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Measuring the impact of digital out-of-home advertising on purchase decisions: A study at high-traffic urban stations with exposure rate as mediator

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Abstract

Digital Out-of-Home (DOOH) refers to a centralized advertising network managed through real-time analytics dashboards and remote control systems, enabling dynamic content delivery and performance tracking using metrics such as impressions, reach, and engagement. Campaign effectiveness increases significantly when content is tailored to nearby audiences, affirming the value of a data driven approach. This study aims to explore the influence of ad frequency, exposure duration, and face detection technology using the YOLOv8 algorithm on audience visual engagement, with exposure rate acting as a mediating variable toward purchase decisions. A qualitative exploratory descriptive approach was adopted to understand audience behavior in high mobility public areas. Data collection was conducted through direct nonparticipant observation at three key transit stations in Jakarta including Sudirman, Manggarai, and Kalibata, combined with documentation from a face detection system capable of identifying gaze orientation and attention span. The YOLOv8 algorithm integrated with lightweight CNN based face recognition was employed to enhance real time tracking accuracy in dynamic environments. Data were analyzed thematically to identify patterns of visual attention and the contextual factors affecting ad engagement. Findings reveal that although DOOH exposure volume is high, actual engagement remains low. This suggests the need for improved evaluation metrics and adaptive strategies to optimize DOOH campaign effectiveness.

Keywords: DOOH, Exposure rate, Face detection, Purchase decision, Visual engagement, YOLOv8.

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1. Introduction

1.1. Background

Out-of-Home (OOH) advertising has evolved into Digital Out-of-Home (DOOH) due to rapid technological advancements. DOOH leverages digital screens and centralized networks to deliver dynamic, contextual, and segmented content based on location, time, and audience characteristics. Unlike conventional OOH, DOOH offers precise performance metrics like impressions, reach, and engagement [1]. DOOH campaign effectiveness increases when advertisements are tailored to their surroundings and displayed with optimal frequency and duration.

Ad frequency (X2) in DOOH is a crucial factor in determining how well advertising messages are conveyed and remembered by audiences. The more frequently an ad is displayed, the greater the likelihood that the message will be absorbed. However, the effectiveness of frequency heavily depends on exposure duration (X3). If too short, the message may not be noticed; if too long, it may lead to visual fatigue. Therefore, a balanced combination of frequency and duration is essential to generate optimal visual engagement from the audience.

A key challenge for Digital Out-of-Home (DOOH) advertising is converting ad exposure into genuine audience attention. In busy urban settings like Jakarta, with numerous distractions, it's hard to capture everyone's focus. Factors such as people being engrossed in their mobile devices, fast-paced environments, and sensory overload contribute to low visual engagement with DOOH screens.

To illustrate the gap between exposure and actual attention, an observation was conducted at three strategic locations in Jakarta: Sudirman, Manggarai, and Kalibata stations. The results revealed that even during 5 hours of peak station activity, only a small percentage of the thousands of passersby actually noticed the screens.

Location	Number of Passersby	Number Who Paid Attention	Engagement Rate
Stasiun Sudirman	17.610	1.740	9.88%
Stasiun Manggarai	25.080	1.260	5.02%
Stasiun Kalibata	6.600	530	8.03%

Visual engagement percentages were below 10% for both DOOH and conventional OOH. This data underscores that advertising effectiveness cannot solely rely on traffic volume or impressions, but requires a more precise approach, such as directly measuring visual engagement.

Face detection technology based on Convolutional Neural Networks (CNN) is increasingly used in this context to track gaze direction and duration of audience attention toward ad screens. This system enables real-time analysis of visual engagement, providing objective data on how long and how many individuals actually view the advertisements. Kocacinar, et al. [2] demonstrated that lightweight CNN-based facial recognition systems operate with high accuracy even when users wear masks, making them suitable for use in dynamic public spaces.

To enhance detection accuracy and efficiency, the YOLOv8 algorithm is among the most advanced real-time object detection models due to its processing speed and stable detection precision. YOLOv8 is ideal for use in real-time systems integrated with edge devices and visual sensors. Mahdi, et al. [3] assert that combining YOLOv8 with facial recognition systems enables fast and accurate detection under various environmental conditions, supporting effective visual engagement analysis in DOOH contexts.

