Characterizing urban lifestyle signatures using motif properties in network of places

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Abstract
The lifestyles of urban dwellers could reveal important insights regarding the dynamics and complexity of cities. The availability of human movement data captured from cell phones enables characterization of distinct and recurrent human daily visitation patterns. Despite growing research on analysis of lifestyle patterns in cities, little is known about the characteristics of people’s lifestyle patterns at urban scale. This limitation is primarily due to challenges in restriction of human movement data to protect the privacy of users. To address this gap, this study constructed networks of places to model cities based on location-based human visitation data. We examined the motifs in the networks of places to map and characterize lifestyle patterns at urban scale. The results show that (1) people’s lifestyles in cities can be well depicted and quantified based on distribution and attributes of motifs in networks of places; (2) motifs show stability in quantity and distance as well as periodicity on weekends and weekdays indicating the stability of lifestyle patterns in cities; (3) networks of places and lifestyle patterns show similarities across different metropolitan areas implying the universality of lifestyle signatures across cities; (4) lifestyles represented by attributed motifs are spatially heterogeneous suggesting variations of lifestyle patterns within different population groups based on where they live in a city. The findings provide deeper insights into urban lifestyle signatures and significant implications for data-informed urban planning and management.

Keywords
Human lifestyle, urban intelligence, network motif, complexity

Introduction
Characterizing lifestyle patterns of people is essential for understanding dynamics and complexity of cities arising from interactions among people, places, and activities (Batty, 2013). Understanding lifestyle signatures in cities could reveal important insights regarding ways people interact with their...
surrounding environment and places to inform urban planning decisions such as facility distribution, equity, sustainability, and resilience (Toole et al., 2015; Maeda et al., 2019).

Lifestyle can be defined based on sequence of life activities that residents in a city implement regularly over the course of a day. These life activities, in most cases, involve visitation to places (also called Points of Interest, POI). Hence, with the growing availability of urban sensing and location-based data, several recent studies have examined human visitation and activities to unveil important characteristics about urban lifestyles (Xu et al., 2020; Zhao et al., 2021; Zhang et al., 2021). However, the existing literature is limited in three aspects. First, the existing studies have examined the combination of visitation to places at the individual user level. Accessing and analyzing user-level movement data are restricted due to privacy protection. Thus, the existing approaches are rather limited in terms of characterizing population lifestyles. Second, the existing studies examining lifestyles are based on some crude classifications of human activities (i.e., home and work), lacking the incorporation of diversified features of POI (e.g., restaurants, hospitals, and grocery stores). Third, the existing research limits in accounting for spatial network structures embedded in urban lifestyles, which inhibits characterizing lifestyle patterns at urban scale.

In this study, we analyzed the subgraph signatures (i.e., motifs) in networks of places (NOP) for mapping and characterizing urban lifestyle signatures. The NOP represents nodes as POIs and links as visitations between POIs during a specific period (e.g., day). First, the NOP for multiple US metropolitan areas (i.e., Harris County, Dallas County, New York County, and Broward County) were constructed using location-based data obtained from Spectus and SafeGraph. Next, two-node, three-node, and four-node motifs without location attributes were examined in the NOP. Finally, homogenized nodes in motifs were encoded with location categories from North American Industry Classification System (NAICS) category code. Statistical measures, including network metrics and motif properties, were quantified to characterize lifestyle signatures. The results demonstrate a multi-faceted portrait of population lifestyles at urban scale, which provides deeper insights into urban complexity and important implications for data-informed urban planning.

**Background**

To obtain comprehensive picture of urban spatial structure, one important aspect of urban dynamics and complexity analysis is the characterization of population lifestyle patterns (Lazer et al., 2009). Human lifestyle analysis focuses on exploring spatial-temporal patterns as well as hidden signatures behind the intra-urban and inter-urban movements (González et al., 2008). Over the past several years, human lifestyle has been growingly investigated. For example, Louail et al. used mobile phone data recorded in 31 Spanish cities to classify cities according to their commuting structure. They found that these cities essentially differed by their proportion between integrated and random flows, whose importance increases with city size (Louail et al., 2015). Daily activity patterns of students, workers, and retirees during the course of California workdays were recognized by using sequences of visits to different places in human mobility networks among different regions (Su et al., 2020). Varying topologies of trip combinations, such as “Home-Work-Home,” were extracted for transit riders from different public transportation systems in Nanjing, China (Lei et al., 2020).

