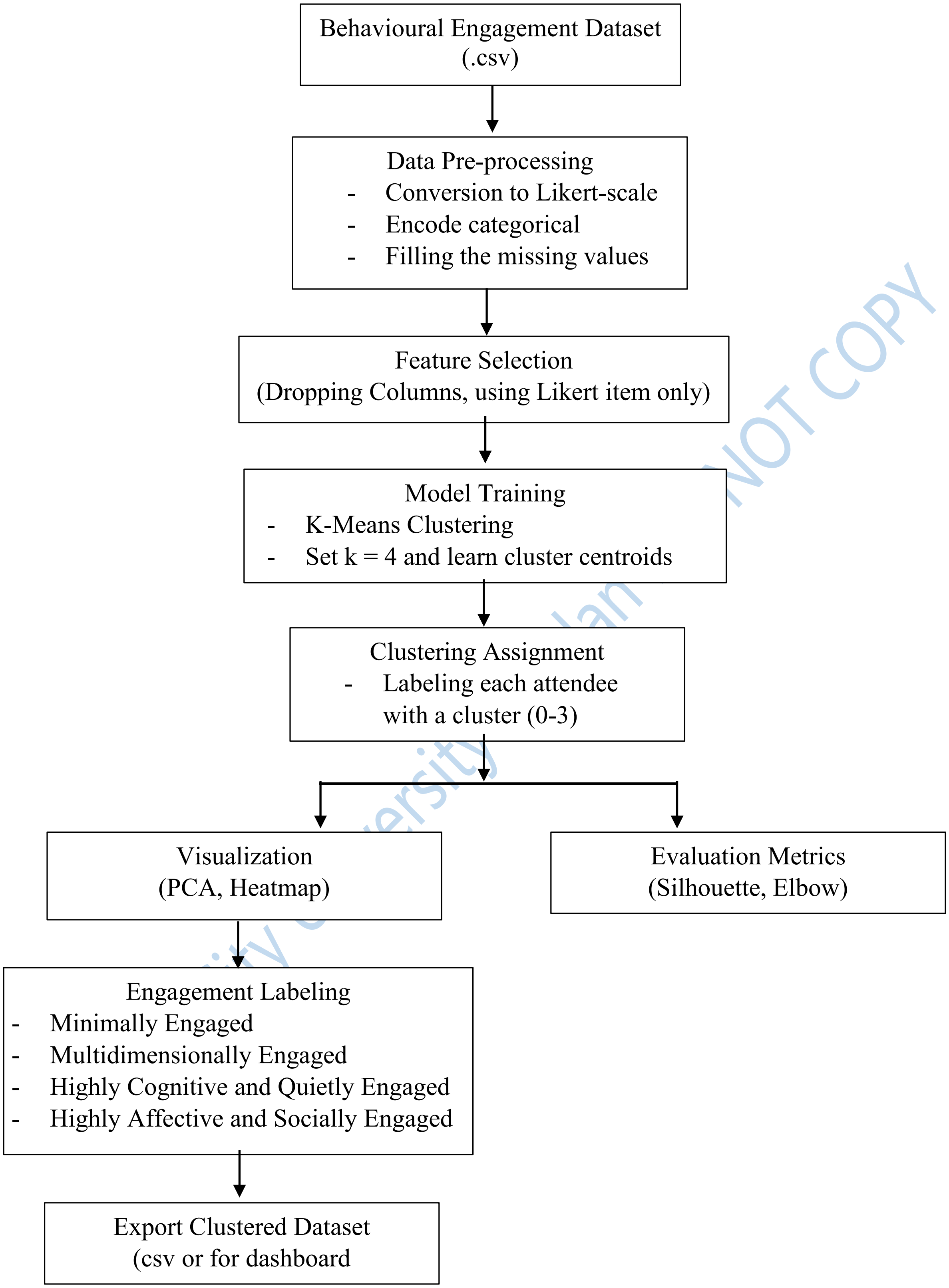


Figure 3.4: Model Learning Architecture

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 pattens 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 patten 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.

Chapter Four

Implementation and Evaluation

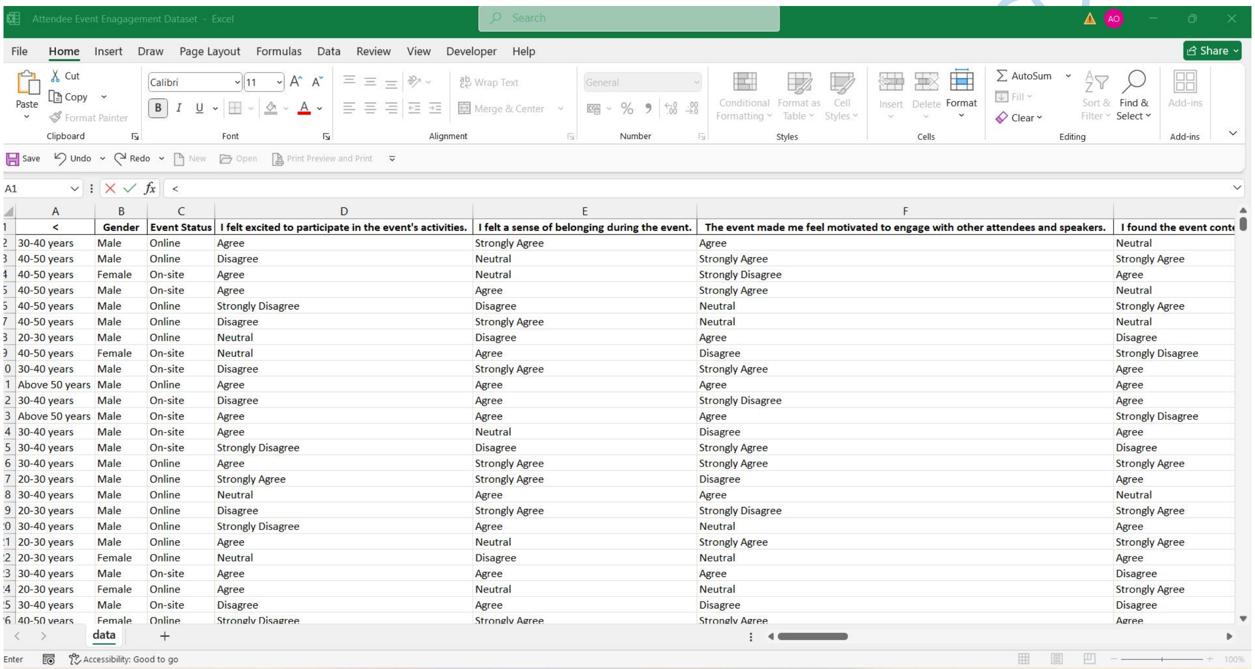
This chapter through the discussion of results shows the in-depth analysis and the proposal discussed in the previous chapter. This chapter highlights different sections according to the results from each objective as tailored to achieve the aim of this research in developing a behavioural analysis model using k-clustering technique for the identification of attendees' engagement. Section 4.1 focused on the data collection and pre-processing in the design of the behavioural analysis model from behavioural data. Section 4.2 shows the implementation of the model using k-clustering for segmentation of attendee engagement. Section 4.3 highlights the performance evaluation outputs of the model used in the segmentation of attendee engagement based on the selected metrics. Section 4.4 focus on the discussion of results in relation to previous literatures.

4.1 Behavioural Data for Attendee Engagement Identification

An in-depth breakdown of previous literatures was reviewed on the understanding of the behavioural engagement data and later categorize to determine the appropriate data for the identification of attendee engagement.

4.1.1 Behavioural Engagement Dataset

The dataset for this research 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. (See Figure 4.1).



<	Gender	Event Status	I felt excited to participate in the event's activities.	I felt a sense of belonging during the event.	The event made me feel motivated to engage with other attendees and speakers.	I found the event conte
30-40 years	Male	Online	Agree	Strongly Agree	Agree	Neutral
40-50 years	Male	Online	Disagree	Neutral	Strongly Agree	Strongly Agree
40-50 years	Female	On-site	Agree	Neutral	Strongly Disagree	Agree
40-50 years	Male	On-site	Agree	Agree	Strongly Agree	Neutral
40-50 years	Male	Online	Strongly Disagree	Disagree	Neutral	Strongly Agree
40-50 years	Male	Online	Disagree	Strongly Agree	Neutral	Neutral
20-30 years	Male	Online	Neutral	Disagree	Agree	Disagree
40-50 years	Female	On-site	Neutral	Agree	Disagree	Strongly Disagree
30-40 years	Male	On-site	Disagree	Strongly Agree	Strongly Agree	Agree
Above 50 years	Male	Online	Agree	Agree	Agree	Agree
30-40 years	Male	On-site	Disagree	Agree	Strongly Disagree	Agree
Above 50 years	Male	On-site	Agree	Agree	Agree	Strongly Disagree
30-40 years	Male	On-site	Agree	Neutral	Disagree	Agree
30-40 years	Male	On-site	Strongly Disagree	Disagree	Strongly Agree	Disagree
30-40 years	Male	Online	Agree	Strongly Agree	Strongly Agree	Strongly Agree
20-30 years	Male	Online	Strongly Agree	Strongly Agree	Disagree	Agree
30-40 years	Male	Online	Neutral	Agree	Agree	Neutral
20-30 years	Male	Online	Disagree	Strongly Agree	Strongly Disagree	Strongly Agree
30-40 years	Male	Online	Strongly Disagree	Agree	Neutral	Agree
20-30 years	Male	Online	Agree	Neutral	Strongly Agree	Strongly Agree
20-30 years	Female	Online	Neutral	Disagree	Neutral	Agree
30-40 years	Male	On-site	Agree	Agree	Agree	Disagree
20-30 years	Female	Online	Agree	Neutral	Neutral	Strongly Agree
30-40 years	Male	On-site	Disagree	Agree	Disagree	Disagree
40-50 years	Female	Online	Strongly Disagree	Strongly Agree	Strongly Agree	Agree

Figure 4.1: Attendees Behavioural Dataset (Source: Researcher Model, 2025)

4.1.2 Data Pre-processing

To have a behavioural engagement database as indicated in Figure 3.2, the raw dataset was cleaned before storing for processing, by remove duplicates. It was found that the dataset was a cleaned version with all records complete, after which the dataset was transformed into a numerical value, firstly, is by transforming the ordinal data into numerical value by using a mapping function in the python programming dictionary according to the rank assigned to the data, followed by the encoding of the nominal data using the label encoding instead of the one-hot encoding, as this gave a full control and transparency of the data. The one-hot encoding was avoided so as to reduce dimensionality as the ordinal preserved the responses ranking (See Figure 4.2 and Appendix I).

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
Age Range	Gender	Event Stat	I felt excit	I felt a sen	The event	I found the	I stayed fo	The event	I actively p	I attended	I engaged	I made me	I actively e	I found it e	Overall, I a	The event	I followed	I accessed th
2	2	1	4	5	4	3	3	2	2	4	4	2	1	3	5	4	4	3
3	2	1	2	3	5	5	3	2	3	4	5	4	4	4	1	5	4	3
3	1	2	4	3	1	4	4	3	5	5	4	1	4	4	2	4	4	1
3	2	2	4	4	5	3	2	3	5	4	2	2	3	4	5	3	2	4
3	2	1	1	2	3	5	2	4	3	4	1	2	5	1	3	4	5	3
3	2	1	2	5	3	3	2	4	2	2	3	4	4	2	5	5	1	4
1	2	1	3	2	4	2	4	4	4	2	4	3	5	1	4	2	4	4
3	1	2	3	4	2	1	3	4	5	3	1	5	5	3	3	4	3	2
2	2	2	2	5	5	4	3	3	4	2	2	3	4	4	2	4	2	1
4	2	1	4	4	4	4	4	4	4	4	4	1	3	1	2	1	3	4
2	2	2	2	4	1	4	4	4	4	3	5	4	3	3	2	4	4	3
4	2	2	4	4	4	1	5	4	5	1	4	4	5	5	5	4	3	4
2	2	2	4	3	2	4	4	4	5	1	5	2	1	2	2	5	5	1
2	2	2	1	2	5	2	2	5	1	2	4	4	4	4	4	4	4	4
2	2	1	4	5	5	5	1	5	4	3	4	5	2	2	4	4	4	3
1	2	1	5	5	2	4	5	4	5	1	5	4	1	1	2	4	5	4
2	2	1	3	4	4	3	5	1	1	4	4	4	4	4	5	3	1	4
1	2	1	2	5	1	5	3	1	4	3	4	1	4	4	3	4	4	4
2	2	1	1	4	3	4	5	4	5	5	3	3	2	2	3	4	4	3
1	2	1	4	3	5	5	1	3	4	5	3	4	5	2	1	3	5	4
1	1	1	3	2	3	4	2	2	1	5	5	2	4	5	4	4	4	1
2	2	2	4	4	4	2	3	3	2	4	4	2	4	4	3	4	3	3
1	1	1	4	3	3	5	1	3	4	5	3	3	3	2	4	3	4	2
2	2	2	2	4	2	2	2	2	1	4	4	5	4	1	5	2	4	4
3	1	1	1	5	5	4	5	4	4	4	3	4	5	2	1	1	4	2

Figure 4.2: Encoded Behavioural Dataset (Source: Researcher Model, 2025)

This encoded dataset was used in the implementation of the model implementation of the model using k-clustering for segmentation of attendee engagement as indicated in Figure 3.2.

4.2 K-Clustering Model Implementation

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 4.1.

Cluster	Cluster Type	Cluster Count	Interpretation
0	Minimally Engaged	3332	Involved in the event but not emotionally or mentally engaged
1	Multidimensionally 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 4.1 shows that 3332 attendees' behavioural patterns are minimally engaged, 2270 attendees were multidimensionally engaged, 2194 were highly cognitive and quietly engaged, and 2177 attendees were highly affective and socially engaged. For better understanding of the distribution and separability of the clusters, the principal component 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 indicate 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.

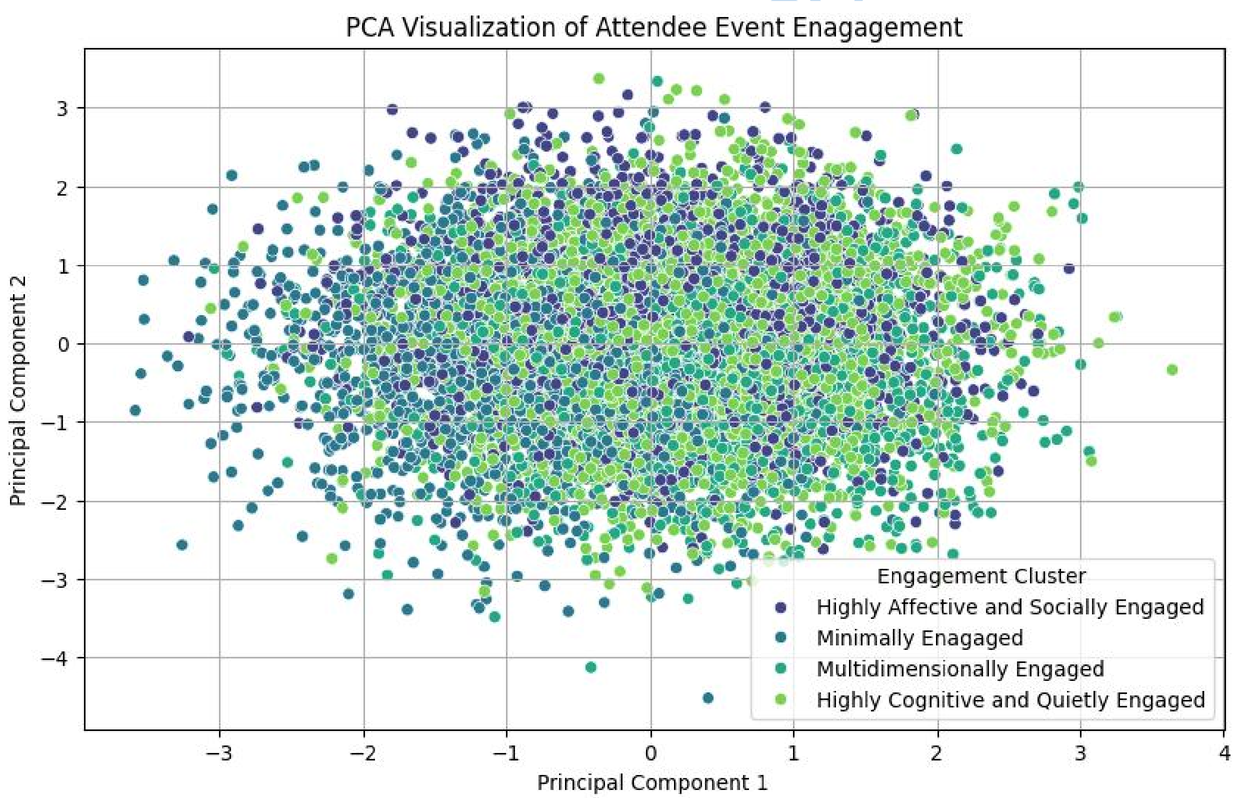


Figure 4.3: PCA Visualization of Attendee Event Engagement

The attendee's engagement cluster was visualized in heatmap as shown in Figure 4.4, 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 and highly affective and low for minimally engaged. For the post-event actions, the multidimensional 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.

