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Digital Advertising in Physical Stores: Measuring Impressions in Digital Out-of-Home Advertising

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Abstract: Digital Out-of-Home (DOOH) advertising combines multimedia display technology, computer vision, and real-time audience profiling in retail and public environments. DOOH measurement does not follow the deterministic methodology of online digital media measurement. DOOH publisher measurements are based on probabilistic inference of sensor fusion, geometry, and behavior rather than deterministic impressions. This paper provides a technical survey of DOOH impression measurement methods. We focus on multimedia sensing, real-time processing, and data-driven optimization in DOOH systems. In this section we discuss four parts of the measurement pipeline. First, we consider traffic volume measurement using optical and wireless traffic fingerprints, dwell time assessment using computer vision and projected ultrasonic waves, demographic models using statistical classification, and opportunity-to-see (OTS) estimation using a mathematical model of attention-weighted exposure probabilities. We also discuss how new technologies, such as state-of-the-art gaze estimation via deep learning, mobile location analytics and programmatic advertising platforms, can assist in measuring and optimizing ad campaigns. These challenges relate to environmental factors affecting sensor performance, noisy crowds, privacy-preserving computation, and the lack of industry measurement standards. The paper suggests that the implementation of a transparent, auditable and standardized infrastructure for measuring impressions will allow strong, reliable and verifiable measurement. It argues that this will enable the DOOH industry to flourish as a reliable data-driven medium.

Keywords: *Digital Out-Of-Home Advertising, Impression Measurement, Opportunity-To-See, Audience Analytics, Programmatic Advertising*

1. Introduction

After rapid growth, Digital Out-of-Home has become one of the most technologically advanced advertising media. Static advertising on posters has transitioned to screens in retail stores, transportation hubs, and public spaces, where out-of-home media owners wish to use real-time audience measurements to target advertising to the right viewer at the right moment. With the channel maturing, the questions for the industry to answer are how we accurately measure the audiences that our screens can deliver. Advertising clients need reliable, comparable, and standardized metrics before they commit meaningful budgets to any medium and, frankly, DOOH hasn't done that yet. We review the state of the art in DOOH impression measurement, covering sensing systems, computational models, and challenges in this field.

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1.1 DOOH as a Multimedia System

DOOH is a complex multimedia system of display hardware, content supply networks, sensors, and analytics. DOOH systems consist of (1) hardware for displaying advertisements, such as LED billboards and LCD screens at variable resolution and viewing angles; (2) content management systems that determine when ads are displayed; (3) sensing hardware for detecting audiences; (4) analytics pipelines for understanding sensor data; and (5) programmatic systems for automated media buying and optimization.

1.2 The impression measurement problem

The major overarching technical challenge is that inference of exposure in a shared physical environment differs from non-shared environments like online advertising, where exposure can be observed directly at the device. DOOH must infer this exposure from environmental sensors, geometric models, and probabilistic attention predictions.

1.3 Multimedia Sensing Requirements

It is necessary to integrate multiple sensing modalities:

- **Sensing Layer:** Optical sensors, wireless signal detectors, ultrasonic sensors
- **Processing Layer:** Computer vision, gaze estimation, trajectory analysis, sensor fusion
- **Analytics Layer:** Geometric modeling, statistical inference, demographic profiling, real-time optimization

1.4 Survey Methodology

We systematically reviewed 50+ papers from ACM Digital Library, IEEE Xplore and advertising research databases on computer vision, multimedia systems, and audience analytics published between 2010 and 2026.

2. Defining Impressions in the DOOH Context

Before a measure can be evaluated, the concept it attempts to measure must be defined. In online advertising, there is a standard definition of an impression based on ad delivery events. Since DOOH does not have a direct equivalent to the concept of a viewable impression, it is particularly important to have precise definitions. The subheadings below discuss the definition of a DOOH impression, the geometric requirements for viewability of an impression, and the time requirements for amassing impressions in an advertising loop.

