TOWARDS ONTOLOGY-ENHANCED MULTIMODAL DIGITAL OUT-OF-HOME ADVERTISING TARGETING

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ABSTRACT

The Digital Out-of-Home (DOOH) advertising industry still struggles to achieve precision in getting audience attention focused, relying mainly on location-based targeting that neglects critical consumer context. This paper presents an Ontology-Enhanced Multimodal Targeting System designed to bridge this gap. The core innovation of the proposal is a domain-specific ontology that integrates anonymized mobile Global Positioning System (GPS) data and real-time contextual inputs (e.g., time, weather). This semantic framework enables the operational advertisement targeting system to move beyond data correlation, inferring audience insights that are synthesized into a composite business-centric Recommendation Score (MR). A field experiment validates the system's performance against a traditional baseline, demonstrating a 220% relative uplift in relevant advertisement impressions. The presented findings establish a quantifiable and privacy-conscious methodology for optimizing DOOH advertising delivery, possibly positioning the proposed ontology-enhanced approach as a foundation for privacy-conscious contextual personalization.

KEYWORDS

Advertising; Digital Out-Of-Home; Mobile GPS; Ontology; Contextual Targeting; Audience

1. INTRODUCTION

Digital Out-of-Home (DOOH) advertising (ad, for short) has transformed public spaces, allowing commercial brands to engage audiences with dynamic and visually catchy content [1]. Unlike traditional static billboards, DOOH displays leverage digital technology to deliver targeted messages, animations, and videos. This shift has opened new opportunities for advertisers to connect with consumers on a more emotional level, fostering higher engagement and brand recall [2, 3]. Furthermore, DOOH is becoming an integral component of omnichannel marketing strategies, enhancing overall campaign engagement and improving cross-channel attribution [4]. However, current DOOH targeting methods often still fall short in achieving satisfactory precision and personalization [5].

Location-based targeting, the most common approach, allocates ad placements purely by geographic coordinates. That provides reach, but overlooks demographics, interests, and contextual factors that shape ad relevance [5, 6, 7, 8]. Industry and academic evidence support this limitation. A paper by Clear Channel UK [9] showed that consumers engage more with ads

David C. Wyld et al. (Eds): DPPR, CNDC, AIAA, DSA, WeST, ACITY, IoTE – 2025
pp. 163-176, 2025. CS & IT - CSCP 2025 DOI: 10.5121/csit.2025.152413

matching their immediate needs, and Nguen et al. [10] found receptivity increases when ad content aligns with contextual conditions— for instance, cold-beverage ads during hot weather.

To overcome these limitations, this study develops an ontology-enhanced multimodal targeting system that integrates anonymized Global Positioning System (GPS) and contextual data to generate semantically rich audience insights. The core innovation is a domain-specific ontology that formally integrates diverse data sources, enabling the operational system to move beyond data correlation. The ontology formalizes knowledge about audience behavior, spatio-temporal context, and ad creatives, enabling reasoning beyond location-based matching. The central research question guiding this study is: How ontology-based multimodal integration can enhance contextual precision and audience relevance in DOOH targeting?

System effectiveness was validated through a field test in Almaty, Kazakhstan, demonstrating a 220% relative uplift in relevant advertisement impressions compared to a traditional baseline. However, the validation utilized a small dataset limited to a single DOOH display, therefore the results are not generalizable across diverse countries, cities, or cultural environments without adapting the domain specific ontology. This limitation frames the study as a practical proof-of-concept. The following Sections describe the methodology, present results, and discuss implications for future research.

2. Previous Research

One can say that programmatic DOOH has fundamentally transformed the advertising landscape by automating the buying and selling of ad inventory, allowing for real-time bidding, data-driven decisions, and streamlined ad serving [3]. This automation opens opportunities for deploying dynamic ad placements allowing for better targeting options.

In recent years, DOOH advertising has mainly focused on location-based placement strategies [1, 11, 12, 13, 14]. Techniques such as geotargeting, geofencing, and proximity targeting have formed the foundation of most successful campaigns [12, 15]. Geofencing, for instance, defines virtual boundaries, capturing mobile device IDs entering these zones to deliver “hyper-targeted ads” [7]. Contextual targeting dynamically adjusts ads based on real-time conditions like weather, time of day, or local events [10]. JCDecaux's research indicates that the brain's response to a DOOH advertisement is 18% higher when its content is contextually relevant [16]. This heightened engagement leads to a 17% increase in a consumer's spontaneous advertising recall, ultimately resulting in a 16% sales uplift following a dynamic DOOH campaign.

