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Beyond 9-to-5: A Generative Model for Augmenting Mobility Data of Underrepresented Shift Workers

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***Abstract*— This paper addresses a critical gap in urban mobility modeling by focusing on shift workers, a population segment comprising 15-20% of the workforce in industrialized societies yet systematically underrepresented in traditional transportation surveys and planning. This underrepresentation is revealed in this study by a comparative analysis of GPS and survey data, highlighting stark differences between the bimodal temporal patterns of shift workers and the conventional 9-to-5 schedules recorded in surveys. To address this bias, we introduce a novel transformer-based approach that leverages fragmented GPS trajectory data to generate complete, behaviorally valid activity patterns for individuals working non-standard hours. Our method employs periodaware temporal embeddings and a transition-focused loss function specifically designed to capture the unique activity rhythms of shift workers and mitigate the inherent biases in conventional transportation datasets. Evaluation shows that the generated data achieves remarkable distributional alignment with GPS data from Los Angeles County (Average JSD < 0.02 for all evaluation metrics). By transforming incomplete GPS traces into complete, representative activity patterns, our approach provides transportation planners with a powerful data augmentation tool to fill critical gaps in understanding the 24/7 mobility needs of urban populations, enabling precise and inclusive transportation planning.**

I. INTRODUCTION

Human mobility modeling is critical for urban planning, transportation management, and public policy development [1], [2], [3]. Accurate representation of how individuals interact with urban environments enables planners and policymakers to design efficient, equitable, and sustainable cities [4], [5], [6], [7]. However, a significant segment of the urban population—shift workers who operate outside traditional daytime working hours—remains understudied despite their considerable presence in urban economies.

Shift workers, including individuals in healthcare, manufacturing, emergency services, and various service industries, constitute approximately 15–20% of the workforce in industrialized societies [8], [9], [10]. Their mobility patterns often differ markedly from typical daytime workers, characterized by intra-day activities extending across midnight boundaries and reduced participation in discretionary activities such as recreation or social events [11]. The lack of tailored transportation services during overnight periods contributes to unique challenges in commuting and accessibility, disproportionately affecting lower-income and minority groups among shift workers [10], [12], [13].

The underrepresentation of shift workers in existing mobility research arises primarily from two interconnected reasons. Firstly, conventional household travel surveys typically undersample individuals working during non-standard hours. Those surveys struggle to contact and capture the behaviors of shift workers with non-standard schedules, leading to data gaps that limit the understanding of overnight mobility needs [14], [15]. Secondly, traditional activity-based travel demand models and agent-based simulations generally rely on these undersampled survey datasets and are predominantly designed to capture within-day mobility patterns. Consequently, they often overlook the distinct overnight patterns involving activities that cross midnight, resulting in inadequate modeling of shift worker mobility [16], [17], [18].

The proliferation of GPS-enabled devices offers an opportunity to address these shortcomings by capturing detailed mobility traces that can supplement the biased survey data. GPS trajectory data provide continuous, high-resolution insights into individual mobility behaviors, potentially bridging data gaps left by conventional survey methods. However, GPS datasets present their own challenges, including temporal inconsistency, fluctuation in coverage rate, and varying reliability due to technical or behavioral factors [19], [20].

To address these challenges, we propose a transformer-based mobility modeling framework specifically designed for shift workers. The transformer's self-attention mechanism efficiently learns temporal relationships between observed activities to infer missing ones, converting partial GPS traces into complete activity diaries. This capability enables the model to accurately capture the unique temporal characteristics of shift worker activity patterns and serves as a powerful data augmentation tool, enriching incomplete GPS data to generate realistic, continuous mobility trajectories. The augmented dataset provides essential input for various transportation applications, including travel demand modeling, public transit scheduling, special-hour signal control, Mobility-as-a-Service (MaaS) platform optimization, and Transportation Network Company (TNC) allocation strategies during special operating hours to ensure an equitable and accessible mobility environment for shift workers [21], [22], [23]. Specifically, our contributions in this study are:

- We propose a novel transformer-based model specifically tailored to enrich and reconstruct fragmented GPS mobility data, generating complete activity chains that capture the distinctive intra-day and overnight mobility behaviors of shift workers. This approach not

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only mitigates biases in conventional survey data but also transforms partial GPS traces into synthetic yet behaviorally valid activity patterns for shift workers. When combined with survey metadata, our approach creates an augmented mobility dataset that effectively rebalances the systemic undersampling of shift workers in transportation planning resources.
- We perform an extensive empirical evaluation using GPS trajectory data from Los Angeles County, demonstrating that our model generates synthetic yet behaviorally valid activity chains, reflecting the unique mobility dynamics of shift worker groups.
- Through comparative analysis with traditional datasets and standard daytime worker mobility patterns, we underscore the distinctiveness of shift workers' mobility needs, highlighting critical implications for equitable and inclusive urban transportation planning.