2.1 Impression Definition

Formal Definition: An impression is an event during which an individual was present in the viewable space of a digital display for the period of time that an advertisement was delivered under conditions sufficient to provide visual perception.

Characteristics:

- Probabilistic nature (inferred from sensors)
- Simultaneous exposure (multiple viewers)
- Environmental dependency (venue, crowd, temporal factors)
- Attention uncertainty (presence ≠ attention)
- Controlled viewing contexts (public and semi-public spaces)

2.2 Geometric Modeling

The impression requires the person to be in the viewable zone, that is, a geometrically defined area of physical space from which the screen is visible , and, at the same time, legible. The viewable zone needs to be defined in terms of the viewing distance, the screen angle and possible occlusions. The model consists of the following components:

- **Viewing Distance:** 1.5× to 10× screen height (varies by content)
- **Viewing Angle:** LCD ±60° horizontal, ±40° vertical; LED ±80° horizontal, ±60° vertical
- **Occlusion Analysis:** architectural structures, environmental objects, dynamic occlusions
- **Sightline Geometry:** Ray-tracing with head height distributions (1.4-1.8m)

Mathematical Formulation:

$V = \{p \in \mathbb{R}^3 : d\_min \leq \|p - s\| \leq d\_max,\ \theta\_h(p,s) \leq \theta\_h\_max,\ \theta\_v(p,s) \leq \theta\_v\_max,\ \neg occluded(p,s)\}$

2.3 Opportunity-to-See versus Verified Exposure

Most DOOH audience measurement systems are based on opportunity to see (OTS) methodology, which measures the estimated number of persons present within the effective viewing area of the display that is in play mode at any point in time. It measures the maximum possible exposure but does not draw visual attention.

Attention-weighted OTS models modify OTS estimates with attentional probabilities estimated based on gaze estimation studies:

- **Opportunity-to-See (OTS):** Total potential audience who can see advertisement at any one time
- **Attention-Weighted OTS:** OTS corrected by attention correction factors (0.3-0.7 depending on venue).
- **Verified Exposure:** use of eye-tracking, gaze estimation or some other explicit measurement of attention
- **Relationship:** Verified Exposure ≤ Attention-Weighted OTS ≤ Raw OTS

2.4 Role of Ad Play Duration and Loop Frequency (Temporal Factors)

- **Ad Play Duration:** 5 to 30 seconds
- Typical Loop Cycle lengths range from 2 to 10 minutes
- **De-duplication and Dwell Time Interaction:** When more than one loop exposure

Timing is also an important factor in measuring DOOH impressions when the advertising displayed on these screens is on a rotating schedule with ads from multiple advertisers. The number of impressions can be measured according to the length of the advertisement and the number of loops. The frequency and de-duplication logic applied to an impression figure should be published whenever such a figure is presented.

3. Core Measurement Techniques

Estimating the number of DOOH impressions requires cross-aggregating many datasets across the audience experience. There is no one dataset that captures all of this information—traffic counts do not capture dwell time, dwell time data does not capture demographics, and neither of those can confirm whether an ad was displayed or viewed. Table 1 summarizes the components of a complete measurement pipeline, the inputs they require, and the limitations each has:

Component	Data Input	Primary Function	Key Limitation
Traffic Volume	Optical sensors, infrared counters, Wi-Fi/Bluetooth, ridership records	Establishes raw audience count near display	Accuracy degrades in high-density and variable lighting
Dwell Time	Computer vision, ultrasonic sensors, device signals	Estimates duration of presence in viewable zone	Cannot confirm visual attention, only proximity
Opportunity-to-See (OTS)	Traffic count, viewable zone geometry, play window	Calculates maximum potential exposure per ad play	Overestimates actual viewership; attention unverified
Attention-weighted OTS	OTS count, gaze probability scores	Adjusts raw OTS by empirical attention probability	Gaze models vary in accuracy across environments
Demographic Modeling	Panel surveys, census data, behavioral segmentation	Estimates audience composition by age, gender, segment	Requires periodic recalibration as demographics shift
Loop Frequency Adjustment	Ad play duration, loop cycle length	Apportions audience share per advertiser per loop	De-duplication logic for repeat exposures remains unsettled
Programmatic Integration	Real-time traffic feeds, audience triggers	Activates delivery when audience conditions are met	Signal latency can misalign delivery with audience presence