Some works [13, 14] describe methods for targeting digital billboards using mobile applications and location data. However, these methods lack knowledge representation and reasoning capabilities, like those which can be obtained from ontology-based systems. Namely, these methods primarily focus on data from social networks or mobile phones, and neglect the importance of contextual factors and the ability to reason about complex relationships between various entities.

2.1. The Role of Ontologies in Semantic Targeting

One of the ways to bridge the gap between raw mobile GPS data and meaningful audience insights is that of adding a semantic layer in between them. Ontologies formally and systematically structure knowledge within a domain, defining concepts and their relationships [17]. They provide a "shared and common understanding" for consistent interpretation across systems and experts. This structured knowledge bases can thus serve as a foundation for reasoning and inference within a particular domain. For instance, an ontology for a university might encompass semantic entities like "courses," "professors," "students," and "departments." Relationships between these entities could include "enrolled in" (student, course), "teaches" (professor, course), and "belongs to" (course, department). Properties of these entities might involve "course name," "professor expertise," "student ID," and "department name."

In the context of DOOH advertising, an ontology could hence encompass entities related to “audiences” (demographics, interests), “locations” (types, surrounding areas), “products” (categories, brands), and the prevailing “context” (time of day, day of week, weather). This approach places itself beyond keyword-based location matching. In fact, semantic advertising networks, like the Lexeme [18], leverage ontologies to enable computers to comprehend ad meaning, website content, and their relationships, improving ad matching on websites. By leveraging these ontology properties in the context of DOOH, a decision support system (DSS) can thus reason about user needs, advertised products, and contextual factors to recommend highly relevant DOOH placements. This capability allows the system to move beyond keyword matching to reason about user needs and contextual factors, aligning with "context-aware" recommendation systems explored in other fields of advertising [19]. This approach can ultimately lead to more impactful, yet privacy-friendly advertising campaigns. The approach proposed in this work thus aligns with the concept of "context aware" recommendation systems explored by other researchers who propose a system for social media advertising targeting based on time, locations, and inferring users' interests [20]. Similarly to that, our proposed DOOH targeting system leverages ontologies and mobile GPS data to create rich user profiles, understand contextual factors, and recommend placements that are likely to resonate with the target audience.

2.2. Points for Consideration

While ontologies offer strong reasoning capabilities, practical implementation in DOOH systems raises several challenges. The development and maintenance of comprehensive ontology require significant effort and domain expertise. The ontology to be built needs to encompass a vast array of entities, relationships, and rules to ensure its effectiveness. It should also be adaptable to incorporate new categories of products, audience segments, and contextual factors as the advertising landscape evolves [21]. Collaboration between domain experts, knowledge engineers, and ethicists is crucial for constructing and maintaining an ontology with strong reasoning capabilities for the system.

Furthermore, data privacy must remain a paramount concern in this research. User profiling data, which forms the foundation of such a system, needs to be collected and utilized in accordance with strict regulations [22, 23]. Anonymization techniques and user consent mechanisms are essential for ensuring ethical data collection and responsible use within the system. Additionally, the accuracy of the system necessarily hinges on the quality of the underlying data [12, 14, 24, 25, 26]. Demographic data, user interests, real-time context information, and historical campaign data all need to be reliable for the system to function optimally. Techniques for data cleaning, outlier detection, and data fusion from multiple sources can be employed to enhance data quality and ensure the system's recommendations are grounded in accurate information. The field test was conducted in a specific geographic area (Almaty, Kazakhstan), which may limit the generalizability of the findings, and the system’s performance relies heavily on the quality of the incoming data, which could vary across different locations. Further research is needed to address these concerns, especially around the ethical implications of data use and algorithmic bias.

3. ONTOLOGY-BASED DOOH ADVERTISING TARGETING SYSTEM

The proposed method centers on transforming raw mobile GPS data into actionable, semantically rich insights about audience through an ontology, for best advertising placement. The mobile GPS data for this research was provided by GeoCTRL AG, and was already anonymized and pre-aggregated based on demographics (gender, age), interests, location, time, and historical data included.

3.1. System Framework

The architecture of the proposed system is shown in Fig. 1. It comprises two main components: (i) a Domain Ontology with a Processing Pipeline (to be discussed Section 3.2) and (ii) the Ad Decision Engine (to be discussed in Section 3.3). Inputs to this system include data provided by advertisers (target audience, product description, and ad creative), mobile GPS data, DOOH Point of Interest (POI) data, and third-party data streams fed via an API. Output consists of automated ad placement, and data to be recorded in Ad Management and Analytics platforms.