By explicitly modeling and augmenting overnight mobility patterns, our approach offers transportation planners and policymakers a vital resource for better understanding and accommodating shift workers.

II. Literature Review

A. Human Mobility Modeling

Early transportation forecasting relied on trip-based models, notably the classic four-step travel demand model. Such models assume average travel patterns and struggle to represent individual heterogeneity [16]. In response, activity-based and agent-based models (ABM) were developed to simulate travel at the disaggregate level [17], [24]. Bowman and Ben-Akiva prototyped ABM models on top of discrete choice models for traffic predictions [18], establishing frameworks that serve as foundations for large-scale traffic simulation [25]. However, traditional ABMs often require extensive calibration using comprehensive datasets and typically focus on regular, within-day travel patterns, neglecting overnight transitions that characterize shift worker mobility.

Over the past decade, ubiquitous data sources—including GPS devices, smartphones, transit cards, and sensors—have propelled a shift from rule-based to data-driven mobility modeling, where machine learning techniques infer travel behavior directly from large-scale mobility traces [26]. Recent deep learning techniques, including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Generative Adversarial Networks (GAN), and Diffusion Models, have achieved prominence in human mobility modeling [27]. These approaches tackle various mobility problems from next-trip prediction to trajectory generation, often outperforming traditional models in capturing complex spatiotemporal patterns. Generative deep learning models now synthesize realistic individual, population-level, and transit mobility patterns, offering data-driven alternatives to rule-based simulators and enabling simulations in data-scarce regions [2], [28], [29].

B. Shift Worker Mobility Research

While mobility modeling has advanced significantly, research specifically examining shift worker mobility remains limited. Recent studies have primarily focused on documenting the challenges rather than developing modeling solutions. Palm [11] quantified how individuals working night shifts were significantly less likely to make discretionary trips compared to those with typical daytime schedules. These findings aligned with other research showing that non-standard schedules create misalignment with conventional social rhythms and reduce participation in community [12]. The methodological approaches in existing shift worker studies have primarily relied on traditional survey instruments with inherent sampling biases [14], [15], limited qualitative interviews, or aggregate transit ridership data that obscures individual-level patterns [13]. Lim et al. [15] identified multiple distinct patterns within night-shift commuting, fixed night vs. rotating shift, highlighting the heterogeneity that complicates modeling efforts. Kapitza [30] demonstrated that nighttime significantly increases car dependency for commuting, with effects varying by gender and urbanity, while Jang [31] revealed that shift workers consistently work longer hours than day workers. Despite these valuable insights, there remains a critical gap in comprehensive temporal mobility modeling approaches specifically designed for shift workers to address the unique spatiotemporal patterns of this population. Transportation barriers faced by late-night travelers further underscore the need for specialized modeling approaches [13], [10].

Our research addresses three key gaps in existing shift worker mobility modeling approaches: (1) the current mobility models failed activities crossing midnight boundaries, (2) the challenges of temporal inconsistency and missing data in GPS trajectories especially during overnight periods, and (3) the need for approaches that preserve heterogeneity among diverse shift worker types. Our transformer-based approach addresses these gaps by directly analyzing fragmented GPS trajectories and generating complete, behaviorally valid activity patterns that capture the unique temporal characteristics of shift workers. This agent-level processing preserves the distinctive features of different shift work schedules while reconstructing complete activity chains from incomplete observations. This enables transportation planners to better understand this underrepresented yet essential workforce segment.

III. Problem Formulation

We focus on developing a data augmentation approach for overnight and shift worker mobility patterns to address the limitations of current transportation models and data collection methods. Our approach aims to generate complete, realistic activity sequences that accurately capture the unique temporal characteristics of shift workers whose activities span evening hours and cross midnight boundaries.

We denote i for an agent (individual). For each agent, we collect a pair of consecutive daily activity chains spanning two days. The activity chain for day d (where $d \in \{1,2\}$)

is represented as $A_d^i = \{a_1^{i,d}, a_2^{i,d}, \ldots, a_{N_d}^{i,d}\}$, where N_d is the number of activities performed on day d.