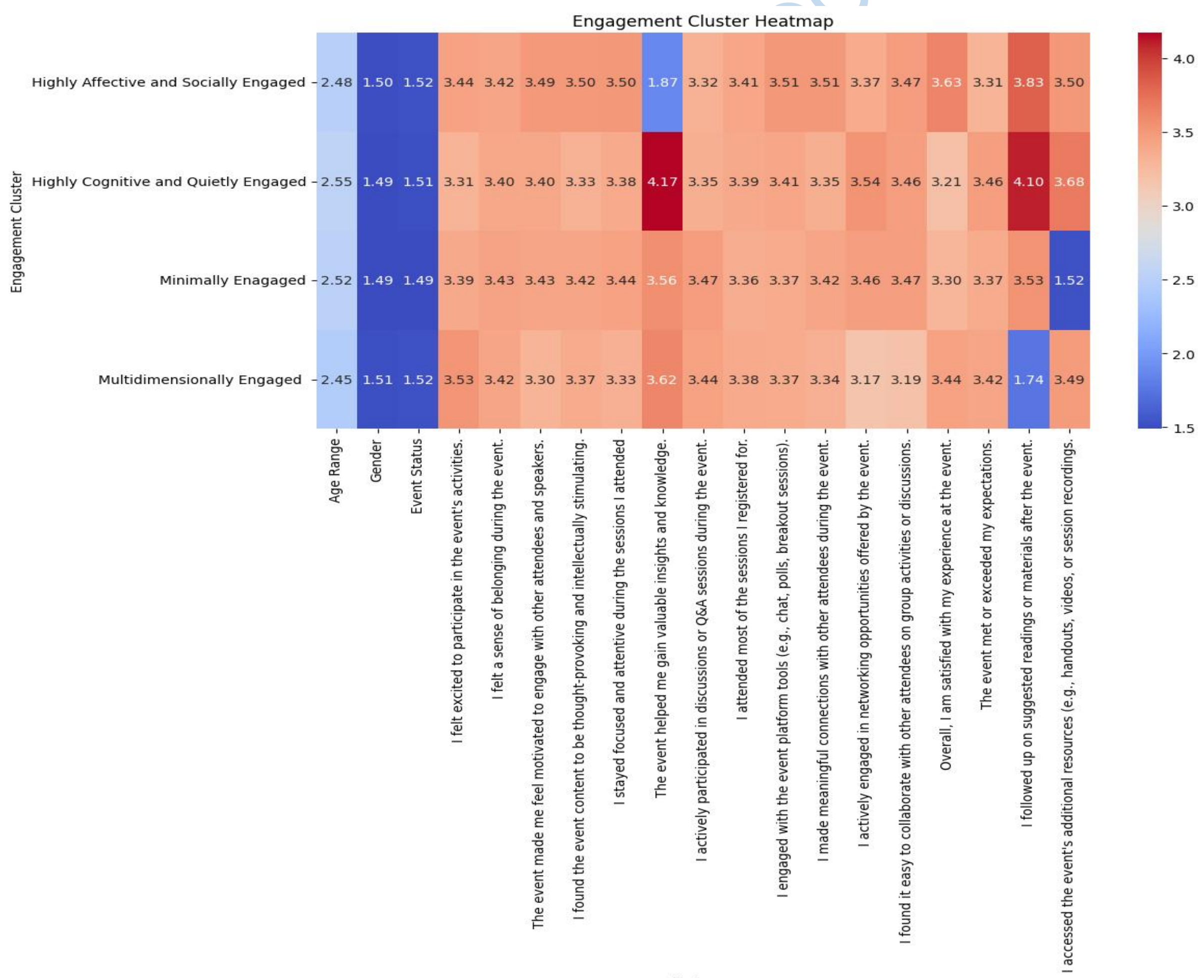


Table 4.4: Engagement Cluster Heatmap

4.3 Performance Evaluation

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 4.5, 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.

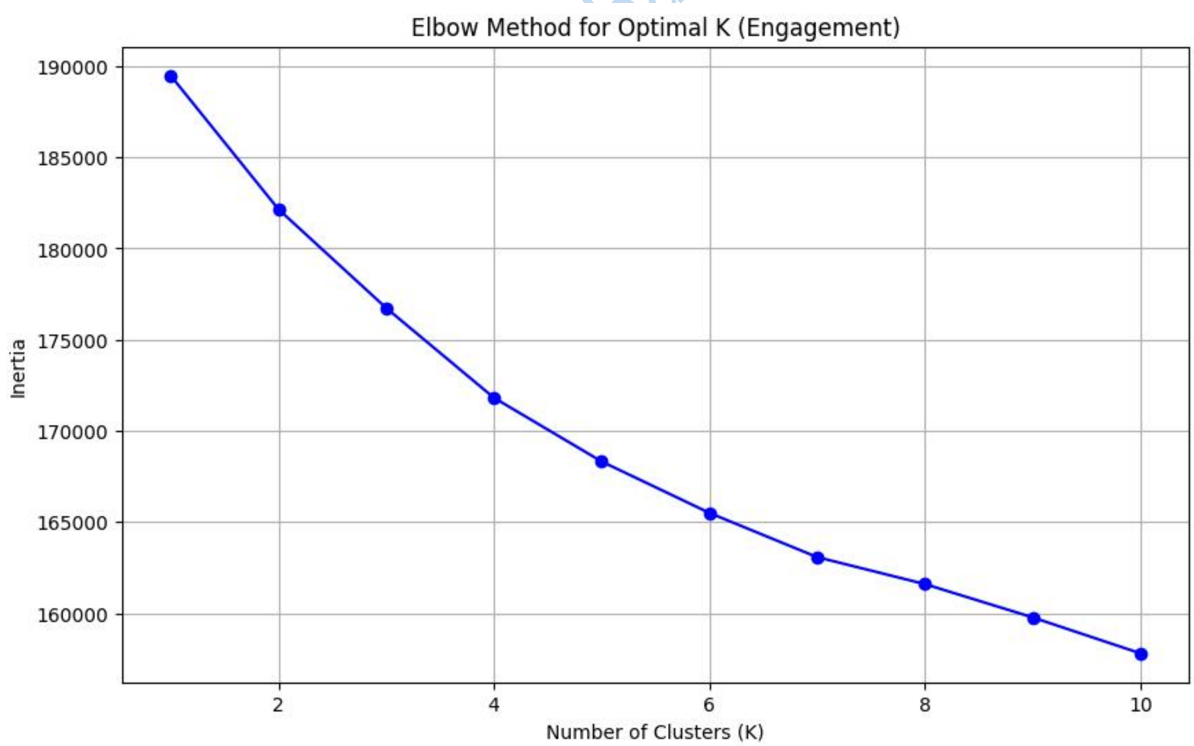


Figure 4.5: Elbow Method for Optimal K (Engagement)

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 rand and good enough for the early-stage attendee segmentation and need further tuning for decision making.

4.4 Discussion of Results

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 multidimensionally 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[1]. 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[2].

The result shows how data-driven segmentation produced useful insights that enhanced engagement and content delivery[3].

One of the main goals of behavioural analysis models which this result has shown is event personalization. The results showed that individualized encounters have a greater impact and are more memorable on attendees which corroborates with one of the objectives of this research[4].

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.

Endnotes

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Chapter Five

Conclusion

5.1 Summary of Results

This study contributes to a growing but still small amount of research on event attendees' behaviors. Growing research may support the creation of a more extensive corpus for comprehending behavioral analysis to enhance attendees' experiences at events, since machine learning techniques are increasingly being used to analyze the behaviors of event attendees.

The research's main objective is to provide answers to the following two questions:

(i) What are the primary behavioral engagement components that improve event participants' pleasure and level of participation?

(ii) In order to improve event experiences, how can K-clustering machine learning techniques be used to analyze data regarding attendees' behavior?

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, multidimensionally 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 multidimensionally cluster was strong and very weak for minimally engaged. The cognitive engagement was very high for cognitive, quiet and multidimensionally 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 multidimensionally 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. In sum, K-clustering technique serve as an important method for understanding both low- and high-involvement of attendees in events

5.2 Recommendations

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 multidimensionally 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.

The result of this research, shows that an intervention can used in re-engagement drive for those attendees who were minimally engaged. Also, in organizing a personalized post-event material, provision of networking tools during the events, provision of thoughtful materials, and lastly improving the social opportunities in future events. Programs that involves attendees meeting and networking should be made more available as it was discovered during the research that socially engaged segments add high engagement and attendees had high satisfaction.

5.3 Contribution to Knowledge

Enhancing events has gained a lot of attention as a result of the widespread use of technology. Among the difficulties in improving events are two primary ones: providing attendees with a personalized experience and maintaining their motivation and engagement. This study suggested grouping event attendees into various involvement level groups using the k-means algorithm. This project is a component of a bigger one that intends to investigate how predictive data mining models may be applied to early detection of weak event segments in an effort to enhance their engagement and satisfaction performance. "What are the main behavioral engagement elements that enhance attendees' engagement and satisfaction in events?" is the first of two research topics specifically examined in this paper. The second question is "How can data about attendees' behavior be analyzed using k-clustering machine learning approaches to enhance event experiences?". In order to achieve this, four cluster labels were found and computed using the provided event log dataset. The experimental result shows that event attendees participate more in highly affective and multidimensional segments.

The methodology used is useful since it can serve as a foundation for detecting disengaged attendees based on their online behavioral clues, even though this study doesn't offer a determining factor for recognizing the quality of involvement in events. Event planners will have the opportunity to enhance their programs and address any potential problems that might be impeding attendees' motivation and engagement if they use these indicators as a foundation for identifying the disengaged attendees.

This also holds true while utilizing other online resources, including surveys or questionnaires. To ascertain which elements were more or less interesting to the participants, a qualitative data analysis can be conducted. In order to increase online attendees' engagement, the findings of this analysis might be utilized to alter the content or offer additional materials according to their preferences.

5.4 Suggestions for Further Studies

A number of concepts can be investigated in future research. To find out if the model is generalizable, the first step is to test it on various event types. Additionally, the average time per session and the overall amount of time spent on a segment should be gathered and taken into account in order to more accurately assess the attendees' level of engagement.

To capture the timestamps of guests' logins upon event registration, this ought to be incorporated into the registration interface. Additionally, rather than waiting until the last minute, this would enable event planners to spot disengaged attendees early on. The effect of the taken engagement measures on the attendees is an additional concept to investigate. To further clarify the importance of each statistic on the attendees' total engagement, the relationship between the metrics and the degree of involvement indicated by the attendees can be examined. The limitation is the attendees engagement cluster are distinguishable but still need an advanced transformation and could be improve with alternative clustering algorithms.

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Appendix

Appendix – Behavioural Dataset Mapping

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
2	2	1	4	5	4	3	3	2	2
3	2	1	2	3	5	5	3	2	3
3	1	2	4	3	1	4	4	3	5
3	2	2	4	4	5	3	2	3	5
3	2	1	1	2	3	5	2	4	3
3	2	1	2	5	3	3	2	4	2
1	2	1	3	2	4	2	4	4	4
3	1	2	3	4	2	1	3	4	5
2	2	2	2	5	5	4	3	3	4
4	2	1	4	4	4	4	4	4	4
2	2	2	2	4	1	4	4	4	4
4	2	2	4	4	4	1	5	4	5
2	2	2	4	3	2	4	4	4	5
2	2	2	1	2	5	2	2	5	1
2	2	1	4	5	5	5	1	5	4
1	2	1	5	5	2	4	5	4	5
2	2	1	3	4	4	3	5	1	1
1	2	1	2	5	1	5	3	1	4
2	2	1	1	4	3	4	5	4	5
1	2	1	4	3	5	5	1	3	4
1	1	1	3	2	3	4	2	2	1
2	2	2	4	4	4	2	3	3	2
1	1	1	4	3	3	5	1	3	4
2	2	2	2	4	2	2	2	2	1
3	1	1	1	5	5	4	5	4	4
3	1	1	2	4	2	3	4	2	3
4	2	2	1	2	4	3	4	3	2
2	2	2	5	2	1	2	3	4	3
1	2	2	4	3	4	4	4	5	4
2	2	1	4	4	5	5	5	2	5
3	2	1	4	5	4	5	2	4	4
1	2	1	3	4	4	4	4	3	4
4	1	2	3	4	4	4	4	3	2
2	1	1	4	5	3	4	4	3	5
2	1	2	4	4	3	2	2	5	2
2	2	2	4	4	4	4	5	3	5
1	1	2	5	3	3	3	4	2	1
4	1	2	2	1	3	1	4	1	5
1	2	1	3	4	5	5	4	3	4
3	1	2	5	3	4	4	3	3	2
1	1	1	4	3	2	1	2	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	2	2	2	4	3	4	2	3	4
4	2	2	3	4	1	4	1	3	4
4	2	2	4	4	5	5	4	3	4
3	1	1	4	4	5	2	3	4	4
4	1	2	4	4	2	2	3	4	5
3	1	2	4	4	4	5	3	2	3
2	1	1	3	3	4	4	1	5	4
4	1	2	4	5	3	4	4	3	5
3	1	2	4	4	2	4	4	5	4
1	2	1	2	5	3	3	1	4	1
3	2	2	1	1	5	3	2	3	3
1	2	1	4	3	4	3	5	5	1
1	1	2	1	3	1	4	3	4	2
4	2	2	1	3	1	3	4	4	1
4	2	2	1	1	5	2	2	2	4
1	2	2	4	2	3	5	3	4	5
4	2	1	2	5	4	2	4	4	5
2	1	1	4	4	4	1	3	5	5
1	1	1	4	5	4	3	5	4	2
1	2	1	4	2	4	3	4	3	3
4	1	1	2	5	2	4	3	5	3
2	1	2	3	1	5	5	1	1	3
3	1	2	4	1	2	1	1	4	5
3	1	1	4	2	1	2	4	5	4
4	2	1	4	4	3	3	3	4	3
2	2	1	3	4	3	4	3	3	4
2	2	1	3	4	2	3	3	5	5
3	1	1	3	4	3	4	3	3	5
1	1	1	3	4	3	2	4	4	5
1	2	2	5	1	3	4	1	4	5
3	2	1	3	5	4	4	5	4	3
4	2	2	1	3	1	4	3	2	4
4	1	1	2	4	5	5	4	4	5
3	2	1	2	3	4	5	2	4	4
4	1	1	2	2	4	5	1	5	4
2	2	1	5	1	4	5	5	1	2
3	2	1	4	1	5	4	5	1	2
1	1	2	4	3	1	2	3	5	1
2	2	1	1	4	3	2	5	1	2
3	1	2	3	5	3	2	5	4	2
3	1	2	3	2	4	3	4	5	4
3	2	2	2	2	3	4	1	1	4
4	2	1	1	2	3	4	3	4	4
4	1	2	3	1	1	4	4	3	2
2	1	1	1	2	2	2	5	5	2

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
2	1	2	2	2	4	4	4	4	4
4	1	2	5	1	4	1	4	1	3
4	2	2	2	5	4	1	2	4	4
4	1	1	2	2	4	3	4	4	4
3	2	2	4	4	5	2	2	3	4
1	1	1	4	4	2	4	4	4	1
1	2	2	4	5	4	5	3	3	4
3	1	2	2	3	5	3	3	4	4
1	1	2	4	4	3	1	4	5	2
3	1	1	5	3	2	4	5	1	5
2	1	2	4	3	3	1	3	4	4
2	1	1	3	2	4	4	5	2	5
3	1	1	1	5	4	5	5	3	5
4	2	1	3	2	2	4	4	3	2
4	1	1	4	3	5	1	3	3	5
4	1	2	4	3	5	1	5	4	4
2	2	1	3	3	5	2	1	5	5
2	2	2	3	4	4	5	4	4	5
2	1	1	2	4	3	4	4	4	5
2	1	2	1	2	3	4	4	3	5
4	1	2	3	2	2	4	5	5	4
3	2	1	4	4	2	1	4	5	3
3	2	1	3	4	5	5	5	4	3
4	2	2	4	3	2	2	4	4	3
1	2	1	2	2	5	3	4	4	5
1	1	2	4	5	5	4	4	5	2
1	1	1	3	3	4	5	1	4	2
3	2	1	3	3	4	4	5	2	2
2	2	2	2	3	3	1	5	1	3
3	1	2	3	4	4	3	3	4	5
3	1	2	4	4	3	4	5	4	1
4	1	1	2	1	3	3	2	1	4
2	1	2	5	3	4	2	3	2	3
2	2	1	3	4	4	5	3	4	4
1	2	1	5	4	5	4	4	1	4
4	1	1	4	5	4	2	2	4	4
4	2	2	5	2	4	5	4	3	2
1	1	1	3	4	4	1	4	5	5
3	1	2	3	2	2	3	3	4	5
2	1	1	4	5	1	5	5	4	3
3	2	1	4	5	4	3	4	4	3
3	1	2	5	4	1	5	5	4	4
3	2	2	4	4	3	5	3	3	2
1	1	2	3	4	3	3	4	4	2
1	2	2	5	2	4	4	1	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	1	2	2	4	5	3	1	3	3
1	2	1	3	4	5	4	4	5	3
1	1	2	2	3	4	4	4	5	2
4	1	2	4	4	4	4	4	4	5
1	2	1	1	2	4	3	1	5	4
3	2	1	5	2	4	4	4	3	3
3	1	2	1	1	2	5	3	5	5
1	1	2	2	2	3	5	4	3	2
3	2	1	4	4	3	4	5	4	2
1	2	1	2	4	3	1	1	1	4
3	2	1	2	3	2	2	3	4	4
2	1	1	1	5	1	2	4	5	5
3	2	1	4	4	1	4	4	3	2
4	2	1	4	5	3	3	1	5	5
4	1	2	4	3	2	1	3	2	4
1	1	2	1	3	2	2	3	5	3
1	1	2	3	1	4	3	3	1	3
4	2	1	4	2	4	5	4	2	1
4	1	1	5	4	3	4	4	1	5
3	2	1	4	1	3	5	2	5	5
1	1	2	4	2	5	1	2	4	1
3	2	1	3	4	5	4	4	2	4
2	2	2	2	2	1	2	4	1	5
2	2	2	1	2	5	3	1	4	4
3	1	1	1	5	2	2	3	2	1
4	1	1	5	4	4	3	4	4	4
3	1	1	4	3	2	1	3	1	2
4	2	1	4	2	4	5	2	4	2
4	2	1	3	5	2	2	4	4	4
3	1	2	5	1	4	5	1	5	3
1	2	1	4	4	2	5	4	2	3
1	1	2	4	3	2	2	1	2	4
4	1	1	2	3	1	5	4	3	5
1	2	2	4	3	3	4	5	4	5
4	1	1	4	5	4	4	5	2	1
3	2	1	2	5	1	4	2	2	5
2	2	1	4	2	4	2	5	2	5
2	2	1	2	5	3	4	5	4	5
3	1	1	2	5	4	4	4	2	3
1	2	2	1	1	1	5	1	4	3
2	1	1	2	4	3	4	1	1	4
3	1	1	3	5	4	1	5	5	5
3	2	2	3	4	5	3	3	3	1
4	2	1	5	3	3	5	5	3	5
4	2	1	3	5	3	1	5	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	2	1	4	5	4	5	4	3	1
3	1	1	5	4	3	2	4	3	4
3	1	1	2	5	1	4	4	4	5
3	2	1	2	3	4	4	1	5	3
4	2	1	1	5	3	4	3	2	3
2	2	2	4	2	4	5	5	4	3
2	1	1	2	5	1	2	3	5	4
1	2	2	1	4	4	5	2	3	5
3	2	1	4	3	4	3	2	4	5
1	2	1	4	2	4	5	2	5	2
1	2	2	4	4	2	5	4	1	4
1	1	1	4	4	5	2	5	3	1
2	1	1	4	5	1	5	3	5	1
4	1	1	5	2	4	5	2	4	4
4	1	1	2	4	5	1	4	3	2
4	2	1	4	3	4	4	4	3	2
3	2	1	4	2	5	1	4	5	4
2	2	2	1	1	4	5	4	3	3
3	2	2	3	1	1	1	4	4	1
3	2	2	1	5	4	5	5	4	2
2	2	2	4	3	3	4	4	4	2
2	2	2	5	5	3	2	2	5	4
3	2	1	2	5	4	4	5	5	4
3	2	2	2	2	4	3	1	4	4
4	1	2	4	4	2	2	3	3	5
1	1	1	4	4	4	3	4	4	4
2	2	2	3	2	5	3	4	3	4
1	2	1	3	4	4	4	5	3	5
3	1	2	2	5	1	1	2	1	4
3	2	1	2	5	4	1	3	1	3
3	2	1	4	4	3	2	3	5	2
1	2	1	2	2	1	1	5	3	1
2	2	1	3	5	5	3	3	5	3
1	2	2	3	4	5	4	1	2	3
3	2	1	4	3	4	1	4	4	3
1	1	2	4	4	1	4	3	4	3
1	1	2	3	1	3	3	4	5	5
4	2	2	2	2	4	4	5	2	3
1	1	1	4	4	4	3	5	5	4
1	1	1	3	2	3	2	4	5	5
2	1	1	4	5	2	2	4	4	5
3	1	2	4	5	4	2	4	4	2
2	1	1	5	1	4	2	2	4	4
3	2	1	4	5	3	5	4	4	2
3	2	1	1	4	2	3	3	2	5

