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The Role of Digital Footprints for Destination Competitiveness and Engagement: Utilizing Mobile Technology for Tourist Segmentation Integrating Personality Traits

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ABSTRACT

This study presents a novel approach to tourism market segmentation by integrating personality traits to enhance traditional demographic methods. In partnership with Cumbria Tourism (local DMO), this study conducted in Cumbria, UK, home of the Lake District National Park, the research utilized 1217 quantitative surveys to analyse visitor personality traits, motivations, and activities. Through factor and cluster analysis, five unique visitor segments were identified: Reserved Explorers, Culturally Curious, Diligent Adventurers, Social Explorers, and Balanced Explorers. Each segment displayed distinctive traits, motivations, and activities, further supplemented by chi-square tests that highlighted socio-demographic differences. The findings underscore the value of incorporating personality traits through digital footprints for dynamic segmentation. This methodology not only offers deeper insights into visitor profiles, but it also aids in developing customized marketing strategies and products, determining activity preferences and providing a competitive edge for tourism destinations globally.

1 | Introduction

The choice of segmentation technique has always been a critical question for Destination Management Organizations (DMOs), generally facing resource constraints and limited market research funds (McKercher et al. 2022). While various segmentation options exist, including socio-demographic, geographical, behavioural, and psychographic factors, in the field of tourism, there is not a universally recognized "best" method, and each segmentation basis has its merits and serves specific purposes (McKercher et al. 2022). Cho, Bonn, and Li (2019), argue that given the diverse range of tourism products, amenities, and services offered by most destinations, describing today's tourists comprehensively has become increasingly challenging. Many researchers still rely on conventional criteria for segmentation, such as socio-demographic factors and trip-related characteristics, including age, gender, travel duration, and travel purpose (Morrison 2023). However, other recent research by Kovačić et al. (2022) highlights that while sociodemographic characteristics may influence tourists' activity choices, they are less critical in determining activity preferences.

Existing segmentation methods in tourism face several challenges and limitations. Traditional approaches often rely on visitor surveys, which can be cumbersome, time-consuming, and prone to biases (Wang, He, and Leung 2018). These surveys, while useful for gathering comprehensive information on visitor profiles, predominantly focus on identifying trends in socio-demographics and the sales of existing tourism products and services. However, they may not fully capture the dynamic and evolving nature of tourist behaviours and preferences (Yavorska et al. 2019).

Integrating technology could respond to these challenges, by leveraging mobile devices for extensive data collection, and developing a transformative solution for advanced tourist segmentation. This approach, advocated by researchers such as Gretzel (2022) and Sigala (2018), enables access to diverse data sets, including geolocation, mobile app usage, and social media interactions. Such rich data sources facilitate the creation of detailed, dynamic market segments, with big data analytics offering actionable insights (Solazzo et al. 2022). The integration of technology, particularly through mobile apps, facilitates the seamless absorption of data, significantly easing the clustering process for DMOs (Hossain and Amin 2015). Mobile apps serve as powerful tools for collecting real-time and diverse data, ranging from user preferences, behaviours and activities to geographical information (Wang, He, and Leung 2018). Behavioural data collection, especially, holds potential for personality psychology, a field traditionally dependent on self-assessment methods (Stachl et al. 2017).

Khoi, Phong, and Le (2020), mentions that the psychology of interaction with experiences depends on personality traits. Previous studies by Kovačić et al. (2022) and Alves et al. (2023), have solidified the understanding of personality traits' influence on activity preferences at a destination, demonstrating the effectiveness of personality traits as predictors of tourist activities. This approach not only improves marketing efficacy, but also meets evolving consumer expectations, fostering a stronger connection between destinations and their audiences (Wei, Önder, and Uysal 2024). However, implementing personality-based segmentation frameworks is challenging due to the difficulty of obtaining these attributes cost-effectively and at scale (Wei et al. 2017).

Despite the extensive body of work on traditional segmentation factors like demographics and travel motivations (Li and Kovacs 2024; Otoo, Kim, and Park 2020), the integration of personality traits in tourist profiling is still an under-researched area (Kovačić et al. 2022; Alves et al. 2023). While previous research by Plog (1974), Cohen (1972, 1974, 1979), and Smith (1977) has highlighted the significance of psychographics in understanding tourist behaviour, these models are often critiqued for oversimplifying the complex motivations and behaviours of tourists. They tend to categorize diverse individual experiences into broad typologies, which may not fully capture the variability and nuances of tourist behaviour. To address this gap, this research utilizes the Big Five personality traits approach which delves into the stable, intrinsic psychological characteristics of individuals (Roberts 2019). This study aims to identify the distinct visitor segments based on personality traits, motivations, and visitor activities in Cumbria. Known for its natural beauty and UNESCO World Heritage Sites like The Lake District National Park, Cumbria attracts around 47 million visitors annually (Cumbria LEP 2023). Cumbria Tourism, the region's official DMO, aims to be the UK's top Tourist Board by exceeding visitor and business expectations (Cumbria Tourism, 2024), and the results of this research will help achieve this aim. This wealth of information enables DMOs to employ advanced clustering techniques, leading to more refined and insightful segmentation of tourist markets, that leads from expectation to prediction. Incorporating personality traits into segmentation models highlights the potential of personalized strategies in the digital age.

2 | Literature Review

2.1 | Destination Management Organizations (DMOs) and Tourism Segmentation

Over the years, Destination Management Organizations (DMOs) have transitioned from being primarily marketing-focused entities to assuming a comprehensive management role (Sotiriadis 2021). This development led to multiple implications in strategic planning, brand identity, value co-creation, visitor experience, and broader engagement in tourism development and sustainability (Novotny, Dodds, and Walsh 2024). Gretzel (2022), argues that increased demand for DMOs to adopt a knowledge management role at the destination level, transformed them into what is referred to as "intelligent agents". This transformation implies that DMOs are expected to effectively utilise the collective knowledge assets of the destination, integrating insights from researchers and governments to ensure sustained viability and success in the global marketplace (Gretzel 2022).

In their quest to comprehend and cater to the diverse needs of their target audience, DMOs employ market segmentation strategies. Market segmentation refers to dividing the broader market into distinct segments based on shared characteristics, allowing DMOs to tailor their strategies to specific groups (McKercher et al. 2022). Traditionally, common criteria for segmenting tourism markets, involve socio-demographic factors (e.g., education, gender, age, family size, income), geographical factors (local versus non-local residents), behavioural factors (preferences, usage frequency, brand loyalty), and psychographic factors (lifestyle, interests, motivation, activities, personality) (McKercher et al. 2022). Over the years, there has been a noticeable shift in focus from socio-demographic to behavioural and psychographic factors, reflecting a deeper understanding of the nuanced and dynamic nature of tourist behaviours and preferences (Li and Kovacs 2024; Otoo, Kim, and Park 2020).

Previous research by Plog (1974), Cohen (1972, 1974, 1979), and Smith (1977) created tourist typologies based on psychological characteristics and preferences to describe tourist behaviours, in the context of destination choices. Cohen (1972) was one of the first to propose a tourist typology, which consisted four categories: the *organized mass tourist*, who prefers package tours, highly organized, and favours familiarity; the *individual mass tourist*, who has more control over their itinerary and is not bound to a group; the *explorer*, who plans trips independently and seeks local interactions without full immersion; and the *drifter*, who is highly independent, without fixed schedules, lives with locals, and prioritizes novelty while minimizing familiarization. Following Cohen's (1972) taxonomy, Smith (1977) developed a classification of tourists, identifying seven types: *explorers, elite tourists, off-beat tourists, unusual tourists, incipient mass tourists, mass tourists*, and *charter tourists*. Smith's (1977) typology has been critiqued by Mehmetoglu (2004), because it was based on specific observations of tourist behaviour in particular contexts, basing tourist classifications on their interactions with the host communities, the degree of adaptation to local norms, and their impact on the destinations they visit.

Plog (1974) is considered a pioneer in the development of a tool for directly measuring tourist personality, which has become a widely recognized psychographic measurement model in the tourism industry. The tool conceptualizes the scale as a continuum, with allocentrism and psychocentrism at opposite ends, and has been used to develop a tourist typology. According to Plog (2002), *allocentric tourists* are characterized by their high level of novelty-seeking behaviour and independence, while *psychocentric tourists* tend to prefer familiar environments, exhibit uncertainty avoidance, and conform to social norms. Plog's model became well-known, prompting researchers to extend it by correlating its dimensions with extraversion (Jackson, Schmierer, and White 1999; Hoxter and Lester 1988), sensation seeking, powerlessness, and generalized anxiety (Griffith and Albanese 1996), activation theories (Nickerson and Ellis 1991).

Using the orthogonal scales of Allocentrics-Psychocentrics and Introversion-Extraversion, Jackson, White, and White (2001) proposed four tourist types—*explorer, adventurer, guided*, and *groupie*, a model later examined by Jackson and Inbakaran (2006). They confirmed that Extraversion and Allocentrism are independent constructs, while Openness to Experience and Allocentrism were found to be correlated, as also suggested by Nickerson and Ellis (1991).

