Who Will Survive and Revive Undergoing the Epidemic: Analyses about POI Visit Behavior in Wuhan via Check-in Records

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A rapid-spreading epidemic of COVID-19 hit China at the end of 2019, resulting in unignorable social and economic damage in the epicenter, Wuhan. POIs capture the microscopic behavior of citizens, providing valuable information to understand city reactions toward the epidemic. Leveraging large-scale check-in records, we analyze the POI visit trends over the epidemic period and normal times. We demonstrate that COVID-19 greatly influences the society, where most POIs demonstrate more than 60% of visit drops during the city lockdown period. Among them, *Tourist Attractions* received greatest impact with a 78.8% drop. *Entertainment*, *Food*, *Medical* and *Shopping* are sensible to the disease before lockdown, and we identify these "early birds" to investigate the public reaction in the early stage of the epidemic. We further analyze the revival trends, generating four different revival patterns that correlated with the necessity of POI functions. Finally, we analyze the perseverance during the COVID-19, finding no large-scale closures compared with the tremendous visit drop. The strong resilience in Wuhan supports the rapid recovery of society. These findings are important for researchers, industries, and governments to understand the city respondence under severe epidemic, proposing better regulations to respond, control, and prevent public emergencies.

CCS Concepts: • **Applied computing → Sociology**; • **Information systems → Data mining**; • **Human-centered computing → Ubiquitous and mobile computing**.

Additional Key Words and Phrases: POI, check-in, time series analyze, COVID-19, data driven

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1 INTRODUCTION

A huge impact on social economics has been identified during the spread of COVID-19 in 2020 [4], where local business faces an unprecedented survival challenge. As the first epicenter in China, Wuhan, a huge city with more than 10 million citizens, received a huge impact. A rational understanding of how megacities react to the epidemic is a heated topic for academia, industry, and government. Previous works mainly focus on self-reported qualitative analysis, which leverages interviews and surveys from interviewees to provide valuable evidence of epidemic impact on small businesses [4] and rural areas [27]. Although in-depth understanding can be provided by these works, qualitative analysis of large-scale Point-of-Interest (POI) visit trends is still lacking to provide intuitions from a data perspective. In this paper, we are curious to investigate the fine-grained visit behavior on full and large-scale POIs during different time periods of the epidemic. Leveraging check-in records from mobile location-based social networks, we conduct POI visit analysis in all Wuhan POIs, which can provide a thorough understanding from the quantitative point of view.

Understanding the fine-grained visit behavior on POIs is an important research question, especially during severe public emergencies like COVID-19. First, as a microscopic indicator of urban behaviors, POI visit behavior collected from mobile check-in records during the epidemic reflects how the city reacts to severe infectious diseases. Second, investigating the decline stage during the early epidemic can generate valuable experiences for understanding human behaviors during severe public emergencies. Finally, by comparison study of pre-lockdown phase and post-lockdown phase, we can evaluate the resilience of a city during the epidemic.

In this paper, we adopt a comparison methodology for the normal period in 2019 and epidemic period in 2020 to obtain a quantitative understanding of POI visit changes. First, we divide the POI visit trend during the epidemic period into the decline stage and revival stage according to the policy timeline. Then we align the normal period comparison with the epidemic period for further investigation. For the decline stage, we analyze the relationship between POI visit changes and lockdown policies to demonstrate the epidemic impact. Then by categorical analysis of different POIs, we identify the most vulnerable part under the epidemic impact in urban life. Before the announcement of city lockdown policies, *Entertainment*, *Food*, *Medical* and *Shopping* POIs are sensitive to the upcoming epidemic, which acts as the "early bird" during the public emergency. Comparing with the normal period in 2019, we perform debiased analysis on "early bird" POIs during pre-lockdown phase, identifying sensitive POIs for the epidemic, which is helpful for the policy-making of targeted assistance. For the revival stage, we recognize different revival patterns on POI categories, evaluating the resurgence speed in Wuhan city. Finally, by comparing the number of POIs in pre-lockdown phase and post-lockdown phase, we analyze the resilience of city and the reasons behind fast resurgence.

Our key findings are summarized as follows:

- We verify the epidemic impact on POI visit trends, and demonstrate that a 59.9% of visit drop exists during the city lockdown period in 2020 compared with the normal period in 2019. Further analyses identify the most vulnerable POIs during epidemic impact, such as *Food*, *Entertainment* and *Tourist Attractions*, which suggests possible risks in long-term lockdown.
- We identify "early birds" during the epidemic, which demonstrate extra visit drop before the release of city lockdown policies. By analyzing their reactions in pre-lockdown phase, we provide understandings of public attitudes during the early epidemic.

- We recognize four distinct resurgence patterns of different POIs, which are correlated with POI functions. Essential POIs such as *Business*, *Shopping* and *Medical* receive faster recovery, and *Tourist Attractions* POIs demonstrate strong rebound after the city un-lockdown.
- We validate the perseverance during the epidemic by comparing the POI numbers in pre-lockdown phase and post-lockdown phase, which can act as a resilience indicator for the city. This resilience is correlated with public attitudes towards the epidemic, where both of them contribute to the rapid recovery of Wuhan society.

2 DATASET

In this study, we mine the underlying POI depression and resurgence patterns through check-in data of one of the largest location-based social network (LSBN) platforms in China. It offers a location-based check-in function for all users without any charge or incentive, providing good user coverage and limited fake check-ins [35]. The POIs represent the microscopic view of a city, which includes all kinds of scenarios in urban life such as restaurants, parks, cafes, and gyms. The POI visit patterns reflect a direct reaction between citizens with the city. For public emergencies such as an epidemic, POIs play an important role in disease transmission, where most superspreading events happened in indoor spaces [22]. For other mobility data such as transportation data collected Apple [2], they cannot distinguish indoor visits from outdoor activities, which lacks enough information for epidemic modeling.

2.1 Data Collection

Our analyses contain the full size of POIs in Wuhan with detailed human-labeled categories. Totally of 67,152 POIs are labeled in 187 fine-grained categories in the accessible data, providing possibilities for detailed analysis. To understand the epidemic impact on human visits, we collect year-on-year records from January 1, 2019 to April 30, 2019 and January 1, 2020 to June 3, 2020 for comparison study. We divide and align the time periods according to the epidemic spreading and control timeline and the Chinese Lunar New Year (detail in 3.2).

During these time periods, we have aggregated visit statistics in each hour for each POI. Auxiliary information of POIs is also provided, including POI name, category, area code, and geographic coordinate. There are 8 first-level categories, 109 second-level categories and 187 third-level categories for analysis, which is shown in Table 1. After the data cleaning process (detail in 3.1), we obtain the new statistics in Table 2. For each of these categories, we visualize the original daily average visit in Fig 1. In Fig 1, we find that noises in the data are noticeable, where high daily visit variance will affect our analyses about medium- to long-term visit trends. This inspires us to perform trend extractions to reduce the randomness of human behaviors in the original data (detail in 3.3).

Table 1. Original POI categories.

Category	Food	Business	Shopping	School	Hotel	Enter-tainment	Medical	Tourist Attractions
Second-level Number	20	4	27	9	10	15	8	16
Third-level Number	67	4	27	9	10	30	24	16

2.2 Ethic Consideration

Careful steps were taken to address privacy issues during the analysis and data mining of the check-in records. First, users are required to digest the Terms of Service, where consent for research studies is required. Second, we

Table 2. Statistics about selected POI categories.