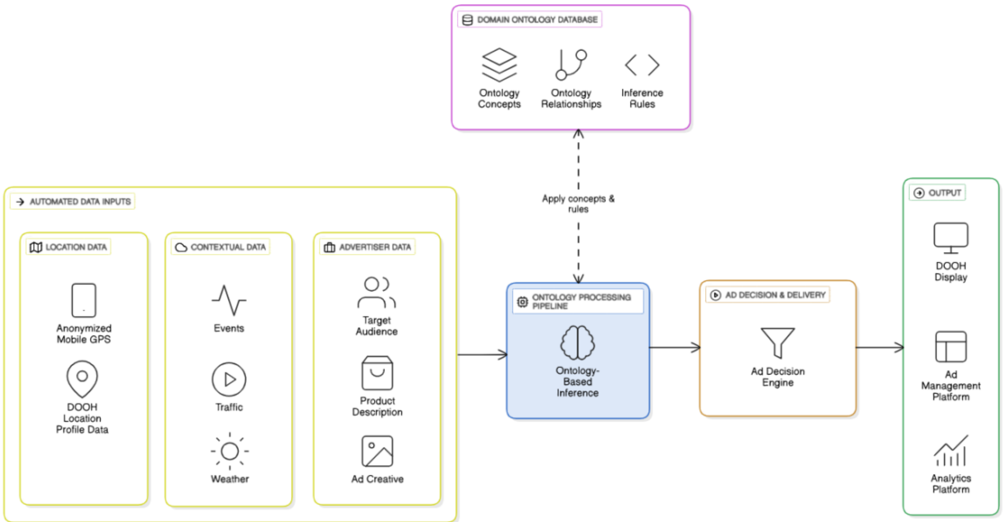

Figure 1. The system framework illustrates the flow of data from Automated Data Input (left/yellow)—encompassing Location, Contextual, and Advertiser Data—through the Ontology Processing Pipeline (center/blue). This data is processed against the comprehensive Domain Ontology Database (top/purple) to perform inferences. The Ad Decision Engine (center/orange) then uses these inferences to select and match the most suitable advertisement, which is subsequently displayed on the DOOH screen and sent to the Ad Management and Analytics Platforms (right/green) for logging and reporting.

As sketched in Fig. 1, the system works as follows. Its core, marked as Ontology Processing Pipeline (center/blue), is a domain-specific ontology, which serves as a formal knowledge graph for the DOOH advertising domain. This ontology refers to the regularly updated Domain Ontology Database (top/purple) that defines key concepts, establishes explicit relationships and inference rules between them.

As shown on the left of the Figure in yellow, the system ingests Automated Data Inputs with Location Data and Contextual Data transmitted via API and Advertiser Data via Web Interface. The system then applies the ontology's inference rules to semantically interpret this raw data. For example, it can infer that a cluster of devices at a specific location and time represents a "Commuter" or "Shopper" cohort, along with their likely intent. This enriched data is then combined with spatio-temporal context to provide a more comprehensive understanding of the audience. Finally, the Ad Decision Engine (center/orange) uses this semantically enriched data and advertiser's data (target audience, product type and ad creative) to select and deliver the most relevant ad creative from a pre-defined inventory to a selected DOOH display. The output indicated to the right in green is also recorded in the Ad Management Platform and Analytic System for logging and reporting.

3.2. Ontology Model Design

A domain-specific ontology for DOOH advertising was thus designed during a co-creation session with marketing industry professionals using the Web Ontology Language 2 (OWL2), the World Wide Web Consortium (W3C) standard for representing formal semantics. It was edited with Protégé [27] and HermiT [28] for automated reasoning and consistency checking. The logical rules for inferring new knowledge were expressed using the Semantic Web Rule Language (SWRL) [29].

This ontology is designed to define key concepts and their relationships in such a way to enable semantic inference for DOOH targeting. The foundation of this knowledge base reported in Box 1, establishes three core sub-concepts: Audience Cohort, derived from aggregated mobile data (including demographics and inferred intent); Spatio-Temporal Context, which captures real-time environmental factors (such as location type, time of day, and weather); and Ad Creative, which categorizes the products and messaging strategy. Crucially, the Key Relationships section in Box 1 defines the logical links between these concepts (e.g., Audience_Cohort is_present_at Spatio_Temporal_Context), providing the structure necessary for the system to reason about the dynamic environment.