In DOOH advertising, the use of face detection and the YOLOv8 algorithm contributes to generating the exposure rate (Z), which refers to the proportion of the audience that actually turns and pays attention to the screen. Exposure rate is a key mediating variable linking ad characteristics (frequency, duration, visual elements) to purchase decisions (Y). A study by Garaus, et al. [4] showed that active visual exposure detected through facial recognition systems significantly increases purchase intention. This highlights the real impact of measured visual engagement on advertising effectiveness.

Therefore, this study aims to analyze the influence of key Digital Out-of-Home (DOOH) variables: ad frequency, exposure duration, and facial detection technology, on consumer purchase decisions. Exposure rate will serve as the mediating variable. This approach is expected to provide a more accurate and objective understanding of DOOH advertising effectiveness in urban public spaces.

1.2. Problem Limitation

This research is limited to analyzing the effectiveness of Digital Out-of-Home (DOOH) advertising in Jakarta, specifically by observing visual engagement and exposure rates through the application of face detection technology at three major commuter stations in the city.

2. Literature Review

2.1. Review of Research Results

2.1.1. Digital Out-of-Home (DOOH) Advertising

Advertising, defined as non-personal, persuasive marketing communication from an identified sponsor [5], often leverages the AIDA model (Attention, Interest, Desire, Action) to guide consumer psychological responses [6]. With technological advancements, advertising has evolved into dynamic forms like Digital Out-of-Home (DOOH), which are digital networks in public spaces managed remotely for real-time optimization based on audience demographics, location, time, and behavior, offering measurable metrics such as impressions, reach, and engagement Wilson [1]. Usman, et al. [7] emphasize using audience data for precise targeting and content relevance through algorithmic segmentation, while Konta and Lisan [8] highlight DOOH's distinctive flexibility, targeting capabilities, and engagement compared to traditional OOH media. Based on these three aspects, the following indicators can be used to assess the effectiveness of DOOH advertising:

1. Flexibility: The ability to update advertising content in real-time based on context, such as weather, time, or local events, without replacing physical materials, a feature known as "real-time creative updates."
2. Targeting: The use of programmatic systems to deliver ads at the most optimal time and place, based on audience proximity or demographic clustering.
3. Engagement: The impact of moving and contextually relevant content, evaluated through metrics such as display duration, audience interaction, and immediate responses (e.g., QR code scans), all of which are more effective than static OOH formats.

2.1.2. Advertising Frequency

Ad frequency, defined as the number of times consumers are exposed to an advertisement within a specific period, is a crucial advertising strategy element believed to enhance recall, shape brand attitudes, and boost purchase intent. Research by Schmidt and Eisend, et al. [9] indicates an inverted U-shaped relationship between ad frequency and attitude toward the ad, where positive effects increase up to an optimal point (around 10 exposures) before plateauing or declining due to wear-out; however, for memory recall, increased frequency shows a continuous positive linear effect. Expanding on this, Burton, et al. [10] found that low ad frequencies (1-2 times) primarily drive purchase intent through affective responses, moderate frequencies (3-10 times) activate cognitive evaluations, and high frequencies (>10 times) surprisingly revert to spontaneous affective responses without strong signs of wear-out, provided the ad quality remains high. Furthermore, Chu, et al. [11] highlight that ad frequency's impact on ad attitudes is significantly moderated by factors like brand image and spokesperson credibility; strong brand image and credible spokespersons can maintain positive attitudes at moderate frequencies, whereas weak elements may accelerate wear-out with increased exposure. To evaluate the impact of advertising frequency, the following indicators are proposed:

1. Number of ad exposures per consumer within a given period, representing the actual frequency level encountered.
2. Recall level of advertisement content, as a cognitive indicator of how well repetition enhances memory.
3. Audience perception of the ad (positive or negative) measures affective reactions to repeated exposure, whether it generates interest or leads to saturation.
4. Wear-out point, observed when excessive exposure results in declining message effectiveness, signaling the need to recalibrate frequency.
5. Frequency effectiveness in influencing purchase intention, referring to how the right frequency strengthens positive attitudes and increases the likelihood of purchase.