Each activity $a_n^{i,d} = [T_n^{i,d}, S_n^{i,d}, E_n^{i,d}]$ consists of: Activity type $T_n^{i,d}$ (from the set of 15 activity categories in Table I), Start time $S_n^{i,d}$ (represented as time slot within the day), End time $E_n^{i,d}$ (represented as time slot within the day). For computational efficiency, we discretize each 24-hour day into 96 time slots, each representing a 15-minute interval. Therefore, $S_n^{i,d}, E_n^{i,d} \in \{1, 2, ..., 96\}$.

Given an observed activity pattern, our objective is to develop a model f_θ that generates activity with precise temporal characteristics of shift workers, including accurate work-sleep cycles, appropriate activity durations, and properly captured midnight-crossing activities: $\hat{A} = f_\theta(A_{obs})$.

To address the critical challenge of fragmented GPS data, we implement a masking approach that explicitly models these observation gaps. We denote the observation mask for day d as M_d^i, where each time slot t has a corresponding mask value $M_d^i[t] \in \{0, 1\}$, with 1 indicating an observed time slot and 0 indicating a gap in observation. This masking mechanism is a key of our solution, enabling our model to learn from incomplete data and generate complete activity chains despite the inherent limitations of GPS trajectories.

Given a dataset $\mathscr{D} = \{(A_1^i, A_2^i, M_1^i, M_2^i) | i \in \{1, ..., I\}\}$ of paired activity chains from I agents, we aim to train a model that minimizes the discrepancy between generated and actual activities while accounting for observation gaps: $\min_\theta \sum_{i=1}^{I} \mathscr{L}(f_\theta(A_1^i), A_2^i, M_2^i)$, where $\mathscr{L}$ is a suitable loss function that evaluates generation accuracy only on observed time slots, places special emphasis on correctly predicting activity transitions, and preserves the temporal patterns characteristic of shift workers.

The trained model serves as a data augmentation tool to bridge gaps in conventional survey data and address the temporal inconsistency issues in GPS trajectories, ultimately enabling more accurate representation of shift worker patterns for transportation planning and policy analysis.

TABLE I
ACTIVITY CATEGORY CODES WITH DESCRIPTIONS [32]

1. Home	6. Shop services	11. Social
2. Work	7. Meals out	12. Healthcare
3. School	8. Errands	13. Worship
4. Caregiving	9. Leisure	14. Other
5. Shop goods	10. Exercise	15. Pickup/Drop

IV. Methodology

A. System Workflow

The shift worker mobility generation system addresses the unique challenges of modeling shift worker activity patterns, which have been traditionally underrepresented in transportation planning. Our workflow, illustrated in Fig. 1, encompasses data processing, model training, and inference stages specifically designed for capturing overnight activity transitions. The process begins with the preparation of paired activity chains from consecutive days, with special attention

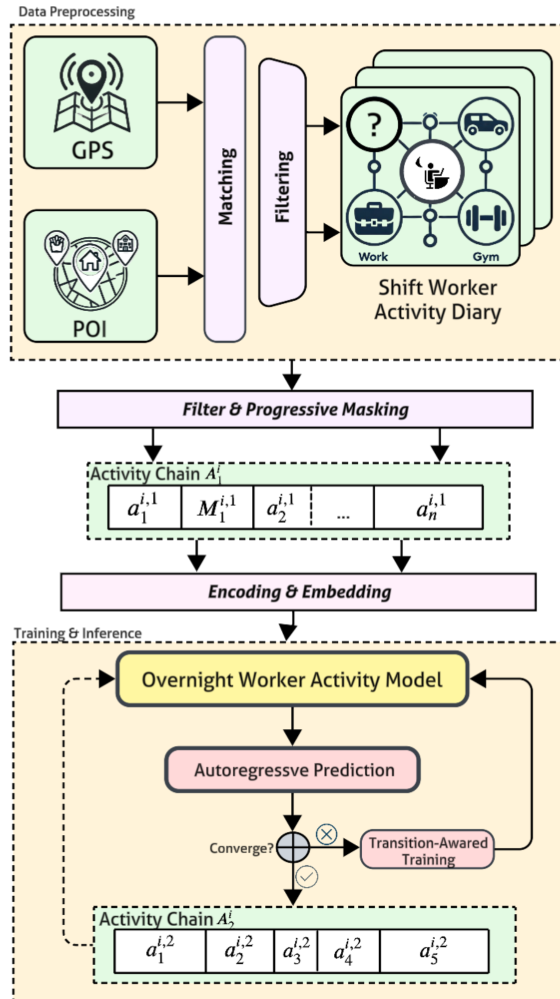

Fig. 1. System Workflow of the Proposed Model

to evening and overnight periods. We processed the GPS points and constructed corresponding masking tensors to address the inherent gaps in GPS data collection, ensuring the model learns from reliable observations while appropriately handling missing data.