Despite growing recognition of the significance of characterizing lifestyle patterns, the existing literature has limitations in three aspects. First, the existing studies have examined lifestyle patterns using movement trajectories at the individual user level. The movement data at user level is not only difficult to access but also presents potential privacy issues. To overcome this limitation, aggregated location-based data that are more privacy-compliant could be adopted. Second, a granular picture of human lifestyles cannot be obtained based on current approaches because most existing studies only focus on places of home, work, and non-work. Urban areas are composed of different POIs, such as restaurants, hospitals, and grocery stores, which contribute to the functionalities of urban locations.
and shaping of lifestyle. Considering various POIs is essential to provide more detailed insights into urban lifestyle signatures. Third, the approaches that examine lifestyles based on sequence of movements do not account for spatial network structures embedded in urban lifestyle signatures. This limitation inhibits characterizing lifestyle patterns at urban scale while accounting for spatial network structures to reveal similarities and differences among lifestyles of residents across different cities.

One approach to analyzing topological signatures in spatial networks is through examining motif. Motif is defined as the interconnection mode that has recurrence frequencies in the real network much higher than those in a randomized network (Dey et al., 2019). Milo et al. (2002) found that motifs ubiquitously exist in universal classes of networks, such as biochemical, neurobiological, ecological, and engineering network (Milo et al., 2002). As basic building blocks in networks, motifs are crucial for understanding the basic structures that control and modulate many complex system behaviors (Benson et al., 2016), which have been widely applied to network function studies in different disciplines in recent years (Stone et al., 2019). Recently, motif has also attracted the attention of researchers in urban studies, who construct motifs arising from human movement trajectories, such as bike-sharing ride records (Yang et al., 2019b) and public transportation card swipe records (Lei et al., 2020), to explore various human movement characteristics. These studies demonstrate the advantages of motifs in tapping into the universal human lifestyle patterns.

Since human lifestyles are shaped by the spatial configurations of POIs, lifestyles then are encoded in motifs of NOP. Also, human visitations demonstrate uneven frequency of different locations, repeatedly returning to certain locations while being less likely to visit new ones (Song et al., 2010a, 2010b). To this end, this study analyzed human visitation datasets at an aggregated level, developed a method to differentiate categories of POIs, and extracted attributed motifs from NOP to characterize urban human lifestyle signatures.

### Methodology

#### Data sources

The data in this study came from two datasets. The first dataset is anonymized and privacy-enhanced mobile phone data provided by Spectus, an offline intelligence and measurement company. The dataset consists of anonymized visitation to POIs in four metropolitan counties in the United States: Harris County and Dallas County in Texas, New York County in New York, and Broward County in Florida. The temporal range is from February 1 through February 28, 2020. This period was selected since it was prior to the COVID-19 pandemic and its associated restrictions and thus could represent normal lifestyle. Moreover, to ensure the stability of the weather, temperature, and social emergency conditions in the four counties under investigation, we thoroughly examined the available data for that specific time period. Our findings indicate that there were no extreme weather events or particularly significant social events during that month in these counties. The dataset includes device ID, POI ID, latitude, longitude, and dwell time of visitation. The location information of POIs was obtained from SafeGraph, Inc., a location intelligence data company. The dataset includes POI ID, location name, and address.

#### Detecting visits from POI to POI

The methodological framework for examining urban lifestyle signatures is shown in Figure S1 in Supplementary Material. This framework consists of four steps. First, we used Spectus dataset to detect visits from starting POI to destination POI. Table “stop” from core data assets in Spectus was used to extract which POI the device has been to. Dwell time, which indicates stop duration of
devices, was used as a criterion for defining a visit. If the duration a device stayed in one POI exceeded the thresholds (2 min), then a visit to that POI was recorded. Combing the time sequence of visits, the starting POIs and destination POIs were identified. In this way, visits from POI to POI were built and aggregated for each day. Then, POI ID was used to merge information between SafeGraph and Spectus and thus visits from POI to POI were affiliated with location information. Finally, all POIs were labeled with NAICS category code, which is the standard used by Federal statistical agencies in classifying business establishments. The illustration of data match process can be found from Figure S2 in Supplementary Material. Figure 1 (level 1 and level 2) illustrates the process of POI-to-POI visit detection.