2.1.3. Ad Exposure Duration

Ad exposure duration refers to the length of time a consumer visually perceives an advertisement, which plays a vital role in determining the effectiveness of a marketing message. According to Wang, et al. [12], overly brief exposure may hinder cognitive processing, especially for ads with complex visual or textual content, while overly prolonged exposure can cause audience fatigue. In the context of Digital Out-of-Home (DOOH) media, Uhl, et al. [13] emphasize that for an advertisement to meaningfully influence brand recall and purchase intention, it must be visible for at least five seconds and with a minimum of 75% on-screen visibility. These parameters help ensure that an ad is not only seen but cognitively processed and emotionally registered. Zhang, et al. [14] further support this by showing that ad effectiveness significantly correlates with the visibility rate and duration of display, making time-on-screen a critical metric for DOOH campaign performance. To assess the impact of ad exposure duration within DOOH environments, several key indicators are outlined as follows:

4. Minimum Effective Duration: The ad must be displayed for at least five seconds to allow cognitive and emotional processing.
5. Visibility Level: At least 75% of the ad's pixels should be visible to ensure sufficient audience attention.
6. Ad Recognition: Measures how well the audience can recall or identify the ad after viewing.
7. Impact on Brand Recall and Purchase Intention: Assesses whether exposure duration influences memory and consumer buying interest.
8. Viewability Classification: Combines duration and visibility.

2.1.4. Face Detection in DOOH

Face detection is a critical component in measuring audience engagement within Digital Out-of-Home (DOOH) advertising, enabling the system to identify presence, exposure duration, and even emotional expressions of viewers. RGB-D cameras can detect human faces at close range with low latency, while the Light and Fast Face Detector (LFFD) algorithm demonstrates high performance with speeds reaching 136.99 frames per second and latency of only 7.3 milliseconds per frame [15]. In addition, Automatic Facial Coding (AFC), based on the Facial Action Coding System (FACS), is employed to recognize facial expressions within less than 100 milliseconds per frame, allowing advertisers to assess emotional responses toward displayed ads [16]. To enhance detection performance, the YOLOv8 algorithm is also utilized, as it provides a strong balance between detection precision and processing speed, making it ideal for face recognition tasks in dynamic environments such as DOOH systems, especially on resource-limited edge devices [3]. Based on these findings, key indicators for evaluating the effectiveness of face detection in DOOH include:

9. Detection latency per frame, reflecting how quickly the system identifies a face in real-time.

10. Frame-per-second (FPS) performance, representing the processing speed for continuous face detection.
11. Mean average precision (mAP), indicating the overall detection accuracy across varied lighting and facial conditions.
12. Multi-scale and multi-angle detection capability, showing the ability to recognize faces of different sizes and orientations simultaneously.

2.1.5. Exposure Rate in DOOH

Exposure rate refers to the frequency and duration with which audiences are exposed to advertising content, directly affecting the effectiveness of marketing communication in Digital Out-of-Home (DOOH) environments. According to Yagi and Inoue [17], repeated exposure only increases consumer preference when accompanied by focused attention, emphasizing that attention is a key prerequisite for the mere exposure effect. Similarly, Burton, et al. [10] explain that the relationship between ad frequency and purchase intention is curvilinear, mediated by both affective and cognitive processes across different exposure levels. To quantify this phenomenon, Šumijaček, et al. [18] developed the Multimedia Ad Exposure Scale (MMAES), which evaluates short-term advertising impact across multiple dimensions including attention, awareness, attitude, resistance, and purchase intention. These metrics are especially relevant in DOOH, where exposure occurs in high-traffic public spaces and measurement must account for short yet intense audience interactions. Based on these findings, the indicators used to measure exposure rate in DOOH advertising are as follows:

13. Ad engagement, measuring how cognitively and emotionally involved the audience is with the advertisement content.
14. Awareness and attitude, assessing the impact of exposure on brand recognition and audience sentiment toward the ad.
15. Psychological resistance (reactance), indicating audience discomfort or rejection due to overly intrusive or frequent exposure.
16. Purchase intention, showing how exposure influences the likelihood of the audience to consider or buy the advertised product.
17. Perceived intrusiveness, reflecting how disruptive or unwelcome the ad is perceived during media consumption.