Recent research (see Table 1) indicates a shift in tourism typology towards more diverse conceptualizations, with studies emphasizing the ongoing deconstruction of established typologies to reveal the diversity of tourism experiences within them (Uriely 2005). For instance, based on Cohen's individual mass tourist type, Wickens (2002) proposed five micro-types of tourists in Chalkidiki, Greece. These include the *Cultural Heritage* type, interested in the region's cultural, natural, and historical aspects; the *Raver* type, attracted to sensual pleasures, beaches, and nightclubs; the *Shirley Valentine* type, seeking romantic experiences with local men; the *Heliolatrous* type, focused on relaxation and sunbathing; and the *Lord Byron* type, who returns annually for familiarity, nostalgia, and a sense of home. Similarly, Øgaard et al. (2019) expanded Cohen's (1979) classification of tourists, while Bayarsaikhan, Kim, and Gim (2020) developed typologies based on destination choice, referencing Plog's (1974) established framework. Research on creative tourism activities (Remoaldo et al. 2020), and sensitive destinations (Jeong et al. 2018) further diversify tourist clustering insights.

However, while traditional psychographic segments, such as Plog's (1974) model and Cohen's (1979) typologies of tourist experiences, have long provided foundational insights into tourist preferences, these frameworks were developed without access to the nuanced, real-time data now available through mobile technology. In contemporary contexts, where preferences and behaviours can shift dynamically, these broad typologies may fall short in capturing the complexity and fluidity of modern tourist behaviour, especially given the transformative role of mobile technology in shaping how tourists interact with tourism activities. For instance, Ahani et al. (2019) applied machine learning to TripAdvisor data to achieve market segmentation of spa hotel travellers, offering insights into specific customer profiles within this niche. Building on the focus of spa hotels, Nilashi et al. (2021) utilised preference learning to refine traveller segmentation further, identifying distinct customer groups for spa hotels in Malaysia. Similarly, Alsayat (2023) applied social data analytics to examine hotel choice behaviours among travellers in Saudi Arabia. Expanding this approach to eco-conscious tourism, Yadegaridehkordi et al. (2021) integrated Multi-Criteria Decision Making (MCDM) and clustering to segment travellers based on online reviews, illustrating the broader utility of data-driven segmentation in hospitality.

Building on this foundation, integrating insights from technology diffusion studies provides a more nuanced and contextually relevant understanding of tourist behaviour, closely aligning with the study's research objectives. In particular, the adoption of the Big Five personality traits approach offers a psychologically detailed alternative to traditional typologies, which can be limiting in an era where data from mobile technology increasingly allows for real-time behavioural insights. Personality traits such as openness, conscientiousness, extraversion, agreeableness, and negative emotionality provide a stable, intrinsic foundation for understanding behavioural tendencies across various contexts, including travel (Roberts 2019). When analysed alongside the continuous data generated through mobile technology, these traits offer a detailed view of individual variations and complex decision-making processes, supporting a more predictive and comprehensive model of tourist behaviour.

Furthermore, motivation is seen as a crucial criterion for segmenting tourists (Shi, Liu, and Li 2018). Recent research by Pan and Shang (2023) emphases on the psychological and physiological drivers of tourists. Empirical studies exploring tourist motivation incorporate various theoretical models, such as the push-pull factor framework (Dann 1977), escape-seeking model (Iso-Ahola 1983), and travel career pattern model (Pearce and Lee 2005). Predominantly, travel motivations like novelty and escape consistently emerged in tourism research despite the common understanding of their complexity depending on the destination (Morrison 2023; Maghrifani, Liu, and Sneddon 2022). The interest in segmenting tourism markets based on travel motivations is growing, as it allows for customising offerings to suit specific tourist groups (Li and Kovacs 2024). For example, VisitScotland employs different segments that are determined by travellers' motivations and behaviours such as adventure seekers, curious travellers, engaged sightseers, food-loving culturalists, and natural advocates (VisitScotland 2024). Similarly, Destination Canada breaks travellers into groups based on their social values and world views, with free spirits, cultural explorers, and authentic experiencers representing its key global markets (Destination Canada 2024).

However, acquiring data on visitor profiles poses significant challenges. Traditionally, DMOs have relied on visitor surveys as a primary method to gain insights into travellers' behaviours (Choe and Fesenmaier 2021). For instance, Cumbria Tourism employs surveys to gather comprehensive information on visitor profiles, covering demographics, visitation patterns, motivations for visiting Cumbria, information sources, transportation, expenditures, activities, overall experiences, and trip

TABLE 1 | Psychographic tourist segmentation studies.

Authors	Main factors	Destination	Methodology	Sample size	Identified segments
Bayarsaikhan et al. (2020)	Plog's personality types Destination choices Travel-related variables	Mongolia	Multinomial logistic regression	406	Psychocentric tourists: Prefer urban tourist attractions. Midcentric tourists: Inclined towards natural-rural areas. Allocentric tourists: Likely to visit primitive areas.
Remoaldo et al. (2020)	Travel motivations Perceptions evaluation of activities	Portugal	Surveys Cluster analysis	814	Novelty-seekers Knowledge and skills learners Leisure creative-seekers
Jeong et al. (2018)	Travel motivations Attitudes Travel-related characteristics	Lao people's Democratic republic	Surveys Factor analysis Cluster analysis	722	Nature and cohesion-seeking tourists Nature-seeking tourists Passive nature-seeking tourists Want-it-all tourists
Øgaard et al. (2019)	Travel preferences, Destination valuations, Destination perceptions	Norway	Surveys Factor analysis Cluster analysis	1162	Cohen's (1972) typology (organized mass tourist, individual mass tourist, the explorer, the drifter) with an additional segment: Lone Explorer, with less emphasis on cultural immersion and social contact
Cohen (1979)	Modes of tourist experience (degree of institutionalization—tour packages, guided tours; novelty vs. familiarity, interaction with local culture, travel independence)	Not specified	Qualitative analysis	Not specified	Organized mass tourist Individual mass tourist The explorer The drifter
Wickens (2002)	Choice of holiday, types of activities, views about the host community	Chalkidiki, Greece	Qualitative analysis	86	Cultural heritage The raver The shirley valentine The heliolatrous The lord byron
Plog (1974)	Psychographic characteristics of tourists (personality-venturesomeness vs. dependability, values, attitudes, interests, and lifestyles)	United States	Qualitative analysis	Over 60 in-depth interviews and monitoring 200 telephone calls;1600 surveys	Psychocentric tourists Near-psychocentric tourists Mid-centric tourists Near-allocentric tourists Allocentric tourists

satisfaction. The latest Cumbria Visitor Survey in 2022 involved face-to-face interactions with over 2000 visitors, at more than 60 locations across Cumbria (Cumbria Tourism 2022). Considering that Cumbria attracts 47 million visitors annually (Cumbria LEP 2023), this approach has limitations in data sample acquisition and effectiveness.

Studies by Wang, He, and Leung (2018) and Önder, Koerbitz, and Hubmann-Haidvogel (2016) highlight the limitations inherent in traditional market research methods, including budget constraints, rigid timeframes, dependence on localized face-to-face surveys, and results that are often narrowly focused on specific demographics. These findings underscore the need for innovative research approaches to overcome these constraints and gain a more comprehensive understanding of tourist behaviours utilizing the technological advancement of mobile devices.

2.2 | Integrating Mobile Technology

The digital transformation of the tourism sector and the widespread adoption of mobile technologies are redefining how destinations engage with and serve visitors (Pappas et al. 2021). As travellers increasingly rely on smart devices to plan, navigate, and share their journeys, mobile technology has become central to destination marketing and management, providing destinations with competitive advantages (Parapanos and Michopoulou 2023; Kim and Kim 2017). Gretzel et al. (2015) highlighted that the collection and organisation of data through digital platforms not only enriches onsite experiences but also strengthens relationships between destinations and visitors, fostering loyalty and satisfaction. With instant access to information, directions, and recommendations, mobile devices support seamless, personalised encounters that meet visitors' rising expectations for dynamic, engaging experiences (Stankov and Gretzel 2020). The importance of these technologies is heightened by the increased competition in the tourism industry, as destinations that make use of mobile technology to interact with visitors in real-time can better meet immediate needs, improving both visitor satisfaction and operational efficiency (Buhalis, O'Connor, and Leung 2022).

Mobile devices also offer unparalleled advantages in data collection, owing to their portability, accessibility, and sophisticated functionalities, such as GPS tracking and sensor technology that record user interactions in real time (Montag et al. 2021). In contrast to traditional surveys which are limited in scope, frequency, and accuracy, data derived from mobile devices can capture human movement, behaviours, and preferences on a large scale, offering invaluable real-time insights (Wang, He, and Leung 2018; Wang, Park, and Fesenmaier 2012). These dynamic data streams reveal nuanced shifts in travel behaviour across varying conditions, such as the distinctions between peak and off-peak seasons or weekday and weekend travel patterns, and the influence of weather or events on visitor flows. By enabling researchers to study both interpersonal similarities and unique visitor behaviours, mobile technology provides a comprehensive understanding of the diverse groups and patterns within the tourism landscape (Wang, He, and Leung 2018). Furthermore, mobile devices enable the tracking of long-term visitor behaviour, which reveals trends in repeat visitation, evolving interests, and destination loyalty, offering a depth of insight that traditional surveys cannot achieve (Wang, He, and Leung 2018). As such, mobile data fills significant gaps in traditional survey methodologies, offering a robust and nuanced view of tourism behaviours that are invaluable for effective planning and destination management.