- **Root Concept:** DOOH_Targeting_Context
  - **Sub-Concept:** Audience_Cohort
    - Attributes:
      - hasDemographic: (e.g., Gender, Age_Group, Income_Level)
      - hasInterest: (e.g., Sports, Shopping, Technology, Travel)
      - hasBehavioralPattern: (e.g., Commuter_Pattern, Shopping_Pattern, Tourist_Pattern)
      - hasInferredIntent: (e.g., Purchase_Intent, Event_Attendance_Intent, Leisure_Intent)
    - **Instances:** Commuters, Shoppers, Tourists, Families, Young_Professionals, Tech_Enthusiasts
  - **Sub-Concept:** Spatio_Temporal_Context
    - Attributes:
      - hasLocationType: (e.g., Transport_Hub, Shopping_Mall, Restaurant, Office_Building, Sports_Venue)
      - hasTimeOfDay: (e.g., Morning_Commute, Lunch_Break, Evening_Entertainment, Weekend_Peak_Hours)
      - hasEnvironmentalCondition: (e.g., Weather_Condition, Traffic_Level)
      - hasLocalEvent: (e.g., Concert, Sports_Match, Festival)
    - **Instances:** Specific locations (e.g., Arbat_Almaty), times (e.g., 0800-0900_Weekday), weather (e.g., Rainy), events (e.g., Almaty_Marathon).
  - **Sub-Concept:** Ad_Creative
    - Attributes:
      - targetsProductCategory: (e.g., Coffee, Sportswear, Electronics, Food_Delivery)
      - hasMessagingStrategy: (e.g., Promotional, Informational, Brand_Building)
      - isDynamic: (Boolean)
    - **Instances:** Specific ad creatives (e.g., Hot_Latte_Ad, Running_Shoe_Ad, Concert_Promo).

Box 1. A Conceptual Framework for DOOH Targeting

- Key Relationships (Excerpt):
  - Audience_Cohort is_present_at Spatio_Temporal_Context
  - Audience_Cohort has_inferred_intent Consumer_Intent
  - Ad_Creative is_relevant_to Audience_Cohort
  - Ad_Creative is_triggered_by Spatio_Temporal_Context
  - Location_Type is_part_of Spatio_Temporal_Context
  - Time_of_Day occurs_within Spatio_Temporal_Context
  - Environmental_Condition influences Spatio_Temporal_Context
  - Local_Event happens_at Spatio_Temporal_Context

Box 1. A Conceptual Framework for DOOH Targeting (continued)

The information reported in Box 2 demonstrates the logical application of the ontology structure through concrete inference rules written in the Semantic Web Rule Language (SWRL). These rules are the "intelligence" layer, leveraging the principles of knowledge graphs to link diverse data points and enable the inference of new, enriched facts. For example, Rule 1 of this excerpt uses the observation of mobile device clusters at a specific Location_Type (Transport_Hub) during a specific Time_of_Day (Morning_Commute) to infer a high-value fact: that the Audience_Cohort is "Commuters" and their has_inferred_intent is "Work_Commute_Intent." This transformation of raw location and time data into semantic intent is the primary mechanism by which the system achieves its advanced targeting capability.

- Rule 1 (Commuter Identification):
  - IF Mobile_Device_Cluster is_observed_at Transport_Hub AND Time_of_Day is Morning_Commute
  - THEN Audience_Cohort is Commuters AND Audience_Cohort has_inferred_intent Work_Commute_Intent
- Rule 2 (Shopping Intent):
  - IF Mobile_Device_Cluster is_observed_at Shopping_Mall AND Time_of_Day is Weekend_Peak_Hours AND Audience_Cohort hasDemographic Age_Group_25-45
  - THEN Audience_Cohort is Shoppers AND Audience_Cohort has_inferred_intent Retail_Purchase_Intent
- Rule 3 (Ad Relevance for Tourists):
  - IF Audience_Cohort is Tourists AND Spatio_Temporal_Context hasLocalEvent Cultural_Festival
  - THEN Ad_Creative targetsProductCategory Local_Attractions AND Ad_Creative hasMessagingStrategy Informational

Box 2. An Excerpt of the DOOH Targeting Rules

Location profiles were defined for common sites containing a DOOH screen.

3.3. The Ontology-Enhanced Targeting Engine

The other main component of the system is an operational recommendation engine that strategically matches audience, product, and contextual factors aimed at optimizing DOOH advertisement placement. Marked as Ad Decision Engine in Fig. 1, this matching feature was achieved through a pipeline of three scoring mechanisms: Location Matching (ML), Context Matching (MC), and a final Recommendation Score (MR).