Our training pipeline incorporates specialized data augmentation techniques that emphasize realistic overnight activity transitions. The model undergoes training with a progressive masking schedule, where the masking ratio increases gradually to enhance the model's ability to infer activities from increasingly sparse observations. This approach mimics real-world scenarios where GPS data collection often suffers from irregular gaps, particularly during overnight periods.

A key innovation in our workflow is the transition-aware training mechanism that places greater emphasis on activity transitions rather than static periods. This addresses the tendency of conventional models to predict overly simplified activity patterns that fail to capture the complex temporal structure of shift worker schedules. The model receives stronger learning signals when predicting transitions between activities, encouraging it to develop more nuanced repre-

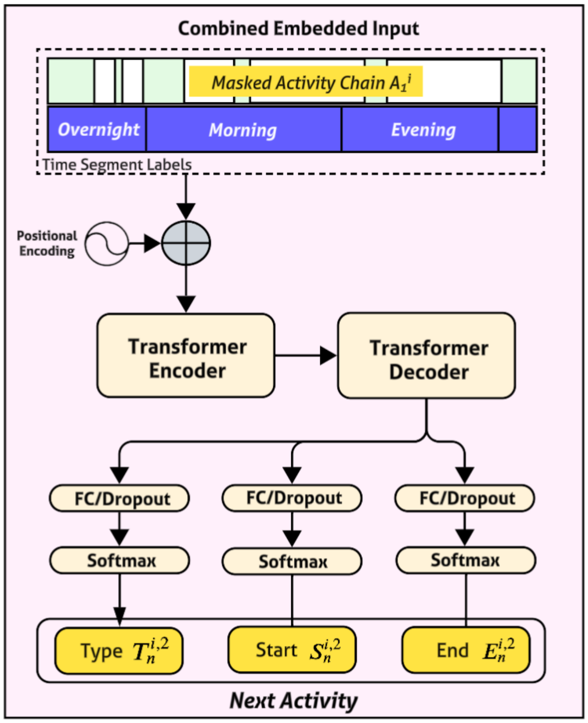

Fig. 2. Network Architecture of the Model

sentations of activity change points. During inference, the trained model generates next-day activity patterns autoregressively, with each prediction conditioned on previously generated activities and the encoded representation of the first day. This sequential generation approach ensures temporal coherence across the generated activity chain.

B. Model Structure

We employ a transformer-based architecture optimized for activity generation, as illustrated in Fig. 2.

1) Combined Embedding Layer: The embedding layer fuses activity type information with temporal context: $\mathbf{e}_t = \mathbf{e}_{\text{act}}(x_t) + \mathbf{e}_{\text{time}}(t)$ where: $\mathbf{e}_{\text{act}}(x_t) \in \mathbb{R}^d$ is the activity type embedding at time t, and $\mathbf{e}_{\text{time}}(t) \in \mathbb{R}^d$ is the period-aware time embedding.

The period-aware time embedding is a key innovation that captures the temporal patterns of shift workers. It contains distinct time periods: $\mathbf{e}_{\text{time}}(t) = \mathbf{e}_{\text{pos}}(t) + \mathbf{e}_{\text{period}}(p(t)) + \mathbf{e}_{\sin}(t)$ where: $\mathbf{e}_{\text{pos}}(t)$ is a standard positional embedding, $\mathbf{e}_{\text{period}}(p(t))$ encodes the period as specified in below, and $\mathbf{e}_{\sin}(t)$ adds sinusoidal features representing time of day.

The period function $p(t)$ is defined as:

$$p(t) = \begin{cases} \text{evening\_start}, & \text{if } t \in [18 \cdot 4, 22 \cdot 4) \\ \text{overnight}, & \text{if } t \in [22 \cdot 4, 6 \cdot 4) \\ \text{morning}, & \text{if } t \in [6 \cdot 4, 10 \cdot 4) \\ \text{other}, & \text{otherwise} \end{cases}$$

For each sequence in the batch, positional indices are created and expanded to match the sequence dimensions. The activity embeddings and time embeddings are then combined through addition to form the final representation that captures both the activity type and its temporal context.