Traditional market research methods, such as surveys and questionnaires, present inherent limitations when it comes to capturing the subtleties of visitor motivations and behaviours, especially when precision is needed for targeted marketing and resource allocation (Wang, He, and Leung 2018; Önder, Koerbitz, and Hubmann-Haidvogel 2016). Mobile technology addresses these limitations by enabling DMOs to move beyond broad demographic profiles and into the realm of rich psychographic and behavioural insights. For instance, as Parapanos (2023) argued, mobile data can be fed into machine learning algorithms that analyse and predict visitor preferences based on actual behaviours and observed patterns, thereby enabling DMOs to deliver highly personalised tourism experiences aligned with individual motivations and preferences. This level of personalisation supports deeper visitor engagement and promotes sustainable tourism practices by catering to those visitors who value and respect the destination, helping to ensure positive impacts on the local environment and economy. Additionally, the use of mobile data not only streamlines the data collection process but also enhances the precision of clustering and segmentation strategies, allowing DMOs to create highly targeted marketing approaches (Hossain and Amin 2015). By developing visitor profiles that capture the distinct motivations and preferences of diverse visitor segments, DMOs are better equipped to craft experiences that resonate with and satisfy visitors, fostering a more fulfilling and impactful tourism experience that enhances the long-term success of the destination.

2.3 | Personality Traits and Digital Footprints

Recognizing individual differences and predicting behaviour accurately (Bäckström et al. 2020), personality traits constitute stable patterns of thoughts, emotions, and behaviours that distinguish individuals from one another (Roberts 2019). By capturing individual differences and predicting behaviour, the exploration of personality traits provides valuable insights into the intricate interplay between personal preferences and travel motivations (Sreen et al. 2023). The Five Factor Model, introduced by Goldberg in 1990, provides a comprehensive taxonomy of personality traits widely accepted in academia and industry (Soto and Jackson 2020; Bleidorn et al. 2019; McCrae 2013). According to trait theory, personalities consist of these Big Five traits: Open-mindedness (desire for intellectual stimulation and variety); Extraversion: (preference for social interaction and optimism); Agreeableness (need for pleasant and harmonious relations); Conscientiousness (willingness to follow established rules and norms); Neuroticism or Negative Emotionality (reflects emotional stability, including feelings of fear, anxiety, and insecurity) (Degnet et al. 2022; Soto and John 2017).

Recent research underscores the strong link between personality traits and visitor activity preferences (Kovačić et al. 2022; Katifori et al. 2019). Alves et al. (2023) emphasize the value in segmenting tourists based on personality, noting correlations between personality dimensions and attraction choices, such as open individuals preferring museums, in contrast to extraverts. Further, Rafiq, Adil, and Wu (2022) demonstrated that extraverts are more inclined towards ecotourism compared to those with neurotic tendencies. This finding is complemented by Kesenheimer and Greitemeyer (2021), who reported that extraverted tourists are more likely to invest in ecotourism to reduce environmental impact. The significance of this outcomes demonstrates that understanding visitors' personality traits can help predict their behaviour on destination.

Technological advancement of mobile devices enhanced the ability to correlate digital footprints with personality traits (Beierle et al. 2020). Digital footprints include data generated from online activities such as location history, app usage, search queries, and social media interactions (Montag et al. 2021). By analysing this data from mobile devices, algorithms can interpret actual behaviours, like how users interact with apps and device functions (Beierle et al. 2020; Hinds and Joinson 2019). For instance, mobile apps can track GPS data to monitor where tourists go, and which places they visit. They can also analyse in-app behaviour to understand user preferences and integrate social media activity to gain additional insights into user personalities (Stachl et al. 2017).

Furthermore, the use of Electronic Data Interchange (EDI) systems enables the seamless exchange of data between organizations, facilitating more comprehensive data collection and analysis (Oleiwi 2023). EDI systems automate the transfer of data, reducing manual errors and ensuring that information is quickly and accurately shared across various platforms (Oleiwi 2023). This interoperability allows for the aggregation of diverse data sources, enhancing the depth and breadth of the data used in tourism profiling. However, it is crucial to ensure that these data collection methods are secure and respect user privacy (Razavi 2020). Encryption protocols and stringent access controls must be implemented to protect sensitive information from unauthorized access and breaches (Stachl et al. 2017). Additionally, addressing potential biases in the data is essential to ensure inclusive and accurate tourism profiling. Data quality issues, such as incomplete or outdated information, must be identified and rectified to maintain the integrity of the profiling process. Regular audits and validation checks can help mitigate these issues, ensuring that the data is reliable and reflective of current trends and behaviours (Madavarapu 2023). By addressing these considerations, EDI systems can significantly enhance the effectiveness of personality-based tourism profiling, offering personalized and enriching experiences for all travellers.

Previous studies investigated the link between the usage of mobile devices with the Big Five personality traits, finding that users high in extraversion have higher tendency for call frequency and more use of photography apps, whereas users high in conscientiousness engage more with work emails and less with entertainment apps (Beierle et al. 2020; Stachl et al. 2017). Furthermore, extraversion and neuroticism users correspond to more frequent phone checks, and agreeableness to higher call frequency, with emotional stability reflected in SMS message patterns (Beierle et al. 2020; Chittaranjan, Blom, and Gatica-Perez 2013).

Research underscores significant correlations between personality traits and digital footprints on social media through mobile devices (Marengo and Montag 2020). For example, extraversion exhibits a robust association with Facebook data, indicating that individuals perceiving themselves as extraverted engage in distinct online behaviours, leading to increased platform activity (Montag et al. 2021). However, the complexities linked to self-report methods, encompassing challenges in introspection, susceptibility to social desirability biases, and inconsistencies arising from variations in the complexity of personality questionnaires, necessitate a crucial examination of innovative approaches that rely on insights derived from digital data (Boyd, Pasca, and Lanning 2020).

Despite existing studies exploring the influence of personality traits and travel motivations on visitor activities (e.g., Kovačić et al. 2022; Alves et al. 2023) and the link between personality traits, activities, and technology usage (e.g., Beierle et al. 2020; Stachl et al. 2017; Chittaranjan, Blom, and Gatica-Perez 2013), the application of personality traits and travel motivations as a basis for segmenting tourist markets represents an innovative approach.

2.4 | Visitor Activities and Digital Footprints

Digital footprints provide a nuanced understanding of travellers' psychographic profiles, including attitudes, interests, and opinions, as reflected in their online activities and interactions (Otoo, Kim, and Park 2020). For example, study by Önder, Koerbitz, and Hubmann-Haidvogel (2016) highlighted how geotagged photos can serve as reliable indicators of tourism demand, revealing attractions to specific destinations or experiences. This approach is further enriched by Cao, Xu, and Xian (2022), who analysed travel texts to uncover the movement patterns of Chinese tourists in Malaysia, shedding light on their preferred attractions and travel routes. Similar study by Vu et al. (2018) employed travel diaries based on venue check-in data, which distinctively highlighted the differing activity interests. Dong et al. (2023) utilise tourism digital footprints to study tourists' spatiotemporal behaviour and recreation preferences, categorizing them into distinct patterns such as “natural landscape” and “historic culture”. Finally, Yu et al. (2016) harnesses the power of data through mobile devices to model user preferences, paving the way for personalized travel package recommendations. These collective studies underscore the comprehensive capacity of digital footprints in mapping out the complex and varied behaviours and preferences of tourists. Previous literature reveals the affection of users with technology in a destination and the importance for DMOs to absorb this information for clustering tourists. Besides the noticeable focus from socio-demographic to behavioural and psychographic factors (Li and Kovacs 2024), limited research has investigated travel motivations, personality traits and visitor activities in tourism segmentation for a local DMO.

2.5 | The Present Study

To address the above research gap, this study aims to identify the distinct visitor segments based on personality traits, motivations, and visitor activities in Cumbria. Effective segmentation is crucial for tailoring content and services (Razavi 2020), specially for DMOs asked to integrate insights from researchers to effectively leverage the collective knowledge. This research primarily focuses on the significant influence of personality traits, travel motivations and visitor activities on behaviours. Whereas limitations from traditional market research methods (Önder, Koerbitz, and Hubmann-Haidvogel 2016), restrain DMOs from collecting accurate data, mobile phone data offer distinct advantages and detailed information on travel patterns (Wang, He, and Leung 2018). The outcome of this study will inform online platforms on mobile devices, developing a management tool in the hands of DMOs. Capitalising on such platform enhances the precision and effectiveness of clustering strategies (Hossain and Amin 2015) empowering DMOs to tailor their approaches to the unique characteristics and preferences of different tourist clusters. The structure of this study is modelled after the approach used by Errichiello et al. (2019). This study poses two key research questions:

RQ1. *What are the distinct visitor segments based on personality traits, motivations, and visitor activities in Cumbria*?