As the first step, advertisers define the target audience (A) and product (P) through a web interface. The system inputs these parameters and maps them to a pre-defined ontology. The ontology’s purpose is twofold. First, it ensures consistency and precision in data mapping. Every advertiser's input is normalized and translated into a standardized format. Second, it enables the creation of multi dimensional vectors for both the advertiser’s target audience (Atarget) and the DOOH location's user profile (Lprof), which can be considered as embeddings. Each dimension of these vectors corresponds to a specific attribute defined in the ontology, such as age, interest, or location type. This vector representation simplifies the complex task of comparing a desired audience with an actual audience into a single mathematical operation: cosine similarity. Cosine similarity is a measure widely used to determine the similarity between two non-zero vectors as an inner product in the vector space. It is defined as the cosine of the angle between these vectors and is commonly used in text analysis to measure document similari

$$cos(\theta)=\frac{A\cdot B}{\|A\|\cdot\|B\|}, \tag{1}$$

where A·B represents the dot product of the vectors, and ‖A‖ and ‖B‖ are the magnitudes (or lengths) of vectors A and B, respectively. The value of this similarity measure ranges from −1 to 1, where 1 indicates that the vectors are identical in orientation, 0 indicates orthogonality, and −1 indicates that the vectors are diametrically opposed.

For example, take the hypothetical campaign as described in Tab. 1, where a target audience defined as "Young Adults (18-24 years old) interested in Sports" is represented. This advertiser’s input is translated into a numerical vector representation. Similarly, a product like "Fitness Trackers" is mapped to its corresponding category and attributes within the ontology.

Table 1. Example of value attribution to Audience and Product

Qualitative Attribute	**Ontology Mapping**	**Vector Dimension**	**Value/Weight**
Target Audience:			
Age Group	AgeGroup_18-24	Dimension 1	1.0
Age Group	AgeGroup_25-34	Dimension 2	0.0
...			
Interest	Interest_Sports	Dimension n	0.8
Interest	Interest_Music	Dimension n+1	0.0
…			
Product:			
Category	Product_FitnessTracker	Dimension x	1
Attribute	Feature_HeartRateMonitor	Dimension x+1	0.9

The numerical values in the Value/Weight column of Tab. 1 are determined by the advertiser's campaign strategy, with 1.0 representing a full match or highest priority. This structured approach ensures that every aspect of the campaign is precisely quantified, setting the stage for the rigorous calculations that follow.

3.3.1. Location Matching(M_L)

In this system, for each DOOH location (L) a user profile vector Lprof is created based on pre-processed anonymized mobile GPS data. This vector contains attributes such as age group percentages and interest category distributions. The location matching score ML is defined using the cosine similarity between the advertiser's target audience vector, Atarget, and the location's user profile vector, L_{prof},

$$M_L=\frac{A_{target}\cdot L_{prof}}{\|A_{target}\|\cdot\|L_{prof}\|}. \tag{2}$$

This choice provides a normalized score between 0 and 1, where 1 indicated a perfect match. The multi-dimensional vectors Atarget and Lprof are constructed using attributes defined in Box 1, encompassing demographics, interests, and behavioural patterns. Dimensionality is determined by the total set of standardized audience attributes in the ontology. Advertiser-defined attributes (e.g., Age_Group) are assigned weights (0 to 1) based on campaign priority, serving as explicit feature weighting for the cosine similarity calculation.

One can now imagine the hypothetical campaign for a "Fitness Tracker" product targeting an audience with a strong interest in Fitness and a Younger demographic. To find ML the system will continue with the following actions:

1. Let the advertiser's vector Atarget be [0.9, 0.0, 0.8]. The dimensions correspond to "Young Adult Presence," "Luxury Shopper," and "Sports Interest," with the values indicating a strong preference for the first and third attributes,
2. Let a specific DOOH location have a user profile vector Lprof of [0.8, 0.5, 0.6]. This location's audience has a reasonable presence of Young Adults and a moderate interest in Sports, but also a significant presence of Luxury Shoppers.