**Generating POI-to-POI networks**

To capture a global picture of human visits, we aggregated all devices’ stay trajectories to construct an undirected and weighted network that represented the sum of visit flows of all devices (level 3 in Figure 1). We named this network as network of places, which is defined as

\[ G = (V, E, W) \]  

(1)

where \( V \) represents POIs, \( E \) represents visits among POIs, and \( W \) corresponds to the counts of visits between two POIs.

**Constructing human visitation motifs**

Motifs are defined as common and recurrent subgraphs in network theory (Dey et al., 2019). In this study, the human visitation motifs denote general urban lifestyle signatures. According to Newman

![Figure 1. Illustration of POI-to-POI visit detection and network generation.](image-url)
 motifs can be identified by exploring the network isomorphism. Let \( G_1 = (V_1, E_1) \) and \( G_2 = (V_2, E_2) \) be two graphs. If \( V_2 \) is a subset of \( V_1 \) \( (V_2 \subseteq V_1) \) and \( E_2 \) is a subset of \( E_1 \) \( (E_2 \subseteq E_1) \), then \( G_2 \) is a subgraph of \( G_1 \). Suppose there is a one-to-one mapping function \( f: V(G_2) \rightarrow V(G_1) \), in which any two nodes \( i \) and \( j \) in \( G_2 \) are adjacent if and only if \( f(i) \) and \( f(j) \) are adjacent in \( G_1 \), then \( G_1 \) and \( G_2 \) are considered isomorphic \( (G_2 \cong G_1) \). The mapping function \( f \) is called an isomorphism between \( G_1 \) and \( G_2 \). When there is a subgraph \( G'_1 \) of \( G_1 \) \( (G'_1 \subseteq G_1) \) and \( G'_1 \) is isomorphic to \( G_2 \), it means an appearance of \( G_2 \) in \( G_1 \). The total number of appearances is the frequency \( F_G(G_2) \) in \( G_1 \). Once the frequency \( F_G(G_2) \) exceeds a predefined cutoff value, \( G_2 \) is considered as a motif in \( G_1 \).

Motifs usually contain limited numbers of nodes, thus indicating the fundamental units to uncover the structural characteristics of a network (Milo et al., 2002). In this study, we scanned the NOP for all possible two-node, three-node, and four-node motifs. Table 1 summarizes basic structural characteristics of all nine motifs identified in this study.

**Characterizing human visitation motifs**

Characteristics of population lifestyles are not only reflected from the number or shape of motifs but also the node attributes. For example, a two-node motif denoting visits from school to pharmacy is quite different from another two-node motif denoting visits from grocery store to shopping mall. Therefore, considering motifs without node attributes could cause serious information loss for identifying unique urban lifestyle signatures. In this study, we affiliated motif nodes with NAICS code to classify POI categories so that to identify heterogeneous lifestyle signatures. NAICS codes along with visualized icons are shown in Table S1 of the Supplementary Material. Three scenarios of enriching unattributed motifs with NAICS code were created in Figure S3 of the Supplementary Material.

Furthermore, attributed motifs can be measured from both spatial and temporal perspectives. Spatially, this study adopted average distance of motifs to measure the variability of lifestyles.

| Motif ID | Motif shape     | Structural characteristic |
|----------|-----------------|--------------------------|
| M2-1     | Edge            |                          |
| M3-1     | Star, chain     |                          |
| M3-2     | Triangular, ring|                          |
| M4-1     | Fully connected |                          |
| M4-2     | 4-Chordal cycle |                          |
| M4-3     | Quadrangle, ring|                          |
| M4-4     | 4-Tailed triangle|                         |
| M4-5     | Chain           |                          |
| M4-6     | Star            |                          |

Table 1. Motif categories in global networks of places.
Average distance of motifs is defined as the sum of the spatial length of each edge divided by the number of edges, where the spatial length of each edge is calculated with reference to the Haversine Formula (Alam et al., 2016) as follows:

\[ D = \frac{\sum_{i,j \in V} 2R \arcsin \left( \sqrt{\sin^2 \left( \frac{\frac{\text{lat}_i - \text{lat}_j}{2}}{2} \right) + \cos (\text{lat}_i) \cos (\text{lat}_j) \sin^2 \left( \frac{\text{lng}_i - \text{lng}_j}{2} \right)} \right)}{e} \]  

(2)

where \( R \) is the radius of the Earth, \( \text{lat}_i, \text{lat}_j, \text{lng}_i, \) and \( \text{lng}_j \) are the radian coordinates of node \( i \) and \( j \), and \( e \) is the number of edges of a motif.