RQ2. *Do visitor segments identified through clustering based on personality traits, motivations, and activities exhibit significant socio-demographic differences*?

3 | Methods

For the purpose of this research, a questionnaire-based approach was used to create clusters, which will inform algorithms essential for advancing to more innovative data collection methods. This is viewed as a critical first step before developing and employing a mobile application for the destination to collect and analyse digital footprints and other data. Similar strategies in other industries, such as the gaming industry where player typologies are identified before informing algorithms (Parapanos 2023), serve as an inspiration. This knowledge is valuable as it addresses a gap in the literature where most destinations rely on traditional segmentation methods primarily based on demographics such as age, gender, and origin.

To achieve the aim this study employed a quantitative cross-sectional survey to investigate the distinct visitor segments based on personality traits, motivations, and visitor activities in Cumbria. Conducted from September 2022 to September 2023, the survey targeted visitors aged 18 and above during both peak and off-peak seasons, using random sampling. The sample is proficient and experienced in using mobile technology while at the destination (Cumbria), reflecting current trends in tourism where digital platforms are crucial.

To pilot test the survey, a qualitative approach was utilized with 10 participants to ascertain the clarity of the survey items. The final version received 1217 responses, representing a 10% response rate. This sample size aligns with statistical guidelines for adequate representation, considering a 50% variance, a 95% confidence level, and a 3% margin of error (Taherdoost 2016). Scales were selected from the literature to measure personality traits (OCEAN Model- Open-Mindedness, Conscientiousness, Extraversion, Agreeableness, Negative Emotionality), using a shortened version of the Big Five Inventory-2 (BFI-2), the BFI-2-S (Soto and John 2017). Travel motivation items were formulated following an extensive literature review (Capar, Pala, and Toksöz 2022; Maghrifani, Liu, and Sneddon 2022; Jeong et al. 2018; Sung, Chang, and Sung 2016; Wong, Cheung, and Wan 2013; Hsu, Cai, and Li 2010; Pearce and Lee 2005), while preferences for activities were also established through an in-depth review of existing literature (Kovačić et al. 2022; Alves et al. 2023, 2020). Each dimension was measured using multi-item measurement scales. Respondents were asked to indicate their agreement on a Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

4 | Results

Statistical analyses were carried out using SPSS version 24.0. After screening the data in SPSS, descriptive statistics provided a comprehensive overview of the sample based on demographic and travel-related characteristics. The sample for the study consisted of 1217 valid questionnaires, with females comprising the majority at 62%. The prevalent age groups of the respondents are in Group 5:60 + yrs., representing 25.2%, and the minority of responses in Group 1: 18-29 yrs., accounting 17.3% of the total respondents. The highest percentage of travellers were British citizens (82.9%), 61% are employed, and 30.6% completed an undergraduate degree. They travel to Cumbria with a partner (42.4%), for leisure (90.4%) (see Table 2).

The validity of the personality traits measured by Confirmatory Factor Analysis, with KMO value at 0.817 exceeds the recommended 0.6 and Bartlett's Sphericity is Sig. at 0.000 indicating that the current data was suitable for factor analysis (Field 2018) (see Table 3).

Exploratory Factor Analysis (EFA) using Principal Axis Factoring identified key dimensions of travel motivations and visitor activities. KMO values at 0.817 and 0.810 respectively, with Bartlett's test significant at 0.000, indicating data suitability for EFA (Field 2018). Five items (travelling to understand more about myself, to be away from the crowds of people, doing adventure activities in the air (e.g., parachute jump, gliding), attending other special events (e.g., wedding, birthday party), exercising (e.g., walking, running, cycling), were not loading hence removed (Hair et al. 2014)). Scale reliability was confirmed with Cronbach's alpha values above 0.70, denoting good internal consistency (Field 2018). The final analysis retained 18 items for travel motivation, revealing five factors accounting for 67.8% variance (see Table 4), and 17 items for visitor activities, revealing five factors explaining 65.49% variance (see Table 5).

To obtain profiles with similar personality traits, travel motivations, and visitor activities, a two-step analysis using hierarchical and k-means techniques was employed, following established procedures in tourism studies (Cha et al. 2024; Ghosh and Mukherjee 2023; Øgaard et al. 2019). This hybrid approach, recommended by Hair et al. (2014), utilized Euclidean distance for measuring similarity and employed the Ward method to ensure maximum homogeneity within each cluster. The initial analysis, guided by the agglomeration coefficient and dendrogram, suggested a five-cluster structure (see Figure 1).

TABLE 2 | Profile of the respondents.

Profile of the respondents							
		Frequency	**Percent**			**Frequency**	**Percent**
Gender	Male	457	37.6	Work status	Employed	742	61.0
	Female	754	62.0		Self-employed	106	8.7
	Prefer not to say	6	0.5		Student	82	6.7
	Total	1217	100.0		Retired	251	20.6
Age	18–29	211	17.3		Unemployed	18	1.5
	30–39	216	17.7		I prefer not to say	18	1.5
	40–49	194	15.9		Total	1217	100.0
	50–59	283	23.3		Employed	742	61.0
	60+	307	25.2	Education	High school	119	9.8
	Prefer not to say	6	0.5		College	266	21.9
	Total	1217	100.0		Undergraduate degree	372	30.6
Nationality	AU Australia	14	1.2%		Master's degree	216	17.7
	CA Canada	13	1.1%		Total	1217	100.0
	CN China	11	0.9%	Travel partner	Alone	201	16.5
	IN India	14	1.2%		With a partner	516	42.4
	GB United Kingdom	1009	82.9%		With family	326	26.8
	US United States	44	3.6%		With friends	155	12.7
	Others	440	9.1%		With a traveling group	11	0.9
	Total	1217	100%		Prefer not to say	8	0.7
Past visits	None	96	7.9		Total	1217	100.0
	One time	218	17.9	Trip purpose	Leisure	1100	90.4
	Two to four times	381	31.3		Business	8	0.7
	Five times or more	512	42.1		Leisure and business	65	5.3
	Prefer not to say	10	0.8		Other	43	3.5
	Total	1217	100.0		Prefer not to say	1	0.1
					Total		100%

Furthermore, in the conducted ANOVA analysis, all variables exhibited statistically significant differences among the clusters ($p < 0.05$) (see Table 6, Figure 2).

Chi-square tests, as noted by Knapp (2018), were employed to analyse demographic differences in the identified clusters. The combination of crosstab analysis and K-means clustering, as described by Ceylan, Çizel, and Karakaş (2021), was used to create tourist typologies and interpret patterns. These tests revealed no significant differences between segments in terms of travel partner ($\chi^2 = 27.2$; $p = 0.13$). Subsequently, new typologies were named based on their key characteristics and dominant traits relevant to this study (see Table 7).

5 | Discussion

The study aims to identify the distinct visitor segments based on personality traits, motivations, and visitor activities in Cumbria. This research is guided by two primary research questions. The first question (RQ1) seeks to identify and characterize the unique visitor segments that emerge when visitors are clustered according to their personality traits, motivations, and activities. The second question (RQ2) explores whether these identified segments exhibit significant socio-demographic differences, thereby providing a deeper understanding of the visitor profile in Cumbria. This approach aims to offer valuable insights into the diverse visitor landscape,

TABLE 3 | Personality traits: Constructs and items.

Factor	Measuring item	Factor loading	Cumulative interpretation variance (%)	Cronbach's α
Negative emotionality	I am someone who is emotionally stable, not easily upset.	−0.824	17.471	0.871
	I am someone who worries a lot.	0.795		
	I am someone who is relaxed, handles stress well.	−0.780		
	I am someone who is temperamental, gets emotional easily.	0.747		
	I am someone who tends to feel depressed, blue.	0.703		
Conscientiousness	I am someone who tends to be disorganized.	0.789	10.147	0.797
	I am someone who keeps things neat and tidy.	−0.742		
	I am someone who is persistent, works until the task is finished.	−0.700		
	I am someone who can be somewhat careless.	0.663		
	I am someone who has difficulty getting started on tasks.	0.632		
Agreeableness	I am someone who can be cold and uncaring.	−0.714	10.061	0.764
	I am someone who is sometimes rude to others.	−0.705		
	I am someone who assumes the best about people.	0.666		
	I am someone who tends to find fault with others.	−0.657		
	I am someone who is compassionate, has a soft heart.	0.653		
Extraversion	I am someone who is outgoing, sociable.	0.755	8.054	0.748
	I am someone who tends to be quiet.	−0.727		
	I am someone who is full of energy.	0.683		
	I am someone who is dominant, acts as a leader.	0.672		
	I am someone who is less active than other people.	−0.492		
Open-mindedness	I am someone who has little interest in abstract ideas.	−0.723	5.903	0.745
	I am someone who is fascinated by art, music, or literature.	0.715		
	I am someone who has little creativity.	−0.662		
	I am someone who has few artistic interests.	−0.641		
	I am someone who is original, comes up with new ideas.	0.612		

Note: Confirmatory Factor Analysis extraction method: Principal Component; Rotation method: Varimax.

