Annals of Tourism Research xxx (xxxx) xxx

Contents lists available at ScienceDirect

Annals of Tourism Research

journal homepage: https://www.journals.elsevier.com/annals-of-tourism-research

Research Note

Movement in tourism: Time to re-integrate the tourist?☆

Bob McKercher [a], Sebastian Filep [b,*], Brent Moyle [c]

[a] Business School, University of Queensland, 293 Queen Street, Brisbane City, QLD 4000, Australia
[b] School of Hotel and Tourism Management, The Hong Kong Polytechnic University, 17 Science Museum Rd, Tsim Sha Tsui East, Hong Kong
[c] Department of Tourism, Sport & Hotel Management, Griffith Business School, Griffith University, Nathan, QLD 4111, Australia

ARTICLE INFO

Article history:
Received 3 December 2020
Received in revised form 18 March 2021
Accepted 21 March 2021
Available online xxxx

Associate editor: Shoval Noam

Keywords:
Big data
Tourist movement
Time
Tourist behaviour

We know a great deal about how and where tourists move and spend their time with the advent of big data (Li et al., 2018). However, we know precious little about why they behave the way they do. Ironically, as researchers move relentlessly onto the big data bandwagon, the risks of producing an even vaster amount of empirical data with little epistemological validity grows exponentially. Big data, defined as massive scale data which is recorded, stored, accumulated and generated by its users (Li et al., 2018) can achieve a lot but it also means the individual tourist is largely forgotten. Qualitative studies on movement in tourism (Cutler et al., 2014) and those that examine the individual tourists (De Cantis et al., 2016) exist, but with the advent of new technology such studies are far from the norm. This research note aims to draw attention to the limitations associated with the proliferation of big data research advocating for greater in-depth, theoretically informed, qualitative, insights into the reasons for tourist decision making in analysing spatial and temporal patterns of tourists.

Time, as a scarce temporal resource can only be spent and not be saved. Lew and McKercher (2006) posited that time spent in a destination area is the most influential criterion shaping tourist behaviours and movements. McKean et al. (1995), argue time rationing is critical, with how people allocate their scarce time budgets not only to influence the trip itself, but also the experience. Researchers have been interested in examining how people spend time since Hagerstrand (1970) first mapped the time-space movement patterns of individuals. With the development of more portable GPS (Global Position System) software and the accompanying GIS (Geographic Information System) technology, this field has advanced rapidly, led by Shoval & Isaacson (2007). Recently, Hardy et al. (2020), developed bespoke technologies to analyse large scale movement patterns for the first time.

☆ Authors' Bio: Professor Bob McKercher of University of Queensland is a Fellow of the International Academy for the Study of Tourism. He has published over 300 scholarly papers and research reports in the field of tourism, including papers on tourist movement studies. Associate Professors Sebastian Filep, The Hong Kong Polytechnic University, and Brent Moyle, Griffith University, have published widely on various tourist behaviour topics. All three authors are on multiple editorial boards of major tourism journals.

* Corresponding author.
E-mail addresses: r.mckercher@uq.edu.au, (B. McKercher), sebastian.filep@polyu.edu.hk, (S. Filep), b.moyle@griffith.edu.au. (B. Moyle).

https://doi.org/10.1016/j.annals.2021.103199

As a result, our understanding of where people spend their time and how much time they spend pursuing specific activities is well developed. However, the increasing reliance on data driven analytics comes at a cost. While we may know what tourists do and how long they spend doing things, we do not know why. Why do people make the decisions they make that translate into observable movement patterns? The very method used nowadays precludes asking and answering that question. The authors feel the human element is being removed from tourism research, with researchers putting faith in descriptive empirical studies that analyse large data sets. Zhang et al. (2012) suggest the body of literature on this topic is limited, lamenting that in tourism movement research, tourist time use remains an understudied area.

The explosion of big data research, coupled with the ongoing popularity of GIS studies, is threatening to eliminate the individual tourist from tourism research. The volume of GIS work grew from 54 cases in 1990 to over 1000 by 2008, and for the last ten years Google Scholar reported about 1500 entries. By comparison, six big data tourism related studies were reported in 1990. This grew slowly until about the year 2011 when 169 cases were reported. Since then, there has been an exponential growth in big data analytics by the end of the year 2019.The growth of big data, and to a lesser extent GIS research, has transformed studies about tourist movements. We have a much better understanding of what people do and where they go. But, does this work help us understand the tourist?