2.1.6. Purchase Decision in DOOH

Consumer purchase decisions are heavily influenced by how advertising information is presented, especially in dynamic digital formats such as Digital Out-of-Home (DOOH). Taylor [19] highlights that DOOH creates a "win–win" environment by enabling dynamic and contextually relevant visual content to engage consumers in public spaces, thus enhancing the immersive quality of advertising. Harms, et al. [20] further demonstrate that ad format significantly affects consumer response, where traditional banner ads are perceived as more credible and trustworthy than native ads, leading to stronger purchase intentions. Adding another perspective, Han and Du [21] show that targeted digital ads originating from e-commerce streamers are more effective at influencing consumer decisions than those delivered by celebrities or bloggers—largely due to perceived authenticity and message-source alignment. These findings affirm that both the ad medium (e.g., DOOH vs. native) and message source play vital roles in shaping purchase intention in digital marketing environments. Referring to Kotler and Keller [22] stages of purchase decision-making, the following indicators can be used to assess how advertising influences consumer purchase decisions in DOOH:

18. Product quality, indicating the degree to which the product meets consumer needs or expectations.
19. Product features, referring to the functions or advantages that distinguish the product from competitors.
20. Product design, representing the visual appeal and stylistic attributes that affect consumer interest.
21. Product price, measuring consumer perceptions of value and pricing fairness.
22. Brand reputation, reflecting trust and positive associations with the brand identity or image.

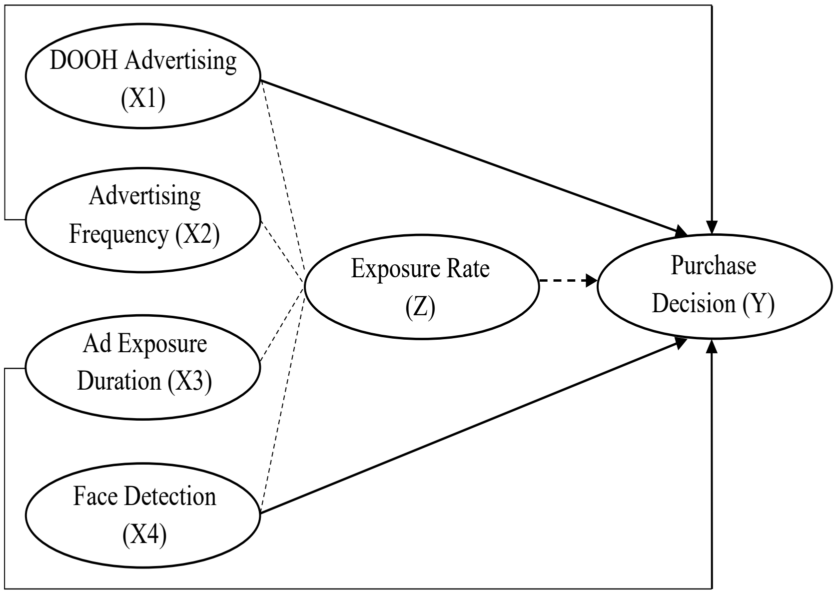

Figure 1.
Research Hypothesis Framework.

2.1.7. Research Hypothesis

This research is designed to explore the impact of DOOH (Digital Out-of-Home) advertising characteristics on exposure rate and consumer purchase decisions. The hypotheses are structured to assess both direct and indirect relationships between the observed variables.

3. Research Methods

This study aims to analyze the influence of advertising frequency, exposure duration, and face detection technology on purchase decisions in the context of Digital Out-of-Home (DOOH) advertising, with exposure rate as a mediating variable. To achieve this objective, a quantitative approach was adopted using the Structural Equation Modeling (SEM) method based on Partial Least Squares (PLS), operated through the SmartPLS 4.0 software.

The PLS method was chosen as it is suitable for complex causal models involving multiple latent variables, including mediating variables, and a variety of indicators. This model can handle data with non-normal distributions and relatively small sample sizes. SEM-PLS also allows for simultaneous analysis of causal relationships between constructs in the model.

The research was carried out in three main stages. First, an in-depth literature review on relevant theories and previous studies. Second, the formulation of a conceptual framework and hypotheses. Third, the collection of primary data through questionnaire distribution to respondents and direct observation at DOOH locations. The data were then analyzed using the SEM-PLS approach.

3.1. Place and Time of Research

3.1.1. Research Venue

This study was conducted at three strategic locations in Jakarta where DOOH screens are installed: Sudirman Station, Manggarai Station, and Kalibata Station.

3.2. Population and Sample

3.2.1. Population

The population in this study consists of public transport users who are exposed to DOOH advertisements in Jakarta, particularly in commuter station areas.

