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25 years of tourist tracking: a geographical perspective

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ABSTRACT

Over the past twenty-five years, conceptualisations regarding where, when and how tourists travel have undergone profound changes. For many years, surveys, maps relying on tourists' recall, and physical surveillance were the only means through which the mobility of tourists could be tracked. The internet, cellular phone networks and satellite-based technology has facilitated new methods to collect data, including Bluetooth tracking, Wi-Fi tracking, mobile phone data, social media and GPS location-based data. It has also facilitated new forms of data, including big data, real-time data collection and continuous tracking data. Moreover, it has enabled new forms of data analysis including automation, artificial intelligence, and predictive analytics. As a result of these innovations, researchers have extended theoretical knowledge within tourism geographies, particularly in relation to tourists' spatiotemporal activity including visitation patterns, activity within specific locations, dispersal patterns and the impact of mobility upon emotions. This paper reviews the history of tourist tracking over the last 25 years, along with conceptual findings that have emerged from innovations in technology. It argues that there have been four stages of tourist tracking, namely: the pre-technology era, the tourist tracking 1.0 era characterised by the emergence of Global Positioning Systems technology, the tourist tracking 2.0 era whereby mobile phone, internet, and location-based technologies were developed, and the recent 3.0 era that is characterised by artificial intelligence, physiological sensors, mobile eye tracking and real time tracking. The paper concludes by highlighting future research needs, including predictive analysis, ethical considerations and use of tracking technology to encourage activity change.

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Introduction

Understanding the essence of tourism flows is one of the fundamental undertakings of tourism geography research and a key issue behind effective destination management and development. In the last two decades, we have witnessed

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unprecedented advances in the collection and utilization of high-resolution data on tourist mobility (Hardy, 2020). This is a result of a variety of technological developments as well as the widespread availability of tracking technologies such as Global Positioning Systems (GPS), mobile positioning, geo-located social media messages, Bluetooth technology and Artificial Intelligence (AI). During the last decade, researchers have also benefitted greatly from the development and widespread use of smartphones, which routinely incorporate several tracking abilities in one device, and can transmit obtained locations easily and cheaply (Birenboim & Shoval, 2016).

In parallel, we are witnessing growing possibilities for analyzing the huge space-time databases created by these tracking technologies. This is due to the continuous development of geographical information science and advances in computing abilities. The opportunity to collect and analyze high-resolution space-time data that covers long periods of time, creates enormous possibilities for initiating new lines of tourism research and formulating new research questions that could not be answered previously (Shoval & Ahas, 2016).

The development of mobile technologies that can be used for tracking—such as GPS and mobile phones—has been very dynamic. These technologies present researchers with several advantages, particularly the opportunity to collect higher quality data. For example, in the case of GPS receivers, the data is continuous and of a high resolution in time (seconds) and space (meters) (Shoval & Isaacson, 2006); and in the case of passive positioning of phones on mobile networks, researchers can track the approximate location of millions of phones, for very long periods of time (Ahas et al., 2010), which has never before been possible in tourism research. Mobile tracking technologies hold clear advantages over traditional methods such as surveys and self-report diaries. They are more accurate, reduce the burden from participants, and are not dependent on respondents' memory (Isaacson et al., 2016). As a result, these technologies have become a central data-collection tool in human mobility studies.

We suggest that the clear shifts in methods through which tourists' mobility may be examined have resulted in distinct tracking eras. In this review paper we assess these eras, starting with a pre-technology era and ending with the current era, characterized by adding information from physiological sensors, mobile eye trackings and real time tracking, predictive analytics, and AI. The review concludes with future research issues, needs and possibilities for tourism research, thus creating a road map for tourist mobility research, now and into the future.

Tracking tourists' mobility: a concise history of tracking

The pre-technology era

Prior to the widespread use of technology to collect mobility data, surveys were highly regarded as the gold standard for collecting tourist behaviour, data due to their ability to collect representative data on income, earning, family size and structure, trip type, and itineraries. Surveys could be conducted in person at locations such as airport departure lounges, *via* mail, or *via* home telephones (whose numbers often had a relationship with respondents' home address), thus facilitating representative sampling. When assessing tourists' behaviour and mobility patterns, these types of surveys were typically conducted at the end of tourists' journeys.