Category	POI Numbers	Percentage
Business	8978	0.248
Food	7983	0.220
Shopping	5023	0.139
School	4171	0.115
Hotel	3944	0.109
Entertainment	3151	0.087
Medical	1866	0.052
Tourist Attractions	1106	0.031

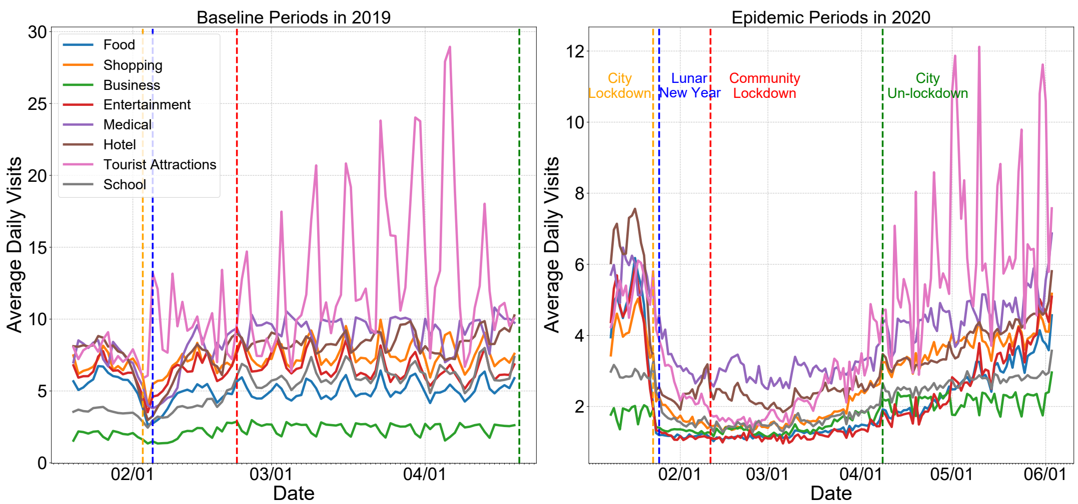

Fig. 1. Daily POI visit on each category.

had preprocessed the data into aggregated anonymous statistics according to the privacy protection process before analysis. All user identifiers were removed during the aggregation process, and all the auxiliary information is strictly restricted to public available POI information (POI name, POI location, etc.). Since no individual behavior exists in our aggregated analyses, we erased the concern of privacy leakage of individual data. Third, all the shared data is stored in a well-protected offline server with limited access to only authorized members of the research team, who were required to assign strict non-disclosure agreements before access the data.

3 METHODOLOGY

In this section, we introduce the methodology of our paper for further analyses. Figure 2 describes the overall structure of our work, where blue parts represent data, green squares correspond to methodology, and orange parts demonstrate the analyses. We first perform data cleaning and completing on the original check-in data, deleting rarely visited POIs and completing missing records. Then we perform data alignment to form comparison data for normal times in 2019 and epidemic periods in 2020. Based on the aligned daily visit time series, we extract the visit trends to evaluate the epidemic impact of the decline stage in 4.1. For the revival stage in 4.2,

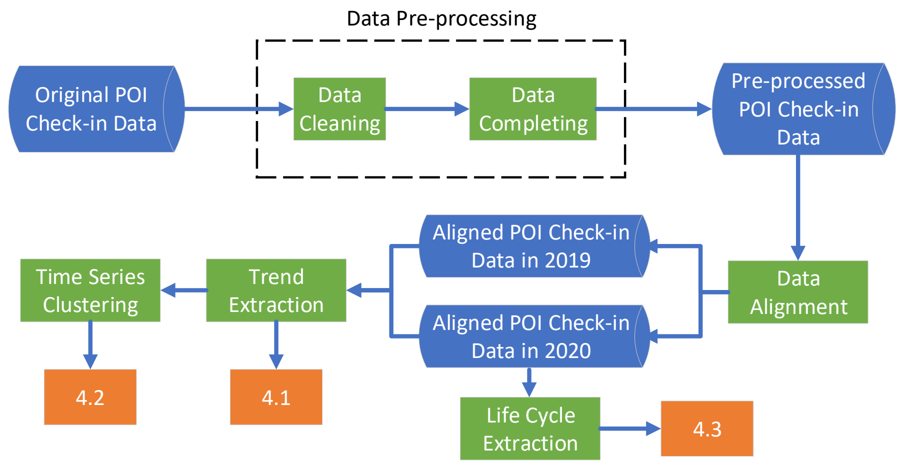

Fig. 2. The flow chart of data processing and further analyses

we summarize the revival patterns of different POI categories by time series clustering. Finally, to generate the resilience metrics in 4.3, we extract the life cycle of each POI during different periods in 2020.

3.1 Data Pre-processing

To better extract the visit trends of different kinds of POIs, we apply data cleaning and completing before the analysis. Considering the power-law distribution of POI visit [6, 35], most of the visits are concentrated in head POIs, resulting in a weaker signal during analysis. To avoid the data sparsity due to the power-law distribution of POI visit, we filter out the long-tail part by selecting POIs with at least 1 visit for 7 days, resulting in 53.0% of all the POIs in Wuhan. It can reduce the noises due to outdated or error POIs, providing more accurate aggregated visit trends. Then we aggregate the hourly visit data into daily level to mine the visit trend for further study. Fine-grained hourly data are valuable for human behavior modeling, while it is a burden for long-term visit trend analysis.

Due to the sparse format of data, POIs without visits are not explicitly demonstrated. To solve this problem, we perform data completion to recover temporal no-visit entries. Temporally no visit is normal in urban space, but long-term vacancy is likely due to POI closing. If a POI has no visit for more than continues 3 days, we fill the discontinues entries with zero within the gap. For long-term vacancies that above 3 days, we preserve the gap.

3.2 Date Alignment

We divide and align the time periods according to the epidemic spreading and control timeline for comparison study. The release date of the city lockdown policy in Wuhan nears the Lunar New Year in China, which is the biggest traditional holiday for Chinese. A considerable number of POIs will have a temporary closure during the holiday, resulting in a different visit pattern from normal days. We align the data of 2020 and 2019 by the Chinese Lunar New Year, which is on January 25 for 2020 and February 5 for 2019. The city lockdown policy was released on January 23, 2020, only two days before the Lunar New Year. We trace back two weeks before the city lockdown as the pre-lockdown phase and select the corresponding lunar date for 2019 as a comparison. For the during lockdown phases, we also select the corresponding date for 2019 according to the lunar date. Since there is no actual lockdown policy in 2019, after lockdown (normal) phase can be treated as any periods away from the Lunar New Year periods, so there are no explicit comparison data. Detailed comparison timeline is available in Table 3. Note that on February 11, 2020 a more severe control policy was released to constraint people in the community.

Table 3. Lockdown timeline for comparison study.

Phase	2020 under the epidemic impact	2019 over the same period
Pre-Lockdown	2020-01-09 ~2020-01-22	2019-01-20 ~2019-02-02
During Lockdown	2020-01-23 ~2020-04-07	2019-02-03 ~2019-04-19
Post-Lockdown	2020-04-08 ~2020-06-03	–

3.3 Trend Extraction

The time series of POI daily visits are greatly influenced by the periodicity of human behavior, where the underlying trend is buried by the noises, as shown in Fig 1. Here, we apply a seasonal-trend decomposition method [11] to extract the trend signal for analysis. We set a 3 day window to extract the visit trend, considering the fast-changing around the release of lockdown policies.

3.4 Time Series Clustering

To understand different resurgence patterns of POIs, we perform time-series clustering on the extracted visit trends after the community lockdown. Here, we perform dynamic time warping (DTW) algorithm [5] to evaluate the similarity between the average trend of visits for each POI category. DTW works better than the traditional Euclidean measurement on time series application [30], which will be helpful for better clustering.