The calculation proceeds with the result

$$M_L = \frac{(0.9 \cdot 0.8) + (0.0 \cdot 0.5) + (0.7 \cdot 0.6)}{\sqrt{0.9^2 + 0.0^2 + 0.8^2} \cdot \sqrt{0.8^2 + 0.5^2 + 0.6^2}} = \frac{1.20}{1.344} = 0.89.$$

This score of 0.89 indicates a strong but not perfect audience alignment, suggesting to the system that this location is a highly viable candidate for ad placement. This example thus shows that this data driven approach is a critical step in providing a quantifiable justification for ad spending and demonstrating return on investment.

3.3.2. Context Matching(M_C)

Noticeably, the context matching score MC is not a simple binary function. It is a graded score from 0 to 1, derived from a set of rules stored in the ontology. These rules can connect product categories with contextual data (C) such as weather reports and time of day. For example, for a "Fitness Trackers" product (P), the system used a rule engine to calculate MC.

The inference engine manages inconsistent or missing data by leveraging the ontology's rule structure. Since is a graded score (0 to 1), rules prioritize high-relevance matches. If a critical contextual data input (e.g., local events) is missing or cannot be reconciled, the system defaults to a conservative score derived from a broad baseline rule, ensuring the final calculation remains operational.

To illustrate this, Tab. 2 presents a pre-defined rule table to calculate the MC score for the hypothetical Fitness Trackers campaign.

Table 2. Example of Contextual Score attribution

Contextual Condition	Rule Logic	M_C Score
Peak Commute/Workout Time and Clear Weather	Time is between 6:00 and 9:00 OR Time is between 17:00 and 19:00 AND Weather is Clear	1
Cloudy Weather	Weather is Cloudy OR Windy	0.9
Off-Peak Daytime	Time is between 12:00 and 15:00	0.7
Rain/Poor Weather	Weather is Raining	0.1
Late Night	Time > 10:00 PM	0.1

In this example, if the current time is 6:30 and the weather is clear, the system identifies that the first rule is met, and the MC score is set to 1.0. If the time were 14:00, the third rule would be instead applicable, yielding an MC of 0.7. The inclusion of a rule for "raining" that overrides other conditions ensures the system understands that outdoor fitness is less relevant regardless of time. This rule-based engine is the practical application of the trend toward dynamic content in DOOH, which allows raw data, such as weather forecasts, to directly impact ad placement and content strategy.

3.3.3. Recommendation Score(M_R)

Finally, the system defines an advertisement placement recommendation score MR. This is a composite score that combines the previously calculated values with a cost factor to provide a single, unified metric that quantifies the overall value of an advertisement placement. MR is defined as

$$M_R = w_L \cdot \mathrm{norm}(M_L) + w_C \cdot \mathrm{norm}(M_C) - w_{cost} \cdot \mathrm{norm}(Cost_L), \quad (3)$$

where all components were first normalized to a [0,1] to prevent scale bias. Before scoring, all component values — ML, MC, and the cost of placement CostL — are normalized to a common scale. This normalization ensures that no single factor dominates the final score due to a disparate numerical range. The weights, wL,wC, and $wcost$ are determined by the campaign's strategic objectives, allowing advertisers to prioritize relevance over cost efficiency, or vice versa. CostL is usually defined by the market values (supply vs. demand) or direct agreements with billboard providers.

Referring to the previous examples for the "Fitness Tracker" campaign, the MR is calculated from the following values:

1. From Location Matching calculation ML=0.89 and norm(ML)=0.89;
2. For Context Matching, assume it is 8:00 but the Weather is Cloudy, making MC=0.9 and norm(MC)=0.9;
3. Assuming the cost of placement at this location, CostL, is $15 per showing, if the market range for costs is from a minimum of $3 to a maximum of $30, it can be normalized using a min-max formula norm($CostL$) = 15−3 30−3 =12 27 =0.44(4).

Depending on the campaign strategy, MR based on these variables may be as follows:

- Strategy A (Relevance-Focused): The advertiser prioritizes audience and context, with weights wL=0.5, wC=0.4, and $wcost$=0.1, so that

$$\mathrm{M}R = 0.5 \cdot 0.89 + 0.4 \cdot 0.9 - 0.1 \cdot 0.44 = 0.761,$$

- Strategy B (Cost-Efficiency Focused): The advertiser is highly budget-conscious, with weights wL=0.3, wC=0.2, and $wcost$=0.5, so that

$$\mathrm{M}R = 0.3 \cdot 0.89 + 0.2 \cdot 0.9 - 0.5 \cdot 0.44 = 0.227.$$

The final scores of this example demonstrate the engine's strategic flexibility. For Strategy A, the high MR score of 0.761 indicates a highly favorable recommendation. For Strategy B, the lower MR score of 0.227 shows that the system recognizes the location is less optimal when cost is the primary concern. This inclusion of a normalized cost factor elevates the engine from a purely technical matching tool to a practical, business-oriented recommendation system. The MR score thus provides a quantifiable proxy for the "value" of a placement, allowing advertisers to choose the optimal balance of relevance and cost, which is a fundamental requirement of any advertising campaign.