3.2.2. Sample

The sample is part of the number and characteristics possessed by the population. In this study, sampling was carried out using the purposive sampling technique. This technique is conducted by selecting subjects not based on strata, random selection, or region, but based on certain objectives [23]. Purposive sampling is a technique for determining samples with specific considerations. This means that each subject taken from the population is deliberately selected based on certain goals and considerations. These criteria included being 17 years old or above, having seen DOOH advertisements at one of the three observation sites in Jakarta, Indonesia (Sudirman Station, Manggarai Station, or Kalibata Station), and willingly participating in the questionnaire. The technique for determining the number of samples in this study uses the Slovin formula. The researcher uses the Slovin formula because, in drawing samples, the number must be representative so that the research results can be generalized, and the calculation does not require a tab le of sample numbers but can be done with simple formulas and calculations.

3.3. Indicator

3.3.1. DOOH

No	Variables	Indicators	Scale	Author
1	Flexibility	Programmatic DOOH allows advertisers to update content quickly without requiring on-site physical changes.	Likerts 1-5	Konta and Lisan [8],Usman, et al. [7] and Wilson [1]
		Real-time creative updates in DOOH reflect high flexibility in responding to weather, time, or local events.	Likerts 1-5	
2	Targeting	Programmatic DOOH uses location-based data to display ads at optimal times.	Likerts 1-5	
		DOOH targeting delivers tailored messages to specific demographics in predefined areas.	Likerts 1-5	
3	Engagement	Context-driven DOOH content produces stronger audience engagement than static OOH ads.	Likerts 1-5	
		Engagement in DOOH is effectively measured through screen time, interaction rate, or direct response indicators.	Likerts 1-5	

3.3.2. Ad Frequency

No	Variables	Indicators	Scale	Author
1	Ad Exposure per Consumer (Frequency)	Each consumer receives a measurable number of ad exposures during a specific period.	Likerts 1-5	Burton, et al. [10] & Schmidt and Eisend [24]& Eisend, et al. [9] & Chu, et al. [11]
2		Ad frequency per consumer helps quantify the actual exposure level within a campaign period.	Likerts 1-5	
3	Ad Recall (Cognitive)	Ad repetition improves the consumer's ability to recall the message content.	Likerts 1-5	
4		Higher recall scores indicate that ad frequency successfully builds memory.	Likerts 1-5	
5	Ad Perception (Affective)	Frequent ad exposure creates a positive impression when the content remains relevant	Likerts 1-5	
6		Overexposure may cause negative attitudes toward the ad message.	Likerts 1-5	
7	Wear-Out Threshold	Ad effectiveness declines when audiences experience excessive repetition.	Likerts 1-5	
8		The wear-out effect signals the need to reduce or adjust ad frequency.	Likerts 1-5	
9	Frequency Effectiveness Toward Purchase Intention	The right ad frequency strengthens positive attitudes that lead to buying interest.	Likerts 1-5	
10		Purchase intention increases when exposure levels align with consumer preferences	Likerts 1-5	

3.3.3. Ad Exposure Duration

No	Variables	Indicators	Scale	Author
1	Minimum Ad Duration	Ads are considered effective when displayed for at least five full seconds	Likerts 1-5	Wang, et al. [12];Uhl, et al. [13] and Zhang, et al. [14]
2		Short ads under five seconds often fail to deliver sufficient exposure to the audience.	Likerts 1-5	
3	Ad Visibility Rate	An ad is visible when at least 75% of its pixels appear on the consumer's screen	Likerts 1-5	
4		Higher visibility percentage improves the chance of an ad being noticed.	Likerts 1-5	
5	Ad Recognition	Consumers are more likely to recognize an ad after experiencing a full visual exposure.	Likerts 1-5	
6		Recognition levels increase when ads are consistently presented under clear conditions.	Likerts 1-5	
7	Impact on Brand Recall and Purchase Intention	Longer display time enhances brand recall among consumers.	Likerts 1-5	
8		Extended exposure strengthens consumer interest in purchasing the product.	Likerts 1-5	
9	Viewability Classification	A combination of 75% visibility and 5-second duration is a valid benchmark for viewability.	Likerts 1-5	
10		Ads with 100% visibility and 5-second duration are classified as highly viewable.	Likerts 1-5	