To be fair, it is recognised that a spectrum exists from individualised to de-individualised tourist data, with big data, GIS and bespoke applications varying in location on the spectrum (Chantre-Astaiza et al., 2019). GPS uses tracking devices to determine exact location during real time. In line with GIS, GPS software collects accurate data on the spatial and temporal patterns of visitors (Hardy, 2020). Bespoke applications, such as Tourism Tracer used in Australia, take this to another level, developing custom and tailored software with solutions created for a specific user group (Hardy, 2020). Such approaches are better in terms of their ability to assess individual tourist behaviours, however they should not be confused with big data, as GPS and bespoke applications rarely involve large samples (Hardy et al., 2020).

Succi and Coveney (2019) note it is too easy to get overwhelmed by big data, noting too much data is as bad as no data. The result is to look for the norm or typical behavioural pattern, while ignoring the all-important outliers. They highlight the substantial difference between correlation and causation, yet, big data often tries to infer causation when it may not be warranted. Noyes (2015) adds that while most analytical tools are set up for quantified information, unstructured and qualitative data often provide the needed context and meaning to make sense of the patterns observed. These issues are especially prescient in tourism research. In fact, the bigger the data set in tourism, the more impressive the graphics appear. But, concomitantly, the bigger the data set, the more generic the movement patterns become. As a result, the all-important 'so what' element is lacking in much of this work. Lew and McKercher (2006) argued conceptually that tourist flows were a function of tourist time budgets, mode of transport, the geomorphology of the destination, the spatial distribution of attraction nodes, destination knowledge (and past visitation experience) and the tourists' own interests. Big data studies confirm the impact of human and physical geography, but cannot consider the element of tourist behaviour.

Ironically, some related pioneering work offering insights into time expenditure as part of tourist behaviour was conducted in the late 1980s and early 1990s. Such studies seem to have fallen out of flavour as more sophisticated data analytical tools were developed. McKean et al. (1995) initially felt time expenditure usually involved trading-off between time spent in transit and time spent in the destination or at desired attractions. How this trade-off is made depends both on how one values the act of travelling and the absolute amount of time available. They discovered some people see transit time a scarce resource, or a cost that must be consumed at the expense of time spent at the destination (Truong & Henscher, 1985). These individuals seek to minimise travel time to maximise time spent at their preferred destination. Such individuals may be described as outcome-oriented individuals. These people are likely to be time constrained, have short vacation time allocations and therefore wish to maximise their time at the destination (McKercher & Lew, 2003). They take short haul, single destination trips, tending to be comprised disproportionately of families (McKercher, 1998).

Transit time may also be seen as a valuable commodity in itself, where the act of getting to the destination is seen as equally or more important than being at the destination. These so-called process-oriented tourists value touring, sightseeing, making multiple stops. They are less time constrained, likely to be on a multiple destination trip, often do not identify any single main destination and describe their journey as a touring vacation (McKercher, 1998). Other studies have identified moderating factors that affect time expenditure decisions. Within a destination, weather can act as a facilitator of or inhibitor to participation (Becken & Wilson, 2013), with temperature, presence or absence of precipitation and unexpected changes in weather conditions being the most important factors (Denstadli et al., 2011). Trip duration (Shoval & Raveh, 2004), whether the place visited represents the main or secondary destination (McKercher, 2001), whether the person is a first time or repeat visitor (Gitelson & Crompton, 1984) also have an impact on time expenditure decisions. The role the destination plays in the overall trip is a critical factor, for the tourist has a far higher psychological investment in the main destination than in stopover destinations (McKercher et al., 2006), but the type of tourist may also play a role (Debbage, 1991).

Big data and GIS research are clearly valuable tools to show us what tourists do, however these studies tease us by offering few insights into the reasons (whys) of tourist decision making and time use. Such questions can primarily be answered through more in-depth, often qualitative, primary data collection. Big data, in particular explicitly precludes the collection of complementary data, while it seems to be largely ignored in many GIS studies. The failure to do so results in a great deal of descriptive work that ultimately cannot ask and answer the all-important 'so what' question. Do we jump off the big data and GIS bandwagon? Of course not. But we have to appreciate its limitations and accept what it can and the many things it cannot do. Perhaps, it is time for some of us to put the software away and actually start to talk to tourists.