3.3.4. Experimental Setup

A field test on the proposal system was conducted on June 28th, 2025 in Almaty, Kazakhstan, at Arbat, a high-traffic pedestrian street. A single DOOH display was used. The experiment consisted of two 10-minute advertisement campaigns with multiple advertising shown. A 30-minute interval separated the campaigns to mitigate carry-over effects. To ensure comparability, both campaigns were conducted under similar environmental conditions, including time of day (14:00-15:00), weather (Sunny, +32 C), and general foot traffic.

The targeting system used anonymized and aggregated mobile GPS data from GeoCTRL AG. This data provided spatio-temporal audience patterns, including dwell times, inferred demographics, and interests. This data served as the primary input for the ontology-enhanced targeting system. A standard digital billboard was used for dynamic content delivery.

A LiDAR-based system, as that proposed in Forster et al. [30], was deployed to measure ad viewability and audience engagement. This system uses 3D point cloud data to identify and track human silhouettes, enabling a privacy-friendly and precise measurement of pedestrians near the display. The LiDAR system continuously measured the number of human silhouettes detected in the viewable zone of the display and their estimated dwell time.

The baseline campaign ran for 10 minutes, where the display showed a generic, location-based ad campaign with sequential, non-responsive advertisement delivery. Besides that, for the targeted campaign the display ran also a 10-minute campaign leveraging the developed ontology-enhanced multimodal targeting system, which selected ads based on audience insights.

The key metric proposed for analyzing data obtained from this study was “Relevant Impressions”, defined as a relative number of human silhouettes detected by the LiDAR system who were exposed to an ad contextually relevant to their inferred cohort and intent. This metric moves beyond traditional "Opportunity to See" (OTS) [31] to measure a more meaningful form of engagement.

4. RESULTS

The dataset gathered is admittedly small, but interesting hints can be derived from it already at this level. The results obtained demonstrate a significant uplift in relevant impressions, validating the effectiveness of the proposed ontology-enhanced targeting system. The consistent foot traffic and total ad impressions observed between the two test periods strengthen the validity of this comparison.

4.1. Performance Comparison

Noticeably, the 10-minute targeted campaign, utilizing the developed artifact, showed a significant improvement in delivering relevant impressions compared to the baseline untargeted campaign (See Tab. 3).

Table 3. Campaign Performance Metrics

Campaign Type	Total Human Silhouettes Detected	Total Ad Impressions	Relevant Impressions	Percentage of Relevant Impressions
Baseline	329	266	49	18.4%
Targeted	316	272	157	57.7%

The total number of human silhouettes (329 vs. 316) and total ad impressions (266 vs. 272), measured as silhouettes facing the screen for more than 2 seconds, remained highly comparable, confirming that both campaigns were exposed to similar audience traffic and viewability conditions. The comparable traffic levels indicate that observed differences derive from targeting logic rather than external variation. The targeted campaign achieved 157 relevant impressions, a 108-impression absolute difference compared to the baseline's 49 relevant impressions. This represents a 220% relative uplift in the number of relevant impressions.

In order to assess the statistical significance of this difference, a two-proportion Z-test was performed on the proportion of relevant impressions out of total ad impressions for each campaign. A two proportion Z-test is a statistical method used to determine if the difference between the proportions of two independent groups is statistically significant [32]. The test begins with a null hypothesis (H0), which assumes there is no difference between the two population proportions, meaning any observed difference is simply due to random chance. The baseline had a proportion of p1 = 49/266 = 0.184, while the targeted campaign had a proportion of p2 = 157/272 = 0.577. The test yielded a p-value of p

$$\mathrm{CI} = \hat{p}_1 - \hat{p}_2 \pm Z_{1-\frac{\alpha}{2}}\sqrt{\left(\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}\right)}. \quad (4)$$

This result strongly supports the hypothesis that the ontology-enhanced system significantly improves targeting effectiveness. Overall, these results align with previous research indicating that targeting "cohorts of users" can yield substantial improvements in ad viewability by the "right people" [33]. The ability of the developed ontology to infer audience intent and context from aggregated mobile GPS data allowed for dynamic ad selection that resonated more strongly with the actual audience present, leading to a higher proportion of impressions being genuinely relevant. This improvement provides empirical support for the ontology's inference mechanism described in Section 3.