3.3.4. Face Detection

No	Variables	Indicators	Scale	Author
1	Face Detection Latency	The system detects a single face in approximately 7.3 milliseconds per frame on edge devices	Likerts 1-5	Low, et al. [25];Höfling and Alpers [16] and He, et al. [15]
2		Fast face detection latency enhances real-time processing on low-power hardware	Likerts 1-5	
3	Frame Per Second (FPS)	The system maintains high-speed processing at 136.99 FPS on a 160×120 resolution	Likerts 1-5	
4		High frame rates support real-time performance in edge-based face detection	Likerts 1-5	
5	Mean Average Precision (mAP)	Face detection achieves over 90% accuracy on the easy benchmark of WIDER FACE	Likerts 1-5	
6		Detection accuracy remains high on medium and hard benchmarks with scores of 88% and 78%	Likerts 1-5	
7	Multi-Scale Detection	The system detects faces of varying sizes using anchor-based regression techniques	Likerts 1-5	
8		Multi-scale detection handles crowded scenes and varying facial orientations effectively	Likerts 1-5	

3.3.5. Exposure Rate

No	Variables	Indicators	Scale	Author
1	Ad Engagement	Audiences feel mentally engaged when an ad captures their attention effectively	Likerts 1-5	Yagi and Inoue [17];Burton, et al. [10] and Šumijaček, et al. [18]
2		Emotional involvement increases when the ad content is perceived as interesting	Likerts 1-5	
3	Ad Visibility Rate	Exposure to ads improves awareness of the advertised brand	Likerts 1-5	
4		Positive attitudes toward the ad develop when the message is clear and relatable	Likerts 1-5	
5	Ad Recognition	Excessive exposure creates psychological resistance to the advertisement	Likerts 1-5	
6		Intrusive messages trigger negative reactions from the audience	Likerts 1-5	
7	Impact on Brand Recall and Purchase Intention	Increased exposure encourages consumers to consider buying the product	Likerts 1-5	
8		High-quality ad content motivates stronger intention to purchase	Likerts 1-5	
9	Viewability Classification	Ads feel disruptive when they interrupt the natural media experience.	Likerts 1-5	
10		Viewers perceive forced exposure as intrusive even when the ad is relevant	Likerts 1-5	

3.3.6. Purchase Decision

No	Variables	Indicators	Scale	Author
1	Product Quality	The product meets consumer expectations in terms of performance and reliability	Likerts 1-5	Chen, et al. [26] Han and Du [21] and Wang, et al. [12]
2		Consumers perceive the product as capable of fulfilling their needs effectively.	Likerts 1-5	
3	Product Features	The product offers useful functions that provide advantages over competitors	Likerts 1-5	
4		Feature variety increases the perceived value of the product.	Likerts 1-5	
5	Product Design	The product's appearance enhances its overall attractiveness.	Likerts 1-5	
6		Consumers are drawn to the visual style of the product.	Likerts 1-5	
7	Product Price	The product's price reflects its quality and perceived value.	Likerts 1-5	
8		Consumers consider the product affordable relative to its benefits.	Likerts 1-5	
9	Product Brand	The brand has a positive reputation in the minds of consumers.	Likerts 1-5	
10		Consumers trust the brand based on past experience or recognition.	Likerts 1-5	

4. Results and Discussion

The results of the discussion will be presented in the form of an existing PLS which will then be formed in modeling which will later have the output of the existing fit model and an example is made as follows:0

4.1. Average Variance Extracted (AVE) dan Composite Reliability

Next, the reliability value can be measured through the Average Variance Extracted (AVE) and Composite Reliability values. The AVE value will show the variance value obtained by each variable. The AVE value test criterion is 0.5; however, the higher the AVE value, the better it will be and it will show a stronger diversity of indicators. Meanwhile, the Composite Reliability value test is > 0.7. The higher the Composite Reliability value, the greater the reliability value of a variable.