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	1	2	5	3	3	5	1	3	2
2	1	1	1	3	1	5	4	5	4
4	2	2	4	4	4	4	1	4	3
1	1	2	4	5	5	5	3	1	1
4	2	1	3	5	1	4	5	4	4
1	2	1	5	2	4	4	4	4	4
3	1	2	4	5	4	1	2	1	5
1	2	2	4	4	1	4	2	3	3
1	1	1	2	3	2	2	4	3	5
3	2	2	4	4	1	3	4	2	5
4	2	2	2	3	5	2	2	3	3
2	1	1	4	4	5	3	4	4	5
3	1	1	2	5	3	1	5	4	3
1	1	2	3	3	1	4	3	3	3
3	1	1	5	4	4	1	4	3	2
3	2	2	5	2	3	3	2	4	4
2	1	1	5	5	3	5	4	1	4
1	2	2	4	2	5	3	5	3	2
4	1	1	4	3	3	3	5	2	4
3	1	2	4	4	3	5	1	3	4
3	1	2	4	4	5	3	5	3	4
3	2	2	2	5	5	3	5	3	4
4	1	1	2	1	5	5	1	5	3
2	1	2	5	3	2	4	4	4	5
2	2	2	4	2	3	1	2	2	1
2	2	2	3	4	5	5	5	4	4
2	2	1	4	3	2	2	4	4	4
2	2	2	2	4	4	4	3	3	4
2	2	2	4	5	4	4	1	3	4
2	2	1	4	4	4	2	5	4	3
4	1	2	4	1	4	5	1	4	1
4	1	1	4	4	2	5	4	4	3
4	2	2	3	4	5	4	5	3	1
2	1	1	4	2	3	4	4	2	2
3	1	2	1	5	4	1	5	5	1
4	1	1	3	3	1	2	1	5	3
4	2	2	4	3	5	3	3	4	1
3	2	2	3	2	4	4	1	3	4
4	1	1	5	4	3	5	3	2	3
1	1	1	3	2	4	3	5	2	5
4	1	1	2	4	1	4	3	4	2
4	2	1	3	2	4	3	1	5	4
1	2	2	3	4	3	4	5	5	4
4	2	1	2	4	4	3	4	3	4
3	1	2	4	4	2	1	4	4	5

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	1	2	5	2	2	3	4	2	4
2	2	2	4	4	3	3	4	3	4
1	1	2	4	1	5	1	5	1	1
3	2	1	5	4	1	4	3	4	1
1	2	2	4	3	4	4	5	4	1
1	1	2	5	3	5	3	3	5	2
1	2	2	4	2	4	4	5	1	1
3	1	1	3	4	4	3	4	1	4
2	1	2	3	5	4	2	4	4	4
1	1	1	2	3	2	3	5	5	2
1	2	2	3	2	4	5	4	4	4
1	1	1	5	4	5	3	5	3	4
4	1	2	2	2	4	3	5	2	5
3	2	1	3	3	2	1	2	5	4
2	2	1	4	4	4	4	1	5	5
4	2	1	4	3	5	4	3	1	3
4	2	1	3	3	3	5	5	1	3
4	2	2	4	4	1	4	4	5	5
1	1	1	4	4	4	2	2	5	5
1	2	2	5	3	4	3	4	4	2
3	2	1	3	3	5	5	4	1	4
4	2	1	4	5	1	4	5	5	4
4	2	1	4	1	4	3	3	2	4
1	2	1	3	5	5	4	3	3	5
3	1	2	1	2	2	4	2	4	5
4	1	2	3	5	3	1	4	5	4
2	1	2	1	5	2	4	4	5	4
1	1	2	4	3	4	1	3	2	4
2	2	1	4	2	4	4	4	3	3
3	1	2	4	1	4	4	4	1	4
3	1	2	3	2	3	3	2	3	2
4	1	2	5	3	2	2	5	4	4
2	2	2	2	4	3	4	4	5	5
2	1	1	3	2	3	4	3	3	4
1	1	1	3	4	3	4	1	2	1
1	1	2	4	5	5	3	4	4	2
3	2	2	5	2	4	3	2	5	5
2	1	1	1	5	2	1	4	3	4
1	1	2	3	5	5	2	2	4	4
1	1	2	3	4	4	5	4	2	3
4	1	2	2	5	3	2	1	2	4
3	2	2	4	2	4	3	3	3	1
4	2	2	4	5	2	4	1	2	5
2	2	1	5	5	4	4	2	4	4
1	2	1	3	2	3	3	5	5	3

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
2	2	2	2	5	2	4	4	5	4
1	2	1	5	4	3	1	3	1	3
2	2	1	5	3	3	5	5	2	4
3	1	1	2	5	3	3	1	4	1
2	2	1	5	3	5	4	4	1	5
3	1	2	5	2	4	4	3	4	5
4	1	1	4	4	5	4	4	3	5
1	2	1	3	2	4	4	4	5	3
1	1	2	1	3	3	4	5	4	3
4	2	1	4	4	4	5	3	3	1
1	2	1	4	4	3	4	3	4	4
4	1	2	5	5	5	5	5	3	5
2	1	2	4	4	4	5	2	4	1
3	1	1	5	2	2	3	1	5	1
1	2	2	4	4	2	3	1	4	5
3	1	1	5	1	4	5	4	5	4
1	1	2	3	5	4	4	3	1	4
4	2	2	5	4	5	4	4	5	5
3	1	1	4	4	4	3	5	1	1
1	2	2	4	1	4	5	3	4	4
2	1	1	4	3	5	5	4	5	2
2	1	2	4	4	5	4	2	3	4
2	1	2	4	2	1	4	5	5	4
1	2	2	3	4	4	4	3	3	4
2	1	1	4	3	5	2	4	3	4
1	2	1	5	5	3	5	2	5	4
2	2	1	4	5	4	4	4	4	3
3	1	1	4	5	4	4	2	3	2
1	1	2	2	5	3	5	4	2	4
2	2	1	5	2	3	4	4	3	3
2	2	1	3	4	2	4	5	5	5
2	2	1	4	3	5	2	3	2	4
3	1	1	2	4	2	4	3	4	2
1	1	1	4	5	4	2	4	4	4
1	2	1	4	4	4	3	4	2	4
4	2	2	4	1	4	5	4	2	3
3	1	1	2	5	2	5	2	4	5
2	1	1	5	3	4	4	4	4	4
4	1	1	4	3	3	2	4	1	3
4	1	2	3	2	4	4	4	4	5
3	1	2	4	3	4	4	4	5	3
4	2	1	5	4	3	3	5	4	2
4	2	1	1	1	5	4	4	4	2
4	1	2	5	4	4	1	4	5	4
2	2	1	1	4	4	4	4	5	3

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	1	2	3	5	4	5	2	5	4
4	1	1	4	5	5	3	4	5	5
4	2	1	3	4	5	4	3	5	5
1	2	2	3	4	5	5	3	2	3
3	1	2	5	2	3	3	4	1	4
3	2	2	2	5	4	5	5	4	3
4	1	2	4	5	4	2	1	5	5
4	2	1	4	4	5	4	2	5	2
3	1	1	3	3	4	4	2	2	2
4	2	2	4	3	5	1	2	3	3
1	1	1	5	4	1	2	3	4	4
2	1	2	3	3	5	2	2	4	3
2	1	2	2	4	4	4	3	4	5
4	2	1	2	4	1	4	4	3	3
1	1	1	1	1	2	4	5	4	2
2	2	2	3	2	3	5	4	1	3
1	2	2	4	4	4	1	3	4	2
3	2	1	3	5	4	4	1	4	5
4	1	2	4	3	4	4	3	1	4
2	2	2	2	5	2	4	4	2	4
2	1	1	4	3	3	4	4	3	2
1	2	2	5	5	2	2	3	4	3
1	2	2	3	2	3	5	5	4	4
4	2	2	5	1	3	1	3	3	1
3	1	1	5	5	3	3	5	2	4
2	1	1	2	4	3	3	1	2	5
3	2	1	4	4	4	3	2	3	5
2	1	2	5	1	4	1	1	2	3
2	1	1	2	2	5	5	4	5	4
3	2	2	4	2	2	1	4	5	4
2	1	1	4	3	4	3	4	3	3
1	1	2	3	4	4	5	5	3	1
1	1	2	4	3	5	4	5	5	2
2	1	2	4	4	5	5	1	1	3
2	1	2	3	2	4	2	3	4	4
1	2	1	3	5	4	2	4	4	4
3	2	2	4	1	4	1	3	3	5
4	1	2	2	4	4	4	4	3	2
2	2	2	3	4	1	2	2	1	5
4	1	2	5	4	2	1	3	5	3
4	2	1	5	2	2	4	2	5	5
1	1	2	4	2	5	2	5	4	5
3	1	1	5	3	1	5	4	5	1
2	1	1	4	4	4	1	4	2	2
1	2	1	4	4	4	4	3	4	1

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
2	1	2	4	5	1	5	3	1	4
4	1	1	4	3	5	4	4	3	2
3	1	2	5	2	4	3	4	4	4
4	1	1	4	1	4	4	1	2	2
4	1	1	1	4	2	5	5	1	4
1	2	1	4	2	4	4	2	4	5
4	2	1	4	3	4	1	5	1	4
3	2	1	5	5	2	4	4	2	4
4	1	1	2	2	5	5	5	5	2
3	1	2	5	5	5	4	4	2	4
3	2	2	5	1	5	5	4	4	4
2	1	2	3	3	1	2	2	2	3
3	2	2	3	2	4	5	4	5	4
2	2	2	3	3	4	4	5	2	4
4	2	2	1	3	5	3	5	5	1
3	2	1	5	3	4	5	5	4	3
1	2	1	2	4	2	4	1	4	4
2	1	1	3	3	5	5	5	4	2
2	2	2	4	5	1	5	1	5	1
3	2	1	4	4	2	4	3	4	4
3	2	1	1	5	4	3	4	2	4
4	1	1	1	5	4	2	3	5	5
1	2	2	3	3	2	4	2	5	1
4	2	1	3	5	5	1	1	4	4
2	2	1	2	2	3	4	3	4	4
2	1	2	4	3	4	3	3	4	2
4	2	1	3	3	4	2	3	5	1
3	1	1	2	4	2	5	4	4	5
3	1	2	4	4	4	5	5	1	3
4	1	2	4	4	5	5	2	4	5
2	1	2	4	4	2	5	4	4	3
2	1	2	5	3	1	4	2	4	3
2	2	2	1	3	1	2	4	5	4
2	1	2	2	3	4	3	5	4	2
2	1	1	5	4	3	5	3	3	4
2	1	2	4	2	5	3	1	5	4
4	1	1	4	1	4	3	4	4	3
2	2	2	2	5	3	4	5	4	4
2	2	1	4	5	3	4	4	4	2
4	1	1	3	5	2	2	5	3	2
4	2	2	2	4	4	1	4	4	3
2	1	2	3	2	4	4	3	4	2
3	2	1	2	3	5	4	5	4	4
1	2	1	5	3	4	3	3	4	1
2	2	1	1	5	1	3	4	4	3

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	2	1	4	4	2	4	3	4	1
4	2	1	1	5	4	3	2	5	4
2	1	2	4	2	4	4	2	5	5
4	2	1	4	4	4	4	4	4	3
1	2	2	2	4	5	4	4	5	1
2	1	1	5	5	4	5	2	5	4
1	2	1	4	4	4	4	3	1	3
2	2	2	3	3	4	4	4	4	1
2	1	2	5	3	3	4	3	4	3
2	2	1	4	3	2	5	2	3	5
4	1	1	3	1	2	2	5	2	4
4	2	1	3	5	4	1	5	4	3
3	1	1	5	4	4	4	4	3	4
2	1	2	3	3	1	4	3	3	4
3	2	1	2	4	4	5	5	5	2
3	2	2	4	3	5	3	4	1	3
1	2	2	2	4	4	2	4	1	1
4	1	1	1	5	5	4	4	3	1
2	2	1	4	5	1	4	3	1	4
2	2	2	3	2	5	4	3	4	2
3	1	2	5	3	5	4	5	4	1
4	2	1	3	2	3	4	5	5	2
4	1	2	3	2	3	4	2	5	5
2	2	2	2	1	3	4	4	5	4
2	1	2	1	5	4	2	5	5	5
2	2	2	4	1	2	5	4	3	3
3	1	1	2	2	4	4	3	5	4
1	1	2	4	2	5	1	2	5	4
1	1	2	4	2	4	5	2	2	4
4	1	2	4	4	4	3	4	1	4
1	2	2	4	4	2	1	5	4	4
4	1	2	5	3	3	3	2	4	5
3	2	1	5	4	1	4	5	2	2
3	1	1	5	4	2	4	5	3	4
2	2	2	4	1	3	2	3	4	5
1	2	2	5	4	4	4	4	5	5
3	1	1	2	1	2	2	5	4	3
3	2	2	5	4	1	5	4	3	4
1	2	2	1	4	3	4	2	2	3
2	1	2	2	2	5	2	1	3	5
3	1	2	5	3	1	4	3	5	3
3	1	2	3	5	3	4	5	1	5
1	2	2	3	5	5	5	5	4	5
2	2	1	5	4	3	2	4	5	3
3	2	1	2	4	3	4	2	3	4
1	1	1	4	5	2	5	3	2	5

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	1	2	4	5	4	2
1	2	2	1	3	2	3	4	5	1
1	1	2	3	1	2	1	5	5	3
3	1	2	3	2	4	2	4	4	4
4	1	1	5	3	4	5	4	3	2
1	1	2	5	3	4	4	4	4	4
3	1	1	1	2	5	4	4	5	1
3	2	1	4	4	3	2	4	3	1
3	2	1	3	3	3	5	3	1	4
1	1	1	3	5	4	4	4	5	2
3	1	2	4	5	3	4	4	4	4
4	2	2	1	4	4	5	4	4	2
1	2	1	3	3	2	1	4	4	5
4	2	1	5	4	3	5	3	4	4
2	2	1	4	4	5	5	4	2	2
2	1	1	3	3	3	5	5	4	5
4	1	1	2	2	4	4	5	4	4
1	1	2	4	3	4	2	2	5	3
3	2	2	2	2	5	4	4	4	3
2	1	1	2	4	5	4	5	2	5
2	1	1	5	2	3	3	5	4	4
3	2	2	5	5	5	5	4	2	2
2	2	2	2	3	5	3	4	4	2
4	2	2	3	5	4	2	4	5	1
3	2	1	5	4	4	3	4	5	4
3	1	2	3	4	4	4	5	2	3
1	1	2	2	3	3	2	4	4	4
4	2	2	5	5	2	4	3	3	3
2	1	1	4	4	4	3	2	5	5
1	1	1	3	1	1	4	2	2	3
2	1	2	5	2	4	5	1	4	5
2	1	2	3	5	4	1	1	4	5
3	2	2	5	4	3	5	4	2	3
2	2	1	4	4	3	5	4	3	3
3	1	2	4	4	5	5	5	4	4
4	1	1	4	4	5	4	3	1	2
3	1	2	3	3	5	4	3	3	3
4	2	1	4	3	4	1	3	3	4
3	2	2	2	1	1	3	5	4	4
2	2	2	5	4	3	2	2	4	4
4	2	1	4	5	1	2	2	1	4
2	2	1	1	1	4	3	3	1	4
4	1	2	4	3	3	4	3	2	4
2	2	2	4	4	5	3	4	1	4
1	1	2	3	4	5	5	5	3	2
4	1	2	3	2	5	3	5	5	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	2	1	2	4	4	3	2	5	4
4	1	1	2	5	3	5	4	3	4
3	2	2	4	3	4	4	4	2	5
1	1	1	5	5	5	4	4	5	3
4	1	1	3	4	3	4	3	2	2
4	1	1	3	2	1	4	4	5	2
2	1	1	1	4	2	5	2	5	3
2	1	1	4	4	1	2	1	2	3
1	2	2	4	4	4	5	2	3	4
3	1	1	5	1	5	3	3	4	4
2	1	1	3	4	4	3	5	4	4
2	1	2	1	1	4	2	4	3	3
1	2	2	4	3	2	4	4	4	4
3	1	1	4	3	4	4	5	4	5
3	2	2	2	5	4	5	4	4	4
3	1	1	4	3	2	3	5	5	2
1	1	2	5	4	1	4	5	4	3
4	1	1	2	4	3	3	4	2	5
2	2	1	3	5	2	4	4	2	3
2	1	1	2	4	5	4	3	2	2
3	2	2	4	4	1	3	2	4	4
1	2	2	2	2	3	1	4	4	3
3	1	2	4	3	2	3	3	3	4
1	1	2	2	4	3	2	2	3	4
2	2	2	4	3	1	4	3	5	5
4	1	1	2	4	2	3	5	5	4
1	1	1	3	4	4	2	1	5	1
2	1	2	2	2	3	3	3	2	5
3	1	1	2	1	2	2	2	1	5
1	2	1	5	4	4	5	1	5	4
3	2	2	3	4	4	5	4	4	1
1	1	1	1	4	1	5	4	4	5
1	1	2	4	4	2	2	1	3	3
2	2	2	2	3	1	4	1	4	2
4	1	1	5	3	4	5	4	4	4
1	1	2	4	3	4	1	4	4	4
3	1	2	4	3	2	4	4	4	4
4	1	2	3	4	3	5	3	4	1
1	2	2	3	1	4	4	2	3	5
4	2	2	4	1	2	3	5	4	4
4	1	2	4	1	4	4	1	4	2
1	1	2	5	4	2	3	5	4	4
4	1	1	4	4	4	4	4	2	1
3	2	2	2	4	4	4	1	5	5
3	1	1	2	3	4	3	2	4	5
1	1	2	1	5	5	4	3	4	5