Table 1: DOOH Impression Measurement Components and Their Functional Roles

3.1 Traffic Volume Estimation

Traffic volume is the basic layer of any impression model and is a prerequisite for measuring dwell time and attention around a given display. There are a variety of sensing technologies that can be used for this, each having advantages and disadvantages in their application.

3.1.1 Optical Sensing

Optically based systems, which can provide spatial data about the audience and are more widely deployed in retail, are based on the following types of sensors:

- **PIR Sensors:** Economical, privacy-maintaining, but low spatial resolution.
- **Stereo Vision:** 3D localization, calibration-dependent, lighting-sensitive
- **ToF Cameras:** 640x480 pixels for real-time 3D imaging with robustness
- **LiDAR:** high-resolution 3D point clouds, high cost/high power
- **Performance:** detection varies from >95% for sparse crowds to <70% for crowds with >1 person/m²

3.1.2 Wireless Detection

Detecting wireless signals can alternatively be used for monitoring, where surveillance with a camera device is not possible, or where privacy is a priority. These technologies operate with varying degrees of precision and scale:

- **Wi-Fi Monitoring:** MAC address detection, probe request frequency analysis
- **BLE Beacons:** 10-50 meter range. Requires Bluetooth to be turned on.
- **Cellular Analytics:** Accuracy of hundreds of meters, usually not for a single screen.

For retail outlets, traffic can vary by season, day of week, and hour of the day. Daily averages can induce large errors into impression estimates if traffic is heavily concentrated in peak traffic periods of the day.

3.2 Dwell Time Analysis

Dwell time is the amount of time a person's gaze is held within the effective viewing area of a display and is one of the most important factors of ad detection and processing.

- **CV-based tracking:** YOLO/Faster R-CNN are DNNs used for pedestrian detection, while SORT/DeepSORT/ByteTrack are multi-object trackers used to maintain the identity across frames.
- **Privacy-preserving:** On-device processing only sends aggregated statistics and does not save identifiable images.
- **Device-Based:** Wi-Fi/BLE dwell estimation with sampling intervals ranging from 1 to 5 minutes

These measurements create dwell time distributions in the impression models, with more weight given to those who spend more time in the viewable area.

3.3 Demographic Modeling

Presence measures like traffic and dwell time have no demographic information, but this can be modeled using external datasets about a location.

- CV-based classification (CNNs classify age/gender from facial imagery with 80-90% benchmark accuracy) also faces bias/fairness concerns.
- **Panel-Based Modeling:** Survey panels establish baseline demographics and extrapolate them using statistical weighting and census/mobility data. **Calibration:** Requires periodic recalibration as demographics change.

3.4 OTS Calculation

The four components—traffic, dwell, viewability geometry, and attention weighting—are turned into an aggregated OTS number by applying the following formula:

OTS = Traffic_Count × P(in_viewable_zone) × P(ad_playing | in_zone) × Attention_Weight

Attention weights between 0.3 and 0.7, based on gaze data from retail stores and public places, depend on factors such as the type of venue and the placement of screens.

4. Emerging technologies

Section 3 discusses the common audience metrics in DOOH. The use of computer vision, mobile data and the programmatic ad infrastructure, which is fast evolving, brings rich promise for greater precision, granularity and real-time usage of audience data in DOOH. This section reviews three developments that are changing the technical capabilities of measuring impressions in DOOH.

4.1 Computer Vision Systems

Computer vision is the most advanced technology used to measure DOOH audience reach; since initial implementations, the technology has included behavioral analysis beyond mere detection. Deep learning has improved the effectiveness and efficiency of these systems in recent years, and edge computing architectures have enabled large-scale, privacy-friendly computer vision to be implemented.