To determine the number of clusters, we use silhouette coefficient [31] to evaluate the clustering result of DTW algorithm. We grid search the number of clusters, and randomly initialize 5 times for each try. According to the silhouette coefficients, we select the elbow point where the quality of clustering does not increase significantly compared with other settings to determine the best cluster number.

3.5 POI Life Cycle Extraction

The sparse format of data also brings difficulty for POI life cycle analysis, since the absence of data can represent no visit and shop close down at the same time. In that case, we cannot directly determine the life cycle from the original data. Here, we assume a POI is alive until the last day of the valid visit, where the in-between discontinuity is temporal closure. This assumption may overestimate the number of vanished POIs, when the POI is still open while lacking valid check-in records in our data. For example, during the epidemic, many schools adopt online teaching [9] as a daily routine. The schools are still on, but students will no check-in at school POIs, resulting in misunderstanding of school POIs' vanishing.

4 RESULTS AND ANALYSES

Since the initial COVID-19 cases emerged in Wuhan at the end of 2019, the disease quickly spread out the city without any notice. Unfortunately, a massive migration, which is known as *Chunyun*, began on January 10 of 2020 to transfer working people to their hometown for the upcoming Chinese Lunar New Year. The city lockdown policy was released on January 23, two days before the Lunar New Year, prohibiting all transportation from outside Wuhan. Series of studies prove that the implementation of inter-city lockdown policy greatly reduces the number of cases, protecting both China cities and other countries [10, 20, 32]. However, the city lockdown policy alone with inner-city lockdown orders for public transportation also brought great impact onto local POIs, which is shown in Fig 1. As the release of the community lockdown policy on February 11, POI visit reached the lowest level. After a 76-day lockdown, Wuhan reopened on April 8 [40], when the POI visit slowly recovers.

Here, we aim to analyze how the city reacts to severe public emergencies such as COVID-19. In the following sections, we divide the whole timeline into two stages: the decline stages and the revival stage. In the decline stage, POI visit trends received a tremendous impact due to the epidemic. Identifying the most vulnerable POIs is a critical factor for the development of targeted aid policies. To do so, we focus on the year-on-year comparison between normal times and the epidemic period, and the self-comparison in the epidemic period itself. For the revival stage, we are interested in the revival patterns of POI visits. What makes the difference of the revival process is of our concern. Finally, we analyze the differences before and after these two stages for a better understanding of the epidemic impact on Wuhan city.

4.1 Decline Stage

4.1.1 Decline Timeline. To understand the decline stage due to the epidemic, we visualize the visit trends of 2019 and 2020 in Fig 3. Differ from Fig 1, we use extracted trends rather than raw data for all the following analyses. From the Fig 3 we can observe that the overall visit in 2020 is smaller than 2019. For the normal times in 2019, there exists a valley around the Chinese Lunar New Year. During the Chinese Lunar New Year holidays, people will close the shop, return to their hometown and stay with the family, resulting in a significant visit drop for most of the POI categories except for *School*, *Business* and *Tourist Attractions*. A week after the Lunar New Year, the visit quickly returned to the normal level for most POIs. While due to the epidemic impact, the visit trends show different patterns in 2020. From the right figure in Fig 3, we identify three steps during the decline stage.

First, before the release of city-lockdown policy, most of the POIs received fewer visits. This phenomenon is a combined effect of the Chinese Lunar New Year and the upcoming epidemic. After the city lockdown policy on January 23, the visit dropped continually, without the rebound period in 2019. Furthermore, after the community lockdown policy stronger control was taken. Most of the POIs reached the lowest level of visit during the epidemic. Interestingly, we notice two rebound categories during lockdown phase in 2020, which are *Hotel* and *Medical* categories. Many hotels served as temporal quarantine sites during the epidemic [41], and the hospital visit is correlated with the spread of diseases.

4.1.2 Estimating Epidemic Impact on POI Visit. Due to the COVID-19 epidemic, the mobility behavior of people was greatly influenced in the early stage of 2020, especially in Wuhan. To quantify the impact of the epidemic, we calculate the daily average visit for each POI category and the relative changes on both year-on-year comparison and self-comparison, revealing the epidemic impact from multiple angles.

Fig 4 depicts the absolute visit volume of different POI categories. Since there was no actual lockdown in 2019, the Chinese Lunar New Year is the only factor affecting the POI visit, which coincides with the beginning of "lockdown" with 2 days. In 2019, most of the categories had a relatively stable performance before the "lockdown" (blue bars) and during the "lockdown" (orange bars) period. For example, the percentages of visit change of *Business*, *Medical*, *Shopping*, *Hotel* and *Entertainment* only reach +10.8%, −0.395%, −6.42%, −1.40%, and −5.34% respectively. The trend of visit change suits well with our knowledge of about the Chinese Lunar New Year. Note that *Medical* enjoys the smallest change among these categories due to the nature of getting diseases. *Food*, *School* and *Tourist Attractions* demonstrate stronger differences in 2019, which corresponds to shop-closing, winter holiday for students and stay with the family habitude. These statistics demonstrate how the Chinese Lunar New Year affects POI visits in normal times. Compared with the visit in 2020, we can discover great differences from the following two aspects.

First, we calculate the visit change between 2019 and 2020 in a year-on-year manner to eliminate the effect of the Lunar New Year. In Fig 5, we find that all the POI categories are less lively compared with the same period in 2019. During the pre-lockdown phase, *Business* received the smallest impact as 5.98%, while *Shopping* and