Temporally, people’s lifestyles vary over time. To avoid chance of error, this study used the average number of attributed motifs on weekdays and weekends in a month to investigate lifestyle differences between weekdays and weekends.

**Results**

**Properties of NOP**

We first investigated properties of the NOP across the study areas. Visualizations of the networks for four counties are shown in Figure S4 in the Supplementary Material. For each network, properties we focused on were the number of nodes, edges, weight of edges, average degree, and clustering coefficient (see Table S2 for results). Harris County has the largest number of nodes and edges, while New York County has the fewest number of nodes, but the second largest number of edges, illustrating that NOP in Harris County is relatively sparse and that in New York County is denser. The total weights of the four counties are more than one million, indicating that the constructed networks are quite large scale. New York County has a much higher average degree among the four counties, illustrating POIs in New York County are interconnected more closely by human visits. Clustering coefficient measures neighborhood density and captures the degree to which the neighbors of this node are linked with each other (Opsahl and Panzarasa, 2009). All cluster coefficients in the four counties exceed 0.2, which demonstrates that the NOPs are likely to shape local clusters, supporting the importance of motifs in characterizing lifestyle signatures at urban scale.

Next, we explored the visit frequency distribution of POIs in the NOP. Probability density function (PDF) and cumulative density function (CDF) of the node degree are calculated in Figure 2(a) and (b). Despite the different geographic and demographic characteristics across the four counties, the patterns of degree distribution are quite similar. There are steep decreases of possibility between the degree range from 10 to 100. The phenomenon indicates the existence of node degree heterogeneity within the NOPs. That is, a large set of visits are unique to individuals and rarely occur, while a small proportion of POIs are kept being visited by all the population.

**Properties of unattributed motifs**

Comparisons for number percentage and average distances among the nine motifs were made to identify similarities and differences across the four counties as shown in Figure 2(c). The distributions of the two metrics are quite similar in the four counties. Four-node motifs have the highest proportion for number percentage (70.12% on average across all counties), indicating that people are more likely to go to four POIs. Among the categories of four-node motifs, it is worth noting that M4-1 and M4-6 account only for very small percentages (0.03% on average for M4-1 and 0.26% on average for M4-6), probably because the lifestyles represented by M4-1 are too complex, while the
lifestyles represented by M4-6 are less efficient. Full statistical properties of the nine motifs across the four counties can be checked in Table S3.

In terms of spatial distance, the average distance of M4-1 (1.651 miles on average across all counties) is the shortest among all motifs (3.407 miles on average for all the other motifs across all counties), and the rest of the motifs are roughly the same. Although M4-1 has the most edges, meaning that this lifestyle involves several POI pairs that are visited altogether in a week, this type of lifestyle occurs primarily among POIs separated by a relatively small distance. In addition, the average distance of motifs in New York County (1.194 miles on average across all counties) is significantly lower than that of the other three counties (3.884 miles on average for all the other motifs across all counties). This finding can be attributed to multiple factors. Firstly, the higher density of POIs in New York County allows individuals to access multiple POIs within relatively shorter distances, reducing the need for longer travel distances between POIs. Secondly, the relatively smaller size of New York County compared to the other three counties imposes constraints on travel flows within the county. This spatial constraint influences the average distance of motifs observed, as travel distances are naturally limited within a smaller geographic area.

To uncover the temporal disparities in the nine motifs, the distribution of daily percentage changes in 1 month for Harris County are shown in Figure 3(a). The whole plot can be found in Figure S5. Percentage changes were calculated based on a weekly pattern to differentiate weekdays and weekends. The moving average curves of the four counties show that the number of motifs was rather stable across all motif categories, despite minor fluctuations in some motifs (e.g., the number

Figure 2. (a) PDF distribution of node degree in NOPs; (b) CDF distribution of node degree in NOPs; (c) distribution of number percentage and average distance in the nine motifs. The percentage (×10%) represented by the dash lines means the percentage of the number of one type of motif to the number of all motifs in this county. The distance (miles) represented by the solid lines means the average distances for all the motifs in this county.
of M4-4 in Harris County fluctuated in the second and third week but stabilized in the fourth week). This indicates that these motifs are stable enough over a considerable period to be adopted to depict lifestyle signatures.