Survey data has facilitated many important insights: Williams and Zelinsky (1970) created a predictive model of visitation, arguing that visitor flows are patterned, predictable and non-random. Years later, Mings and McHugh (1992) used survey data to develop a theory that two factors affect movement of independent travellers: destination and tourist characteristics. They also theorised that four trip patterns exist within destinations: a direct route; a partial orbit; a full orbit; and a fly drive pattern (Mings & McHugh, 1992). Following this, Oppermann's (1992) survey research assessed intranational tourist behaviour and identified that destinations are subjects to areas of concentration, directionality, and market segment dispersal. Oppermann (1995) then proposed seven possible itinerary types for international tourists. Building on from previous work, Flogenfeldt (1999) used survey data to argue that nationality alone has no significant influence on the itinerary that visitors take. In the same year, Tideswell and Faulkner (1999) conceptualised factors likely to influence dispersal in regional visitation including pleasure holidays, small travel party size, long haul visitors, rental or private vehicles as transport, and wide use of information sources.

The concept of distance decay was also conceptualised *via* survey research. McKercher and Lew (2003) found distance has a decaying effect on demand for international travel, and for destinations reliant on airlines, demand for tourism decreases with distance. Lau and McKercher (2006) then developed three factors that influence tourists' movement: human factors such travel party, personal motivations and prior visitation to the destination; physical factors such as weather and location of attractions; and time factors, including time in the destination and the total trip duration. Following this, Masiero and Zoltan (2013) used survey research to posit that tourists' decisions over the distance they will cover is linked to their choice of transport—notably public versus private transport.

Surveys have also been used to collect mobility pattern data, by asking respondents illustrate on maps where they travelled. While this method has been used to understand broad mobility patterns, it has been noted that it is limited in terms of its ability to understand precise information on where and when tourists stop, and their speed, without requiring them to record onerous amounts of data. Nevertheless, itinerary mapping *via* surveys has been useful in determining tourist flows, directionality and routes in particular areas; where tourists stop, and what activities they engage in on specific routes (Connell & Page, 2008).

While itinerary mapping *via* surveys can produce data on where tourists recall they have travelled, Shoval et al. (2011) note that analysis is complex, as it must account for individuals' movements, including both their mobility and stops. Moreover, survey methods in themselves are limited as they are unable to collect continuous, detailed temporal and spatial on the actual path of tourists (Hardy, 2020). Their reliance on recall from tourists has been flagged as a problematic issue (Shoval & Isaacson, 2007), as has the time that surveys require for people to complete them, particularly given tourists are highly mobile and on leisure time (Dolnicar & Grün, 2013). Surveys also assume literacy which is not ubiquitous, even in developed countries (Hardy & Pearson, 2016), and their questions are prone to cultural bias- it has been demonstrated that participants from different cultures respond to survey questions in very different ways (Dolnicar & Grün, 2013).

The tourist tracking 1.0 era

Global Positioning Systems (GPS) technology was developed by the United States of America and the Soviet Union for military purposes in the 1970s and made available by the U.S.A. to non-military users in the in the late 1990s (Shoval & Isaacson, 2010). Prior to the early 2000s, GPS data was collected using standalone units that users would carry, but technological advances and miniaturisation mean that that GPS capability is now routinely included in smart phones and watches.

GPS technology facilitates continuous mobility tracking through space and time. Until recently, researchers relied on the use of standalone units that research participants would carry. This method produces spatiotemporal data only if researchers want to know who travels where, GPS-generated data must be synced with surveys containing demographic information. Early GPS loggers were also very limited by their battery life - often to around 14 h of tracking time (Edwards & Griffin, 2013). Despite these limitations, many early studies utilised this method and created significant geographic advances in our knowledge of the spatiotemporal activities of tourists. For example, McKercher et al. (2012) used GPS combined with surveys and determined that first-time visitors' mobility patterns tend to reflect an 'overview' of destinations. This involves moving widely through destinations and visiting well known attractions for longer periods of time. Conversely, repeat visitors concentrate their activities and visit fewer places.