2) Transformer Architecture: Our model utilizes a transformer encoder-decoder architecture with modifications specifically tailored for activity sequence modeling. The encoder processes the embedded day 1 activities to create context-aware representations that capture temporal dependencies within the input sequence. The decoder then autoregressively generates day 2 activities one time slot at a time. To improve training stability and generation quality, we employ teacher forcing with probability p_{tf}, where ground truth values are occasionally used as decoder inputs instead of predicted values. The final output layer maps the decoder representations to activity type probabilities through a softmax function. Our implementation uses 4 layers in both encoder and decoder, with 8 attention heads and hidden dimension of 128, striking a balance between model capacity and computational efficiency.

C. Loss Function Design

Our loss function design addresses the unique challenges of shift worker activity generation through several complementary components.

1) Cross-Entropy Loss: The foundation of our loss function is the standard cross-entropy loss that measures the discrepancy between predicted and target activity types: $\mathscr{L}_{CE}(\hat{\mathbf{Y}}, \mathbf{Y}) = -\sum_{t=1}^{96} \log(\hat{\mathbf{Y}}_{t,y_t})$ where y_t is the target class index at time t.

2) Transition-Aware Loss: To capture the temporal structure of activity patterns, we introduce a transition-aware loss that emphasizes correct prediction of activity transitions: $\mathscr{L}_{trans} = 1 - \text{F1}_{transitions}$ This component uses precision and recall of transitions with a tolerance window to accommodate slight temporal shifts, rewarding the model for correctly predicting when activities change.

3) Distribution Matching Loss: To ensure the overall distribution of activities is realistic, we include a distribution matching component based on JSD (Jensen-Shannon divergence): $\mathscr{L}_{dist} = JS(P_{\hat{\mathbf{Y}}} \parallel P_{\mathbf{Y}})$

JSD is a symmetric measure of similarity between two probability distributions, defined as:

$$JS(P \parallel Q) = \frac{1}{2} KL(P \parallel M) + \frac{1}{2} KL(Q \parallel M)$$

where $M = \frac{1}{2}(P+Q)$ is the midpoint distribution, and $KL(P \parallel Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)}$ is the Kullback-Leibler divergence.

In our context, $P_{\hat{\mathbf{Y}}}$ represents the distribution of generated activities across all time slots, and $P_{\mathbf{Y}}$ represents the distribution of true activities. This encourages the model to maintain appropriate proportions of different activity types, preventing overrepresentation of common activities while ensuring rare activities are still captured in the generated sequences.

4) Soft Label Loss: The soft label component provides smoother supervision around transition points by using weighted combinations of activity types: $\mathscr{L}_{soft} = -\sum_t \sum_c \tilde{y}_{t,c} \log(\hat{y}_{t,c})$ where $\tilde{y}_{t,c}$ are soft targets that blend between adjacent activities near transition points, allowing the model to learn more nuanced representations of activity changes.

Our final loss function combines these components with configurable weights:

$$\mathscr{L}_{combined} = \mathscr{L}_{CE} + \alpha \cdot \mathscr{L}_{trans} + \beta \cdot \mathscr{L}_{dist} + \gamma \cdot \mathscr{L}_{soft}$$

All components incorporate masking to handle observation gaps, ensuring the model is only trained on valid data points while preserving the temporal continuity of activity patterns.

V. Experiment

A. Data Overview and Preprocess

a) Comparative Analysis of Survey Data Under-representation: The examination of the activity distribution histograms in Table II reveals significant discrepancies between the household travel survey (HTS) and GPS-derived activity patterns. While both datasets contain a mix of shift and 9-to-5 workers, the magnitude of early/late hour representation differs dramatically. For work activity start times, the HTS data shows substantially lower early morning work starts (0-6 AM) at only 7.3% compared to 18.5% in the GPS data. Similarly, evening work starts (6-12 PM) shows 4.2% in HTS versus 7.5% in GPS data. The home activity distributions further reinforce this pattern: morning home arrivals (6-12 AM), which would typically correspond to shift workers returning home, show a striking disparity with only 4.6% captured in HTS compared to 15.4% in GPS data. These systematic discrepancies across both work and home activities confirm our hypothesis that traditional transportation surveys significantly underrepresent non-standard schedules, particularly those of shift workers who comprise an essential segment of the urban workforce. The predominance of conventional 6-12 AM work starts (61.1% in HTS vs. 52.2% in GPS) and evening home returns (6-12 PM) in survey data demonstrates how traditional data collection methods skew toward capturing standard 9-to-5 work schedules while systematically missing shift worker mobility patterns.