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
2	2	2	3	3	4	4	5	2	2
2	2	1	1	2	3	5	1	5	5
3	1	2	1	5	4	4	4	3	4
3	1	1	3	2	3	3	5	4	2
2	1	2	4	2	1	5	5	2	3
4	1	1	4	2	2	2	4	4	3
1	2	2	3	1	2	1	1	2	5
2	2	2	4	4	4	3	5	2	3
4	1	2	4	5	5	3	4	3	2
1	1	2	5	4	5	2	2	5	2
3	2	1	4	5	3	4	2	4	5
3	2	2	3	4	5	4	3	2	4
1	1	2	4	4	5	4	5	4	5
1	2	2	2	2	4	4	2	4	1
4	2	2	5	2	4	4	2	4	4
2	2	1	2	4	2	1	2	2	3
2	2	1	3	2	5	1	5	5	4
3	1	2	4	4	2	4	4	3	2
4	2	1	5	3	4	4	5	4	5
1	1	1	1	5	4	3	5	5	3
3	1	2	3	1	1	4	2	5	4
3	1	2	3	5	2	4	1	5	1
1	1	1	4	5	5	4	1	5	2
4	1	1	4	2	5	1	5	3	1
3	2	2	3	4	5	5	4	4	4
2	2	2	3	1	5	5	1	5	4
2	2	2	3	3	4	4	4	1	3
2	1	2	4	5	3	5	2	3	2
2	1	1	5	1	5	1	4	4	3
1	1	1	3	3	4	5	3	3	2
2	1	2	4	5	4	1	1	3	2
1	2	2	4	4	5	2	2	2	4
2	1	1	5	5	3	4	2	5	3
1	2	2	2	4	5	2	4	4	4
1	1	2	5	3	5	4	1	1	3
2	2	2	4	4	3	1	4	3	3
1	2	1	5	4	3	5	4	4	2
2	2	2	4	3	5	3	4	4	4
1	2	1	2	5	1	4	3	3	4
2	2	2	4	4	3	3	4	4	1
1	1	2	4	2	3	5	3	5	2
2	2	1	1	3	4	4	5	5	5
1	1	2	2	1	3	2	2	4	2
4	2	1	3	4	4	1	4	1	4
3	1	2	2	5	1	4	3	4	4
2	1	1	4	1	4	5	3	3	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	2	1	2	5	3	5	3	3
1	2	1	4	3	5	2	4	4	4
4	2	1	4	1	4	5	3	1	3
3	2	1	2	4	2	5	4	3	5
3	1	2	2	4	5	4	2	2	4
2	1	2	4	3	3	4	3	4	2
2	2	2	1	3	5	3	3	5	2
4	2	1	4	4	4	3	4	4	4
4	1	2	3	5	2	5	5	4	4
1	1	1	2	4	1	2	1	4	2
3	2	1	4	5	4	2	4	2	4
3	1	1	4	1	4	4	5	5	3
2	2	2	3	5	4	4	4	3	4
2	1	2	4	4	4	3	4	5	5
4	2	2	2	1	1	5	2	1	3
4	2	1	1	5	1	5	2	5	5
4	2	1	5	4	4	4	3	2	1
4	2	2	3	4	4	1	4	3	1
1	1	2	1	2	5	3	2	5	2
4	1	2	1	2	4	2	4	3	3
4	2	1	3	4	2	2	4	4	3
3	2	2	2	4	4	4	4	3	4
2	1	1	4	2	4	4	4	4	4
2	1	1	2	4	4	5	1	4	2
3	1	2	2	4	2	2	4	5	3
4	2	2	4	5	4	4	3	5	5
2	1	2	4	4	2	5	2	5	4
4	2	2	2	3	4	4	5	1	1
1	2	2	5	4	4	4	3	3	4
2	2	2	1	1	5	4	3	1	2
3	1	2	5	4	4	5	2	4	4
4	2	1	2	4	5	3	3	3	4
3	1	1	3	3	1	1	2	4	5
2	2	2	3	4	4	4	5	4	4
1	2	1	1	4	4	4	5	5	3
4	2	2	4	5	1	4	5	5	5
4	1	1	4	4	5	4	1	3	5
3	2	2	4	2	4	2	4	5	4
4	1	1	3	4	4	2	2	5	1
2	2	1	4	4	1	4	5	4	2
2	2	2	2	4	4	4	2	4	1
1	1	2	4	2	5	5	5	5	4
1	1	2	5	5	4	2	3	3	4
1	2	2	5	3	3	4	1	2	3
3	1	2	5	4	5	2	5	1	2
2	1	2	3	1	3	4	5	3	3

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	1	2	4	5	3	4	2	5	4
4	1	2	5	4	5	3	3	3	5
4	2	1	4	2	2	3	4	5	4
1	2	1	5	3	4	5	4	5	3
4	1	2	2	2	5	4	5	5	2
3	1	2	4	4	5	5	5	4	5
1	2	1	4	4	2	5	3	4	4
2	2	2	3	5	2	4	5	4	2
2	2	1	3	5	4	5	4	4	3
4	2	1	5	4	5	2	2	4	3
4	1	2	3	2	2	5	5	5	5
4	2	2	2	3	2	3	4	3	5
3	2	2	4	3	4	3	1	3	3
1	1	1	1	5	4	4	2	2	2
3	2	2	2	4	5	4	4	4	3
4	1	1	3	3	4	3	5	1	2
4	1	2	5	5	2	2	4	4	3
3	2	1	4	3	5	2	3	3	4
4	2	2	4	4	2	5	2	3	5
3	2	1	2	1	4	5	4	2	4
2	2	1	3	3	4	5	5	4	4
4	1	2	4	4	1	5	3	5	2
3	1	1	4	5	4	3	5	3	5
3	2	2	1	4	2	4	3	2	4
3	2	1	4	4	3	4	1	4	4
4	1	2	4	5	4	1	3	4	2
1	2	1	3	1	4	4	5	2	4
1	1	2	4	5	1	5	5	2	3
2	1	1	5	4	1	5	4	4	3
4	1	2	5	2	1	1	4	2	4
4	1	2	4	5	5	4	4	5	3
3	2	2	4	2	1	5	3	2	3
4	2	1	4	4	4	3	3	4	3
2	2	2	2	2	5	5	4	3	2
1	2	2	2	2	2	3	5	5	5
1	2	2	4	3	2	1	4	5	3
2	2	2	5	5	5	4	2	5	5
3	2	1	4	3	3	4	5	4	4
2	2	2	4	4	4	4	2	2	3
3	1	1	4	5	3	3	4	2	1
2	1	1	2	5	3	4	4	5	1
3	2	2	3	4	3	4	4	4	5
3	1	1	5	4	3	3	4	5	3
1	2	2	5	3	3	5	5	3	4
2	1	1	5	4	2	5	5	4	5
1	1	1	1	3	4	4	1	2	1

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	2	1	1	4	4	2	5	4	3
4	2	1	1	5	3	5	4	4	4
3	1	2	4	3	2	5	4	2	5
4	2	1	1	4	4	4	4	3	2
2	1	1	4	1	4	2	1	4	4
4	2	2	4	4	4	1	5	4	2
1	2	1	4	4	4	4	4	2	4
4	1	2	4	3	5	3	1	5	1
4	1	2	2	5	5	5	2	3	4
1	2	1	1	3	5	4	4	4	5
1	1	1	1	4	4	4	5	4	4
3	1	1	3	4	2	2	3	5	4
2	2	1	4	4	3	3	4	2	5
3	1	1	2	3	3	5	4	4	3
1	1	2	5	5	2	3	4	2	5
3	1	1	4	4	2	4	4	3	4
2	2	1	3	5	1	5	2	1	1
1	2	2	5	4	3	4	4	3	4
2	2	2	4	1	5	1	4	3	1
4	2	2	4	4	2	2	4	4	5
4	2	1	5	3	2	5	4	2	5
1	1	1	4	4	4	2	4	3	4
4	2	1	4	5	1	3	4	5	3
1	1	2	5	4	3	4	4	5	4
4	2	2	4	3	5	4	1	4	4
2	1	2	4	4	1	3	3	4	4
4	1	1	5	5	1	4	3	1	5
4	2	2	4	1	4	5	4	4	5
4	2	2	4	4	2	3	2	5	4
2	2	1	3	3	2	3	3	2	2
3	2	2	5	5	4	1	3	4	3
3	1	2	1	2	1	4	1	3	4
3	2	1	5	4	4	2	4	2	5
1	2	2	4	2	1	4	4	5	3
4	1	2	2	5	1	2	3	1	1
2	1	2	5	5	3	2	3	4	4
3	2	2	4	1	3	4	4	4	2
2	2	2	4	4	4	1	4	4	4
4	2	1	4	1	5	2	5	4	2
4	1	1	4	4	1	1	4	5	5
3	1	2	2	4	4	4	2	2	4
2	1	1	2	2	2	4	3	4	5
4	2	1	4	4	4	4	2	3	4
4	2	2	2	3	3	4	4	5	4
3	1	1	4	4	5	2	4	2	1
1	2	2	5	4	2	4	4	4	2

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	2	3	4	5	5	4	4	4
4	2	1	4	1	5	4	3	3	4
3	1	1	5	2	4	4	4	3	4
3	2	2	2	2	4	4	5	3	2
4	2	1	4	5	4	2	3	4	2
3	1	1	5	2	3	2	3	2	1
3	1	2	2	3	2	5	5	1	3
3	2	1	1	4	5	3	1	3	2
4	2	2	1	1	1	3	3	4	4
1	2	2	4	3	1	4	1	1	4
3	2	1	3	4	3	5	5	1	4
1	1	2	4	3	4	4	3	2	5
3	1	1	3	4	1	3	4	4	3
2	2	2	2	2	5	3	4	5	4
4	2	2	2	2	4	2	4	3	4
3	2	2	4	3	5	4	4	3	4
1	1	2	4	4	5	3	4	3	2
1	2	2	2	3	3	5	1	4	4
1	2	2	4	3	4	3	5	1	1
4	1	2	3	4	5	1	2	4	2
2	1	2	4	3	5	1	3	5	2
2	2	2	3	5	4	4	2	4	4
3	2	2	5	5	4	2	4	2	3
1	2	1	4	5	4	4	3	4	4
1	2	1	2	4	4	5	4	3	3
2	2	2	1	2	2	3	1	1	2
4	2	1	4	4	4	3	2	5	1
2	2	1	5	3	5	5	3	3	2
2	2	1	4	5	4	4	1	3	4
3	2	1	3	4	4	5	3	2	2
3	2	2	5	5	4	2	2	4	2
3	2	2	4	5	2	4	2	2	3
1	1	1	4	1	4	3	4	1	2
1	1	2	2	4	4	2	1	4	4
2	1	1	5	5	3	4	3	4	2
1	1	2	3	4	5	3	5	2	4
2	2	1	1	5	4	4	4	4	5
3	2	1	2	3	1	3	2	3	4
2	2	2	5	2	3	4	2	4	4
2	2	2	4	4	1	5	5	4	4
4	1	1	5	4	4	4	4	3	2
1	2	1	4	4	3	5	5	4	3
1	1	2	1	2	5	3	3	3	4
1	1	2	5	5	3	2	5	5	2
4	2	2	2	3	4	3	5	4	4
4	1	1	5	4	5	2	1	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	2	1	4	4	4	4	2	5	4
4	2	1	5	5	5	3	4	4	5
2	1	1	5	4	2	1	3	5	4
3	1	2	2	4	2	4	3	4	4
3	1	2	4	3	5	1	5	5	4
2	1	1	1	3	5	2	3	5	4
4	2	2	2	2	5	3	3	4	3
2	2	1	5	3	4	4	3	4	3
1	1	1	3	4	5	3	1	4	3
3	1	2	3	3	4	5	4	5	4
1	2	2	2	5	1	2	4	2	4
4	1	2	3	3	3	4	5	1	2
2	1	1	4	3	2	2	2	4	4
2	1	1	5	2	4	4	3	5	1
1	1	2	5	4	4	4	5	3	4
2	2	2	3	3	5	4	4	2	1
1	2	2	3	4	1	1	4	4	4
3	1	2	1	3	2	1	3	1	4
2	1	1	5	3	1	2	2	5	3
2	1	1	3	5	1	1	4	5	5
3	1	2	4	4	4	4	4	3	4
4	1	1	1	4	3	1	4	4	3
4	2	1	3	3	3	2	5	3	4
4	2	2	4	4	5	2	1	3	4
2	2	1	4	5	1	3	3	4	3
2	1	2	3	3	2	5	4	4	1
1	1	1	5	1	2	4	4	1	5
2	2	1	2	4	5	1	5	4	1
3	1	2	3	5	3	3	4	4	4
4	1	1	3	3	5	3	3	3	5
1	2	2	5	2	2	5	5	5	1
3	2	2	1	3	4	2	1	4	3
2	2	2	1	2	4	4	3	2	3
1	2	1	3	5	2	2	4	3	4
4	1	2	4	4	4	4	5	5	3
1	1	1	4	4	3	3	1	5	4
1	1	2	3	5	4	2	1	5	5
3	1	1	5	3	5	3	3	2	2
4	1	1	2	4	5	5	2	1	4
4	2	1	4	5	5	2	4	2	4
4	1	2	4	3	3	4	2	4	3
4	2	2	4	2	3	1	2	5	3
2	2	2	4	2	4	4	4	1	3
2	2	2	3	1	2	3	4	2	4
4	2	1	3	4	5	4	3	5	3
2	2	1	2	4	4	4	2	2	5

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	2	1	5	4	4	3	2	1	5
3	2	1	4	3	3	4	4	4	2
3	2	2	4	4	4	3	5	2	4
2	2	2	1	4	2	3	2	4	2
1	1	2	4	4	3	4	2	3	2
4	2	2	4	4	5	2	4	4	5
4	2	2	4	3	2	2	3	4	4
1	1	2	4	4	3	2	5	3	4
4	2	2	2	4	5	3	3	2	1
1	2	1	2	4	5	4	4	2	3
2	1	2	5	4	3	4	3	4	5
1	2	2	3	3	1	5	4	5	1
2	2	1	4	4	1	5	3	4	4
4	1	1	5	3	4	2	3	1	4
2	2	1	4	3	4	5	4	4	4
2	2	1	2	2	5	4	3	3	2
3	1	1	3	1	4	3	4	2	1
4	1	1	4	3	4	2	5	5	2
4	1	2	5	3	1	3	4	1	1
3	2	2	1	5	4	4	1	5	1
1	2	2	2	1	5	4	4	5	5
1	1	1	3	2	4	5	4	1	3
1	2	1	4	4	3	2	3	4	5
3	1	2	4	3	4	3	2	4	3
3	1	1	3	1	4	4	5	4	2
1	2	2	5	4	4	4	4	1	4
4	1	1	4	5	2	2	3	2	5
2	1	2	5	5	2	4	4	4	3
4	2	1	5	4	3	5	1	4	5
1	1	1	1	5	4	4	4	2	1
4	2	1	4	4	3	3	2	4	5
1	2	1	3	1	5	3	1	2	5
4	1	2	2	1	4	2	2	4	5
3	1	2	5	4	3	5	3	4	5
3	2	2	5	4	2	5	3	2	3
3	2	1	5	3	4	2	2	5	1
4	1	1	4	1	4	3	5	3	5
3	1	2	4	2	4	3	4	5	5
1	1	2	4	4	3	4	4	4	4
2	1	1	3	4	1	1	2	2	1
2	2	2	4	5	3	1	4	4	4
3	2	1	5	3	2	3	4	5	4
4	1	1	3	4	5	3	3	4	1
4	1	1	2	5	1	3	4	4	3
4	1	1	1	4	4	4	5	4	2
4	1	1	1	3	3	4	5	5	5

Age Range Gender Event Stat I felt excite I felt a sen The event I found the I stayed fo The event I actively p

4	2	1	4	4	5	3	4	4	5
3	2	2	5	5	2	3	4	3	2
4	1	2	1	3	1	5	4	3	3
4	1	1	4	1	4	2	1	2	3
1	1	1	4	2	1	4	2	5	2
1	1	1	4	4	4	5	5	4	4
3	1	2	4	2	4	4	2	5	4
1	2	2	3	2	2	5	2	5	1
2	2	2	4	2	3	3	5	2	1
4	1	1	4	4	5	4	5	4	3
1	1	1	5	5	3	4	3	4	4
3	2	2	2	3	1	4	4	5	3
2	1	2	3	3	2	4	5	2	5
2	1	1	5	4	3	4	3	3	3
4	2	2	5	3	4	4	4	5	4
2	1	1	5	4	4	4	1	3	2
1	1	1	1	4	2	2	5	4	4
2	1	1	4	4	4	5	4	4	5
3	2	1	4	1	2	4	1	4	1
3	2	2	3	1	4	4	5	5	2
3	1	1	5	2	3	3	1	4	5
4	2	2	4	4	2	4	2	5	5
4	1	2	2	4	3	4	5	5	3
4	2	2	4	2	4	4	4	4	1
4	2	2	5	3	4	5	4	3	5
3	2	2	4	2	3	4	5	5	4
3	1	1	3	3	4	3	4	3	3
4	2	2	1	2	4	5	2	1	5
3	2	2	3	5	4	2	5	4	3
3	1	1	4	2	5	1	4	3	4
3	1	1	3	5	4	4	4	3	4
4	1	2	4	4	3	1	5	2	2
4	2	2	5	4	3	3	3	4	3
3	1	2	4	3	2	5	4	1	4
1	2	1	4	2	1	4	1	5	5
4	1	2	2	4	2	2	4	4	3
1	1	2	5	5	3	2	3	2	4
4	1	1	3	4	4	2	3	1	4
1	1	2	4	3	4	4	3	4	2
3	1	2	2	5	4	5	4	5	4
3	1	2	2	3	1	4	4	1	5
2	2	1	4	1	3	2	2	3	1
1	1	2	1	4	2	5	4	4	2
4	2	1	1	4	2	5	5	5	2
1	1	2	2	4	3	4	2	3	3
1	2	2	5	4	4	4	2	4	4
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p