TABLE 4 | Travel motivation and visitor activities: Constructs and items.

Factor	Measuring item	Factor loading	Cumulative interpretation variance (%)	Cronbach's α
Nature escape	I travel to Cumbria to admire and be close to nature.	0.922	23.695	0.767
	I travel to Cumbria to get a better appreciation of nature.	0.778		
	I travel to Cumbria to escape from the daily routine.	0.436		
Self-development	I travel to Cumbria to develop my skills and abilities.	0.653	13.234	0.765
	I travel to Cumbria to get outside of my comfort zone.	0.649		
	I travel to Cumbria to gain a sense of accomplishment.	0.602		
	I travel to Cumbria to experience a new culture and meet new people.	0.438		
Relationship and recognition	I travel to Cumbria to share skills with others/showing what I can do.	0.655	6.737	0.700
	I travel to Cumbria to connect with friends or relatives living in other locations.	0.621		
	I travel to Cumbria to meet new people who enjoy the same things as I do.	0.602		
	I travel to Cumbria as it is a destination that would impress others.	0.442		
Autonomy	I travel to Cumbria to do things my own way.	0.792	4.761	0.877
	I travel to Cumbria to be independent.	0.782		
Nostalgia	I travel to Cumbria to think about good times I have had in the past.	0.854	3.228	0.871
	I travel to Cumbria to reflect on past memories.	0.832		
Novelty and stimulation	I travel to Cumbria to experience thrills or excitement.	0.669	2.930	0.702
	I travel to Cumbria to explore the unknown/do something new.	0.592		
	I travel to Cumbria to seek fun and enjoyment.	0.574		

Note: Exploratory Factor Analysis: Extraction method: Principal Axis Factoring, Rotation method: Varimax.

contributing to more targeted and effective tourism strategies in the region.

5.1 | RQ1

This study found five clusters (Reserved Explorers, Culturally Curious, Diligent Adventurers, Social Explorers and Balanced Explorers) of tourists visiting Cumbria. This is to suggest that a mobile platform recognizing tourists' segments in the county of Cumbria will cluster them into groups with different characteristics based on their personality traits, travel motivations and activities in the destination. Algorithms will be formed based on the interactions of tourists with the technology and patterns will reveal the cluster each tourist is more likely to belong to. This section will present and discuss the characteristics of these clusters and the strategies to create engagement with them.

TABLE 5 | Visitor activities: Constructs and items.

	Measuring item	Factor loading	Cumulative interpretation variance (%)	Cronbach's α
Local culture	While in Cumbria, I choose to visit monuments (e.g., castles, churches, historic houses) parks, and gardens.	0.835	20.823	0.799
	While in Cumbria, I choose to visit museums.	0.821		
	While in Cumbria, I choose to visit exhibitions/art galleries.	0.671		
	While in Cumbria, I choose to visit archaeological sites/ruins.	0.536		
	While in Cumbria, I choose to take boat trips to explore the destination.	0.503		
Thematic activities	While in Cumbria, I choose to engage in thematic sports (e.g., horse riding, archery).	0.786	15.968	0.786
	While in Cumbria, I choose to participate in food and beverage masterclasses.	0.689		
	While in Cumbria, I choose to participate in sporting competitions (e.g., trail running, cycling competition).	0.643		
Recreation and adventure	While in Cumbria, I choose to practice wild swimming/forest bathing.	0.725	9.057	0.700
	While in Cumbria, I choose to practice hiking/mountaineering/long walks in nature.	0.669		
	While in Cumbria, I choose to do adventure activities on water (e.g., sailing, canoeing, diving, jet skiing).	0.594		
	While in Cumbria, I choose to do adventure activities on the land (rock climbing/abseiling/off road).	0.487		
Entertainment	While in Cumbria, I choose to attend cultural activities/artistic performances.	0.916	5.040	0.723
	While in Cumbria, I choose to attend festivals/concerts.	0.538		
	While in Cumbria, I choose to take boat trips for the historical value of the route.	0.520		
Health and wellbeing	While in Cumbria, I choose to go to a SPA/beauty centre.	0.838	4.049	0.862
	While in Cumbria, I choose to undergo health and wellness treatments.	0.804		

Note: Exploratory Factor Analysis: Extraction method: Principal Axis Factoring, Rotation method: Varimax.

5.2 | Cluster 1—The Reserved Explorers

This cluster named Reserved Explorers due to their personality characterised by the lowest open-mindedness (18.89) and extraversion (15.50) scores, which indicates a preference for familiar, comfortable, and more solitary travel experiences. They also have the highest negative emotionality (21.00) among all clusters, which might influence their choice of more predictable and less adventurous travel experiences. Their travel motivations align with nature escape (13.16) and self-development (10.83).

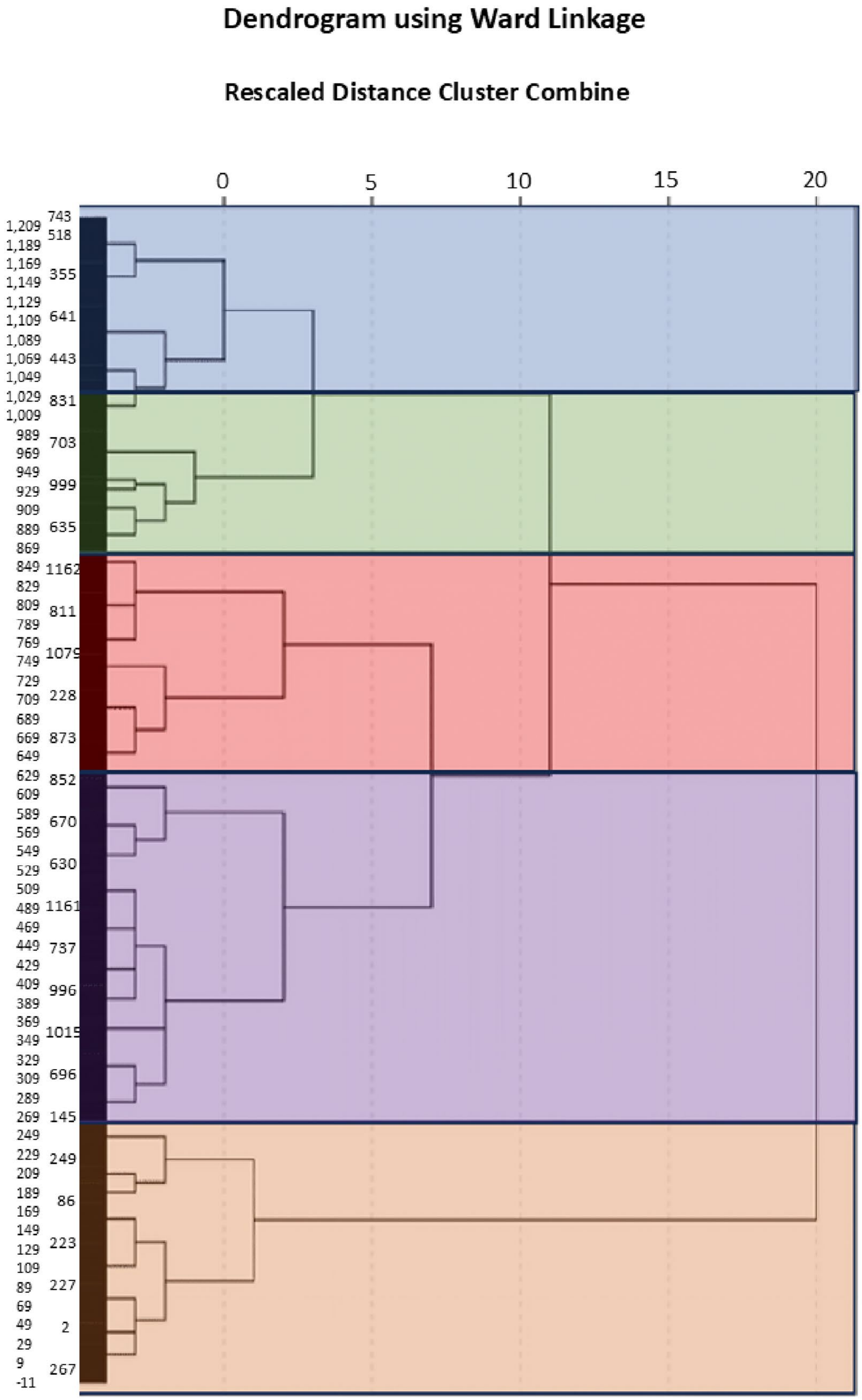

FIGURE 1 | Dendrogram with clusters (results from hierarchical clustering).

With a high interest in local culture (16.01), this cluster's interests involve immersion in local activities, such as visiting museums, art galleries, archaeological sites, and less aligned with high-energy activities like entertainment and adventure.

Demographically, this cluster is predominantly female (80.5%), with a notable presence across 50–59: 49 (23.9%) and 60+: 61 (29.8%) age groups. Most travellers in this cluster are from the United Kingdom (82.9%), and the educational background is

TABLE 6 | Mean score of segments.