From a weekly perspective, both the number of motifs on weekdays and weekends generally follows a cyclical pattern across the four counties. For example, during weekdays, the number of M2-1 in Harris County almost always started to drop on Monday, and dropped to the lowest level on Tuesday, then raised quickly on Wednesday and Thursday, and finally dropped slightly on Friday. On weekends, the number of M2-1 was always much lower on Sundays than on Saturdays. Except for M4-4, the rest of motifs basically had similar changes as M2-1, but the magnitude of the changes varied. In addition, the variation of percentage change of motif number on weekdays was significantly smaller than that on weekends. In Harris County, for example, most of the motifs varied within 20% on weekdays, among which a significant proportion of the variations were even within 10%. However, most of the motifs’ change on weekends exceeded 20%. This indicates that lifestyles on weekdays are more stable, while more unstable on weekends.

To uncover the spatial disparities in these motifs, the distribution of the percentage changes in average distance for nine motifs in 1 month is shown in Figure 3(b). The whole plot can also be found in Figure S6. The moving average curves for the four counties were rather flat, showing that average distances of all motifs hardly changed overtime. The percentage change of all motifs was less than 5%, especially for M3-2, M4-1, M4-2, and M4-3, whose percentage change was close to zero. This result indicates that most people have fixed visitation patterns which produce stable lifestyle signatures at urban scale. Obviously, the change in distance on weekends is also greater than that on weekdays. However, the tendency seems to be more chaotic, suggesting that people enjoy more flexible lifestyle patterns on weekends, such as choosing to go a farther place for shopping or dining. In general, the percentage change of motif number and average distance show
that people’s lifestyles can be well depicted and quantified by the nine motifs. Moreover, the two
metrics are observed to be quite different within a week between weekday and weekends.

Properties of attributed motifs

Although unattributed motifs identified directly from the NOP have revealed the temporal and
spatial characteristics of urban lifestyle signatures from a topological perspective, we also explored
the lifestyle heterogeneity by differentiating the motifs based on node attributes. The node attributes
in motifs cover 20 categories of POIs by NAICS code. Figure 4(a) shows the visit frequency for all
categories, which show similar patterns across the four counties. Retail trade was the most fre-
quently visited POI, the percentage of which exceeds 22%. Then, POIs in category of accom-
modation and food services ranked second, followed by other services.

To have a finer-grained understanding of urban lifestyle signatures, the top three ranked POI
categories were selected and further specified into twenty subcategories by the four-digit NAICS
code. The ranking for Harris County is shown on Figure 4(b). The whole results can be found from
Figure S7 in Supplementary Material. Restaurants and other eating places took the lead with more
than 20% of the visits across all counties. Personal care services and health and personal care stores
were in the second and third place in Harris County, Dallas County, and Broward County. The
commodities and services provided by POIs in these subcategories are closely related to people’s
basic needs of life, which explains why these POIs are nearly the most frequently visited. Gasoline
stations, grocery stores, and automotive repair and maintenance occupy the top five positions in
these three counties, illustrating the importance of automobile usage and food consumption in
people’s daily life.

![Figure 4](image-url)

**Figure 4.** (a) Visiting frequency distribution of POI categories; (b) visiting frequency distribution of top 20 subcategories in Harris County; (c) frequency distribution of attributed motifs in Harris County. Icons represent POI categories, among which links of identical color represent attributed motifs. The frequency percentage of each motif was calculated and marked next to the link.
The distribution of visiting frequency to POIs in New York County is different from those in the other three counties. Clothing stores surprisingly ranked third and drinking places ranked fifth, while gasoline stations, grocery stores, and automotive repair and maintenance, which ranked higher in the other counties, ranked lower in New York County. As a dense metropolitan area, New York’s bustling commercial facilities and convenient public transportation system have changed people’s lifestyles to a certain extent. People in New York County have a much greater preference for fashion and entertainment than people from other counties. Likely owing to the highly developed public transportation network and denser distribution of POIs, residents are less reliant on automobiles in New York County.

Then, we selected the top 10 attributed motifs ranked by frequency for each category of motifs in the four counties. Figure 4(c) shows the frequency distribution of attributed motifs in Harris County. The plot of all the other counties can be found in Figure S8. For two-node attributed motifs, the “services of retail trade—accommodation & food services” and “retail trade—other services” were among the top four across the four counties, indicating that these services satisfy basic life needs. An interesting finding is that lifestyle “retail trade—retail trade” ranked top three in the other three counties but not for New York County. The phenomenon that “retail trade—retail trade” is less popular may provide insight into a new trend of lifestyle changes. Although purchasing commodities is essential for all the population, visiting stores may not be the only way. With more developed online shopping and logistic systems, population in New York County could order online and have commodities delivered to their houses. Lifestyle “accommodation & food services—real estate rental & leasing” ranked third in New York County, indicating the importance of residence, which may be a major concern in a highly urbanized area.