1	2	2	4	5	1	2	5	2	4
4	2	1	5	5	5	1	3	4	4
3	1	2	2	4	3	4	4	4	3
1	2	2	4	4	3	3	3	4	1
4	1	1	4	5	5	4	3	5	5
1	1	2	2	5	5	1	4	4	3
1	2	2	4	3	4	4	4	4	2
3	1	2	4	2	2	5	1	5	4
2	2	1	5	4	1	3	1	4	4
4	1	1	2	4	2	4	4	3	4
4	2	1	5	3	1	3	3	4	4
3	1	1	3	4	3	3	4	3	4
4	1	1	1	1	2	3	4	3	2
1	2	2	1	4	4	4	3	3	2
4	1	2	2	4	4	4	4	1	4
4	1	1	4	5	2	5	4	2	5
2	2	2	3	5	4	4	4	5	5
3	1	1	2	4	4	5	3	4	3
1	2	2	5	5	1	4	4	2	3
1	1	2	4	4	5	3	4	4	4
3	2	1	2	2	4	5	4	5	2
4	2	2	4	5	5	5	2	4	3
4	2	2	4	2	1	3	4	4	2
1	2	2	5	4	5	4	4	3	4
1	1	2	3	3	5	4	5	4	5
3	2	1	4	4	2	4	3	4	4
1	1	1	5	2	4	4	1	4	1
2	2	2	3	3	4	5	2	3	5
2	2	1	2	3	3	2	3	4	4
2	2	1	4	4	3	4	4	5	2
3	2	1	3	2	1	2	4	2	4
3	2	2	3	4	4	3	1	5	4
1	2	1	3	4	2	3	2	3	4
4	2	1	3	5	2	3	4	1	4
2	2	2	3	4	4	4	4	5	4
2	2	2	5	2	2	5	2	4	2
4	2	2	3	4	4	4	4	4	2
4	2	1	4	4	3	4	4	4	4
4	1	1	1	1	4	4	3	3	4
2	1	2	4	2	5	4	4	4	3
4	1	1	1	4	2	4	3	3	4
1	1	2	2	4	4	4	4	2	2
3	1	2	4	5	3	4	1	3	5
4	1	2	3	1	4	3	4	5	3
4	1	1	4	3	4	3	5	4	2
3	1	2	4	5	2	3	4	4	2
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	2	1	2	4	3	4	4	4	4

2	1	1	4	4	2	2	3	4	3
3	1	2	1	5	1	1	3	4	3
4	2	2	2	4	4	4	3	2	4
2	1	1	4	4	5	3	3	5	2
4	2	1	1	5	2	2	4	5	5
3	1	1	3	3	5	1	4	4	3
1	2	2	5	3	4	3	5	5	5
2	1	2	3	1	4	5	3	3	4
4	2	2	5	2	4	2	2	1	2
4	1	1	4	3	3	4	4	2	3
1	1	2	5	4	4	3	3	5	4
2	1	2	4	5	5	2	4	4	3
3	1	1	2	2	3	4	5	2	4
3	2	1	4	3	4	3	5	2	2
1	1	2	2	1	4	4	3	2	4
4	2	1	4	4	4	3	4	3	5
1	1	1	5	3	3	2	4	3	4
2	1	1	3	3	3	4	5	4	4
1	1	1	5	4	2	3	5	4	1
4	2	1	5	4	1	3	2	5	5
2	2	1	4	5	4	5	1	4	4
3	2	2	4	4	5	1	2	2	1
2	2	1	3	3	2	3	1	4	5
4	1	1	2	5	5	5	4	4	5
2	1	2	4	1	3	3	3	5	5
2	2	2	4	2	4	1	5	5	3
4	1	2	4	5	2	4	4	5	3
2	1	1	5	5	5	3	4	5	5
4	2	2	2	2	2	2	5	5	4
2	2	2	5	5	4	5	4	4	1
2	2	2	3	4	2	3	4	5	3
2	2	2	5	4	3	4	2	2	3
2	1	2	4	5	5	5	5	4	4
1	2	2	2	2	4	4	4	2	3
1	1	1	4	1	5	4	4	4	4
1	2	1	2	3	4	3	5	4	5
4	1	1	4	5	3	3	2	1	4
3	1	2	4	4	4	3	2	4	5
3	2	2	4	4	2	2	3	2	5
2	1	2	4	2	2	2	2	5	3
1	2	1	4	5	5	4	1	4	3
2	2	1	5	5	4	2	2	3	2
2	1	1	1	4	5	5	2	3	3
2	2	1	5	3	5	4	5	4	2
2	1	2	1	2	2	2	4	4	3
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	2	5	4	4	4	1	5	4
3	1	2	5	5	2	5	2	4	4

1	1	1	4	4	2	4	1	3	4
2	2	1	3	4	3	3	1	2	4
3	2	2	3	5	4	4	2	2	3
1	2	2	5	5	3	3	4	2	4
3	1	2	5	3	5	3	2	3	4
2	1	2	5	5	5	2	3	2	3
1	1	1	4	2	4	5	4	2	1
1	1	1	5	1	3	4	4	4	2
1	1	2	3	3	4	3	3	1	3
1	1	2	4	4	1	5	2	4	4
3	1	2	1	2	2	4	2	2	5
3	1	1	1	5	4	5	5	3	4
3	2	1	4	1	4	3	5	4	4
2	1	2	1	3	4	5	2	3	3
3	2	2	1	5	2	2	2	4	3
3	1	1	1	2	4	5	2	3	1
4	1	2	3	4	3	2	2	3	5
2	2	1	4	3	1	4	4	4	3
4	2	1	5	5	4	5	4	2	5
2	1	2	4	4	4	2	2	4	5
1	2	1	4	2	4	4	1	1	3
4	2	2	4	4	3	4	1	4	1
3	2	1	4	4	4	4	4	5	4
2	2	2	4	3	2	2	5	5	5
1	1	1	5	3	1	4	4	3	5
4	1	2	4	1	5	2	1	4	5
4	2	1	5	3	4	5	2	2	4
4	1	2	3	5	4	5	5	4	3
4	1	1	4	3	4	2	1	5	4
1	2	1	5	4	5	4	1	5	4
3	2	2	2	2	1	3	3	2	4
1	2	2	4	2	2	4	1	5	4
1	1	1	1	4	4	4	2	4	1
4	2	1	3	3	1	5	4	4	5
3	2	2	4	4	4	4	3	4	5
2	2	1	4	3	4	4	4	1	4
4	2	1	1	1	4	4	2	1	3
4	1	1	4	4	4	5	1	3	2
2	1	2	4	3	4	4	4	1	4
4	2	2	3	4	4	5	4	5	3
4	2	1	5	5	5	2	4	2	3
2	2	1	2	1	5	5	2	5	3
1	2	2	4	2	2	5	3	4	3
2	2	2	2	2	2	5	4	3	1
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	1	1	4	5	4	2	5	4	3
3	1	2	1	2	1	3	5	5	3
1	2	1	5	3	4	2	4	2	4

3	1	1	5	1	3	5	5	5	4
1	1	2	3	5	4	2	4	4	1
3	2	1	4	4	3	1	4	4	3
1	1	1	2	4	4	4	4	2	1
3	1	2	2	5	5	2	1	5	3
2	2	1	3	3	4	4	3	4	2
1	2	2	5	3	3	4	2	2	5
4	1	1	5	3	3	5	3	3	1
4	1	2	5	3	5	2	4	4	4
4	2	1	5	4	1	5	5	4	2
3	2	2	1	4	4	3	4	4	3
2	2	1	1	4	2	5	5	5	4
4	2	1	3	2	5	5	4	3	4
2	1	1	3	3	1	2	4	5	1
3	2	1	4	5	4	5	4	2	4
1	2	2	4	4	4	5	5	4	5
3	1	1	4	5	1	3	4	4	2
1	1	2	3	3	2	3	4	4	4
3	2	1	5	3	5	5	2	1	2
4	2	1	4	4	4	4	5	5	4
3	1	1	4	4	4	1	4	1	5
1	2	1	5	4	5	2	2	2	3
4	1	1	2	3	4	5	3	2	5
2	1	1	3	3	2	4	4	4	4
4	1	2	1	3	1	4	4	4	4
3	1	2	3	4	1	1	5	5	5
3	2	1	4	3	2	3	4	2	2
4	2	1	3	4	5	1	1	4	2
2	2	2	5	4	3	4	4	1	4
3	2	2	5	5	2	2	2	5	2
2	2	1	3	2	2	1	5	2	1
2	1	1	4	5	4	5	2	4	3
2	2	1	5	3	5	1	4	5	3
4	2	1	1	3	3	3	2	3	5
1	1	1	5	2	3	5	1	5	2
1	2	2	5	5	3	3	1	5	4
2	1	1	3	2	1	3	5	5	4
4	2	1	4	5	5	4	4	5	2
3	2	2	5	4	2	5	2	4	2
1	1	1	4	5	4	2	3	4	5
1	1	2	2	3	4	4	3	4	1
4	2	1	4	4	5	4	4	2	4
1	1	2	3	5	4	3	1	3	4
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
2	1	1	1	3	1	4	4	1	4
1	1	1	3	5	4	5	5	5	4
3	2	1	5	4	3	5	4	4	2

4	1	2	4	2	4	4	2	4	5
1	1	1	4	1	3	5	5	1	1
3	1	1	1	4	5	3	3	5	2
2	2	2	4	4	5	4	4	3	3
1	1	2	4	4	2	2	4	3	4
2	2	2	2	1	5	5	3	5	4
2	1	1	2	3	4	2	4	5	5
4	1	1	2	4	4	3	3	4	5
2	2	1	5	3	5	5	4	4	4
1	2	2	2	4	1	1	4	3	2
2	1	2	3	2	2	5	3	3	4
4	1	1	1	5	2	1	4	3	1
1	1	2	4	1	1	4	3	5	5
2	2	1	4	2	1	1	3	4	4
4	1	2	4	4	3	4	1	4	5
1	2	2	4	4	4	3	4	3	4
1	2	2	2	1	5	4	3	4	5
1	2	2	1	4	2	3	2	4	5
3	2	2	3	3	1	1	1	3	1
4	1	2	4	3	2	2	1	4	5
2	1	1	4	4	4	4	4	4	3
1	2	1	2	4	1	4	5	3	2
3	1	2	4	4	4	4	3	5	4
1	2	1	3	3	3	4	2	3	4
1	1	1	2	4	3	3	2	5	1
1	1	1	4	1	3	2	3	4	4
3	1	1	4	5	3	3	4	3	4
4	1	1	4	4	5	4	5	5	3
1	2	2	5	4	1	1	5	1	4
4	2	1	4	4	4	2	2	2	4
2	2	2	5	4	4	4	2	3	2
2	2	1	2	5	4	4	3	3	4
1	2	2	4	3	1	5	5	3	4
1	1	1	4	3	3	3	2	2	3
3	1	2	5	5	3	4	1	2	4
3	2	1	2	5	4	5	4	4	4
3	2	2	3	2	2	1	5	5	4
1	1	2	4	4	4	4	5	4	1
1	2	2	4	4	2	4	4	4	4
3	1	2	2	1	5	4	2	1	4
2	2	2	4	4	5	2	4	1	4
3	1	1	4	3	4	4	4	2	5
4	1	2	5	4	3	5	5	5	5

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
2	1	1	2	3	5	4	2	2	4
4	1	2	5	3	2	3	2	2	4
3	2	1	5	4	3	5	4	5	5

3	1	2	2	4	4	3	4	3	4
1	2	2	3	4	5	5	5	4	1
4	2	1	5	4	5	5	3	1	5
4	1	2	2	3	4	4	4	2	4
2	1	1	3	2	1	4	3	5	1
4	2	2	4	5	4	5	4	3	2
4	2	2	2	5	3	4	4	4	4
2	1	2	4	4	4	5	3	5	1
4	1	2	2	4	3	1	2	5	2
2	2	2	1	3	2	3	4	2	4
2	1	1	1	5	4	5	5	4	4
1	2	1	5	2	1	4	2	5	4
2	2	1	1	4	5	3	2	4	2
1	1	2	4	5	5	1	2	4	3
4	1	1	3	4	3	4	4	3	1
1	2	2	1	4	4	4	3	3	4
2	2	1	4	4	4	3	3	1	3
1	2	2	5	4	3	4	3	4	5
4	1	1	3	2	2	4	2	4	4
4	1	1	5	4	2	5	3	2	3
4	2	2	3	5	5	4	4	3	1
3	2	2	3	4	4	3	1	5	4
4	2	2	3	3	1	4	5	2	2
1	2	1	2	4	4	2	3	2	3
2	2	2	1	4	4	4	5	2	3
3	1	1	4	4	5	5	2	5	1
3	2	1	2	5	3	3	3	1	3
4	2	1	2	4	5	1	4	3	4
4	1	1	3	1	3	3	3	3	4
4	2	1	4	1	5	5	3	2	4
3	1	2	1	4	2	3	3	4	3
2	1	1	2	3	5	2	4	3	5
1	1	2	5	4	2	4	2	4	5
1	1	1	4	4	1	2	3	4	2
4	1	1	4	2	1	2	5	3	4
3	1	1	4	2	4	5	1	4	3
1	1	2	4	4	3	4	5	2	2
1	1	2	4	3	2	5	2	4	4
2	1	1	4	5	4	4	1	4	5
1	2	2	3	4	3	4	1	5	1
4	1	2	4	3	4	3	1	4	4
1	1	1	4	5	5	4	4	5	4
2	2	1	5	4	3	3	4	2	5
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	1	1	4	4	4	3	2	4	2
4	1	2	5	3	4	4	4	2	5
3	1	2	2	2	3	4	1	5	2

2	2	2	4	4	5	4	1	3	3
1	2	2	2	1	4	3	3	2	5
3	2	2	5	5	4	2	2	3	3
2	2	2	5	3	5	3	2	2	4
2	1	2	4	4	5	4	1	3	4
2	2	2	5	4	4	4	4	4	2
2	1	1	4	5	5	5	4	5	3
3	2	1	2	3	1	3	4	2	2
3	1	1	4	3	4	4	1	2	4
4	1	2	3	5	2	2	4	3	5
3	2	2	5	2	4	5	5	2	3
4	2	1	4	4	2	4	5	3	1
1	2	2	4	3	3	4	4	2	2
4	2	1	5	2	3	5	2	3	4
1	2	2	5	3	1	5	4	4	4
2	2	1	4	5	5	2	2	2	5
4	2	1	5	3	1	4	3	4	5
3	2	2	5	5	5	3	2	4	4
4	1	1	4	5	2	4	5	5	4
3	2	1	3	4	4	4	2	4	1
2	2	2	2	5	4	5	3	1	4
3	2	2	3	3	2	4	3	2	3
4	1	1	3	1	3	2	5	4	5
2	2	1	4	5	5	1	4	4	3
2	1	2	3	5	5	4	5	4	5
4	2	2	4	5	2	3	3	2	2
4	1	1	1	1	4	4	3	4	5
2	2	1	4	5	5	2	3	2	3
2	1	2	1	4	2	4	4	5	1
2	1	2	2	4	3	4	4	3	4
1	2	1	4	1	4	4	1	4	4
1	2	1	3	4	4	5	2	4	5
2	1	1	3	4	2	5	4	1	4
1	2	1	1	4	4	1	1	5	2
4	1	1	4	2	2	3	3	5	1
2	2	1	4	2	5	2	4	4	4
2	1	2	5	4	5	3	1	2	3
4	1	2	4	5	4	4	3	3	5
2	2	1	4	4	3	3	1	2	4
4	1	1	4	4	4	3	2	3	3
1	1	1	2	5	2	5	4	3	2
4	2	1	5	4	1	5	5	2	2
2	2	1	4	5	4	4	5	3	5

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	2	1	1	3	2	5	3	2
1	2	1	2	3	4	5	4	3	2
4	2	1	4	2	3	2	2	1	3

4	2	1	1	5	2	4	2	5	4
3	2	1	1	3	5	3	1	1	2
4	2	1	3	2	2	4	3	5	3
3	1	2	5	5	4	1	3	3	2
4	2	2	4	4	3	5	3	5	4
3	2	1	4	2	5	4	4	2	5
4	2	2	4	3	2	2	4	2	4
4	1	2	4	2	4	1	3	4	3
2	2	2	4	1	2	5	5	4	3
3	1	1	3	4	2	5	4	4	3
2	1	2	4	4	3	3	4	4	3
1	2	2	4	3	2	4	1	2	1
3	1	1	4	4	4	4	4	3	4
4	2	1	4	5	4	3	4	5	3
4	2	2	4	3	3	4	4	3	4
4	1	1	3	5	3	4	5	3	3
3	1	2	3	3	3	5	3	4	5
2	1	2	4	4	5	3	3	4	4
3	1	1	2	4	5	4	4	3	4
1	2	2	3	4	4	5	2	2	4
2	1	1	5	1	4	5	3	4	4
2	2	1	2	1	4	3	5	1	3
2	2	2	4	4	5	2	2	5	3
1	2	2	4	1	5	2	1	5	4
4	1	2	4	5	4	4	3	4	2
2	2	1	3	2	3	1	1	5	2
3	2	1	4	3	4	5	5	5	4
4	2	1	1	2	5	4	2	5	4
2	1	1	4	5	2	3	4	1	4
1	2	2	3	1	4	2	5	2	3
3	2	1	3	5	2	1	5	3	4
2	1	1	2	4	5	5	4	4	3
3	2	1	3	3	2	4	4	4	3
3	1	2	4	1	3	5	3	4	5
1	2	2	3	4	4	5	1	4	1
2	1	2	3	5	4	5	1	4	4
4	1	2	5	4	4	5	4	5	2
3	1	2	3	3	4	5	4	2	4
3	2	1	3	4	3	5	1	4	1
4	2	1	1	5	1	2	4	4	5
3	1	2	4	2	1	4	5	2	2
4	1	1	5	4	4	3	3	1	2
3	2	1	2	2	5	2	4	2	4
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	2	2	4	4	2	5	4	3	2
3	2	2	5	3	2	2	3	2	4
3	2	1	5	3	4	1	4	2	2

2	1	2	5	5	4	5	5	3	5
1	1	2	3	4	1	4	5	2	4
2	1	2	4	5	4	4	4	3	4
4	1	1	5	4	3	4	2	1	4
1	1	1	4	4	4	3	4	4	5
4	1	1	1	3	4	3	3	3	4
1	2	1	5	5	3	4	5	3	3
3	2	2	4	3	4	4	5	4	4
3	1	2	5	3	4	5	3	2	2
2	2	2	4	5	4	4	5	2	2
2	1	2	2	3	4	3	4	3	1
3	2	1	4	4	4	2	4	3	3
1	2	1	4	4	1	4	4	5	4
2	2	1	2	5	4	5	5	1	4
4	1	2	4	3	1	2	4	5	2
2	2	1	4	5	1	4	4	4	5
2	2	2	4	2	4	5	2	1	4
4	2	1	5	5	5	5	3	4	3
2	2	2	5	2	5	4	2	4	3
2	2	1	4	5	4	3	4	5	3
2	2	2	4	3	4	1	3	3	5
3	2	2	3	4	3	3	4	4	5
1	2	1	1	3	4	2	5	3	5
4	2	1	4	1	3	3	5	3	4
2	2	2	5	3	4	4	3	5	3
1	1	1	5	4	5	5	3	2	2
4	1	2	4	4	2	4	3	2	2
1	1	1	4	4	4	5	3	3	1
1	2	1	3	2	2	3	5	4	5
3	2	2	3	5	4	4	3	5	4
3	1	1	5	2	1	4	3	2	4
4	2	1	4	3	4	3	4	1	2
4	2	2	5	2	3	2	4	1	3
3	2	2	4	4	5	1	3	4	4
4	2	2	2	1	2	3	4	4	1
3	1	2	4	4	4	3	4	4	5
2	2	2	3	4	2	4	4	4	1
2	1	2	1	4	1	4	4	4	1
2	1	1	5	3	5	4	4	1	5
1	2	1	4	5	4	4	5	2	5
3	1	2	5	1	1	4	2	1	2
2	2	1	5	2	5	4	2	5	1
3	1	2	3	3	3	2	4	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	2	1	4	4	2	2	2	4	5
1	1	1	1	5	3	5	4	4	2
2	1	1	4	5	1	4	5	1	2