Final cluster centers							
	Cluster						
	1	2	3	4	5	*F* test	ANOVA Sig.
Open mindedness	18.89	24.42	22.01	20.94	20.11	71.904	0.000
Conscientiousness	20.85	19.91	24.56	22.55	24.06	68.390	0.000
Extraversion	15.50	20.26	22.56	20.06	20.63	132.822	0.000
Agreeableness	23.65	22.47	25.80	23.72	23.71	29.008	0.000
Negative emotionality	21.00	18.85	13.56	16.34	12.84	191.012	0.000
Nature escape	13.16	13.43	13.01	7.72	12.80	389.144	0.000
Self-development	10.83	13.41	15.56	13.47	11.45	96.165	0.000
Relationship and recognition	8.52	9.68	12.78	12.81	8.97	148.781	0.000
Autonomy	6.32	7.22	8.12	9.02	6.45	104.958	0.000
Nostalgia	6.56	6.38	7.63	6.32	5.84	25.388	0.000
Novelty and stimulation	10.06	11.44	12.51	11.25	10.87	46.610	0.000
Local culture	16.01	17.51	18.00	10.63	13.44	175.364	0.000
Thematic activities	4.96	5.77	7.76	8.78	5.03	134.451	0.000
Recreation and adventure	10.15	12.47	13.41	8.75	11.12	87.939	0.000
Entertainment	6.82	8.10	9.97	11.51	6.08	247.890	0.000
Health and wellbeing	3.61	3.84	5.16	3.67	3.41	35.950	0.000

varied, including high school (12.2%), college (27.3%), undergraduate (29.3%), master's degree (13.2%), and postgraduate (11.7%) levels. Overall, these tourists prefer structured and predictable travel experiences, valuing comfort, and familiarity over novelty and adventure.

The characteristics of this cluster should allow mobile platforms effective marketing strategies to promote nature getaways, serene landscapes, and cultural heritage tours to appeal to this group's distinct preferences for cultural and nature exploration. Users in this platform will receive travel packages with less social experiences in less crowded settings that align with their reserved nature.

5.3 | Cluster 2—The Culturally Curious

This cluster owes its name to the highest score in open-mindedness (24.42) and lower negative emotionality (18.85). Tourists within this cluster characterized by a strong curiosity and willingness to engage in new experiences. Their moderate conscientiousness (19.91) and extraversion (20.26) suggest a balanced approach to planning and social interactions. Their travel motivations are geared towards self-development (13.41), novelty and stimulation (11.44), and they have a high interest in local culture (17.51), and recreational adventure (12.47).

A diverse group in terms of age and nationality, with a skew towards younger and middle-aged adults 18–29 (21.3%); 30–39 (20.8%); 40–49 (16.2%). The majority is actively employed (58.3%), and substantial proportion of travellers are from the United Kingdom (77.8%). The educational background is varied, with a noticeable representation of those with undergraduate (32.9%) and postgraduate (21.8%) qualifications.

Overall, this cluster includes individuals who seek culturally enriching experiences, are open to new ideas and adventures, and value a mix of structured and spontaneous travel activities. Technology recognizing tourists within this segment will promote marketing strategies focusing on the unique and diverse offerings of the destination, highlighting off-the-beaten-path and culturally enriching experiences, but also adventure sports, nature trails, educational workshops, and opportunities for self-discovery and adventure.

5.4 | Cluster 3—The Diligent Adventurers

Members in this cluster characterized by the highest conscientiousness (24.56), extraversion (22.56) and agreeableness (25.80) among all clusters, combined with lower negative emotionality (13.56), indicating a preference for well-organized and harmonious social interactions. Their motivations in self-development (15.56), relationship recognition (12.78), nature escape (13.01), and novelty and stimulation (12.51) reflect a desire for enriching, fun and meaningful travel experiences. This cluster demonstrates the highest affinity for nostalgia (7.63) compared to others, reflecting a fondness for reminiscing past experiences. This group demonstrates a significant

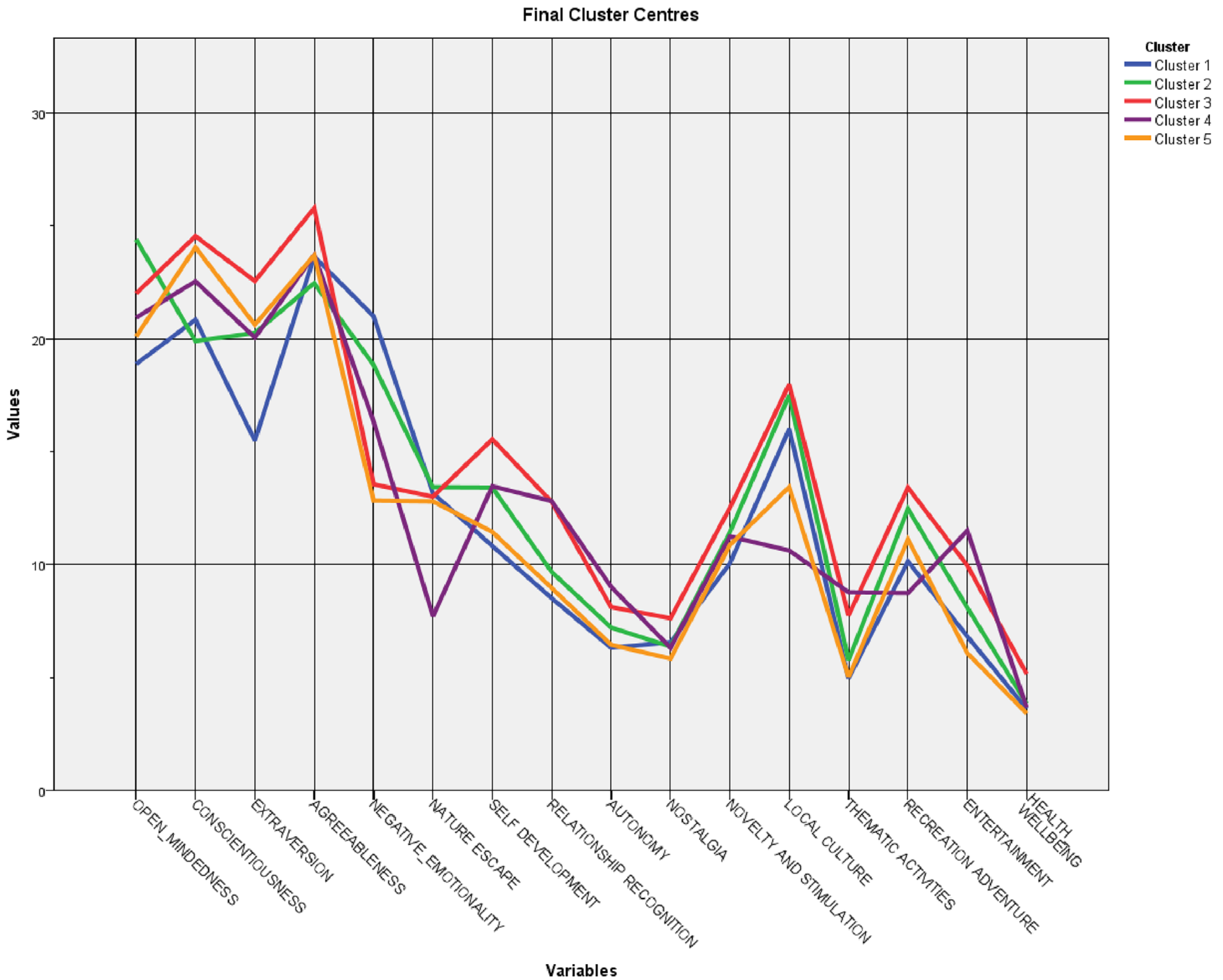

FIGURE 2 | Cluster centres.

interest in local culture (18.00), favouring museum visits, historical exploration, but also recreational adventures (13.41). Additionally, they show the greatest preference for health and wellbeing activities (5.16) among all clusters, indicating a focus on experiences that enhance physical and mental wellness.

Demographically, this cluster comprises more female (59.8%) than male (37.9%) travellers. The age distribution shows a balanced representation across different age groups, with a notable presence in the 50–59 (24.9%) and 60+ (24.9%) categories. A considerable proportion of travellers in this cluster are from the United Kingdom (79.3%). In terms of education, a notable number of individuals have an undergraduate (28.2%) degree, and the majority visited the destination 5 times or more (56.0%).

Overall, they represent tourists who value structured, enriching, and socially fulfilling travel experiences, combining a desire for personal growth with a preference for comfortable and familiar settings. Tourists clustered in this group by the mobile platform will receive marketing offers focused on opportunities for cultural learning, community interaction, and health and wellbeing related activities.

5.5 | Cluster 4—The Social Explorers

This cluster named Social Explorers because of their elevated levels of open-mindedness (20.94), conscientiousness (22.55), extraversion (20.06), and agreeableness (23.72), with a lower level of negative emotionality (16.34). Motivations of these tourists show a strong inclination towards relationship recognition (12.81) and autonomy (9.02), enjoying recognition for their unique choices while also valuing the freedom to explore and engage with the destination on their own terms. With a strong preference for entertainment (11.51), and thematic activities (8.78), this cluster has a desire for excitement and stimulation during their travels.