4.1.1 Deep Learning Detection

- **YOLO:** Real-time (30–60 FPS), >90% accuracy (YOLOv8)
- **Faster R-CNN:** Higher accuracy, lower frame rates (5–15 FPS)
- **RetinaNet:** Balanced accuracy-speed for crowded scenes
- **Tracking:** SORT (efficient), DeepSORT (robust re-ID), ByteTrack (state-of-the-art)

4.1.2 Gaze Estimation

- **Appearance-Based Models:** 5–10° angular accuracy from facial imagery
- **Head Pose:** Coarse gaze proxy (yaw, pitch, roll)
- **Attention Scoring:** Gaze direction + viewing distance + dwell time + environmental context
- **Validation:** Venue-specific calibration with ground-truth eye-tracking required

4.1.3 Privacy-Preserving Computer Vision

Modern DOOH deployments use privacy-preserving image processing techniques whereby images are analyzed locally on-device and only aggregated information is shared with backend reporting systems.

- **On-Device Processing:** Edge computing, aggregate-only transmission
- **Anonymization:** Face blurring, pose-only estimation, differential privacy
- **Federated Learning:** Distributed training without centralizing raw video

4.2 Mobile Location Analytics

Mobile location analytics provides a strong complementary source of audience intelligence, enabling inference of human traffic around DOOH displays beyond what static sensor networks achieve.

4.2.1 Data Sources

- **GPS:** 5–10m outdoor, unavailable indoors
- **Wi-Fi Positioning:** 10–50m, requires dense infrastructure
- **Cellular:** 100–1000m, broad coverage but imprecise
- **BLE Beacons:** 1–10m, requires beacon deployment

4.2.2 Applications

- **Trajectory Mining:** Movement patterns, traffic flows, dwell hotspots
- **Visit Frequency:** Reach/frequency estimation, new vs. returning visitors
- **Catchment Analysis:** Geographic distribution, geo-targeted campaigns
- **Cross-Venue:** Consumer journey patterns (with privacy protections)

4.2.3 Limitations

- **Sampling Bias:** 5–20% population coverage, requires statistical weighting
- **Spatial Accuracy:** Indoor positioning challenges
- **Temporal Resolution:** 1–5 minute intervals limit precision
- **Privacy:** GDPR/CCPA compliance requirements

4.3 Programmatic DOOH Platforms

Programmatic DOOH platforms ingest audience measurement data into automated advertising marketplaces, allowing advertisers to programmatically target inventory based on predicted audience profiles and near real-time environmental conditions.

4.3.1 Architecture

- **SSPs:** Aggregate inventory, standardized APIs
- **DSPs:** Programmatic bidding, targeting criteria
- **DMPs:** Centralized audience data
- **RTB:** Auction-based buying, dynamic pricing

4.3.2 Targeting

- **Demographic:** Delivery when audience matches targets

- **Behavioral:** Inferred behaviors/interests
- **Contextual:** Weather, events, time, traffic
- **Footfall:** Volume threshold triggers

4.3.3 Optimization

- **DCO:** Real-time creative selection
- **Pacing:** Budget management, frequency capping
- **Feedback Loops:** Performance metrics inform bidding
- **Latency:** 1–5 second signal-to-activation delay

5. Challenges and Limitations of Current Practices

Despite the technological advances described above, DOOH impression measurement faces a number of structural challenges. No technology so far has been able to address these challenges across the entire measurement process, from the initial collection of raw sensor data through to the final impression count. These challenges result in limited comparability, reliability, and advertiser confidence in current DOOH impression measures. Table 2 describes the origin of these challenges and their impact on operations.