4	1	1	4	3	2	5	4	5	5
4	1	2	4	4	2	4	2	2	5
2	1	1	4	2	4	4	2	4	3
4	2	2	4	5	4	5	3	1	2
2	1	2	5	3	2	5	3	2	2
3	1	1	5	4	2	4	4	4	2
1	1	1	5	4	5	5	3	5	4
1	2	2	3	5	5	5	4	4	4
4	1	2	5	4	5	4	2	3	4
2	2	2	2	4	4	3	4	4	1
1	1	2	4	4	5	4	5	3	5
1	1	2	2	4	3	4	3	4	5
4	2	2	5	1	4	1	2	5	4
1	1	1	4	4	3	4	3	4	5
2	2	1	2	3	2	3	5	2	2
4	1	2	2	2	4	4	4	1	5
2	1	1	4	2	3	4	5	3	5
2	1	2	5	4	4	2	4	5	4
2	2	1	3	4	4	1	5	3	5
4	1	1	1	3	2	5	1	4	4
3	2	2	2	4	5	5	4	5	2
1	2	2	2	4	3	1	5	3	5
3	1	2	5	4	4	4	5	3	2
3	2	2	3	1	4	5	4	4	3
1	1	1	5	2	4	5	4	5	3
1	2	2	5	3	2	1	5	3	2
3	1	2	4	5	5	2	4	2	1
3	1	2	2	2	3	4	5	4	3
1	2	2	5	2	4	5	3	2	4
4	1	2	2	1	4	4	4	1	4
4	2	2	3	3	4	2	3	3	4
3	2	1	1	4	4	4	4	4	5
3	1	2	2	3	3	4	2	1	1
1	1	1	4	4	2	4	3	5	5
2	1	1	5	2	4	1	1	4	4
4	1	2	3	5	4	1	4	4	2
1	1	1	4	3	4	3	5	3	2
2	1	2	3	2	4	2	1	2	3
3	1	1	4	4	4	5	1	4	2
1	1	1	5	4	5	1	1	3	3
1	2	2	4	5	4	2	1	2	2
3	2	1	2	4	4	5	2	4	4
1	2	1	5	4	5	5	3	1	2
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	2	2	4	4	4	5	2	4	5
2	1	1	3	2	2	4	3	5	5
4	1	2	3	3	5	4	4	4	4

1	2	2	5	4	4	4	1	5	2
2	2	1	4	3	4	4	3	5	4
3	1	1	3	4	3	4	5	3	3
4	2	2	4	3	3	3	4	4	3
1	1	2	4	5	2	4	2	3	4
4	2	1	2	4	5	3	4	3	4
3	1	2	1	5	4	3	2	5	4
2	1	2	2	2	5	4	5	5	3
1	2	1	1	2	1	4	1	4	3
4	2	1	4	3	4	4	4	5	5
3	1	2	2	5	2	1	3	4	4
1	1	1	5	3	4	4	2	4	4
1	1	2	4	1	3	4	4	3	2
4	1	2	2	3	4	4	4	1	2
4	1	1	3	4	2	3	3	5	5
2	2	2	4	3	4	1	5	5	3
1	1	1	4	5	4	3	4	4	3
2	2	1	2	2	5	4	4	5	1
1	2	2	5	2	2	2	4	3	1
1	1	1	4	5	1	5	5	1	2
1	1	1	4	2	5	3	2	4	5
3	1	1	2	1	3	3	5	5	2
2	2	1	2	2	3	4	4	2	4
4	1	2	4	4	2	2	5	4	4
4	1	2	1	3	4	2	4	3	5
2	1	1	2	3	5	4	5	2	4
3	2	2	1	4	1	3	3	3	5
4	1	1	4	2	3	5	2	5	4
4	1	1	3	1	4	3	4	3	4
3	1	2	5	5	4	2	1	5	4
2	1	2	4	5	2	3	3	4	5
4	2	1	2	4	4	1	2	3	4
4	2	2	3	4	2	2	4	1	5
4	1	2	1	4	4	2	4	3	3
2	1	2	1	5	4	2	1	4	2
2	1	2	2	3	3	5	4	4	5
1	1	2	4	4	1	1	2	2	5
3	2	1	5	3	3	2	4	3	5
2	2	1	3	3	2	5	3	4	2
2	1	1	1	4	1	5	2	5	2
3	2	1	5	4	4	5	4	2	3
3	1	1	4	3	3	5	5	4	4
4	1	2	3	4	3	4	2	3	5

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	2	1	5	4	3	3	3	4	3
2	2	1	3	3	5	4	5	4	1
2	1	1	3	2	5	5	4	3	5

1	1	1	2	4	4	5	1	4	2
3	2	1	4	3	5	5	5	4	2
4	2	2	5	2	5	2	3	4	4
2	1	1	5	3	4	4	2	2	5
3	1	1	3	3	4	4	5	2	2
1	1	2	3	3	5	3	1	3	3
3	1	2	1	2	4	4	5	3	4
3	1	1	4	1	4	3	4	5	4
4	1	1	5	1	2	4	4	3	4
2	1	2	5	1	2	3	1	4	4
3	2	2	3	2	5	4	3	4	3
4	2	1	4	4	4	3	3	4	2
2	2	2	5	2	3	3	1	4	1
1	2	1	1	3	3	2	2	4	4
4	2	1	1	4	4	4	3	4	4
4	1	2	1	5	2	5	3	4	5
3	1	2	5	4	5	2	4	4	4
2	2	2	5	1	1	2	5	3	4
4	1	2	3	4	3	5	4	4	2
1	1	1	4	5	3	4	4	3	5
1	1	1	4	4	2	5	3	4	2
3	1	2	4	5	4	3	4	5	4
2	2	1	5	5	4	4	5	3	4
1	1	1	1	3	4	4	2	2	4
1	2	2	5	3	5	5	4	4	1
1	1	2	1	4	5	2	3	3	4
4	2	1	4	1	1	1	4	4	5
2	1	1	5	2	4	5	4	1	4
4	1	2	3	4	4	4	4	1	3
4	1	1	3	1	4	3	4	4	4
2	2	2	2	3	2	4	5	3	3
4	1	2	4	5	4	4	5	3	4
2	2	1	3	1	5	3	4	5	3
1	1	1	3	4	3	5	4	2	1
3	1	2	5	4	5	3	5	4	4
4	1	2	5	3	5	3	4	4	4
4	1	1	4	5	4	5	4	3	4
2	2	2	1	1	4	4	1	4	4
2	1	1	5	5	1	2	5	4	3
2	2	1	1	2	5	4	3	2	4
4	2	2	4	3	5	3	2	3	3
3	1	2	1	5	5	3	2	3	5
4	1	2	2	3	3	4	2	3	3
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	2	1	4	3	3	2	1	2	2
1	2	2	2	1	2	2	3	4	4
3	2	1	4	4	4	1	4	5	5

2	1	2	3	4	5	4	5	3	1
3	2	1	2	1	3	4	4	4	2
3	2	1	4	5	3	5	3	4	4
4	2	1	4	2	1	2	5	5	2
4	1	2	4	1	2	3	4	4	3
4	2	1	5	4	3	2	4	4	4
3	1	1	3	3	4	4	5	4	1
3	1	1	5	2	4	3	2	5	4
3	2	2	5	4	5	5	2	3	4
4	2	2	2	3	3	5	2	4	4
4	1	1	5	4	3	2	4	4	2
4	2	2	4	2	5	5	4	4	4
3	2	1	4	4	5	4	4	4	5
2	2	2	3	4	4	5	3	5	4
2	2	1	4	5	4	4	3	5	3
3	2	1	3	4	5	4	3	2	4
3	1	2	3	5	4	5	1	1	1
2	1	2	4	3	2	3	4	5	4
2	2	2	5	2	1	5	1	5	1
3	2	2	3	4	3	3	3	1	2
1	1	2	2	1	3	3	4	3	4
4	2	2	3	4	5	5	4	3	5
1	1	2	4	4	3	2	5	5	5
1	2	1	4	3	5	5	2	2	4
2	1	1	4	4	2	4	1	4	3
4	1	2	3	5	4	2	4	3	4
4	1	2	4	5	4	5	4	5	2
4	1	2	5	4	4	5	3	4	5
3	2	1	5	4	2	5	4	5	4
1	2	2	4	4	3	4	4	5	4
3	1	2	2	3	4	5	5	3	5
2	1	1	3	5	4	2	5	4	1
4	1	1	2	5	3	3	2	2	1
1	2	1	4	5	4	4	1	1	2
2	1	2	3	4	1	1	1	2	4
3	1	2	2	4	4	1	4	4	4
4	2	2	5	5	4	3	1	5	5
1	2	2	2	4	1	5	3	1	3
4	1	2	4	3	5	5	4	4	5
3	1	1	4	2	4	4	5	5	3
2	2	2	4	1	2	4	4	5	3
4	2	1	4	5	3	4	3	4	3
2	2	2	2	5	4	4	4	3	5
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	1	2	3	5	5	4	2	2	2
4	1	1	4	4	2	4	2	4	4
1	1	1	5	5	4	4	1	3	3

3	1	2	5	5	2	1	2	2	4
4	2	1	4	4	2	3	4	4	3
4	2	1	4	4	3	1	5	4	2
1	2	1	4	3	4	3	2	3	4
3	1	1	4	3	5	2	2	5	5
1	1	2	5	3	5	3	4	1	2
2	1	1	3	1	5	3	5	4	1
4	2	1	5	5	4	4	3	3	4
3	2	1	2	4	4	3	4	3	4
3	1	2	3	5	5	5	2	5	2
4	1	1	4	2	2	5	4	4	5
2	2	1	5	5	4	5	2	2	4
1	1	2	1	4	4	4	5	3	5
4	1	2	1	3	3	5	5	5	2
2	2	1	5	4	3	4	3	3	2
1	2	1	4	1	5	4	2	5	5
1	1	2	3	2	2	2	4	2	4
2	2	1	5	4	5	2	5	5	3
2	2	1	3	5	2	5	4	4	4
3	2	1	4	4	3	2	2	2	3
2	1	2	4	5	4	4	2	3	4
1	1	2	3	4	4	4	5	4	3
2	2	1	3	5	3	1	1	2	4
1	1	2	4	3	4	4	3	3	4
3	2	2	5	5	5	3	5	3	5
3	1	2	4	2	1	4	4	1	4
1	1	2	5	5	4	4	2	5	5
1	1	2	3	4	1	4	4	3	1
1	1	1	4	4	3	3	5	1	2
3	2	1	5	2	4	4	4	5	3
1	2	2	3	2	3	4	1	5	1
2	1	1	1	4	4	5	5	3	2
1	1	2	4	5	1	5	5	4	4
1	1	2	4	2	3	3	5	4	4
2	2	2	1	5	4	2	2	5	2
2	1	1	1	4	5	3	3	4	3
3	1	2	4	1	5	3	3	5	1
2	2	2	3	2	2	4	2	2	2
3	2	2	3	2	4	1	1	4	4
3	2	1	4	5	4	1	5	3	2
4	2	1	4	5	5	4	5	2	2
2	1	1	4	5	4	3	3	1	5
3	2	1	2	5	5	3	3	2	2
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	1	1	4	5	4	2	4	4	4
2	1	2	4	4	4	2	5	5	3
3	1	1	2	4	4	3	3	3	1

3	1	1	4	4	5	5	3	4	2
3	2	1	1	4	3	5	4	3	3
1	2	2	4	5	3	3	2	3	1
2	2	1	3	5	5	3	4	2	1
1	2	1	5	3	5	1	5	2	2
2	1	2	5	2	1	4	4	1	4
1	1	2	3	4	4	2	5	2	4
1	1	1	4	5	3	4	4	4	1
3	1	1	4	2	5	3	4	5	1
3	1	1	5	1	5	2	5	4	3
1	2	2	3	4	4	5	4	1	5
1	2	2	4	2	5	2	4	4	3
2	1	1	4	3	4	1	3	2	5
3	2	1	4	3	2	2	4	2	2
3	1	1	5	1	4	5	4	5	3
3	1	2	4	5	5	4	1	4	1
2	1	1	5	5	5	2	4	3	2
2	1	1	3	4	1	3	5	1	1
4	2	1	1	1	5	1	5	2	1
4	1	1	3	4	2	3	4	4	1
4	1	2	3	3	3	2	5	1	2
1	1	1	5	5	4	5	5	3	1
1	1	1	3	3	4	3	5	3	5
3	2	1	2	3	2	5	1	2	5
3	2	1	4	1	1	4	4	1	4
4	2	2	3	1	4	5	5	4	4
4	1	1	4	4	4	4	3	1	4
3	2	1	5	3	4	4	3	2	2
4	1	2	3	1	4	2	5	1	2
3	2	2	1	3	3	4	4	3	5
3	2	2	2	5	2	4	5	5	5
4	1	2	4	1	3	3	2	2	4
1	2	2	4	4	1	1	5	5	1
3	1	1	4	4	3	4	2	5	3
3	1	2	5	5	4	4	4	4	4
1	2	2	5	5	5	5	5	4	4
4	1	2	5	4	3	5	5	4	5
3	1	1	1	1	5	2	3	4	5
3	2	2	1	2	4	5	5	3	2
1	2	2	4	4	1	5	5	2	2
2	2	1	5	4	4	2	3	3	3
3	1	1	3	4	3	1	4	4	3
3	2	1	4	4	5	4	4	4	2
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	2	2	2	4	5	4	2	5	4
4	2	2	4	1	2	2	2	1	3
1	1	2	3	5	2	4	5	4	3

1	1	1	4	4	5	1	1	3	4
3	1	2	4	3	4	4	3	4	5
4	2	2	4	1	3	4	4	1	1
4	1	2	4	2	4	4	4	5	4
2	2	2	4	4	3	4	3	3	2
1	1	2	4	4	1	2	4	1	4
1	1	1	4	1	3	5	3	5	4
4	2	2	3	2	1	4	4	4	4
2	2	1	2	2	4	5	4	5	2
3	2	1	1	2	5	5	5	4	4
2	1	1	5	4	5	4	3	3	2
4	2	2	1	1	3	5	4	2	1
2	2	2	3	4	5	4	4	5	3
1	1	1	4	5	1	5	3	1	5
3	2	2	5	5	5	4	2	4	1
1	1	1	5	4	5	3	2	2	4
3	2	1	4	4	4	3	2	2	3
2	2	2	2	4	4	4	4	4	4
2	1	2	3	1	3	5	4	5	1
2	1	1	5	1	2	5	4	5	2
4	2	2	5	2	4	4	2	4	3
1	1	1	4	5	2	4	4	3	1
1	2	1	4	5	1	3	4	4	4
3	1	1	2	3	4	2	3	2	3
4	1	1	4	4	3	4	5	5	1
4	1	2	3	5	3	2	4	1	1
4	2	2	3	3	4	5	4	2	4
3	2	2	5	1	3	2	3	4	3
4	1	1	4	4	4	5	4	4	3
4	2	1	3	5	2	2	4	3	1
1	2	2	3	4	5	2	5	2	5
2	1	1	4	2	3	4	5	5	5
4	1	1	3	3	4	3	5	3	2
4	1	1	2	3	4	4	2	3	4
4	2	1	3	4	1	3	3	4	4
4	1	2	4	2	3	4	3	1	5
3	2	2	1	4	4	4	4	4	4
4	1	2	5	5	4	4	4	5	1
4	2	2	4	4	3	4	3	4	4
3	1	2	4	4	3	2	5	5	2
4	2	2	4	2	3	4	4	1	4
2	1	1	5	4	3	5	5	4	5
2	2	1	4	5	1	4	5	5	2
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	1	1	2	3	5	3	4	4	4
1	2	1	4	2	4	5	4	2	4
4	2	2	1	3	2	4	1	4	2

3	2	2	5	3	4	4	3	4	5
3	2	2	4	2	4	4	3	4	2
2	1	2	4	3	2	5	4	4	4
2	1	1	1	4	3	3	1	2	5
1	2	1	1	4	4	3	5	3	3
4	1	2	4	5	3	4	4	3	1
3	1	2	4	4	1	2	4	4	5
2	2	1	5	4	5	5	5	5	2
3	1	1	4	2	4	3	2	4	3
3	2	1	3	4	1	3	5	5	3
1	1	2	4	4	2	3	4	3	1
2	2	2	5	3	2	1	4	4	5
3	1	1	1	3	5	4	4	4	3
4	1	2	3	2	2	5	1	5	4
4	2	2	2	2	3	1	2	1	4
1	1	2	1	4	3	3	3	3	4
3	2	2	3	5	1	4	5	3	5
4	1	1	3	5	5	5	4	3	5
4	2	1	3	5	4	5	3	4	4
2	2	1	3	3	3	5	1	3	4
1	2	1	5	1	5	5	5	5	3
3	1	1	4	1	1	5	4	1	4
2	2	1	4	4	3	3	4	1	2
3	1	2	4	4	5	2	3	1	4
3	2	2	5	5	5	4	4	3	4
3	2	1	2	2	4	5	2	4	2
1	2	1	3	2	3	5	5	5	5
3	2	2	3	3	3	5	5	1	3
4	1	2	4	5	4	4	3	4	1
4	2	2	3	4	5	3	5	4	4
4	2	2	5	5	2	5	2	1	3
1	1	2	5	2	5	3	5	3	4
1	2	1	2	3	4	3	5	4	5
1	1	1	4	5	4	4	4	2	3
4	1	1	2	4	3	5	2	3	4
1	1	1	2	4	4	1	5	4	5
2	2	1	2	4	2	3	4	4	5
2	2	2	3	3	4	4	4	3	1
2	2	2	4	2	1	4	5	3	5
1	2	1	5	4	4	4	4	3	4
2	1	2	3	3	5	4	3	3	4
1	1	2	4	4	5	1	3	3	2
2	1	2	1	2	5	5	2	2	4
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	2	1	5	5	3	4	4	3	3
2	1	1	2	3	2	5	4	3	3
1	1	2	4	2	4	3	3	4	2