Table 1.
Average Variance Extracted (AVE) dan Composite Reliability.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Ad Frequency	0.992	0.992	0.993	0.931
DOOH	0.986	0.986	0.988	0.934
Face Detection	0.971	0.971	0.975	0.829
Purchase Desision	0.969	0.969	0.973	0.780
Rate Exposure	0.979	0.979	0.982	0.844
Ad Exposure Time	0.989	0.989	0.990	0.907

Next, it can be seen in Table 1 that the Composite Reliability value for Purchase Decision is 0.973, Exposure Rate is 0.982, Ad Frequency is 0.993, DOOH is 0.988, Face Detection is 0.975, and Ad Exposure Time is 0.990. The Average Variance Extracted (AVE) value for Purchase Decision is 0.780, Exposure Rate is 0.844, Ad Frequency is 0.931, DOOH is 0.934, Face Detection is 0.829, and Ad Exposure Time is 0.907. All variables have an AVE value greater than 0.5 and a Composite Reliability value greater than 0.7, which indicates that all variables in this study are declared reliable.

4.2. Hypothesis Testing

After conducting the outer model and inner model analysis tests, the next step is to analyze the measurement results of structural relationships or relationships between constructs (hypothesis test). In hypothesis test ing, it can be seen from the t- statistical value and probability value. For hypothesis testing, namely by using statistical values, for alpha 5% the t - statistical value used is 1.96. So that the criteria for accepting or rejecting the hypothesis Ha is accepted and H0 is rejected because the t-statistic > 1.96. To reject or accept the hypothesis using probability, Ha is accepted if the p value < 0.05.

Table 2.
Path Coefficient.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values	Status
Advertising Exposure Time -> Rate Exposure	0.514	0.515	0.026	19.732	0.000	Accepted
Ad Frequency-> Rate Exposure	0.688	0.688	0.033	20.616	0.000	Accepted
DOOH -> Purchase Desision	0.751	0.749	0.069	10.837	0.000	Accepted
DOOH -> Rate Exposure	0.744	0.645	0.055	6.793	0.000	Accepted
Face Detection -> Purchase Desision	-0.179	-0.177	0.077	2.317	0.021	Accepted
Face Detection -> Rate Exposure	0.310	0.408	0.059	8.162	0.000	Accepted
Rate Exposure -> Purchase Desision	0.415	0.415	0.042	9.796	0.000	Rejected

Hypothesis 1 Advertising Exposure Time → Rate Exposure

This relationship evaluates the influence of Advertising Exposure Time on Rate Exposure. Based on the path coefficient results, the Original Sample value is 0.514, the t-statistic is 19.732 (> 1.96), and the P Value is 0.000 (< 0.05). This indicates that Advertising Exposure Time has a positive and significant effect on Rate Exposure, meaning longer ad visibility time increases the likelihood of audience attention.

Hypothesis 2 Ad Frequency → Rate Exposure

The effect of DOOH on Purchase Decision yields a path coefficient of 0.751, with a t-statistic of 10.837 (> 1.96) and a P value of 0.000 (< 0.05). This demonstrates a strong and significant positive relationship between DOOH advertising and Purchase Decision.

Hypothesis 3 DOOH → Purchase Decision

This analysis investigates the effect of Digital Out-of-Home (DOOH) advertising on Purchase Decision. The Original Sample value is 0.751, the t-statistic is 10.837 (> 1.96), and the P Value is 0.000 (< 0.05). The result indicates that DOOH has a strong positive and significant effect on consumer Purchase Decision.

Hypothesis 4 DOOH → Rate Exposure

This relationship explores the influence of DOOH on Rate Exposure. The Original Sample value is 0.744, the t-statistic is 6.793 (> 1.96), and the P Value is 0.000 (< 0.05). These findings confirm that DOOH advertising has a positive and significant impact on exposure rate, enhancing the probability of visual engagement from passersby.

Hypothesis 5 Face Detection → Purchase Decision

This analysis evaluates the effect of Face Detection on Purchase Decision. The Original Sample value is –0.179, the t-statistic is 2.317 (> 1.96), and the P Value is 0.021 (< 0.05). It can be concluded that Face Detection has a significant but negative effect on Purchase Decision, possibly due to privacy concerns or discomfort among viewers.

Hypothesis 6 Face Detection → Rate Exposure

This analysis tests the relationship between Face Detection and Rate Exposure. The Original Sample value is 0.310, the t-statistic is 8.162 (> 1.96), and the P Value is 0.000 (< 0.05). These results show a positive and significant effect, indicating that face detection technology helps increase audience exposure rate, likely by attracting or holding visual attention.