Declaration of competing interest

None.

References

Becken, S., & Wilson, J. (2013). The impacts of weather on tourist travel. *Tourism Geographies*, *15*(4), 620–639.

Chantre-Astaiza, A., Fuentes-Moraleda, L., Muñoz-Mazón, A., & Ramirez-Gonzalez, G. (2019). Science mapping of tourist mobility 1980–2019. Technological advancements in the collection of the data for tourist traceability. *Sustainability*, *11*(17), 4738.

Cutler, S., Carmichael, B., & Doherty, S. (2014). The Inca Trail experience: Does the journey matter? *Annals of Tourism Research*, *45*, 152–166.

De Cantis, S., Ferrante, M., Kahani, A., & Shoval, N. (2016). Cruise passengers' behaviour at the destination: Investigation using GPS technology. *Tourism Management*, *52*, 133–150.

Debbage, K. (1991). Spatial behavior in a Bahamian resort. *Annals of Tourism Research*, *18*(2), 251–268.

Denstadli, J., Steen Jacobsen, J., & Lohmann, M. (2011). Tourist perceptions of summer weather in Scandinavia. *Annals of Tourism Research*, *38*(3), 920–940.

Gitelson, R., & Crompton, J. (1984). Insights into the repeat vacation phenomena. *Annals of Tourism Research*, *11*(2), 199–218.

Hagerstrand, T. (1970). What about people in regional science? *Papers of the Regional Science Association*, *24*(1), 6–21.

Hardy, A. (2020). *Tracking tourism movement and migration.* Oxford, UK: Goodfellows.

Hardy, A., Birenboim, A., & Wells, M. (2020). Using geoinformatics to assess tourist dispersal at the state level. *Annals of Tourism Research*, *82*, 102903–102917.

Lew, A., & McKercher, B. (2006). Modeling tourist movement: A local destination analysis. *Annals of Tourism Research*, *33*(2), 403–423.

Li, J., Xu, L., Tang, L., Wang, S., & Li, L. (2018). Big data in tourism research: A literature review. *Tourism Management*, *68*, 301–323.

McKean, J., Johnson, D., & Walsh, R. (1995). Valuing time in travel cost demand analysis: An empirical investigation. *Land Economics*, *71*(1), 96–105.

McKercher, B. (1998). The effect of market access on destination choice. *Journal of Travel Research*, *37*, 39–47.

McKercher, B. (2001). A comparison of main destination and through travellers at a dual purpose destination. *Journal of Travel Research*, *39*(4), 433–448.

McKercher, B., & Lew, A. (2003). Distance decay and the impact of effective tourism exclusion zones on in international travel flows. *Journal of Travel Research*, *42*(2), 159–165.

McKercher, B., Wong, C., & Lau, G. (2006). How tourists consume a destination. *Journal of Business Research*, *59*(5), 647–652.

Noyes, K. (2015). Why big data isn't always the answer. *Computerworld*. Available: https://www.cw.no/artikkel/big-data/why-big-data-isnt-always-answer.

Shoval, N., & Isaacson, M. (2007). Tracking tourists in the digital age. *Annals of Tourism Research*, *34*(1), 141–159.

Shoval, N., & Raveh, A. (2004). The categorization of tourist attractions: The modeling of tourist cities based on a new method of multivariate analysis. *Tourism Management*, *25*(6), 741–750.

Succi, S., & Coveney, P. (2019). *Big data: The end of the scientific method?* Royal Society Publishing https://royalsocietypublishing.org/doi/10.1098/rsta.2018.0145.

Truong, T., & Henscher, D. (1985). Measurement of travel time values and opportunity cost model from a discrete-choice model. *The Economic Journal*, *95*(June), 438–451.

Zhang, H., Zhang, J., & Kuwano, M. (2012). An integrated model of tourists' time use and expenditure behaviour with self-selection based on a fully nested Archimedean copula function. *Tourism Management*, *33*(6), 1562–1573.