TABLE II

Comparison of activity start time distributions between traditional survey (HTS) and GPS data

Time Period	Work Activity (%)		Home Activity (%)	
	HTS	GPS	HTS	GPS
0-6 AM	7.3	18.5	40.2	35.3
6-12 AM	61.1	52.2	4.6	15.4
12-6 PM	27.4	21.8	24.4	25.3
6-12 PM	4.2	7.5	30.7	24.0

b) GPS Dataset for Modeling Shift Worker Mobility: To address these representation gaps and develop models that accurately capture shift worker mobility patterns, we require data sources that better represent this population's travel behaviors. In this study, we utilize Los Angeles County as our target test region due to its diverse population and varied work schedules. Our dataset consists of GPS trajectory data collected over a six-month period, which undergoes comprehensive preprocessing to extract meaningful activity patterns.

The preprocessing pipeline begins with GPS stay point extraction from raw trajectory data. We then semantically enrich these stay points through a multi-source POI (Points of Interest) dataset annotated with activity types using large language models. These semantically enriched stay points are aggregated at the agent-day level to construct activity chains. Details of the procedure are in our previous work [33].

To identify shift workers, we apply specialized filtering criteria designed to distinguish this population from traditional 9-to-5 workers. The key identification markers include: (1) presence of work activities during evening hours (18:00-22:00), (2) work activities spanning midnight boundaries, and (3) sustained work periods during typical sleeping hours (22:00-06:00). Through this process, we identified 208,350 entries of pairwise activity sequences—each entry representing two consecutive days from the same agent with shift work patterns.

B. Experimental Setup

Our transformer model was implemented in PyTorch and trained on an NVIDIA L40S GPU. We partitioned the dataset using an 80-10-10 split, resulting in 166,680 sequences for training, 20,835 for validation, and 20,835 for testing. The hyperparameters of the training are as following: training for 50 epochs with a batch size of 256, Adam optimizer with an initial learning rate of 1×10^{-4}, weight decay set to 1×10^{-5} for regularization, gradient clipping with a threshold of 1.0, and dropout rate of 0.1 applied to all layers.

The core architecture consisted of a transformer encoder-decoder with 4 layers each, 8 attention heads, and a model dimension of 128. We utilized period-aware temporal embeddings specifically designed to capture the distinct patterns of shift workers, with particular attention to evening start (18:00-22:00), overnight (22:00-06:00), and morning transition (06:00-10:00) periods. For our loss function, we implemented a transition-aware component with tolerance parameter $\tau = 2$, allowing transitions to be predicted within a small window of time slots. This approach specifically addresses the challenge of capturing activity transitions accurately, rather than simply predicting static activities.

C. Evaluation Methodology

Evaluating human mobility models presents unique challenges compared to standard generation tasks. Individual-level accuracy metrics are often inadequate due to the inherent stochasticity and variability in human behavior. Instead, we adopt a distribution-based evaluation approach that assesses whether the model captures the statistical properties of human mobility at a population level. We evaluate our model by comparing the distributions of various mobility characteristics between generated and real-world shift worker sequences. This approach allows us to assess whether the model has learned the underlying patterns governing shift worker mobility. For quantitative comparison, we employ JSD, as already expanded in the methodology section. JSD

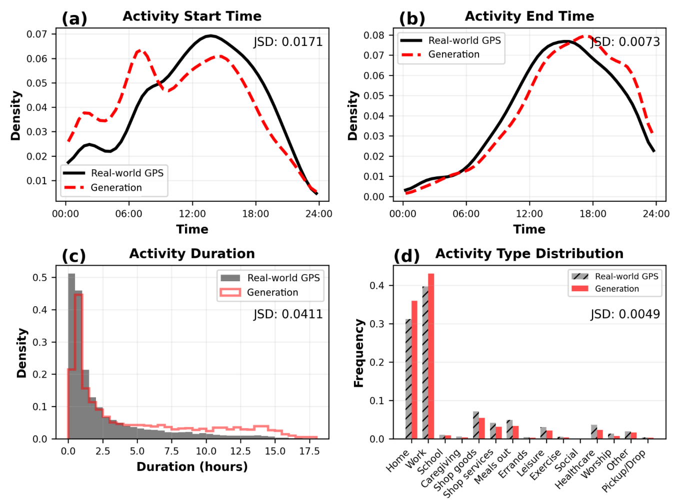

Fig. 3. Comparison of distributional characteristics between generated and real-world mobility patterns

values range from 0 to 1, with 0 indicating identical distributions and values closer to 0 representing better matches.