GPS technology has also led to understandings of how tourists use time. Grinberger et al. (2017) theorised that 'activity time' is crucial in impacting the spatial distribution of tourism activity and Shoval et al. (2011) demonstrated that accommodation has a significant impact on tourist behaviour. Further work by Birenboim et al. (2013) demonstrated that tourists behave with distinct activity rhythms across the day, week and seasons. Similarly, Meijles et al. (2014) found the motivation to visit a national park is associated with the speed at which the group will travel.

Despite GPS' ability to collect high resolution data in time (seconds) and space (meters), it is subject to limitations. First, the technology relies on the ability of the tracking device to be able to access a line of sight with satellites in the sky, therefore signals can be limited when devises are indoors, in thick forest, or in cities with skyscrapers that obstruct lines of sight with satellites (Pettersson & Zillinger, 2011). It has also been suggested that the act of asking a participant to carry a logger may result in participants changing their behaviour (Winters et al., 2008).

Tourist tracking 2.0 era

The advent of the mobile phone, smart phone and social media marked a significant new era in tourism research. Mobile phones enabled intercept phone surveys to be conducted in real time, and smart phone functionality has enabled a variety of new methods to collect vast amounts of data, *via* Wi-Fi and Bluetooth technology (using internet protocol, or IP addresses), and apps which collect, or allow users to identify, their location-based data.

Bluetooth data has facilitated understandings of crowd movement at festivals (Versichele et al., 2012); within cities (Yoshimura et al., 2017) and tourist's attractions (Yoshimura et al., 2014). Consequently, it has demonstrated that the path sequences of both long and short stay tourists through attractions is similar, regardless of the time that tourists spend in them (Yoshimura et al., 2014). Wi-Fi scanning has been less commonly used, possibly due to its ability to only track slow moving objects, such as pedestrians. Importantly, Bluetooth and Wi-Fi produce mobility data only, thus excluding socio-demographic information (Hardy, 2020). Furthermore, Verischele et al. (2012) note that Wi-Fi and Bluetooth data collection is 'non-participatory' because individuals are not always required to provide their consent to be tracked.

The technology turn facilitated the development of social media platforms which now serve as significant data sources (Chen et al., 2021). Such is the rate of some platforms use that it has been argued their data can used as a proxy for visitation numbers (Levin et al., 2017). Social media data can be assessed in a variety of ways to determine mobility:

1. Collecting a sequence of individuals geotags or hashtags to determine how they move through destinations (Rossi et al., 2018); or
2. Collecting geotags or hashtags for a single location to determine crowding and usage (Shi et al., 2017).

Some websites allow geo-tagged data to be used en masse, providing it to researchers *via* an application programming interface (API). This has resulted in significant methodological findings: Tenkanen et al. (2017) compared Instagram, Twitter and Flickr and found that relationships existed been the number of posts and actual visitation to parks.

In addition to social media, tourists' mobility may also be tracked using the GPS enabled location-based function that is embedded in many apps. When users install apps, they are often asked to consent to the use of the data collected by the app for commercial purposes. The use of this mobility data is growing in popularity amongst destination management authorities who purchase it to gain insights into tourists' mobility. While it is limited to GPS data, vast amounts of spatiotemporal big data can be collected using this method, although it has scarcely been used within academia.

The technology turn has also facilitated the use of mobile phone positioning data to determine tourist mobility. This data is collected when mobile phones communicate with mobile phone towers and can provide vast amounts of time-stamped data. While its use in research is limited due to privacy concerns, when it has been used, it has resulted in conceptually significant insights. This is due to its ability to track tourist movements in a far larger geographic scale of analysis—regional, national, or even global scales—resulting in complex models for understanding travel patterns. Pioneering work was conducted by an Estonian group of researchers (see Ahas et al., 2007, 2008) who used cellular network information on a national scale to gain insights into the activities of foreign tourists in

Estonia (e.g. Nilbe et al., 2014) and seasonal moves related to second homes by domestic tourists in Estonia (Silm & Ahas, 2010). In China, Zhao et al. (2018) sourced the same type of data and assessed the impact of travel party size on dispersal. They found that tourists in large groups did not travel as far as individuals and couples (Zhao et al., 2018). While mobile phone data collection does not provide socio-demographic data on the user, methodological advances have determined how tourists can be identified: for example Vanhoof et al. (2017) created an algorithm that automatically defined domestic tourists' destination by finding the cell tower with the highest ratio of mobile phone activity, and most days of usage, along with an algorithm to classify business versus leisure travel (Vanhoof et al., 2017).