Challenge	Primary Source	Pipeline Stage Affected	Operational Impact
Environmental Variability	Screen placement, lighting, occlusion, fixture layout	Traffic counting, viewability modeling	Inconsistent accuracy across venue types
Crowd Flow Bias	Channeling and clustering in high-density spaces	Traffic volume estimation	Systematic over- or undercount of audience
Sensor Degradation	High pedestrian density, irregular flow, poor lighting	Data acquisition	Reduced detection reliability in real-world conditions
Privacy Regulation	Data minimization laws, biometric inference restrictions	Demographic modeling, location data use	Reduced granularity of available audience signals
Re-identification Risk	Anonymized data combined with auxiliary sources	All data layers	Limits permissible data fusion and retention.
Absence of Standards	No universal impression definition or audit framework	Reporting and comparison	Cross-publisher figures not directly comparable
Methodological Fragmentation	Varying viewability zones, dwell thresholds, attention weights	Impression calculation	Impression inflation incentives without transparency

Table 2: Challenges Affecting DOOH Impression Measurement Reliability

5.1 Environmental variability and standardization issues

These unintended variances are not always predictable, nor able to be controlled to mimic the controlled environment of a lab or the standardized rendering environment of a web browser, nor eliminated. Sensor performance and viewability modeling can differ from site to site across a media owner's or venue's physical environments. Major sources of environmental variability are:

- **Lighting:** Optical sensors are sensitive to sunlight, shadows, and darkness.
- **Architecture:** Occlusions, reflections, and ceiling height impact coverage.

- **Screen position:** Screen mounting height, viewing angle, and distance to pedestrians can vary tremendously.
- **Crowd Density**: Accurate for sparse (>95% accuracy), not dense crowds (<70% accuracy).

Standards that specify fixed viewability regions or attention decay curves often rely on simplifying assumptions that only hold in some environments, and so viewability measurements should be based on characteristics of the environment where they are measured.

5.2 Statistical Uncertainty in High-Traffic Environments

Even with well-calibrated sensors, the statistical models that convert the raw number of detections to an estimate of impressions have their own noise, and this noise tends to increase in complex, high-density scenes. Furthermore, real-world pedestrian behavior violates the assumptions in most impression models.

- **Non-Independent Movement:** Groups and social forces violate the independence assumption in pedestrian models.
- **Channeling/Clustering:** Self-organization of pedestrians is observed in most traffic simulations where pedestrians are treated as individual particles.
- **Dwell Time Distributions:** Heavy-tailed distributions with high variance challenge simple models.
- **Temporal Patterns:** Strong hourly/daily/weekly/seasonal patterns require dynamic modeling.

If these impression models are not ground-truthed against environment-specific pedestrian behavior, a systematic overcount or undercount of advertising exposure may occur.

5.3 Privacy Regulation and Data Constraints

However, the richest audience data (exact geographical points, facial data, and biometric data) is the most limited by the provisions of privacy law. Privacy guardrails for collecting physical-world data are becoming stricter as regulators begin to focus on this area. This narrows the range of techniques and data sources that can be used to estimate DOOH audiences. Key regulatory frameworks include the following, each with diverse impacts:

- **GDPR:** Lawful basis, data minimization, purpose limitation, storage limitation, and right to erasure.
- **CCPA:** Right to know, delete, and opt out of data sale.
- **Biometric Laws:** Illinois BIPA requires consent and has strict liability.
- **Impact:** Limits facial recognition, location tracking, and data retention.

The potential for re-identifying individuals from nominally anonymized datasets combined with other data sources highlights the need for a privacy-by-design approach to all audience measurement pipelines.

5.4 Absence of Industry-Wide Standards

Beyond these technical issues, there is a more fundamental problem for addressing them: The DOOH industry has not reached agreement on what constitutes an impression, what the measurement method should be, and how the methods should be audited. The lack of standards creates challenges for advertisers, publishers and the reputation of the channel as a whole. Some of the more prominent problems are

- **Definitional Inconsistency:** Varying definitions of impression, viewability, and attention across providers.
- **Methodological opacity:** Proprietary algorithms restrict independent replication and assessment.
- **Inflation Incentives:** Commercial interests prefer large impression numbers rather than accurate measurement.
- **Audit Challenges:** Independent verification is difficult without agreed-upon standards.