Demographically, this is a slightly female-dominated composition (61.7%) and a notable presence in the 18–29 (20.9%) and 30–39 (21.3%) age groups, indicates younger demographic. Most of the travellers are from the United Kingdom (80.2), with a sizeable portion being employed (64.4%) or self-employed (19.8%). The educational background is varied, with a substantial number of individuals holding undergraduate (29.6%) and master's degrees (18.2%).

TABLE 7 | Profiles of clusters.

Visitor profile	Reserved explorers (Cluster 1)	Culturally curious (Cluster 2)	Diligent adventurers (Cluster 3)	Social explorers (Cluster 4)	Balanced explorers (Cluster 5)	Total	Chi-square p-value
	Count (% within Cluster number of case)						
Gender							
Male	38 (18.5)	96 (39.8)	96 (37.9)	96 (43.4)	131 (37.6)	457 (37.6)	43.717 $p=0.000$
Female	165 (80.5)	118 (54.6)	144 (59.8)	156 (61.7)	171 (56.6)	754 (62.0)	
Age							33.984 $p=0.026$
18–29	36 (17.6)	46 (21.3)	35 (14.5)	53 (20.9)	41 (13.6)	211 (17.3)	
30–39	29 (14.1)	45 (20.8)	45 (18.7)	54 (21.3)	43 (14.2)	216 (17.7)	
40–49	28 (13.7)	35 (16.2)	41 (17.0)	46 (18.2)	44 (14.6)	194 (15.9)	
50–59	49 (23.9)	39 (18.1)	60 (24.9)	50 (19.8)	85 (28.1)	283 (23.3)	
60+	61 (29.8)	50 (23.1)	60 (24.9)	48 (19.0)	88 (29.1)	307 (25.2)	
Nationality							229.222 $p=0.022$
AU Australia	0 (0.0)	4 (1.9)	1 (0.4)	3 (1.2)	6 (2.0)	14 (1.2)	
CA Canada	0 (0.0)	5 (2.3)	2 (0.8)	1 (0.4)	5 (1.7)	13 (1.1)	
CN China	6 (2.9)	3 (1.4)	0 (0.0)	2 (0.8)	0 (0.0)	11 (0.9)	
IN India	0 (0.0)	3 (1.4)	6 (2.5)	4 (1.6)	1 (0.3)	14 (1.2)	
GB United Kingdom	186 (9.7)	168 (77.8)	191 (79.3)	203 (80.2)	261 (86.4)	1009 (82.9)	
US United States	1 (0.5)	13 (6.0)	14 (5.8)	6 (2.4)	10 (3.3)	44 (3.6)	
Work status							60.366 $p=0.000$
Employed	119 (58.0)	126 (58.3)	154 (63.9)	163 (64.4)	180 (59.6)	742 (61.0)	
Self-employed	12 (5.9)	20 (9.3)	32 (13.3)	21 (19.8)	21 (7.0)	106 (8.7)	
Student	13 (6.3)	25 (11.6)	5 (2.1)	25 (9.9)	14 (4.6)	82 (6.7)	
Retired	49 (23.9)	38 (17.6)	44 (18.3)	36 (14.2)	84 (27.8)	251 (20.6)	
Unemployed	7 (3.4)	3 (1.4)	1 (0.4)	5 (2.0)	2 (0.7)	18 (1.5)	

(Continues)

TABLE 7 | (Continued)

Visitor profile	Reserved explorers (Cluster 1)	Culturally curious (Cluster 2)	Diligent adventurers (Cluster 3)	Social explorers (Cluster 4)	Balanced explorers (Cluster 5)	Total	Chi-square p-value
	Count (% within Cluster number of case)						
Education							38.612 $p = 0.007$
High school	25 (12.2)	12 (5.6)	22 (9.1)	26 (10.3)	34 (11.3)	119 (9.8)	
College	56 (27.3)	28 (13.0)	57 (23.7)	61 (24.1)	64 (21.2)	266 (21.9)	
Undergraduate	60 (29.3)	71 (32.9)	68 (28.2)	75 (29.6)	98 (32.5)	372 (30.6)	
Master's Degree	27 (13.2)	50 (23.1)	46 (19.1)	46 (18.2)	47 (15.6)	216 (17.7)	
Postgraduate	24 (11.7)	47 (21.8)	40 (16.6)	32 (12.6)	49 (16.2)	192 (15.8)	
Past visits							50.577 $p = 0.000$
None	14 (6.8)	27 (12.5)	11 (4.6)	21 (8.3)	23 (7.6)	96 (7.9)	
One time	36 (17.6)	43 (19.9)	41 (17.0)	48 (19.0)	50 (16.6)	218 (17.9)	
Two to four times	83 (40.5)	64 (29.6)	52 (21.6)	76 (30.0)	106 (35.1)	381 (31.3)	
Five or more times	70 (34.1)	77 (35.6)	135 (56.0)	107 (42.3)	123 (40.7)	512 (42.1)	
Travel partner							27.200 $p = 0.130$
Alone	33 (16.1)	37 (17.1)	43 (17.8)	50 (19.8)	38 (12.6)	201 (16.5)	
With a partner	97 (47.3)	90 (41.7)	97 (40.2)	89 (35.2)	143 (47.4)	516 (42.4)	
With family	57 (27.8)	57 (26.4)	61 (25.3)	76 (30.0)	75 (24.8)	326 (26.8)	
With friends	14 (6.8)	30 (13.9)	34 (14.1)	34 (13.4)	43 (14.2)	155 (12.7)	
With a traveling group	2 (1.0)	2 (0.9)	2 (0.8)	2 (0.8)	3 (1.0)	11 (0.9)	
Trip purpose							26.065 $p = 0.053$
Leisure	192 (93.7)	193 (89.4)	206 (85.5)	226 (89.3)	283 (93.7)		
Business	0 (0.0)	1 (0.05)	3 (1.2)	2 (0.8)	2 (0.7)		
Leisure and Business	6 (2.9)	16 (7.4)	22 (9.1)	14 (5.5)	7 (2.3)		
Other	7 (3.4)	5 (2.3)	10 (4.1)	11 (4.3)	10 (3.3)		

Overall, this cluster is socially engaged, culturally open, and dynamic, with interests in interactive and themed travel experiences. Algorithm clustering tourists in this group will emphasize promoting opportunities for social interaction and community engagement, such as local festivals, group tours, social gatherings, and networking events, but also authentic local experiences that allow them to immerse themselves in the destination's culture.

5.6 | Cluster 5—The Balanced Explorers

Lastly, Balanced Explorers exhibit high levels of open-mindedness (20.11), conscientiousness (24.06), and agreeableness (23.71), with higher extraversion (20.63) and the lowest negative emotionality (12.84) among the clusters. Their travel motivation reveals significant inclination towards nature escape (12.80), suggesting a desire to enjoy natural environments and seek relaxation away from their usual settings. Their interest in self-development (11.45) indicates a preference for experiences that contribute to personal growth and learning. With a notable interest in local culture (13.44), they enjoy immersive experiences that involve understanding and engaging with the cultural aspects of their travel destinations. Additionally, their affinity for recreation and adventure (11.12) suggests they are also drawn to activities that offer physical engagement.

Demographically, this cluster consists of an older age group, with a considerable proportion in the 50–59 (28.1%) and 60+ (29.1%) age brackets. The gender distribution comprises 56.6% females, with many travellers being from the United Kingdom (86.4%). The educational background is diverse, with a notable presence of individuals with undergraduate (32.5%) and postgraduate (16.2%) degrees.

Overall, these tourists seek travel experiences that offer a mix of cultural immersion, personal growth, natural escapism, and recreation. Mobile technology will promote activities that focus on personal growth, with customizable itineraries that allow them to choose a mix of nature and culture.

The current study extends Plog's (1974) foundational research on tourist typologies by identifying similar behavioural typologies within the same destination. Tourists are categorized into five clusters: Reserved Explorers, Culturally Curious, Diligent Adventurers, Social Explorers, and Balanced Explorers—each with distinct preferences and motivations that align with Plog's psychocentric-allocentric spectrum. Plog's Dependables prefer familiar, safe, and structured destinations, often revisiting the same locations for predictability and comfort. In contrast, Venturers seek unique, less touristy destinations, embracing novel experiences and cultural immersion. The Reserved Explorers resemble Dependables in their preference for familiar, low-intensity experiences and predictability. Conversely, the Culturally Curious illustrate Venturers in their open-mindedness and eagerness for diverse cultural activities. The Diligent Adventurers and the Social Explorers bridge the gap, incorporating elements of both Dependable and Venturer characteristics. Diligent Adventurers align with the structured and health-conscious aspects of Dependables, but are open to cultural activities like Venturers. Social Explorers share Venturers' enthusiasm for new experiences and stimulation but also value relationships and group activities like Dependables. Finally, the Balanced Explorers align with the mid-centric position on Plog's continuum, blending aspects of both Dependables and Venturers with their high open-mindedness and extraversion, while appreciating structure and comfort. These findings reveal that the diversity in traveller behaviours and motivations extends beyond the choice of destination, highlighting the varied ways in which different types of tourists engage with and experience the same destination.