Tourist tracking 3.0 era

The emergent Tourist Tracking 3.0 era is characterised by the development of bespoke technologies, artificial intelligence and tourists' real time reactions. One of the first indicators of this new era was the development of bespoke research apps, developed to collect synchronous socio-demographic and time-space data. This technique eliminated the need to sync differing data sets and ensured that those providing the data (tourists) were doing so with their ethics and consent. The work by Hardy et al. (2017) and Raun et al. (2020) were world firsts, as their apps produced data where tourists were tracked, with their consent, for their entire journeys throughout destinations. The apps resulted in new conceptual understandings regarding tourists' dispersal patterns (Hardy et al., 2020a) and the impact that travel through time and space has upon tourists' wellbeing (Hardy et al., 2022).

More recently, tourist tracking research has begun to explore emotions in real time. Early work by Kim and Fesenmaier (2015) presented the feasibility of studying the objective emotions of tourists visiting a destination by tracking their electro dermal activity (EDA) over time and space. Soon after, Shoval et al. (2018) employed four data-collection techniques simultaneously to conduct a comprehensive and integrative investigation of the tourism experience in time and space. They utilised high-resolution locational data derived from GPS and cellular network locations; real-time surveying techniques employed through the Experience Sampling Method (ESM), including location-triggered and time-triggered surveys; physiological measures of emotion (SCL); and traditional surveying techniques such as questionnaires. Shoval et al. (2018) also used ambulatory sensing techniques, including objective measures of tourists' emotions during their visit, combined with real-time questionnaires that were triggered by a participant's specific location in the city and/or by time intervals. This approach enables scholars to integrate subjective and objective measures, thus facilitating a richer understanding of the experiences of an individual. It also allows researchers to synchronise individuals' location data with their physiological data which can lead to the identification of consistent and recurring emotional responses to tourist attractions (Shoval et al., 2018). In more recent work, emotions have been measured using virtual reality, as a means to influence pre-purchase decision making and mobility choices (Tussyadiah et al., 2018), as well as during the experience (Neuburger et al., 2018; Buhalis, et al., 2019) Research has largely focussed on VRs ability to create emotions, and impact intensions (Yung et al., 2021), as opposed to its impact upon emotions that are felt through time and space.

The launch of Chat GPT and other generative artificial intelligence (AI) tools in late 2022 gave much attention to the role that AI can play in making recommendations for personalised travel recommendations (Çolak, 2023). While platforms such as ChatGPT do not access social media posts or internet browsing history prior to making recommendations (as is the case with other internet tools, resulting in personalised ads being pushed to individuals, based on their browser history). the strength of generative AI tools such as ChatGPT is its ability to assist and influence tourist mobility in real-time by making suggestions to users such as itinerary suggestions, assistance in emergencies (Wong et al., 2023)) and suggestions based on users' past interactions with the platform.

Beyond generative AI, other forms of AI can be used by researchers to predict future tourist mobility patterns using a subfield of AI called machine learning. .Machine learning uses algorithms to learn from data sets and make predictions without the requirements for human intervention (Almomani et al., 2022). The ability for machine learning to predict, and particularly to undertake tourism demand forecasting, has received much attention in recent years (Núñez et al., 2024). Using this approach, Hardy et al. (2020b) used machine learning to predict where tourists would travel within a National Park, used a deep-learning approach to predict the mobility of short-term internation tourists in international countries. Used a big data set- namely web search traffic- and a machine-learning approach to predict tourist mobility and arrivals. It has been argued that artificial intelligence-based approaches do not depend on the statistical characteristics of specific datasets, are more able to dela with data noise and biases, thus are more accurate in their ability to predict tourists' mobility patterns (Li et al., 2016).