We evaluate our model by comparing the distributions of various mobility characteristics between generated and real-world shift worker sequences. This approach allows us to assess whether the model has learned the underlying patterns governing shift worker mobility. For quantitative comparison, we employ JSD, as already expanded in the methodology section. To demonstrate the superiority of our model architecture, we also conducted benchmark comparisons against an LSTM with Attention model trained on identical data sources. We evaluate the following distributional characteristics: (1) temporal distributions of activity start and end times, (2) activity duration distributions, (3) activity type frequency distributions, and (4) work-specific temporal distributions. Additionally, we present a comparative analysis with 9-to-5 workers and NHTS (National Household Travel Survey) data to demonstrate the distinctive mobility patterns of shift workers and validate our model's ability to capture these unique characteristics.

D. Results and Analysis

1) Overall Distribution Alignment: Fig. 3 presents the distributional comparison between our model's generation and real-world GPS for the test set. In Fig. 3 (a) and (b), we observe a strong alignment in activity start time (JSD = 0.0171) and end time (JSD = 0.0073) distributions. This low divergence indicates that our model effectively captures the temporal dynamics of activity transitions throughout the day. The end time distribution shows particularly strong alignment, suggesting the model has learned realistic activity durations and transition patterns.

Fig. 3 (c) demonstrates good correspondence in activity duration distributions (JSD = 0.0411). We observe a slight tendency in the generated distribution to favor longer activities while underrepresenting very short activities. This phenomenon can be attributed to the inherent limitations of GPS data, where signal interruptions often fragment continuous activities into shorter segments with gaps. Conversely, the model learns to predict more realistic continuous activities, which better represents actual human behavior patterns rather than being influenced by data collection artifacts. This finding aligns with Palm's research [11], which revealed that shift workers are less likely to engage in discretionary trips, typically have shorter duration than mandatory activities, compared to 9-to-5 workers.

The activity type distribution shown in Fig. 3 (d) exhibits excellent alignment (JSD = 0.0049) between generated and real-world GPS frequencies. Mandatory activities show slightly higher prediction rates, while non-mandatory activities are marginally under-predicted. This asymmetry reflects the challenge in modeling discretionary activities, which exhibit greater variability and are influenced by contextual factors not captured in our input features.

Table III presents the JSD metrics comparing our model against an LSTM with Attention baseline. The results demonstrate the exceptional performance of our approach across all evaluation dimensions. Our model achieves lower divergence from real-world GPS distributions, particularly in the activity start and end time distributions. Overall, our model's average JSD (0.0176) is significantly lower than the LSTM baseline (0.0621), confirming that the transformer architecture with period-aware embeddings and transition-focused loss is substantially more effective at capturing shift worker mobility patterns. The consistently lower JSD values across all metrics validate our architectural design choices and demonstrate our model's ability to generate highly realistic activity sequences that closely match real-world shift worker behaviors.

TABLE III
JSD Comparison Between Models Against GPS Data

Metric	Our Model	LSTM w/ Attn
Start Time	0.0171	0.0653
End Time	0.0073	0.0752
Duration	0.0411	0.0800
Activity Type	0.0049	0.0280
Average JSD	0.0176	0.0621

2) Work Activity Pattern Analysis: Fig. 4 specifically analyzes the temporal distribution of work activities, which are particularly relevant for our target population. The work activity start time distribution (JSD = 0.0089) reveals distinctive bimodal peaks at early morning (00:00-03:00) and late evening (21:00-24:00) hours, characteristic of overnight shift schedules. Fig. 4 also presents a comparative analysis of work activity patterns across different data sources: our generated shift worker patterns, real-world GPS overnight patterns, normal worker patterns from our dataset, and NHTS worker patterns. The stark contrast between overnight and regular worker patterns is immediately apparent. While normal workers and NHTS data show concentrated work start times in morning hours (07:00-09:00), shift workers exhibit peaks during late evening and early morning hours. The generated distributions (red dashed lines) closely track the

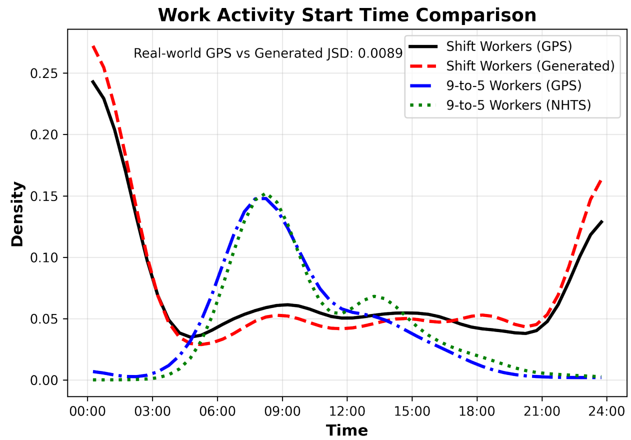

Fig. 4. Comparison of work activity patterns between different worker types

real-world GPS distributions (black solid lines) for both work start and end times, capturing the characteristic overnight peaks at both ends of the day. This comparison validates our model's ability to reproduce the distinctive temporal signatures of shift workers accurately.