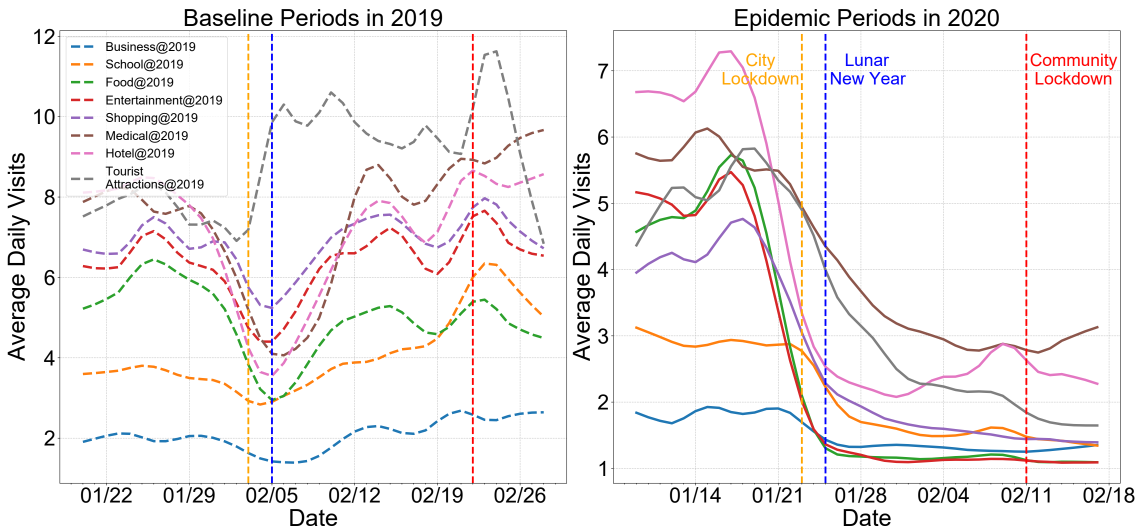

Fig. 3. Time series of decline stage in 2019 and 2020

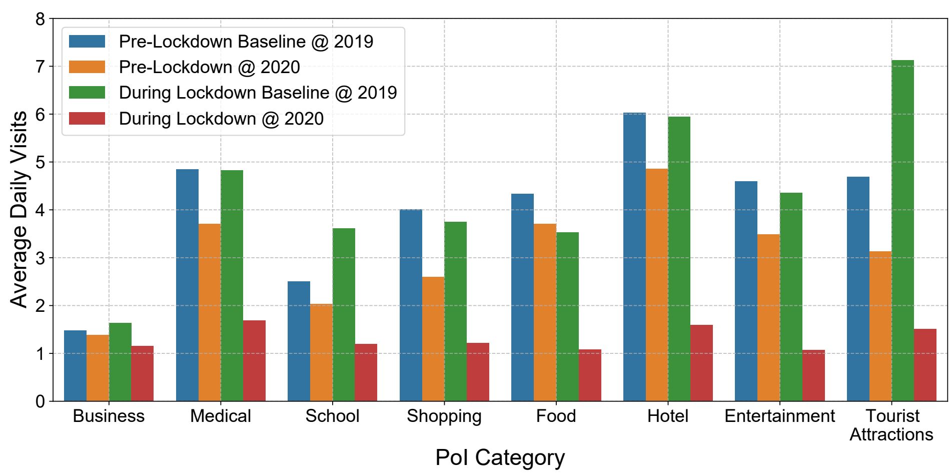

Fig. 4. Changes of POI visit during different periods in 2019 and 2020.

Tourist Attractions received greatest influence as 35.1% and 33.2%. Similar impact has been found in previous epidemics [15, 21], where people tend to maintain visits for "essential" POIs prior than "non-essentials". The weighted average of visit drop in pre-lockdown period is 18.2%, which is significantly smaller than 59.9% during the lockdown period. From the comparison during the lockdown period in 2019 and 2020, we can find that the least infected POIs are *Business*, with 29.3% visit drop. While for all other POI categories, the average mobility drops by more than 65%. These phenomena indicate great differences exist between the POI visit patterns of 2019 and 2020, where significant visit drop demonstrate in 2020.

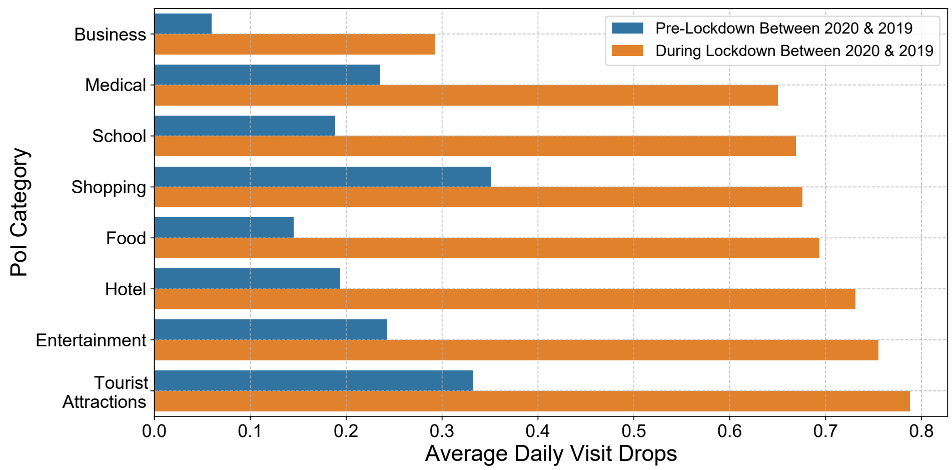

Fig. 5. Relative POI visit changes over the same period in 2019 and 2020.

Second, to better investigate how the city lockdown policy affects POI visit patterns, we also perform self-comparison between pre-lockdown phase and the lockdown phase in 2020. From Fig 6, we can find that most of the POIs share a more than 50% of visit drop compared with the pre-lockdown period in 2020. Differ from Fig 5, *School* and *Tourist Attractions* have relatively small drops as 41.1% and 51.7% accordingly. Besides, *Food* category got the strongest shock during the lockdown. Fig 6 demonstrate the pure effect of lockdown policy on POI visit, further validates the epidemic impact.

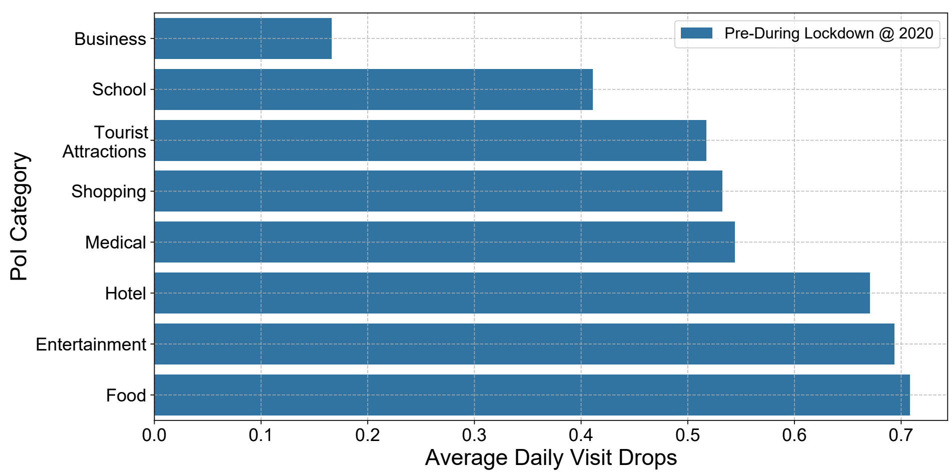

Fig. 6. Relative POI visit changes between lockdown phase and pre-lockdown phase in 2020.

In conclusion, the POI visit behavior in 2020 is greatly suppressed compared with 2019 in two different aspects. Compared with 2019, the absolute quantity of visits declines in both pre-lockdown phase and lockdown phase. Besides, the release of lockdown policy in 2020 further reduced the POI visit in all categories. Non-essential POIs like *Tourist Attractions*, *Entertainment* and *Food* received strong impact in 2020, which are the most vulnerable parts of urban life. For example, the fully reopen of indoor POIs such as movie theaters began on May 8, while great economic losses had been evaluated [28, 38]. Targeted assistance to these vulnerable POIs is of great importance to balance the revival process of all industries.

4.1.3 Identifying Early Birds before the Epidemic. As a microscopic indicator of social-economic activity, the impact of the epidemic is reflected in the POI visit trends before the official release of city lockdown policies. Some specific POIs are more sensitive to the epidemic, acting as the "canary in the coal mine" during the epidemic. Here, we identify these early birds before the release of lockdown policies, which will be helpful to understand the reaction of megacities towards the epidemic.

From the previous analysis, we have noticed that the visit during pre-lockdown phase drops significantly. In Fig 5 we calculate the daily average visit for the whole pre-lockdown phase in 2019 and 2020. Further analyses of pre-lockdown time series are necessary to validate the differences in decline patterns, which will be direct evidence of epidemic impact.

Fig 7 demonstrates the POI visit time series before city lockdown in 2019 and 2020. We should note that the release of city lockdown was two days before the Chinese Lunar New Year, which causes the visit drop for both 2019 and 2020. For the visit trends in 2019 (dashed lines), we find that *Business* and *School* receives the smallest impact. New Year holidays for most of the jobs start from two days before the Chinese Lunar New Year, which is later than the city lockdown. The students often have a one-month holiday around the Lunar New Year, which also causes the steady trend. For other categories like *Hotel*, *Entertainment*, *Shopping* and *Food*, there exists a peak around 10 days before the Lunar New Year. As the New Year holiday approaches, visits drop. While for the trends in 2020 (solid lines), all the heights are relatively lower, agreeing with Fig 6. Differ from normal times, many of POI categories demonstrate tremendous decrease before city lockdown, such as *Hotel*, *Food*, *Entertainment* and *Shopping*. *Tourist Attractions*, *Medical* alone with *School* and *Business* are relatively stable. These categories are possible "early birds" before the city lockdown.