Similarly, certain clusters show clear parallels with Cohen's (1972, 1974, 1979) types, indicating that contemporary travellers often blend characteristics, revealing more nuanced and diverse behaviours and motivations than Cohen's original framework implies. For instance, the Reserved Explorers align with the Organized Mass Tourist in their preference for familiarity and structure, but their deep interest in local culture adds complexity not captured by Cohen's (1972) typology. Similarly, the Culturally Curious share the Explorers' openness to new experiences and cultural engagement, but their balanced approach to planning introduces a structured element not typically associated with Explorers. The Diligent Adventurers combine the organized, enriching experiences of the Individual Mass Tourist with a strong focus on health, wellbeing, and cultural activities, reflecting evolving traveller priorities. Social Explorers, reminiscent of Drifters in their quest for novelty and social interaction, also value comfort and structure, blending spontaneity with planning. The Balanced Explorers integrate the adventurous spirit of Explorers with the structured comfort of Individual Mass Tourists, demonstrating a mix of open-mindedness, conscientiousness, and extraversion.

5.7 | RQ2

This study explores whether identified segments exhibit significant socio-demographic differences, providing a deeper understanding of the visitor profile in Cumbria. Results underscore the superiority of personality trait-based segmentation over traditional methods based on demographics or travel patterns. Delineating these distinct tourist segments, the study provides invaluable insights for the tourism industry, informing targeted marketing, efficient resource allocation, product development, and customized services (Cha et al. 2024).

This research recognizes the noticeable shift in focus from socio-demographic to behavioural and psychographic factors, (Li and Kovacs 2024) and offer a more intricate understanding of tourist behaviours and preferences. This approach, combining personality traits, travel motivations and activities, achieves a multidimensional analysis, enriching the understanding of tourist segments. Results explain detailed and accurate profiling of tourists, addressing the dynamic complexity of contemporary tourist behaviour, a dimension often overlooked by conventional segmentation.

Furthermore, research expands on the use of technology as a vital, dynamic tool for the evolving creation of tourist clusters. Digital footprints offer a more precise and efficient data collection than traditional data collection methods like surveys and interviews, providing insights into tourists' behaviours. This technique is less labour-intensive and enables the collection of larger, year-round data samples, leading to a more comprehensive understanding of tourist activities (Dong et al. 2023). Digital footprints' benefits include precise location tracking, detailed behavioural data, reduced costs, and the capacity to manage large sample sizes. These advantages significantly improve the control and understanding of the diversity in individual recreational behaviours (Barros, Gutiérrez, and García-Palomares 2022). Analysing behavioural patterns through mobile phone usage and digital interactions allows for finer distinctions in tourist groupings. Dolnicar and Leisch (2017) highlight the importance of using various algorithms and conducting iterative analyses in data-driven tourist segmentation to accommodate variability in results and the exploratory nature of such studies.

6 | Conclusion

The study identifies the distinct visitor segments based on personality traits, motivations, and visitor activities in Cumbria. This research is guided by two primary research questions:

- (RQ1) seeks to identify and characterize the unique visitor segments that emerge when visitors are clustered according to their personality traits, motivations, and activities.
- (RQ2) explores whether these identified segments exhibit significant socio-demographic differences, thereby providing a deeper understanding of the visitor profile in Cumbria.

Traditionally, tourist segmentation heavily relies on demographic and behavioural data collected through surveys, which can be cumbersome, time-consuming, and prone to biases. The quantitative analysis of 1217 surveys revealed five distinct visitor segments (Reserved Explorers, Culturally Curious, Diligent Adventurers, Social Explorers, Balanced Explorers) in Cumbria with distinct behaviours. These profiles highlight the heterogeneity within Cumbria's visitor market concerning their personalities, motivations, and preferred activities.

6.1 | Theoretical Implications

Despite existing studies exploring the influence of personality traits and travel motivations on visitor activities (e.g., Kovačić et al. 2022; Alves et al. 2023) and the link between personality traits, activities, and technology usage (e.g., Beierle et al. 2020; Stachl et al. 2017; Chittaranjan, Blom, and Gatica-Perez 2013), the application of personality traits and travel motivations as a basis for segmenting tourist markets represents an innovative approach for a local DMO. Currently, local DMO uses surveys to gather comprehensive information on visitor profiles, covering demographics, visitation patterns, motivations transportation, expenditures, activities, overall experiences, and trip satisfaction. Technology now allows for more sophisticated and continuous data collection methods, which significantly enhance segmentation accuracy and relevance. Traditional methods, like the one-off surveys conducted once every 2 years, offer limited insights and quickly outdated results. Our research incorporating digital footprints and real-time data can provide a more dynamic and ongoing understanding of tourist behaviours. This shift from static to continuous data collection is a crucial theoretical contribution, emphasizing the importance of real-time analytics in tourism studies.

Employing factor analysis and clustering techniques, this multidimensional segmentation model surpasses conventional demographic or motivation-based approaches, contributing to theoretical enrichment within the field of tourist segmentation and destination management. Thereafter, this study adds theoretical contributions to advance understanding of destination management and tourist segmentation.

While there are clear parallels between certain clusters and tourist typologies such as Plog's (1974) and Cohen's (1972, 1974, 1979), contemporary travellers often embody a blend of characteristics from multiple typologies, indicating that tourist behaviours and motivations are more nuanced and diverse than what these original frameworks suggest. This underscores the inadequacy of rigid categorizations. Travelers today are more likely to exhibit fluid preferences that shift based on context, personal development goals, and situational motivations. As a result, the diversity and complexity in traveller behaviours highlight the need for more dynamic and flexible frameworks to better understand and cater to the multifaceted nature of contemporary tourism. This nuanced understanding can enhance destination marketing, travel planning, and the overall tourist experience by acknowledging and accommodating the broad spectrum of traveller preferences and motivations.

Furthermore, while the specific clusters identified in our study are tailored to a particular destination, the underlying methodology is applicable and can be adapted to various contexts. It is likely that different clusters might occur in different destinations or tourism businesses. This flexible framework allows for its application across different destinations and types of tourism products. For instance, other tourism destinations, hotels, or theme parks can adopt this methodology to better understand and segment their visitors.

6.2 | Practical Implications

The practical implications offer valuable insights for Cumbria's tourism industry. The identified visitor clusters provide a basis for tailoring marketing communications and product development to align with the unique preferences of each segment, thereby fostering enduring relationships and loyalty. Moreover, the study suggests that DMOs can benefit from integrating digital footprints, such as mobile app usage, to continuously and in real-time update tourist clusters. Implementing personality traits in the segmentation process enhances adaptability and reflects evolving behaviours, aligning with the contemporary trend of utilizing technology for more efficient and insightful tourism research.

For instance, we suggest using a mobile app informed by our algorithms, DMOs can continuously track and analyse visitor behaviour, leading to more precise and actionable insights. This approach not only enhances the segmentation process, but also allows DMOs to tailor their marketing efforts more effectively, responding promptly to emerging trends and preferences. The study informs DMOs that their market can be clustered based on digital footprints, which challenges the traditional socio-demographic segmentation. This strategy encourages DMOs to capitalise on available technology and digital footprint gaining competitive advantage through more personalise experience and effective marketing. By embracing these advancements, DMOs can transition from periodic, limited data collection through surveys to a continuous, data-driven approach through mobile apps algorithms, enabling them to identify and track behaviours more accurately and adapt their strategies in real time. Overall, this study provides initial guidance for DMOs globally and encourages further research into the necessary capacities and strategies to navigate the ongoing digital transformation in tourism.

7 | Limitations and Future Research

The study is limited to visitors within Cumbria, warranting cautious extrapolation of findings. Future studies can validate if similar clustering patterns manifest in other destinations. Additionally, qualitative investigations can provide deeper insights into the cognitive and emotional factors underlying cluster behaviours. Longitudinal designs tracking future travel patterns may also substantiate cluster distinctions. Overall, this study serves as a foundation to re-examine tourist segmentation through an expanded lens encompassing personality, motivation, activities, and demographic variables within varied geographical contexts.

Future research will build upon the theoretical groundwork laid in this study by transitioning to practical implementation for collecting actual usage data, focusing on participants' digital footprints. This includes developing and deploying a mobile application designed to gather and analyse digital footprints and other relevant data, with the goal of refining and adapting identified clusters based on real-world behavioural patterns. The initial phase has established a foundational knowledge base necessary for advancing to more sophisticated data collection methodologies. Integrating digital footprints into the analysis is crucial for gaining a comprehensive understanding of contemporary tourist behaviours and motivations. While the current work remains theoretical, upcoming phases will involve practical application and experimentation, guided by insights gained from this study. This approach aims to enhance the validity and applicability of findings, contributing to the ongoing evolution of tourism research and practice.

Data Availability Statement

Data will be made available from corresponding author upon reasonable request.

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