Hypothesis 7 Rate Exposure → Purchase Decision

This section evaluates the effect of Rate Exposure on Purchase Decision. The Original Sample value is 0.415, the t-statistic is 9.796 (> 1.96), and the P Value is 0.000 (< 0.05). This implies that Rate Exposure has a positive and significant impact on Purchase Decision, confirming that higher exposure engagement can drive consumer action.

Table 3.
Indirect Path Coefficient

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values	Status
Advertising Exposure Time -> Rate Exposure -> Purchase Desision	0.213	0.214	0.027	7.982	0.000	Accepted
Ad Frequency -> Rate Exposure -> Purchase Desision	0.286	0.285	0.027	10.738	0.000	Accepted
DOOH -> Rate Exposure -> Purchase Desision	0.298	0.235	0.023	8.796	0.000	Accepted
Face Detection -> Rate Exposure -> Purchase Desision	0.217	0.256	0.025	6z.160	0.000	Accepted

Hypothesis 8 Advertising Exposure Time -> Rate Exposure -> Purchase Desision

Advertising Exposure Time indirectly influences Purchase Decision through Rate Exposure. The path coefficient shows an Original Sample value of 0.213, with a t-statistic of 7.982 (> 1.96) and a P Value of 0.000 (< 0.05). These results indicate a positive and significant indirect effect, suggesting that longer advertising exposure time enhances the likelihood of purchase by increasing exposure rate.

Hypothesis 2 Ad Frequency -> Rate Exposure -> Purchase Desision

Ad Frequency has an indirect positive impact on Purchase Decision via Rate Exposure. The Original Sample value is 0.286, the t-statistic is 10.738 (> 1.96), and the P Value is 0.000 (< 0.05). This confirms a statistically significant indirect relationship, meaning that frequent exposure to ads contributes to higher purchase decisions through greater exposure engagement.

Hypothesis 3 DOOH -> Rate Exposure -> Purchase Desision

DOOH advertising indirectly affects Purchase Decision through Rate Exposure. The analysis reveals an Original Sample value of 0.298, a t-statistic of 8.796 (> 1.96), and a P Value of 0.000 (< 0.05). This demonstrates a strong and significant indirect effect, indicating that digital out-of-home media can influence purchasing behavior more effectively when visual exposure is optimized.

Hypothesis 4 Face Detection -> Rate Exposure -> Purchase Desision

Face Detection also shows a meaningful indirect relationship with Purchase Decision through Rate Exposure. With an Original Sample value of 0.217, a t-statistic of 6.160 (> 1.96), and a P Value of 0.000 (< 0.05), the results reflect a positive and significant effect, implying that identifying audience presence supports better exposure measurement and ultimately influences purchasing decisions.

5. Conclusions, Implications, and Suggestions

Based on the research conducted on the effectiveness of Digital Out-of-Home (DOOH) advertising in urban public spaces using technological variables such as face detection and YOLOv8, several conclusions can be drawn. First, Exposure Rate significantly influences Purchase Decision, indicating that audiences who engage visually with DOOH content are more likely to proceed toward making a purchase. Second, Ad Frequency and Ad Exposure Time both strongly affect Exposure Rate, showing that repeated and sustained visibility of advertisements plays a critical role in capturing audience attention. Third, while DOOH directly affects Purchase Decision, its indirect influence via Exposure Rate is minimal. Similarly, Face Detection contributes very little both directly and indirectly to increasing purchase decisions.

The findings suggest that visual engagement, as measured through exposure rate, is a crucial mediating factor in evaluating DOOH effectiveness. This implies that metrics such as impressions and display time alone are insufficient without accounting for actual audience attention. As such, future DOOH strategies should focus on optimizing content visibility duration and placement frequency to enhance viewer interaction. Incorporating technologies like face detection should be done with caution, especially considering the potential for privacy concerns which might negatively affect consumer behavior.

Several strategic recommendations are proposed. First, advertisers should optimize screen locations and timing strategies to ensure high visibility during peak pedestrian traffic. Second, content should be dynamically designed to maintain attention within the first few seconds, maximizing the impact of exposure duration. Third, companies should carefully consider the use of detection technologies, ensuring transparency and ethical data use to maintain public trust.

Overall, this study contributes to the growing body of knowledge on DOOH advertising by integrating technological performance metrics with consumer behavior insights. It offers practical implications for advertisers, technology developers, and urban planners seeking to increase the relevance and impact of outdoor digital advertising in metropolitan environments.

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