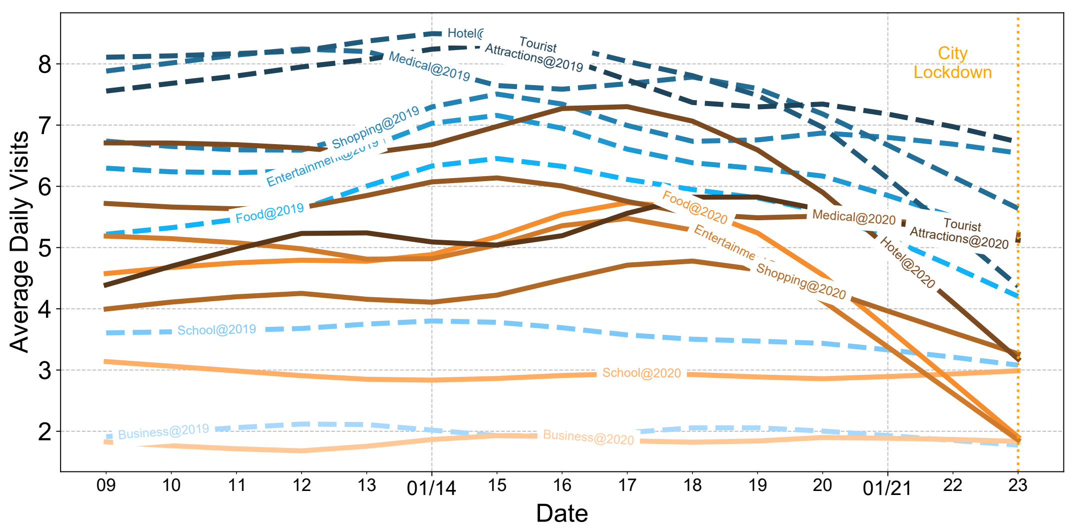

Fig. 7. POI visit trends during pre-lockdown phase.

To quantify the visit drops before the city lockdown, we calculate the average visit in the first week as the baseline, and compare it with the last day of pre-lockdown phase. In Fig 8, we can find that most of the categories have a slight decline before "lockdown" in normal times, except for *Shopping*. There is a 21.4% and 31.4% visit drop for *Medical* and *Hotel* respectively, and a 10.9% increment for *Shopping*. While for the epidemic period in 2020, the reduction patterns are very different. *Entertainment*, *Food*, *Hotel* and *Shopping* demonstrate a greater reduction over 35% percent. All these four categories share a higher reduction than normal times, which means the consumer categories are more sensitive to epidemics. Differ from previous research on epidemic [3, 29], we do not observe panic buying behavior before the city lockdown in Wuhan. One of the possible reasons is that people may underestimate the severity of COVID-19 epidemic during the initial outbreak. Besides, the smaller reduction of *Medical* POIs is also an important indicator: more people went to hospital is a clear signal for upcoming epidemics.

According to the relative visit change of the above "early bird" categories, we investigate their importance towards the early sensitivity in Fig 9. In all of the visit changes, *Entertainment* and *Food* POIs are most sensitive that are responsible for nearly 60% of visit change of these "early bird" categories. *Medical* and *Shopping* POIs have equal sensitivity for the upcoming epidemic, while *Hotel* are relatively insensitive.

According to the previous analysis, we identify the "early birds" before the city lockdown phase. However, we only observe early visit drops before the city lockdown, with the absence of panic buying behavior. These unusual changes of POI visit reflect social behavior in a microcosmic view, which will be important for understanding public behavior during the initial stage of the epidemic.

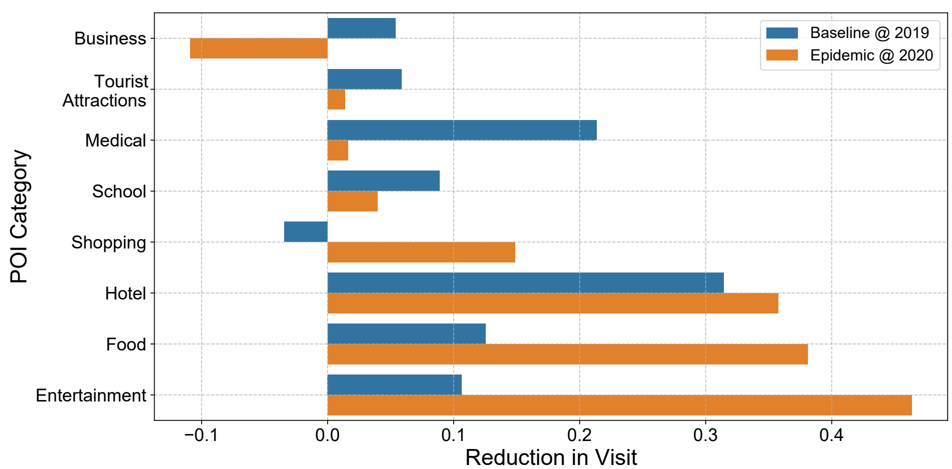

Fig. 8. Relative POI visit drops during pre-lockdown phase between 2019 and 2020.

4.2 Revival Stage

4.2.1 Revival Timeline. To understand the revival process of the POI visit, we visualize the time series of the recovery phase in Fig 10. After the community lockdown on February 11, the POI visit reached a relatively stable level. Most of the POI categories reached the lowest visit around March 1, except for *Medical*, *Hotel* and *Tourist Attractions*. *Medical* and *Hotel* POIs began to resurge after March 7, and *Tourist Attractions* had an early revival since February 26. *Shopping* POIs had a relatively quick recovery since March 9. Other POI categories began to recover in the following week, but with a much slower speed. After the city un-lockdown on April 8,

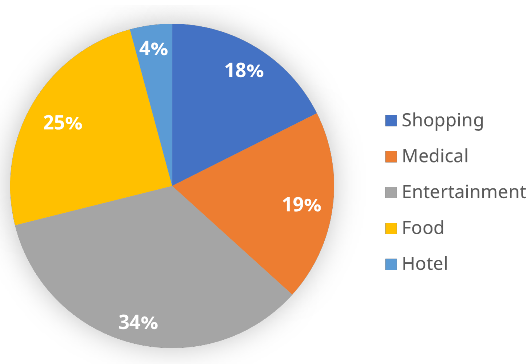

Fig. 9. Early bird percentages of different POIs.

Food and *Entertainment* recovered quickly. Other categories basically maintain the same recovery speed before un-lockdown, except for *Business* and *School* that can leverage remote working or online teaching. The fast revival of *Shopping* and *Tourist Attractions* since the lockdown phase may reflect two basic needs for people in difficulty: one for basic living, and another for spiritual comfort.

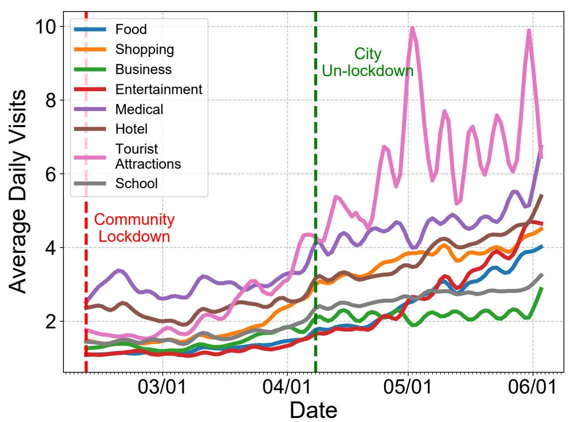

Fig. 10. Time series of Revival Stage in 2020.