Summary of the four eras of tourist tracking

Consumption of places for the purpose of tourism, albeit in cities, urban or wilderness environments, has accelerated during the past decades. So too has the desire to understand the positive and negative social, cultural, and economic impacts of tourism (Mashkov & Shoval, 2023). Arguably, one of the biggest challenges for researchers is the ability to access timely, accurate and high-resolution data. Relatively recent technological advancements, most notably the proliferation of tracking technologies, real-time surveying techniques using smartphones, artificial intelligence and ambulatory sensing, have allowed researchers to advance these research needs.

One example of a theory that benefits from the high resolution data in time and space that is collected by tracking technologies is the theory of *Time geography*, which focuses on the constraints and trade-offs that occur when people find themselves having to divide a limited amount of time between various activities in space (Shoval, 2012) It was developed the Swedish geographer Torsten Hägerstrand and it was one of the earliest analytical perspectives used to analyse patterns of human activity (Gregory, 2000). However, due to the methodological complexity involved in studies mobility of tourists, ' little attention has been paid to these important aspects of time and space in tourism research.

The introduction of tracking technologies, the spread of increasingly sophisticated geographical information systems (GIS), capable of providing detailed computational representations and more precise measurements of basic time-geographic entities, including space-time paths and prisms, and sequence alignment methods (SAM) persuaded a growing number of researchers to return to the time geography fold. A better understanding of the logic of visitor activities in time and space could not only serve a number of practical purposes in tourism industries, planning, and management, but also develop the existing concept of time geography and considerably enlarge the theoretical foundations of tourism research.

Gaps in the literature and future research directions

The development of new technologies creates many research needs. One question that requires resolution, with regards to both traditional survey methods and tracking devices, is whether tourists, once they know they are being followed or are involved in mobility research, change their activity, and, if so, how?

Another question relates to the large amounts of data that are accumulated when using digital methods, which require algorithms for automatic analysis. There is a need to coordinate the algorithms and software that is being developed by growing numbers of research teams around the globe to be standardized, thus facilitating common analytical measures and comparison.

There is also a need to use big data and large data sets to develop new theories regarding the spatial activity of tourists, and particularly their influence on destinations. The calculation of physical and social carrying capacities, and ultimately the attainment of sustainability may be monitored within a destination, using this approach. These developments were not possible using the data sources that were available prior to the tourist tracking 3.0 era.

The development of real time technology has created exciting new possibilities for future research. App based technology and the ability to push notifications to tourists while travelling, mean that there is now an ability to encourage behaviour change. Further research is needed to determine the efficacy of this method to reduce crowding and overtourism, encourage dispersal, or reduce unacceptable behaviours. There is also a need to understand factors beyond tourists' socio-demographic status that affect their behaviour. Field experiments that use technology offer the opportunity to identify how tourists respond contextual situations such as amount of crowding, light intensity, atmospheric ambience, or even factors such as how tourists interact with locals, the built environment or open spaces.

In addition to methodological possibilities, there is also a pressing need for the consideration of the ethics and consent of tracking tourists. Kozinets (2019, pp. 195) argues that:

> … a significant number of people – very likely a majority – would prefer that researchers should not use their social media data and information in their investigations.

It has been suggested that while 'Terms and Conditions' may outline how data will be shared for research purposes, many users do not read these. Moreover, in relation to social media, not all individuals have high levels of computer literacy, thus they may not realise their posts are publicly available (Hardy, 2020). The use of technologies that obtain the exact locations of research participants at any given moment can cause infringements on the privacy of the participants. This adds a geographical dimension to the surveillance society (Lyon, 2001) and the ability to better track the digital individual (Curry, 1997). Further research is needed to explore the ethical and moral issues surrounding the use of these technologies.

Conclusion

The potential improvements in the implementation of tracking technologies for tourism research and practice can enhance the benefits of using those methods for researchers and practitioners alike. These, combined with the enormous advances in tracking technologies over the past 25 years, leave no doubt that the future of tracking technologies in tourism will be exciting and dynamic, providing researchers with invaluable insights and information.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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