4.2. Limitations and Critical Discussion

This experiment was intended only to provide a practical proof-of-concept for the proposed approach. It is important to acknowledge its limitations to contextualize the findings.

Measurement alignment is the most important limitation to be considered. The definition of "relevant impressions" is based on the system's inference of audience intent. Whereas an improvement on OTS, it is still just an approximation of true engagement. The correlation between the inferred "relevant" interest and a viewer's actual interest assumed but not directly measured.

Secondly, as the scale of the study only allowed for single screen location with a limited campaign time, the experiment served only as practical proof-of-concept. Since the findings come from a single DOOH display in one specific urban location in the city of Almaty in Kazakhstan, the results may not be generalized to other countries, cities, display types, or audience demographics. Also, domain specific ontology design might need to be adapted to specific cultural characteristics of a region or nation. In addition, the experiment was limited to two 10-minute windows. While the overall traffic was consistent, a larger sample size over a longer duration and different contextual and environmental conditions would provide a better basis for generalization.

Lastly, the advertisements used for the targeted and baseline campaigns were different. While selected for their relevance, the general appeal of the creative may have influenced engagement, a variable that was not fully controlled.

5. CONCLUSIONS AND FURTHER RESEARCH

This paper presented a comprehensive theoretical and, hopefully, practical framework for advancing DOOH advertising targeting through an innovative ontology-enhanced multimodal approach. This proposal is shown to be designed to timely match needs consequent to the current significant growth of the DOOH market, and the critical need for more advanced targeting methods.

The proposed method addresses these challenges by applying a domain-specific ontology that transforms mobile GPS, traffic, weather, and event data into semantically rich audience insights. This ontological layer provides the context and inference required to identify dynamic “cohorts of users,” thereby moving beyond location-only targeting. Additionally, the framework integrates multimodal data fusion to support a holistic understanding of audience environments.

The significance of this research is hoped to lay in its dual academic and practical contributions. As an academical contribution, it is hoped to advance the field of computer science through novel applications of data fusion and ontology, and, as to marketing, through the development of a new paradigm for DOOH advertising targeting. As a practical contribution, the field test results in Almaty can demonstrate a performance uplift that translates directly into a compelling business case for both DOOH media owners and advertisers. The system provides a quantifiable justification for ad spending that goes far beyond traditional OTS metric. The inclusion of a normalized cost factor (norm($CostL$)) within the final Recommendation Score formula (MR) makes the system a practical, business-oriented tool. The two example strategies discussed—one focused on relevance and the other on cost efficiency—clearly show the system's flexibility in meeting different campaign objectives.

This integration of a cost factor could make of the approach a crucial commercial innovation, because it means that the proposed system is not just a theoretical research artifact, but it is a deployable solution that can directly contribute to a higher return on advertising budget. By allowing advertisers to weigh the value of relevance against the cost of placement, the system can provide a strategic decision-support tool, thereby moving DOOH from a broad-reach medium to a performance-oriented channel.

Furthermore, the use of a privacy-friendly LiDAR systemin conjunction with anonymized GPS data is a critical practical detail. This multimodal approach addresses one of the most significant challenges in modern advertising: data privacy. By relying on anonymized, aggregated mobile data for profiling and a privacy-by-design LiDAR system for physical presence confirmation, the system offers a powerful targeting solution without violating individual privacy. This positions the proposedtechnology as a responsible and future-proof solution in the environment ofstrict data protection regulations.

In conclusion, the positive resultof this pilot study hints to an agenda for future research which could focus on both scaling the artifact and ensuring its ethical integrity. To validate the generalizability of domain-specific ontology, follow-up field tests should be conducted across multiple, diverse geographic and cultural environments over longer periods. This expansion must be coupled with continuous enhancement of the domain ontology contents, involving collaboration with regional industry professionals to adjust the rules for audience inference, assessing the model's relevance to regional and cultural specificities. A critical area of future investigation could be also related to the ethical framework: rigorous research will be required to mitigate potential algorithmic bias, ensuring the targeting algorithms do not unintentionally reinforce existing societal biases by overlooking or excluding diverse communities. Finally, future operational research should focus on market fairness, designing protocols that manage the inevitable oversupply of highly-scored ad placements and guarantee that "minority ads," or campaigns aimed at niche audiences, are also adequately represented within the dynamic inventory.

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