For three-node attributed motifs, the most frequently present lifestyles were still those encompassing visits to retail trade and accommodation and food services in Harris County, Dallas County, and Broward County. The top three lifestyles in these counties encompassed around 20% in M3-1 and more than 10% in M3-2, illustrating lifestyles in these areas had a consistent pattern. While in New York County, the top three lifestyles accounted only 6% and 8%, suggesting a more heterogenous distribution of lifestyles. This finding reveals that population in New York County prefers to adopt more heterogeneous lifestyles.

For four-node attributed motifs, the top-ranked motifs showed consistent patterns regardless of motif structures in all four counties. These motifs shared nodes with the same attributes, suggesting that people may follow different trajectories but visit roughly the same categories of POIs. The identical categories of POIs and various co-visiting patterns showed both the commonality and heterogeneity of people’s lifestyles. Compared with two-node and three-node motifs, the four-node motifs had three distinctive features. First, POIs of retail trade had much higher frequency to be involved in the top ranked motifs, illustrating that commodity purchase plays an even more important role as lifestyle complexity increases. Second, the percentage of various four-node attributed motifs was more even, showing more diversity in urban lifestyles. Third, POIs with the categories of health care and social assistance, finance and insurance, educational services, and real estate rental and leasing appeared more often in four-node motifs, which implied significant dimensions of urban life, such as residence, finance, health care, and education for certain population subgroups.

Since POIs adopted in this study were affiliated with geo-information, we measured average distance of attributed motifs during weekdays and weekends to explore potential temporal patterns. Attributed motifs whose average distance ranked top 20 are shown in Figure 5. The disparity of lifestyles regarding average distance can be examined from two aspects. First, the most obvious observation is that average distance on weekends is longer than that on weekdays, which is consistent with the common sense that people tend to travel a longer distance during weekends because of fewer time constraints they may be bound by on weekends. Second, attributed motifs ranked in the top three are quite different between weekdays and weekends. On weekends, the
dominant POI categories are retail trade and accommodation and food services. On weekdays, in contrast, although these two categories also occupy a major proportion, visits to other POI categories, including health care and social assistance, and finance and insurance are noted. The greater diversity of POI categories shown on weekdays may be explained by multiple reasons. For example, people visit certain POIs only during weekends. POIs in the aforementioned categories usually have longer business hours on weekdays, which could facilitate more visits.

Figure 5. Average distance distribution for attributed motifs. Each bar is labeled with motif ID and icons representing POI categories. The left part shows the ranking on weekdays, and the right part shows the ranking on weekends. The scales of vertical axis in subgraphs are different. All data are in miles.
Discussion and conclusion

The overarching goal of this study is to gain insights into detailed human lifestyle signatures in urban environments. We constructed multiple motifs extracted from NOP to represent differentiated lifestyles in metropolitan areas. Considering Harris County, Dallas County, New York County, and Broward County in the U.S. as cases, we have experimentally demonstrated a multi-facet portrait of urban lifestyles.

The statistical measures of the NOP reveal macroscopic characteristics of human lifestyles. The results show the disparity between POI number and visits results in a high average degree and clustering coefficient. This tendency, to some extent, contributes to the formation of motifs that represent the prevalent visitation structure. Further, by examining PDF and CDF, we find that the node degree approximates power-law distribution. This finding demonstrates that the greatest number of human visitations are concentrated in a small set of POIs, while some other POIs are rarely visited, which is consistent with previous studies on urban mobility (Di Clemente et al., 2018; Lenormand et al., 2015). Moreover, all the four counties exhibit similarity of their NOP, demonstrating consistency in the general structure of human visitations, despite the significant differences in socio-demographic dimension and spatial structures.