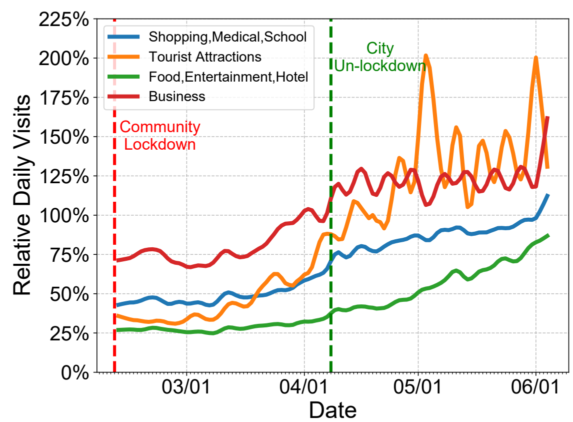

Fig. 11. Different revival patterns of POIs

4.2.2 Recognizing Different Revival Patterns. We perform clustering on different kinds of POIs to get the common patterns of revival in Fig 11. Here we adopt the first week of pre-lockdown phase as the baseline visit, quantifying the percentage of recovery for each category. After automatically selecting the best cluster number, we obtain four different revival patterns. For *Food*, *Entertainment* and *Hotel*, these POIs got the greatest shock during the lockdown, and have the slowest recovery in post-lockdown phase. It fits our understanding since these POIs do not belong to life-essential ones. *Shopping*, *Medical* and *School* categories received moderate impact, and they also got a relatively slow revival. Differ from *Food* etc., these POIs began to recover before un-lockdown since they are more necessary for life. *Business* POIs received the smallest impact during the epidemic, and got recovered before the un-lockdown. After the release of un-lockdown policy, it had more visits than the baseline. For the *Tourist*

Attractions, it also suppressed greatly. However, it got an early recovery before the un-lockdown, and reached a very high level during the post-lockdown phase. The fast recovery is consistent with [13], which is a positive reflection of public attitudes towards the expectation of epidemic controlling [14]. From the above analyses, we can set up the linkage between POI functions with the resurgence patterns. For the non-essential POIs like *Food*, *Entertainment* and *Hotel*, they demonstrate the greatest impact and slowest recovery during the epidemic. For POIs with more importance for daily life, *Shopping*, *Medical* and *School* demonstrate a faster revival at the end of the lockdown period. *Business* POIs maintain the basic economy of the society, which received the least level of impact during the epidemic and showed strong revival during the lockdown period. Finally, as the mental relief, *Tourist Attractions* demonstrated the fastest recovery among all the POIs in our analyses even though a strong impact was identified during the early stage of community lockdown.

4.3 Perseverance during the Epidemic

Epidemics greatly changed our life. We are required to wear masks, washing hands frequently, and keep social distance from others. In order to investigate the invariability during the epidemic, we compared the number of POIs in pre-lockdown and post-lockdown phases to evaluate the resilience of Wuhan city. As an important research topic in urban science, city resilience describes the capacity of cities to function so that all citizens can survive and thrive in front of public emergencies [17].

From previous analyses, we have known that the POI visit got a significant suppression during the lockdown period (Fig 5, 6). However, the number of POIs is relatively stable during the epidemic, as shown in Fig 12. In Fig 12 we calculate the active POIs in pre-lockdown phase and post-lockdown phase, finding that although all POI categories have fewer POIs after the lockdown, the degree of reduction is limited. The overall number of POIs maintains stable during the lockdown. In contrast to the findings in [4], we do not observe large-scale closures in Wuhan POIs, which is a good sign of the city resilience.

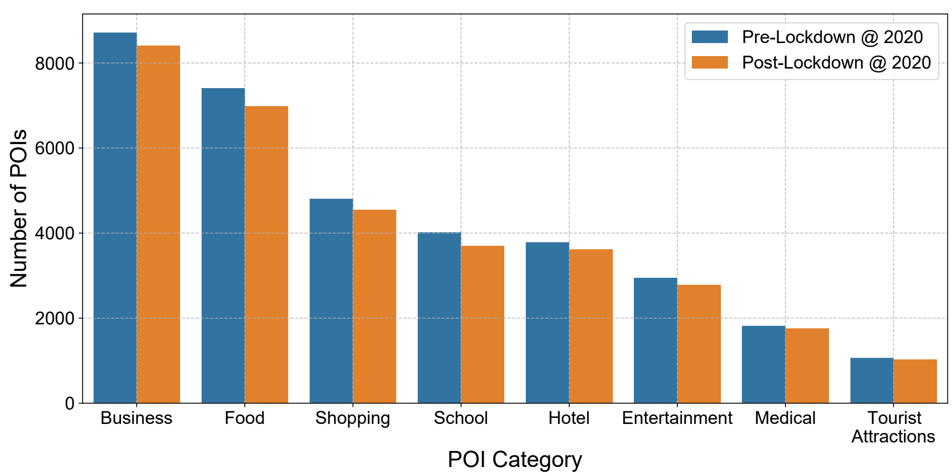

Fig. 12. Resilience of POI infrastructures.

The change of POI numbers can be split into two parts: some old POIs vanished, and some new POIs emerge. We also calculate the relative percentage of vanished and emerging POIs in each category in Fig 13 and 14. For the vanished POIs in 13, we find that most of the POI categories have a below 5% decrease in POI numbers, such as *Shopping*, *Hotel*, *Medical*, etc. However, *School* POIs seem to the receive greatest influence of more than 7%

decreasing, which disobey our understanding. Since we can only infer the possible life cycle of POIs according to the check-in behavior, *School* POIs which greatly leveraging online teaching during the epidemic [9] may receive much fewer check-ins than other categories. Except for *School*, the top 3 influenced categories are *Food*, *Entertainment* and *Shopping*. While for new emerging POIs in 14, *Shopping* and *Business* are leading strength after the lockdown. *Tourist Attractions* and *Medical* POIs also demonstrate great liveliness during the epidemic. Two famous hospitals during the epidemic are Leishenshan Hospital and Huoshenshan Hospital, which are built for COVID-19 patients in ten days.

From the above analysis, we have witnessed the strong resilience of Wuhan during the epidemic. Surveys from [4] demonstrate that people's expectation of epidemic duration is correlated with the closure rate. Considering the high resilience of Wuhan city, this phenomenon may indicate an optimistic public attitude towards epidemic control. A similar correlation between the fast revival of *Tourist Attractions* and the resident attitudes towards the government controls is identified in [14], which also demonstrates the relatively optimistic public emotion during the later period of the epidemic. The optimistic attitudes as the spiritual inspiration [24], along with the physical existence of POI infrastructures support the fast revival in Wuhan.