The clear divergence between shift worker patterns and those of normal workers (blue dash-dot lines) and NHTS workers (green dotted lines) in Fig. 4 further demonstrates this bias. The latter two groups show nearly identical distributions with pronounced morning peaks for work start times and afternoon peaks for work end times, confirming that traditional surveys predominantly capture conventional 9-to-5 work schedules. This visualization powerfully demonstrates how transportation planning based solely on traditional survey data would systematically exclude the mobility needs of shift workers.

These results validate our approach to modeling shift worker mobility patterns and highlight the importance of developing specialized models for this significant yet often overlooked population. By supplementing traditional survey data with synthetically generated shift worker patterns, our model helps create more inclusive and representative datasets for transportation analysis, ensuring that the needs of all worker populations are considered in infrastructure and service planning The low JSD values across multiple distribution comparisons indicate that our transformer-based approach with period-aware embeddings and transition-focused loss functions effectively captures the complex temporal dynamics unique to shift workers.

VI. Discussion

The model introduced in this paper offers several significant implication to the field of urban mobility modeling, particularly for addressing the persistent underrepresentation of shift workers in transportation planning.

Our transformer-based approach demonstrates exceptional predictive power in capturing the heterogeneous mobility patterns of shift workers. By taking a single day's activity diary as input and accurately forecasting next-day patterns, the model preserves individual-specific characteristics that traditional aggregated approaches often overlook. Unlike conventional ABM or generic DL-based mobility generation models that typically ignore intraday connections due to their single-day generation nature, our approach excels at representing shift work where major activities frequently span midnight boundaries. This personalization is particularly valuable for shift workers, whose schedules vary significantly across different occupations and industries, from healthcare to manufacturing to service sectors.

The model effectively addresses a fundamental challenge in GPS trajectory data: quality fluctuation and missing observations. Through our period-aware embeddings and masking mechanisms, the system learns to infer activities during data gaps, creating complete and behaviorally valid activity chains. This capability transforms fragmentary mobility traces into comprehensive activity diaries suitable for transportation planning applications, enhancing the representation of populations traditionally undersampled in conventional surveys.

While our experiments focused on one-day-to-one-day generation, the autoregressive nature of our model architecture enables bootstrapped long-term prediction. By feeding predicted outputs back as inputs, planners can generate extended activity chains spanning multiple days or even weeks. This feature is particularly valuable for simulating shift work patterns over longer time horizons, capturing weekly or monthly rotation schedules common in many shift-based occupations.

Furthermore, by preserving each agent's home and work locations, the anchoring points for the most dominant transitions in urban contexts, our model provides transportation policymakers with valuable demand estimation for late-night worker commutes. This information can guide decisions about transit operating hours and deploy regions, identify service gaps, and inform targeted improvements for overnight transportation services.

Limitations: Our GPS data inherently undersamples certain demographics due to smart device accessibility barriers. Additionally, activity detection relies on GPS-POI matching with rule-based assumptions [33], introducing potential biases. The fragmented nature of GPS means we cannot identify all shift workers, particularly those with irregular schedules. However, our model's adaptability enables leveraging improved datasets without architectural changes, and our framework's reliance on widely available GPS and POI data enables deployment across diverse urban environments.

VII. Conclusion

This paper addresses a critical gap in urban mobility modeling by developing a transformer-based approach specifically for overnight shift workers. Our model achieves remarkable predictive accuracy, with JSD values below 0.02 for temporal distributions, validating its effectiveness in generating realistic activity chains for this underrepresented population segment. Beyond its technical merits, this work serves as a call to action for the transportation planning community to recognize and prioritize the mobility needs of shift workers—an essential workforce that keeps our cities functioning around the clock yet remains systematically overlooked in policy decisions. Our approach provides transportation planners with a powerful tool to fill critical gaps in understanding the 24/7 mobility needs of urban populations, enabling more inclusive transportation planning. Future work could model seasonal variations, incorporate contextual features such as weather, and integrate with spatial models for comprehensive transportation demand forecasting, ultimately contributing to more equitable urban mobility systems that serve all residents regardless of their work schedules.

VIII. Acknowledgement

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