By investigating the properties of unattributed motifs, the results demonstrate that people’s lifestyles show long-term stability in both motif quantity and distance and exhibit different periodic recurrence patterns on weekdays and weekends. The results indicate the stability of lifestyle signatures during weekdays and less stability during weekend, which is consistent with the insight that individuals show strong regularities of movements that tend to follow certain typical motifs, as reported in previous studies (Cao et al., 2019; Di Clemente et al., 2018; Schneider et al., 2013a, 2013b). Moreover, people are more inclined to conduct lifestyles in a manner of four-node structures. We conjecture that one major reason for this finding is that such lifestyle is more efficient and have easier access to resources. The result is in line with some empirical studies on the human activities in metropolitan cities, which find that residents in urban areas have simple but settled daily activity routines (Yin and Chi, 2020; Yang et al., 2019a). This finding can be further explained by the possible determination of the abundance level of urban resources (i.e., bus stations, shopping malls, and hospitals). Population with more abundant urban resources and higher-level socioeconomic level may have more efficient lifestyles.

Finally, the exploration of attributed motifs provides insights to the spatial and temporal heterogeneity among different lifestyles. From the spatial perspective, this study finds that people visit a variety of different POIs. Previous explorations of lifestyles have focused solely on a few types of visitation patterns, such as home and work (Huang and Wong, 2016; Jurdak et al., 2015; Xu et al., 2015), and there is no clear depiction of the complete pictures of lifestyle signatures embedded in different POI categories. This study not only constructs a more complete mapping of diverse urban lifestyle patterns but also reveals the frequently visited POIs represented by attributed motifs. From the temporal perspective, this study shows distinctions in different lifestyles between weekdays and weekends using attributed motif quantity and average distance, which is a complement to the study of urban morphology and structure. In addition, it is worth noting that although, in general, the four counties in our study are similar in terms of lifestyle patterns, there are still some differences in the case of New York County. These differences, according to the analysis in this study, are not unrelated to the socio-demographic dimensions within this county. Previous studies have also suggested the need for more integration of infrastructure and geographic features of society, such as income, race, or ethnicity, when conducting lifestyle interpretation in one region (Moro et al., 2021), which motivates us to provide more insights into diversified lifestyles in the future.

The findings obtained in this study have multiple contributions and implications for urban planning and development. Understanding human lifestyle patterns has been a fundamental problem
in urban science and city planning. While the universal laws and predictability of lifestyle patterns have been unveiled in the previous studies, the interaction among population and locations enabled by access to anonymized and aggregated databases is still an area of active study and promises further insights into populations and their lifestyles. First, this study advances the understanding of the stability and regularity of urban lifestyles that interact with different locations, which allows us to focus more on population dynamics in cities beyond the standard origin–destination studies of human movement. Therefore, insights revealed by evaluation of this type of data would be important to inform urban planners when proposing appropriate policies, including redistributing existing facilities and developing new facilities on the premise of meeting the needs of residents. Second, this study exhibits the heterogeneous nature of visitations to urban facilities. The insight provides a deeper understanding of urban structure, which thus can help policymakers evaluate their urban development strategies, especially urban resource allocation and city planning. Last, this study reveals locations with large visitations will attract more visits, while those with fewer visitations will continue to remain in the same state. Therefore, the role of facility accessibility in these locations is central to improving urban and transportation planning. Also, the approach presented in this study provides a data-driven and quantitative way to compare different cities and evaluate the relationship between lifestyle signatures and city-level measures such as energy usage, equity, and access.

This work also has couple of limitations, which could be addressed in the future. First, lifestyle patterns may vary among people with different social-demographic attributes, such as race and income. Quantifying the relationship between social-demographic characteristics and lifestyle patterns contributes to the understanding of social variations of urban structures. In our datasets, however, we cannot obtain social-demographic information about individuals due to privacy protection concerns. Future studies could find ways to integrate our anonymized location-based data with other datasets to examine the influence of social-demographic features on human lifestyles. Second, this study mainly investigates the similarities of lifestyle patterns across various counties. It should be noted that, although our case studies verify the similarity among counties from disparate regions of the United States, the sample size is still small and concentrates in metropolitan-type counties. Future studies should expand the sample counties based on factors such as population, urban typologies, and road networks to unravel the disparities of human lifestyles in different counties in association with urban characteristics.

**Code availability**

The code that supports the findings of this study is available from the corresponding author upon request.

**Declaration of conflicting interests**

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Data availability statement

All data were collected through a CCPA- and GDPR-compliant framework and utilized for research purposes. The data that support the findings of this study are available from Spectus and SafeGraph, but restrictions apply to the availability of these data, which were used under license for the current study. The data can be accessed upon request submitted on cuebiq.com and safegraph.com. Other data we used in this study are all publicly available.

Supplemental Material

Supplemental material for this article is available online.

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