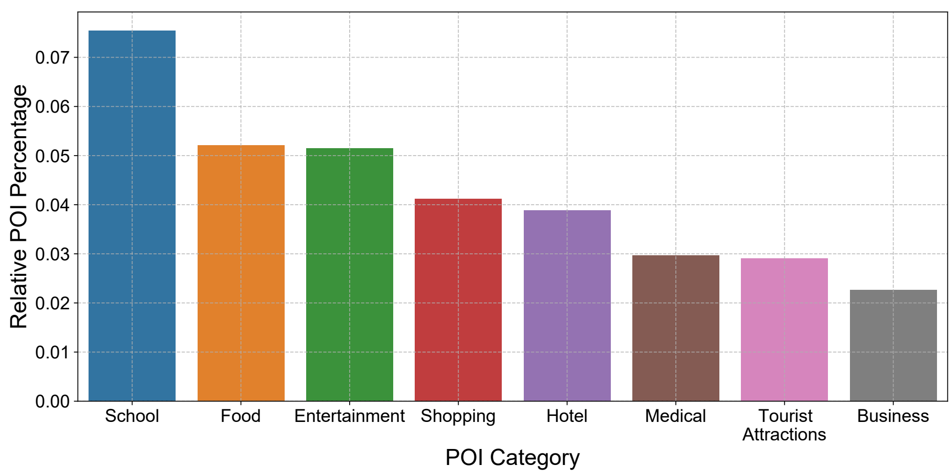

Fig. 13. Percentage of vanished POIs in each category

5 DISCUSSION AND RELATED WORK

Existing works have provided valuable knowledge on POI visit modeling for epidemic prediction [7], urban planning [16, 25], recommendation [33, 36] and other important applications. Chang et al. [7] leverage the POI visit records to facilitate epidemic modeling. Li et al. [23] use POI visit records to evaluate the effect of social distancing policies on controlling the urban hot-spot population. Zhang et al. [39] propose a new recommendation framework to connect users and POIs by user opinion modeling. Luo et al. [26] leveraging POIs in different levels of spatial granularity to model the interaction between human and POIs. The increasing availability of POI visit records [19] further motivates the investigation on POI visit modeling, which has become a heated research topic.

To evaluate the epidemic impact on POIs, a popular approach is by self-reported interviews or surveys of local companies. Bartik et al. [4] perform a large-scale survey on more than 5,800 small businesses during the COVID-19 period. They find that massive layoffs and closures happened in small businesses, and people's expectation of epidemic length is negatively correlated with the risk of closure. Mueller et al. [27] investigate the impact of

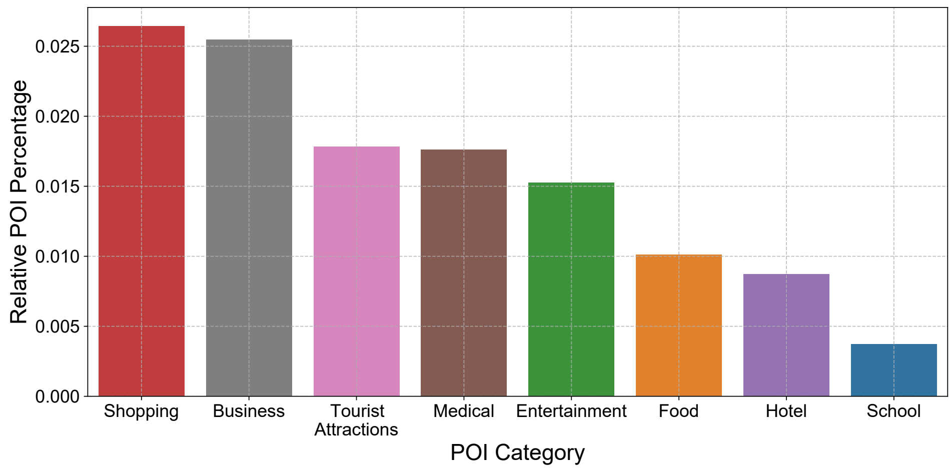

Fig. 14. Percentage of emerging POIs in each category

COVID-19 on rural America, and find that the overall life satisfaction, mental health and economic outlook received strong negative feedback. However, these self-reported expectations and satisfaction are not enough to represent the overall public attitude towards the epidemic. Besides, although this qualitative cognition provides valuable knowledge on evaluating the mental impact of the epidemic, we still need quantitative analyses to evaluate how people's behavior changes during the epidemic.

For quantitative analyses based on human mobility, there are two major types: one for *intra-city analyses*, another for *inter-city analyses*. Google Community Mobility Reports [1], Apple Mobility Trends Reports [2] and our work belong to the intra-city analyses, while Yuan et al. [37] and Zhou et al. [40] belong to the inter-city analyses. Intra-city analyses focus on human mobility within the same city, where microscopic data (such as POI check-ins) are needed to provide understanding about fine-grained social-economic behaviors of citizens. However, inter-city analyses focus on the macroscopic human mobility patterns (often acquired by train/airplane records) to study the disease spreading or migration patterns. For *intra-city analyses*, Google Community Mobility Reports [1] provides a global view of community mobility patterns in many different countries, although due to service coverage it lacks China cities. Noticeable differences exist between Google Community Mobility Reports [1] with our work. First, from the data perspective, the Google Community Mobility Reports cannot provide day-to-day changes analyses since it adopts different baselines for comparison, which prohibits time-series analyses in our work. It also forbids comparison between different categories of POIs due to the baseline selection, which has been done by our data since we have the absolute volume of visits. Our data includes full volume POI information including physical location, which will be helpful for more fine-grained future studies. Second, although Google provides valuable data for academia, it lacks the necessary analyses to mine the underlying human behaviors. The main contribution of our work is that we reveal how megacities react to the epidemic from microscopic human behavior patterns. Finally, as mentioned earlier, in this work we fill the blank of intra-city behavior patterns in China. For *inter-city analyses*, Yuan et al. [37] focus on epidemic modeling by a simple yet effective regression model that uses immigrants and conformed cases to predict cumulative infected cases outside Wuhan. Kraemer et al. [20] validate the correlation between inter-city transportation policy with epidemic spreading, and Jia et al. [18] further propose a "risk source" model that uses exponential functions to evaluate the correlation between intra-city population flow with infection risks in destination cities. Different from these papers, our work focuses on the microscopic human behavior patterns under the epidemic impact, rather than epidemic transmission patterns in these papers.

More general analyses are available for a better understanding of the epidemic leveraging statistical data. Ozili et al. [28] summarize the spillover due to COVID-19 on different parts of the global economy, such as travel industry, hospitality industry, sports industry, etc. Other works provide understandings about the social behavior changes during the epidemic. Prentice et al. [29] analyze the panic buying behavior during COVID-19 through publicly available Twitter posts, suggesting that timely intervention policies are correlated with panic buying behavior. Goolsbee et al. [15] use cellular phone records on customer visits of individual businesses to analyze driving factors for epidemic impact. Their results show that the legal restrictions only responsible 7% of behavior changes during the epidemic, and individual choices correlated with anxiety of getting infected is much more important. However, researches that cover the whole timeline of the epidemic is still lacking, which can reveal the full reaction of cities towards public emergencies.

Differ from all these previous works, in this paper we focus on the quantitative analyses on POI visit changes in different periods of the COVID-19 epidemic. Leveraging the POI check-in data, we first analyze the epidemic impact on different kinds of local POIs with regards to the normal period. It reveals the most vulnerable part of urban life under severe public emergencies. Our results demonstrate that *Tourist Attractions*, *Entertainment*, *Food* and *Hotel* received the biggest impact during the city lockdown phase, demonstrating the behavior shift from "non-essential" to "essential" categories [15]. Our analyses also identify "early bird" POIs in pre-lockdown phase, which demonstrate unusual visit drops than the baseline period. The identification of the "early birds" is helpful to understand the social behavior during the initial stage of epidemic. Leveraging time series clustering technique [5, 31], we recognize four different revival patterns for POIs, which correlated with the POI functions in urban life. The fast revival of *Tourist Attractions* is consistent with [13], which is positively correlated with the confidence of government to control the disease and recover the local tourism industry [14]. Finally, our results demonstrate that high resilience exists during the epidemic periods in Wuhan, where large-scale POI closure not happened. The existence of these POI infrastructures is one of the reasons for the fast revival of Wuhan POI visits. Xu et al. [35] demonstrate that 43% of check-in data may be inaccurate in LSBNs, which may hinder the credibility of research that leveraging check-in data. While in our analyses, we aggregate the check-in records from the POI perspective, which reduces the impact of inaccurate check-ins caused by a small proportion of users. Besides, our analyses on the POI visit trend are not sensitive to the correct timing of check-ins. Delay check-ins within the same day make no difference in our aggregated analyses, which is an important part of inaccurate check-ins.