2	1	1	3	4	4	5	2	3	4
1	1	1	4	5	4	5	2	4	3
1	2	1	1	5	1	2	2	5	4
2	1	2	2	5	3	4	4	4	3
2	1	1	5	2	4	1	4	4	3
4	1	1	4	4	4	4	5	4	4
2	2	2	5	1	4	3	3	4	5
1	2	1	4	3	3	3	3	1	1
2	1	1	1	1	5	5	4	4	3
1	2	2	3	4	4	3	4	5	2
3	1	1	4	3	4	3	3	4	2
4	1	2	5	4	5	2	2	4	3
1	2	2	1	4	1	4	3	5	5
3	1	1	1	3	5	1	5	2	5
4	1	2	4	2	5	3	3	3	4
1	2	1	4	3	4	3	5	4	4
2	1	2	4	2	5	2	5	5	4
4	2	2	5	5	1	4	4	4	5
1	1	2	4	4	5	4	4	4	1
2	1	2	3	5	3	2	1	2	3
2	2	2	2	2	4	5	5	4	3
2	1	2	5	4	3	5	2	2	4
2	2	2	3	5	1	3	4	2	4
3	2	2	2	2	3	5	5	2	4
1	1	2	4	1	5	4	4	3	4
4	2	2	2	3	4	5	2	5	4
4	1	2	5	5	4	3	3	2	5
2	2	2	3	2	2	4	4	4	2
3	2	1	4	4	4	4	4	4	4
2	1	2	4	5	4	4	3	4	5
2	1	2	1	3	4	2	1	4	4
4	2	1	4	1	2	3	4	2	4
4	1	1	3	1	4	4	3	1	1
3	2	2	5	4	5	2	2	1	1
1	2	1	4	4	2	1	3	3	3
3	2	1	4	4	2	4	4	2	4
4	1	2	2	3	1	4	4	4	3
2	1	1	5	3	4	1	4	2	4
4	1	2	2	3	1	4	4	4	1
3	1	1	2	4	1	5	4	4	3
1	2	2	2	2	3	3	4	2	5
3	1	1	5	1	4	2	3	4	2
3	2	1	3	4	3	1	4	5	4
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	2	1	2	5	3	3	4	5	5
4	2	1	4	4	4	2	3	2	4
3	2	1	5	2	4	4	1	4	5
4	2	1	1	3	2	1	1	4	5

4	1	1	5	4	3	3	3	5	2
4	2	2	4	2	4	3	3	1	5
2	2	2	3	3	5	3	4	5	4
1	1	2	4	5	3	3	3	4	1
3	1	1	5	5	3	5	1	4	5
1	1	2	1	2	2	4	2	4	5
4	1	1	4	1	5	5	4	2	2
2	2	2	3	5	1	4	4	3	1
3	1	2	4	4	4	2	3	4	2
4	2	2	4	1	5	2	4	4	4
3	1	1	4	2	4	4	4	2	3
4	1	2	5	3	3	3	3	3	3
1	1	2	4	4	3	3	4	4	4
2	1	1	4	5	5	4	2	4	5
1	2	2	2	2	5	4	4	4	4
3	1	2	4	4	4	4	4	5	3
1	2	1	3	1	1	4	1	3	5
1	1	2	2	4	4	1	4	1	5
2	2	2	4	4	5	3	5	2	2
1	2	2	1	4	2	3	5	2	1
4	2	1	3	3	5	3	3	3	3
4	2	2	4	3	3	1	4	3	4
2	2	1	4	5	4	4	5	5	5
2	2	2	4	4	2	5	4	5	5
4	1	2	3	4	4	3	4	3	1
3	1	1	1	3	2	4	4	1	3
2	2	1	4	3	2	5	2	4	4
3	1	2	5	5	3	4	5	1	2
2	1	2	5	4	3	4	4	5	1
4	1	1	2	4	4	3	4	1	5
4	1	1	2	4	4	3	5	3	4
4	1	1	2	5	4	5	2	3	5
1	2	2	1	2	5	4	4	3	3
1	1	2	2	5	5	4	2	4	5
1	1	1	4	5	4	5	2	2	5
4	1	1	4	4	1	5	5	4	5
4	1	1	4	3	5	5	3	1	2
2	1	2	5	3	5	3	4	4	4
4	1	2	2	5	5	5	3	3	4
2	1	2	5	5	4	5	4	4	3
4	1	1	2	4	4	4	3	4	1
3	1	1	4	2	5	4	4	1	4
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	1	1	1	4	5	3	4	5	5
1	1	1	4	4	4	4	5	3	4
4	1	2	5	4	2	4	1	3	4
1	2	1	5	5	3	4	3	5	5

3	1	1	4	1	5	5	4	5	3
2	2	2	3	3	3	4	1	3	2
4	1	1	3	4	2	4	5	2	5
2	2	1	1	5	2	5	1	2	4
1	1	2	4	2	2	4	4	3	4
3	1	2	4	4	1	3	5	3	5
1	2	1	4	5	5	3	4	2	4
2	1	2	1	5	3	1	3	2	5
1	2	1	2	3	4	4	5	2	1
1	2	1	5	2	4	2	3	5	4
4	1	2	3	2	4	4	3	3	4
1	2	1	1	4	3	2	3	4	1
4	2	1	4	4	3	2	5	2	3
1	2	2	5	5	5	3	4	5	2
1	2	1	1	4	4	3	5	4	4
4	1	2	2	4	2	2	3	5	3
1	1	1	3	2	2	2	2	4	4
2	1	1	5	4	2	4	4	2	3
1	2	1	3	2	3	1	4	4	4
1	2	1	2	3	4	5	4	2	2
2	1	2	2	2	2	4	5	2	5
2	2	1	5	2	1	2	3	4	4
1	2	1	2	2	2	5	4	5	3
4	2	1	5	3	4	2	2	5	4
3	2	1	5	3	2	3	3	1	3
2	2	1	2	4	5	5	5	5	3
3	1	1	4	4	2	2	3	3	4
1	1	2	2	4	4	3	5	1	3
4	1	2	5	2	5	3	1	3	1
2	1	1	1	3	2	3	4	4	3
4	1	2	5	3	1	5	2	4	4
1	1	2	4	5	2	4	2	4	5
2	1	1	4	3	3	4	3	3	1
1	1	2	1	2	4	4	4	4	3
3	2	1	4	1	4	5	5	4	3
4	1	1	2	5	5	3	4	4	4
1	2	1	4	5	3	1	4	5	4
4	2	2	4	4	5	5	4	2	2
1	2	1	1	5	4	2	1	2	4
1	1	1	2	1	3	4	2	5	4
4	1	1	2	4	2	4	3	4	4
4	1	2	2	4	5	3	5	5	5
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
2	1	2	3	2	4	3	5	4	4
1	2	1	2	3	4	4	1	4	4
1	1	2	4	1	5	4	5	1	4
4	2	1	1	5	5	3	4	4	4

1	2	1	1	3	4	4	4	2	4
3	2	2	5	5	1	4	4	4	5
4	2	1	3	4	1	2	4	5	4
4	2	2	1	4	4	5	4	4	2
3	2	2	2	2	2	3	4	4	3
4	2	1	3	2	3	2	2	3	5
4	1	1	4	1	1	4	4	3	1
2	2	2	3	4	4	1	5	5	5
2	2	1	5	1	1	4	5	5	2
1	1	2	3	5	4	4	3	1	2
4	2	2	4	1	3	2	3	4	4
1	2	2	5	4	4	4	2	4	5
4	2	1	5	3	5	5	5	1	4
2	2	2	1	5	5	2	4	4	4
2	2	2	2	4	2	3	3	4	3
1	2	1	3	4	5	3	5	5	2
1	2	1	4	1	3	4	5	5	1
1	1	1	5	3	5	3	4	4	1
3	1	1	3	3	5	3	4	3	5
4	1	2	4	3	2	1	5	4	3
2	2	2	4	4	4	4	5	2	2
4	1	2	2	3	1	4	5	4	5
1	2	2	5	4	4	1	3	4	4
3	2	1	4	3	3	4	4	4	3
1	2	1	2	3	3	1	1	2	4
4	1	2	5	5	4	1	5	5	1
4	1	2	4	4	4	2	4	4	1
1	2	2	5	2	2	4	3	5	3
3	2	1	3	4	2	4	4	1	5
2	1	2	1	4	4	4	5	5	4
2	2	2	5	2	4	4	2	4	5
2	2	1	4	1	5	2	4	1	5
4	1	2	2	4	4	3	2	4	3
2	2	2	4	4	2	5	4	4	4
3	1	2	1	3	5	1	5	5	5
3	1	1	4	3	5	2	3	4	3
1	1	2	5	4	5	3	2	1	4
4	1	1	4	4	5	2	3	2	1
3	1	2	1	4	4	3	2	5	5
2	2	2	5	1	4	4	4	3	2
2	1	1	3	4	4	4	3	3	5
4	1	2	4	1	3	4	2	1	4
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	2	1	4	2	4	2	2	4	4
3	1	1	4	4	5	1	4	3	4
2	1	2	1	2	4	2	2	1	4
4	2	1	4	5	5	3	3	4	4

2	1	2	4	4	4	1	5	5	4
4	2	1	1	3	2	1	4	4	2
3	1	2	4	2	5	5	2	2	2
2	1	2	5	3	4	3	1	5	5
3	1	1	3	4	1	4	3	5	3
1	2	1	4	1	4	4	2	3	4
1	1	1	5	4	4	4	4	3	3
3	2	1	2	5	4	1	4	2	5
4	1	1	4	4	1	3	3	5	2
3	1	2	5	5	4	4	1	4	5
4	1	1	3	4	1	4	3	3	2
4	1	1	4	2	3	4	4	3	4
2	1	1	2	5	3	2	5	5	1
3	2	1	5	2	5	4	4	1	3
4	1	1	3	3	5	1	3	3	5
2	1	1	3	4	4	5	3	3	4
2	2	2	2	5	4	3	4	4	1
3	2	2	3	4	4	4	4	4	4
1	2	1	3	5	1	3	4	3	3
2	1	2	5	3	4	3	5	4	4
3	2	2	3	2	4	5	4	3	4
3	2	2	2	4	4	2	4	4	2
2	2	2	5	3	3	4	5	2	5
3	1	2	2	4	3	4	2	3	2
4	2	2	1	4	1	1	2	5	3
4	2	2	4	3	5	4	3	4	2
3	1	1	1	3	4	2	4	4	4
3	1	2	5	3	2	1	1	3	4
2	2	2	4	3	5	2	3	3	2
4	2	1	1	1	3	5	4	5	4
3	1	2	4	3	5	3	2	2	4
3	1	1	3	5	2	2	4	4	1
3	2	2	1	4	4	4	4	4	4
1	1	2	4	3	4	3	5	4	1
4	1	1	3	3	4	2	5	3	2
1	1	2	1	3	2	2	1	4	1
4	1	2	4	4	5	4	3	3	5
3	2	2	5	4	3	5	5	4	3
4	2	1	5	4	2	5	3	3	3
4	2	1	2	2	3	2	2	2	3
1	1	1	4	3	2	5	1	2	4
1	2	1	4	5	2	1	4	4	5

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	1	1	1	1	4	5	3	4	2
3	1	2	4	4	4	3	4	3	3
1	2	2	5	2	1	3	1	3	2
4	1	2	3	3	4	3	4	5	3

3	2	1	3	2	4	5	5	5	3
3	1	2	4	3	2	3	2	5	2
3	1	1	5	4	2	4	2	2	3
3	1	2	1	3	2	1	5	2	3
3	2	2	3	5	5	3	2	5	3
4	1	1	5	1	5	2	2	5	4
3	1	1	4	4	5	5	4	4	4
4	1	1	2	3	2	5	4	3	4
1	2	2	2	3	2	1	4	2	5
3	2	1	1	2	2	4	5	5	1
3	2	2	4	4	1	3	4	4	5
3	1	1	3	4	5	5	2	1	1
4	1	1	4	3	2	2	1	1	5
4	2	2	4	4	5	4	2	5	2
1	1	2	3	4	4	3	3	1	4
3	1	2	4	3	1	2	1	4	4
1	2	1	4	3	4	3	5	2	4
1	1	2	2	1	5	4	4	2	4
2	2	2	3	4	4	5	5	4	3
4	2	1	4	4	4	2	5	3	3
1	1	1	4	5	5	5	4	4	2
4	1	2	5	2	4	4	5	5	5
4	2	1	4	3	4	4	5	1	4
2	1	1	3	4	2	4	2	3	1
4	1	1	3	4	1	3	1	3	5
3	1	1	3	4	5	3	3	4	4
2	2	2	5	1	2	4	4	4	4
2	2	2	4	3	2	3	5	4	4
2	1	2	5	5	4	3	2	4	4
3	2	1	4	2	4	4	2	3	5
1	2	1	4	4	4	3	4	4	4
3	1	2	1	2	3	5	1	4	4
1	2	1	5	1	5	5	4	4	4
3	1	2	3	4	5	2	4	3	4
3	1	2	4	4	3	3	3	3	3
4	1	1	4	2	4	1	3	2	4
4	1	1	4	5	4	4	2	4	3
4	1	2	5	1	3	4	5	3	3
3	1	2	3	4	4	2	2	2	5
2	1	1	2	1	2	4	3	4	3
4	2	2	3	3	4	1	5	3	2
3	1	2	5	3	4	2	1	4	4
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	2	2	1	4	3	3	4	1	4
1	1	2	4	4	2	4	4	4	5
3	2	2	5	5	2	4	5	5	3
2	1	2	2	4	4	4	3	2	3

3	2	1	2	4	4	2	4	4	4
3	2	1	1	3	3	1	4	4	4
3	1	2	4	5	2	4	3	3	4
2	1	1	3	2	3	4	1	5	4
1	1	1	3	4	2	5	3	3	4
3	1	2	5	2	5	5	5	4	4
4	2	2	4	1	5	2	2	3	5
2	2	1	4	2	4	5	3	4	3
1	2	1	2	5	3	2	5	5	4
2	2	2	4	3	2	5	4	2	5
2	1	1	3	2	3	2	4	4	3
1	1	2	5	5	5	5	4	4	1
4	2	2	4	1	3	4	4	4	5
3	2	2	4	4	5	2	4	2	3
3	2	2	3	2	3	5	5	4	4
2	1	2	3	5	4	4	3	4	3
2	2	1	4	3	4	5	4	2	3
4	1	1	4	3	3	2	2	5	5
4	1	1	2	5	5	4	4	4	4
1	2	2	4	1	1	5	4	3	4
3	1	2	3	3	4	4	1	4	3
1	1	2	3	4	3	4	4	3	2
2	1	2	4	4	2	4	4	5	4
2	1	2	4	4	2	5	3	4	5
4	1	2	5	4	4	2	4	3	1
4	2	2	3	4	3	3	5	3	4
3	1	2	4	5	4	5	3	1	4
3	2	2	4	2	5	1	4	4	3
3	2	1	4	1	1	4	4	4	4
3	1	2	1	3	3	5	5	4	5
3	1	1	2	4	5	2	3	4	4
3	2	2	1	2	3	2	3	1	4
2	2	2	4	3	5	2	1	4	2
2	2	1	4	3	4	4	5	2	5
3	1	2	4	4	1	5	2	1	3
2	1	1	2	3	1	4	4	3	1
3	2	1	4	4	3	5	4	4	3
4	1	2	5	2	3	4	5	4	1
2	2	2	2	3	2	4	4	4	5
2	1	2	4	4	2	2	5	2	4
2	2	2	5	1	2	1	4	4	1
4	1	1	3	2	4	1	1	4	5
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
3	2	2	1	5	4	5	2	5	3
4	2	1	4	4	2	1	5	1	4
3	1	1	3	5	2	1	3	5	4
1	1	1	4	5	3	1	4	5	2
1	1	2	4	3	5	4	4	4	5

3	2	2	4	3	2	4	3	3	4
3	1	1	2	5	1	4	5	3	5
4	1	1	4	4	1	3	1	1	4
3	2	1	3	1	4	4	5	1	3
4	1	1	5	4	2	3	4	4	4
3	1	2	3	5	5	4	3	5	4
3	1	1	3	2	4	3	2	1	1
1	2	1	4	4	4	4	5	4	4
1	1	2	3	5	2	2	1	1	2
2	2	2	5	4	4	4	3	1	4
4	2	2	4	2	3	3	3	3	4
3	1	1	4	4	4	5	5	1	1
4	2	1	3	5	4	3	1	2	2
1	1	2	2	1	5	4	4	4	5
2	1	1	3	1	3	2	3	4	1
2	1	1	4	5	1	5	2	2	2
1	1	2	4	3	5	3	3	4	5
4	2	2	4	1	1	3	5	1	5
2	2	2	5	5	3	1	3	1	5
3	1	1	1	5	4	4	2	4	3
2	1	1	3	4	1	1	5	3	3
3	1	1	4	4	4	3	1	2	5
3	2	2	4	4	5	5	2	4	3
2	1	2	3	3	4	5	2	5	4
2	2	2	1	5	4	2	2	4	5
3	1	1	4	5	3	4	1	4	4
3	2	1	3	5	4	5	1	3	2
2	2	1	4	4	1	4	4	4	4
2	1	1	1	5	3	5	3	3	2
2	2	1	4	1	4	3	2	2	5
4	2	2	3	4	1	3	2	4	3
2	1	2	5	4	4	5	4	4	3
1	1	1	2	5	4	3	3	1	4
3	1	1	4	2	4	2	4	4	4
4	1	1	2	3	4	4	4	4	3
3	2	1	3	3	5	4	4	2	1
1	2	1	4	1	4	5	4	3	5
1	2	1	2	5	4	5	2	4	2
4	1	1	1	3	2	1	4	4	3
4	1	2	4	4	4	5	5	4	4
3	2	1	4	4	4	4	1	4	5

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
1	1	2	1	2	4	2	4	5	3
3	1	1	5	2	5	4	5	3	2
4	1	1	3	4	4	4	4	3	5
4	1	1	4	5	3	3	2	1	3
1	2	1	5	4	4	2	3	4	5
4	2	1	4	5	3	4	5	4	2