A similar industry-level consensus on definitions, calibration and auditing processes, which the MRC performs for online ad publishers, would help strengthen the long-term credibility of the DOOH marketplace.

6. Future Research Directions

As outlined in Section 5, the challenges described above lead to a coherent research agenda for the entire DOOH measurement domain such that the road ahead to success requires the overall progress in the different sensor and modeling approaches to achieve privacy, accuracy, cross-channel comparability and methodological transparency in an integrated manner. Four research priorities are defined below:

6.1 Privacy-Preserving Measurement

Given the tightening privacy regulations, the call is for measurement architectures that can produce audience estimates without relying on individual-level data. Some technical approaches show promise:

- **Federated Learning:** Distributed ML training without centralizing raw data.
- **Differential Privacy:** Calibrated noise prevents re-identification.
- **Homomorphic encryption:** Computation on encrypted data without decryption.
- **Secure Multi-Party Computation:** Collaborative analytics without data sharing.

6.2 Attention Verification

The most compelling evidence for the effectiveness of attention-based impressions versus more direct presence-based impressions would be methods of determining whether the person's gaze was truly oriented towards the screen, but existing gaze estimation methods are difficult to deploy reliably at scale. Research priorities include:

- **Scalable Eye-Tracking:** Cost-effective, scalable solution for eye-tracking in retail environments.
- **Neurophysiological Signals:** EEG, pupillometry, and cognitive engagement indicators.
- **Implicit Interaction:** Touchscreen, QR codes, and gesture recognition as engagement proxies.
- **Validation Studies:** Ground-truth attention measurements to calibrate probabilistic models.

6.3 Cross-Screen Attribution

As consumers move across physical and digital spaces, connecting DOOH impressions to downstream consumer actions has become critical to understanding the full consumer journey. However, establishing this link has posed a technical challenge for the advertising industry. Key research challenges include:

- **Multi-Touch Attribution:** Linking DOOH impressions to online/mobile conversions.
- **Unified Measurement:** Combined measurements for DOOH, mobile, desktop, and TV.
- **Privacy-Preserving Linking:** Attribution without individual-level tracking.
- **Causal Inference:** Deals with distinguishing correlation from causation in exposure-outcome models.

6.4 Industry Standardization

However, technical innovation alone will not close the measurement credibility gap for DOOH and agreements around common definitions, audits and transparency are necessary across the industry. Standards initiatives have several purposes:

- **Measurement Standards:** Industry-wide definitions (IAB, MRC, DPAA frameworks).
- **Audit Frameworks:** Independent verification and certification programs.
- **Transparency Requirements:** Methodology disclosure and accuracy reporting obligations.
- **Data Sharing:** Anonymized benchmark datasets for research and calibration.

Conclusion

This paper has illustrated how the DOOH advertising industry has a range of systems to measure impressions that span computer vision, multimedia systems, mobile computing and advertising analytics. Key impression metrics, such as traffic counting, dwell time, demographic modeling and OTS calculation, can be combined to create an audience profile for media planning and programmatic campaign execution.

Improved computer vision, mobile location analytics, and infrastructure for programmatic advertising are increasing measurement accuracy and narrowing the gap between estimated and actual audience exposures. Remaining challenges include variability in sensor performance due to environmental factors, statistical and other uncertainties in pedestrian modeling, privacy-preserving computation, and development of common market metrics.

It includes areas such as privacy-preserving measurement methodologies, attention verification tools, cross-screen attribution, and standardization efforts. A transparent, auditable, and standardized impression measurement infrastructure is important for enabling the sustainable development of DOOH as a reliable data-driven advertising channel. The depth and quality of the channel's advance will also rely on the strength and openness of its measurement infrastructure as much as on the enhancement of screen and creative capabilities.

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