5.1 Research Implications

Our study provides important intuitions for academia, industry, and government. For academia, our work provides thorough analyses about how megacities react to the public emergency during different time periods. Leveraging mobile check-in records, we successfully mine the decline stage and revival stage of public behaviors during the COVID-19 epidemic in Wuhan city. We have identified different impacts on POI visit patterns, which is direct evidence of previous qualitative analyses about epidemic impact [4, 27]. Meanwhile, it is important to call for attention to the in-depth understanding of vulnerabilities within each POI category. *Business* POIs demonstrate the slightest visit loss in our analyses, while *Tourist Attractions* showed a 78.8% drop compared with normal times. The inner mechanisms of these vulnerabilities are of great interest to research communities. For the identified "early birds" POIs before the official release of city lockdown, their visit changes imply the public attitudes towards the disease in the early stage. Differ from [29], we do not recognize panic buying from our analyses in Wuhan before city lockdown. Thorough interviews are needed to investigate the reasons behind this phenomenon. Besides, our work summarizes four revival patterns of POI visit in the latter period of the epidemic, and we demonstrate the correlation between POI functions with the discovered visit patterns. This finding further validates the behavior shift during the epidemic described in [15], where people will reallocating visits from “non-essential” to “essential” POIs. Finally, city resilience is also a heated topic in academia [12, 17]. In this work, we have demonstrated strong resilience within Wuhan city, where large-scale of closures did not happen. Since the risk of closure is negatively correlated with the expected length of the epidemic [4], we can regard this phenomenon as a relatively strong belief of a bright future for Wuhan citizens, suggesting further studies to verify.

For the industry, our work highlights the possible impact on different POI categories during the epidemic, especially during the early stage where people may lack reasonable knowledge to justify the severity of the disease. Affected industries can benefit from the social behavior analyses before the implementation of city lockdown to prepare for possible panic buying behavior, making sure the resources supplement during public emergencies. Although intervention methods being taken by different countries are similar, such as social distancing and compulsory mask-wearing, the control densities vary [29]. For the strong control in China, the closure order for indoor activities continued until May 8, with the release of regular epidemic prevention and control policy states that “indoor venues such as theaters, amusements are allowed to hold all kinds of necessary activities under technical guidelines about control measures”. During the continued lockdown periods, vulnerable industries such as *Tourist Attractions* and *Entertainment* should adopt active risk management methods to prevent the negative effect of long-period lockdown. For example, online retailing of local tourist souvenirs is a possible solution to attract potential tourists after the lockdown period, which follows our analyses of fast recovery of *Tourist Attractions* POIs in Wuhan and other research in [13]. With the strong impact of COVID-19 in the film industry [28], some film publishers also turn to online streaming to minimize the losses [38]. Our work evaluates possible risks for industries during different periods of the epidemic, providing experiences for risk control of industries.

For the government, it is of crucial importance to set up a series of policy reactions to tackle severe public emergencies such as COVID-19. Our work demonstrates no panic buying before the city lockdown in Wuhan, which suggests good guidance of public emotions, while may also cause the underestimate of the severity of the epidemic. Governments should make sure the resource supplements during the lockdown period in that scenario. Leveraging the visit behaviors of early bird POIs, decision-makers can identify the public attitudes towards possible public emergencies. Besides, according to the analyses of most vulnerable industries during the epidemic, the government is supposed to support and protecting them from closure to ensure fast revival after the crisis. The correlation between the great resilience of Wuhan POIs and the fast revival is a valuable experience for other governments to digest.

5.2 Limitations

Although we do our best to make sure reliability during the analyses, limitations still exist for future work. First, our analyses concentrate on a single city. Due to the data availability, currently we only have POI check-in records in Wuhan. POI check-in data reveals the microscopic economics of local business, which are sensitive in many cities. Fortunately, Wuhan is a representative city that under the epidemic impact. As the first epicenter in China, Wuhan provides valuable experiences for other cities to fight the disease. For example, the modular hospital in Wuhan has been accepted by many other cities [8, 34], and the fast recovery of tourist attractions is also been validated in other cities [13]. However, more general patterns of epidemic impact on other cities are still needed. Second, due to the privacy issue, acquiring fine-grained individual traces for POI visit calculation is not possible. In that case, we adopt check-in data from location-based social network platforms to represent visit behaviors. Although the no-incentive feature of the platform increases the quality of check-in behavior, we still cannot guarantee the reality and comprehensiveness of records due to fake check-ins [35] and miss check-ins. To increase the quality of data, more auxiliary data should be collected, i.e., the distance between the check-in POI location and users’ real locations, to help justify the reality of records. Third, the POI candidate list during the check-in process is maintained by the location service provider. The update frequency of POI list during the epidemic may not be timely, which can underestimate the new-emerging POIs during our analyses. Given the update frequency of the POI list, we can better determine the number of new-emerging POIs during the epidemic. Finally, from the check-in data we cannot directly determine the POI life cycle. Although the data cleaning and completion increases the data quality, our algorithm for POI life cycle extraction may still cause some misjudges. More complementary data of POI status should be collected in future works to confirm the POI life cycle.

5.3 Future Works

In this work, we focus on the behavior analyses of Wuhan POI check-ins to provide intuitions about how the megacity responds to a severe epidemic, while important future works are worth exploring. First, currently the POI check-in data is limited in Wuhan. Although it is a good example of megacities in China since it is the first epicenter with more than 10 million citizens, we still need to extend our analytical framework to other cities given corresponding check-in data, generating a thorough understanding of city reactions towards the epidemic. Second, although we propose an analytical framework to mine the underlying patterns (in Fig.2), algorithms that can provide more accurate results are still lacking. For example, in future work we can design a self-supervised online algorithm that leverage user check-ins to calibrate active POI lists in map services, rather than the current life cycle extraction (section 3.5) that use a static policy to determine active POIs. Third, leveraging the analyses provided by this work, we can propose upstream models to provide more fine-grained results. For example, we identified "early bird" POIs that are sensitive to the epidemic, which are possible indicators of disease transmission since the POI visit represents the cognition towards the infection. It's a possible future work to propose an epidemic model that leverages the visit patterns of "early bird" POIs to predict the number of confirmed cases of a city, following the "risk source" model in [18] but in an intra-city manner.

6 CONCLUSION

In this work, we analyze the POI visit patterns during the epidemic period in 2020. First, we introduce the POI visit timeline of 2019 and 2020 during the decline stage, demonstrating great differences due to the epidemic. Second, we perform year-on-year comparison and self-comparison to quantify the visit drop, revealing the most vulnerable part of urban life under the epidemic impact. Third, we identify the early birds in pre-lockdown phase, which will be beneficial for understanding the early reaction of the society toward the upcoming epidemic and lockdown policies. Fourth, we recognize different revival patterns of different POIs as four different types, which correlate with POI functions. Finally, we highlight the resilience of a city during the epidemic by the statistics of POI numbers. The existence of POI infrastructures is important for the fast recovery of social-economic after public emergencies.

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