2	2	2	3	4	4	4	4	2	5
1	2	2	4	1	4	2	3	5	5
2	1	2	4	4	3	5	4	4	4
1	1	2	5	1	4	5	5	5	5
4	2	2	4	3	3	4	4	3	4
4	2	1	5	4	5	5	4	4	2
1	2	2	5	5	2	5	3	3	2
4	2	1	3	5	5	2	4	4	3
3	2	1	3	5	2	4	4	4	3
4	1	1	5	2	4	4	4	4	4
2	1	2	1	4	4	4	5	1	3
1	1	2	3	4	4	4	4	4	2
3	1	1	1	1	5	4	5	3	1
3	2	1	5	2	4	5	2	3	4
4	1	1	3	5	4	5	2	4	5
2	1	2	3	5	5	5	5	4	5
4	2	1	3	2	3	1	3	3	4
3	2	1	4	5	3	4	4	3	5
1	2	2	2	4	2	4	4	5	2
3	1	1	4	5	3	4	2	1	2
2	2	2	1	4	5	5	3	4	3
1	1	2	3	3	5	3	4	2	5
4	2	1	5	3	2	4	3	3	5
2	1	1	4	3	4	4	3	1	5
3	1	1	5	3	3	3	2	4	5
2	2	2	4	5	3	3	1	1	1
1	2	2	4	4	5	4	5	5	1
4	1	1	4	3	1	4	5	1	4
2	1	2	1	1	2	3	3	4	4
1	2	1	5	4	3	5	5	3	4
1	2	2	4	2	2	4	1	3	4
2	1	1	1	3	1	4	2	5	4
4	1	2	3	2	4	2	1	2	2
3	2	1	4	3	4	5	1	4	4
2	1	1	4	5	4	4	3	1	3
4	2	1	3	5	4	4	4	1	1
1	2	1	2	4	4	1	5	5	3
3	1	2	2	5	2	2	2	5	2
1	1	2	1	3	4	3	4	4	4
1	2	2	4	4	5	2	3	4	2
Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	1	2	4	5	4	4	4
3	2	2	5	2	2	2	5	4	1
4	1	1	3	4	3	2	4	5	2
2	2	2	4	4	5	5	4	4	3
4	1	1	1	5	4	5	1	3	4
3	2	1	4	2	5	5	2	5	5

4	2	1	4	4	3	5	4	5	5
1	1	2	5	2	4	5	2	4	4
1	2	1	2	4	5	4	1	2	4
3	1	1	3	2	3	5	1	5	4
1	2	2	2	1	2	3	1	4	1
2	1	2	3	4	5	4	4	5	3
1	1	1	5	4	4	5	4	5	1
4	1	1	3	4	4	4	5	1	3
3	2	2	5	4	2	3	2	4	3
2	1	1	4	1	4	1	1	3	4
1	2	2	5	4	5	4	1	1	4
2	1	1	2	3	3	3	2	3	3
2	1	2	5	4	4	3	4	3	4
2	2	2	3	3	5	1	4	4	4
1	1	1	5	4	5	4	1	2	2
4	2	2	2	2	3	3	2	1	5
2	1	1	5	2	2	4	4	4	2
1	2	2	4	5	3	2	5	5	4
3	1	2	1	3	5	4	4	3	2
2	1	1	5	4	4	4	2	4	2
2	2	1	2	1	3	1	3	3	4
2	2	1	5	3	2	4	4	1	3
1	1	1	3	3	4	4	3	3	2
3	1	2	3	4	4	5	1	4	3
1	2	2	1	4	3	2	4	3	1
1	2	2	5	4	2	4	5	4	3
3	1	2	2	3	5	4	5	4	1
3	1	2	4	5	1	1	2	3	2
3	2	1	5	1	1	5	2	2	5
1	2	2	2	4	3	5	3	3	4
1	2	1	3	4	2	4	2	5	3
2	2	1	5	5	4	4	5	5	3
3	2	1	5	4	4	4	5	5	4
2	1	1	4	2	4	3	4	5	1
1	1	2	1	5	5	1	1	3	5
2	1	2	1	3	4	5	4	1	5
2	2	2	5	4	1	1	4	2	5
1	1	2	5	4	5	3	4	5	3
2	1	2	3	3	4	4	4	4	2
4	1	2	5	3	2	5	4	1	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1

2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2
2	1	2	5	4	4	5	2	3	4
4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4
3	2	2	3	3	5	2	4	4	5
2	2	1	4	2	2	2	3	3	4
1	2	2	5	4	5	3	4	3	3
1	1	2	2	4	5	1	4	3	3
1	1	1	2	3	4	4	5	5	2
1	1	2	4	3	4	4	2	4	4

]	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1

2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2
2	1	2	5	4	4	5	2	3	4
4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4
3	2	2	3	3	5	2	4	4	5
2	2	1	4	2	2	2	3	3	4
1	2	2	5	4	5	3	4	3	3
1	1	2	2	4	5	1	4	3	3

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1

2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2
2	1	2	5	4	4	5	2	3	4
4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4
3	2	2	3	3	5	2	4	4	5
2	2	1	4	2	2	2	3	3	4
1	2	2	5	4	5	3	4	3	3
1	1	2	2	4	5	1	4	3	3
1	1	1	2	3	4	4	5	5	2
1	1	2	4	3	4	4	2	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1
2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2

2	1	2	5	4	4	5	2	3	4
4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4
3	2	2	3	3	5	2	4	4	5
2	2	1	4	2	2	2	3	3	4
1	2	2	5	4	5	3	4	3	3
1	1	2	2	4	5	1	4	3	3
1	1	1	2	3	4	4	5	5	2
1	1	2	4	3	4	4	2	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1
2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2

2	1	2	5	4	4	5	2	3	4
4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4
3	2	2	3	3	5	2	4	4	5
2	2	1	4	2	2	2	3	3	4
1	2	2	5	4	5	3	4	3	3
1	1	2	2	4	5	1	4	3	3
1	1	1	2	3	4	4	5	5	2
1	1	2	4	3	4	4	2	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1
2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2
2	1	2	5	4	4	5	2	3	4

4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4
3	2	2	3	3	5	2	4	4	5
2	2	1	4	2	2	2	3	3	4
1	2	2	5	4	5	3	4	3	3
1	1	2	2	4	5	1	4	3	3
1	1	1	2	3	4	4	5	5	2
1	1	2	4	3	4	4	2	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1
2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2
2	1	2	5	4	4	5	2	3	4
4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1
2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2
2	1	2	5	4	4	5	2	3	4
4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4
3	2	2	3	3	5	2	4	4	5
2	2	1	4	2	2	2	3	3	4
1	2	2	5	4	5	3	4	3	3
1	1	2	2	4	5	1	4	3	3
1	1	1	2	3	4	4	5	5	2
1	1	2	4	3	4	4	2	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1
2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2
2	1	2	5	4	4	5	2	3	4
4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4
3	2	2	3	3	5	2	4	4	5
2	2	1	4	2	2	2	3	3	4
1	2	2	5	4	5	3	4	3	3
1	1	2	2	4	5	1	4	3	3
1	1	1	2	3	4	4	5	5	2
1	1	2	4	3	4	4	2	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1
2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2
2	1	2	5	4	4	5	2	3	4
4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4
3	2	2	3	3	5	2	4	4	5
2	2	1	4	2	2	2	3	3	4
1	2	2	5	4	5	3	4	3	3
1	1	2	2	4	5	1	4	3	3
1	1	1	2	3	4	4	5	5	2
1	1	2	4	3	4	4	2	4	4

Age Range	Gender	Event Stat	I felt excite	I felt a sen	The event	I found the	I stayed fo	The event	I actively p
4	1	1	4	2	4	3	4	5	3
2	2	1	3	4	4	3	3	1	4
1	1	2	5	3	3	4	5	2	2
4	1	2	5	4	4	3	1	1	5
3	2	1	4	3	5	2	4	2	4
2	1	1	1	4	4	1	5	5	1
2	2	2	5	4	4	4	2	4	1
2	1	2	4	4	4	4	2	1	2
2	1	2	5	4	4	5	2	3	4
4	1	2	5	4	5	4	4	5	5
4	1	1	5	4	4	1	1	2	1
2	1	2	4	4	4	4	4	2	5
1	1	1	5	2	4	1	4	1	4
3	2	1	5	5	5	2	5	4	4
2	1	1	3	4	2	5	1	4	4
2	1	2	5	3	4	4	5	4	1
3	1	2	3	3	3	2	1	4	4
4	2	2	5	3	5	4	2	3	3
4	2	1	5	3	4	4	4	5	2
4	2	2	2	4	2	2	4	4	5
2	2	2	5	4	3	4	5	5	1
1	1	2	3	4	5	4	3	2	3
1	1	2	5	5	3	5	4	2	1
1	2	2	5	5	5	3	3	4	4
1	1	2	2	4	5	4	2	2	2
1	1	1	4	4	4	5	5	2	2
3	1	1	4	4	3	3	3	5	2
4	1	2	2	4	1	1	2	2	5
1	2	1	2	5	2	3	1	2	3
4	2	2	3	2	3	4	4	5	3
1	2	1	1	2	4	4	1	5	2
4	2	2	4	4	3	1	5	4	4
2	2	2	2	4	3	5	4	4	3
3	1	2	2	3	3	2	4	4	3
4	1	2	4	4	2	2	5	2	5
1	1	1	5	5	5	5	5	1	2
4	2	2	5	4	4	1	3	4	3
1	2	1	4	4	4	4	4	4	4
1	2	2	2	2	4	5	1	3	4
4	1	2	3	4	2	3	3	4	4
3	2	2	3	3	5	2	4	4	5
2	2	1	4	2	2	2	3	3	4
1	2	2	5	4	5	3	4	3	3
1	1	2	2	4	5	1	4	3	3
1	1	1	2	3	4	4	5	5	2
1	1	2	4	3	4	4	2	4	4

Appendix I: Mapping Code

```
from google.colab import drive

drive.mount('/content/drive')

import pandas as pd

bd_data = pd.read_excel('/content/Attendee Event Enagagement Dataset.xlsx')

bd_data.head(1)

#mapping the data

likert_map = {

    'Strongly Disagree': 1,

    'Disagree': 2,

    'Neutral': 3,

    'Agree': 4,

    'Strongly Agree': 5

}

likert_columns = bd_data.columns[3:]

bd_data[likert_columns] = bd_data[likert_columns].replace(likert_map)

bd_data.head(1)

# Check the actual unique values in the columns

print("Unique values in Age Range:\n", bd_data['Age Range'].unique())

print("Unique values in Gender:\n", bd_data['Gender'].unique())

print("Unique values in Event Status:\n", bd_data['Event Status'].unique())

bd_data.head(1)

bd_data['Event Status'] = bd_data['Event Status'].astype(str).str.strip().str.title()

bd_data['Event Status'] = bd_data['Event Status'].map({'Online': 1, 'On-Site': 2})
```

```
# Step 3: Clean and map 'Age Range'
bd_data['Age Range'] = bd_data['Age Range'].astype(str).str.strip().str.title()
bd_data['Age Range'] = bd_data['Age Range'].map({
    '20-30 years': 1,
    '30-40 years': 2,
    '40-50 years': 3,
    'Above 50 years': 4
})
# Step 4: Clean and map 'Gender'
bd_data['Gender'] = bd_data['Gender'].astype(str).str.strip().str.title()
bd_data['Gender'] = bd_data['Gender'].map({'Female': 1, 'Male': 2})
bd_data.head(1)
file_path = "/content/ateg_data.csv"
bd_data.to_csv('ateg_data.csv', index=False)
file_path
```

Appendix II: K-Means Clustering Code

```
from google.colab import drive
drive.mount('/content/drive')
import pandas as pd
een_dataset = pd.read_csv('/content/drive/MyDrive/Attendee Event Enagagement Numeric Dataset.csv')
display(een_dataset)
#import warnings
#warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score
#standardazation of Attendee Event Enagagement Numeric Dataset
scaler = StandardScaler()
ee_scaled_data = scaler.fit_transform(een_dataset)
#application of K-means for 4 clusters
kmeans = KMeans(n_clusters=4, random_state=42)
engagment_clustering= kmeans.fit_predict(ee_scaled_data)
```

```
#assignment of cluster labels to the dataset
een_dataset['Engagement Cluster'] = engagment_clustering
print(een_dataset['Engagement Cluster'].value_counts())
print(een_dataset.head())
engagment_clustering_profiling = een_dataset.groupby('Engagement Cluster').mean(numeric_only=True)
print(engagment_clustering_profiling)
engagment_Label = {
    0: 'Minimally Enagaged',
    1: 'Multidimensionally Engaged ',
    2: 'Highly Cognitive and Quietly Engaged',
    3: 'Highly Affective and Socially Engaged'
}
een_dataset['Engagement Cluster'] = een_dataset['Engagement Cluster'].map(engagment_Label)
e_visual = PCA(n_components=2)
evisual_pca = e_visual.fit_transform(ee_scaled_data)
plt.figure(figsize=(10, 6))
sns.scatterplot(x=evisual_pca[:, 0], y=evisual_pca[:, 1], hue=een_dataset['Engagement Cluster'], palette='viridis')
plt.title('PCA Visualization of Attendee Event Enagagement')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
```

```
plt.grid(True)
plt.show()
engagement_score = silhouette_score(ee_scaled_data, engagment_clustering)
print(f'Silhouette Score: {engagement_score}')
print(f"Inertia (WCSS): {kmeans.inertia_}")
inertia = []
k_engage = range(1, 11)
for k in k_engage:
    kmeans_engage = KMeans(n_clusters=k, random_state=42)
    kmeans_engage.fit(ee_scaled_data)
    inertia.append(kmeans_engage.inertia_)
plt.figure(figsize=(10, 6))
plt.plot(k_engage, inertia, marker='o', linestyle='-', color='b')
plt.title('Elbow Method for Optimal K (Engagement)')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia')
plt.grid(True)
plt.show()
engage_summary = een_dataset.groupby('Engagement Cluster').mean(numeric_only=True)
print(engage_summary)
een_dataset.to_csv('Attendee Event Enagagement Numeric Dataset.csv', index=False)
een_dataset.to_excel('Attendee Event Enagagement Numeric Dataset.xlsx', index=False)
```

```
file_path = "/content/Attendee Event Enagagement Clustered.csv"
een_dataset.to_csv(file_path, index=False)
file_path = "/content/Attendee Event Enagagement Clustered.xlsx"
een_dataset.to_excel(file_path, index=False)
file_path
print("Attendees Engagement Clustered Dataset Saved Succesfully")
engagement_summary = een_dataset.groupby('Engagement Cluster').mean(numeric_only=True)
print(engagement_summary)
!pip install streamlit
import streamlit as st
#loading the clustered data
engage_build = pd.read_csv('/content/drive/MyDrive/Attendee Event Enagagement Clustered.csv')
st.title('Attendees Engagement Clustered')
st.subheader('Engagement Cluster Summary')
st.write(engage_build['Engagement Cluster'].value_counts())
#PCS for visualization
st.subheader('Attendee Event Enagagement Projection')
numeric_data = engage_build.select_dtypes(include='number')
#numeric_data = engage_build.select_dtypes(include='number').drop(columns=['Engagement Cluster'])
e_visual2 = PCA(n_components=2)
evisual2_pca = e_visual.fit_transform(numeric_data)
```

```
engage_build['PC1'] = evisual2_pca[:, 0]
engage_build['PC2'] = evisual2_pca[:, 1]
fig, ax = plt.subplots(figsize=(10, 6))
sns.scatterplot(x='PC1', y='PC2', hue='Engagement Cluster', data=engage_build, palette='viridis',
ax=ax)
plt.title('PCA Visualization of Attendee Event Enagagement')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.grid(True)
st.pyplot(fig)
#view
st.subheader('View Attendee Engagement Cluster')
st.dataframe(engage_build)
st.download_button(
    label="Download Attendee Engagement Data",
    data=engage_build.to_csv(index=False).encode('utf-8'),
    file_name='Attendee Event Enagagement Clustered.csv',
    mime='text/csv'
)
cluster_summary = engage_build.groupby('Engagement Cluster').mean(numeric_only=True)
st.subheader('Engagement Cluster Summary')
st.write(cluster_summary)
print(cluster_summary)
```

```
average_column = engage_build.mean(numeric_only=True)

print(average_column)

cluster_average = engage_build.groupby('Engagement Cluster').mean(numeric_only=True)

print(cluster_average)

cluster_avg = cluster_average.mean(axis=1)

print(cluster_avg)

plt.figure(figsize=(12, 6))

sns.heatmap(engagement_summary, annot=True, cmap='coolwarm', fmt=".2f")

plt.title('Engagement Cluster Heatmap')

plt.ylabel('Engagement Cluster')

plt.xlabel('Features')

plt.tight_layout()

plt.show()

plt.figure(figsize=(12, 6))

sns.countplot(data=engage_build, x='Age Range', hue= 'Engagement Cluster', palette='viridis')

plt.title('Engagement Cluster Distribution'

plt.xlabel('Engagement Cluster')

plt.ylabel('Count')

plt.xticks(rotation=45)

plt.tight_layout()

plt.show()
```

Biodata

Personal Data:

Surname:	AFIKODE
Other names:	SAMSON
Date of Birth:	27 MAY, 1978
Gender:	Male
Local Government Area:	Ibadan South -East
State of Origin:	Oyo State
Nationality:	Nigerian
Marital Status:	Married
Religion:	Christianity
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Lead City University, Toll gate, Ibadan, Oyo state 2023 till date (M.sc, Computer and Information Science).

Olabisi Onabanjo University, Ago-Iwoye. 2003 – 2008 (B.sc Computer Science and Economics).

Olabisi Onabanjo University, Ago Iwoye. 2001 – 2003 (Diploma in Data Processing).

Wesley College of Science, Elekuro Ibadan, Oyo State. 1995- 1998 (Senior school Certificate).

Membership of Professional Bodies:

ANTP Association of Nigerian Theatre Arts Practitioners (Member).

PEPVAN Professional Event Planners and Vendors Association of Nigeria (Member).

Work Experience with Dates:

Ladox Engineering Shell Residential Area Port Harcourt Rivers -State (Technician) –June 2005 – September 2005.

ICT Governor's Office Oke-Imosan, Abeokuta, Ogun State. (Computer Engineer) –SIWES March – August 2007.

NYSC Ministry of Youths & Sports MKO Abiola Stadium Kuto Abeokuta Ogun State - 2008-2009.

JIDE-GBITE PRODUCTIONS – 2007 till date.

INEC Adhoc Staff Kajola local Government -2011.

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Extra Curricula Activities:

Youth Adviser: C&S Church Ile-Ayo International Progressive Estate P&G Oluyole Estate Extension, Ibadan.

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……………………………….   …………………………

Signature   Date

University Compliance Certification

This is to certify that the Thesis of Adegbite Babajide Samson with Matriculation Number LCU/PG/006063, in the department of Computer Science, Faculty of Basic and Applied sciences, 178 Lead City University, Ibadan is in Full compliance with the approved University format and style.

……………………………………..   ……………………………….

Signature   Date