

Attention-Driven Rendering And Interface Adaptation Using Eye-Tracking Data

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ABSTRACT

This study investigates computational attention mechanisms in digital luxury interfaces using eye-tracking and predictive modeling. Across three experiments (N = 180), ocular biometric measures, including fixation duration, saccadic frequency, and fixation density, were analyzed during exposure to high-fidelity fashion stimuli containing aesthetic and brand-specific elements. Results showed that aesthetic fixations were the strongest predictors of brand attention, accounting for 40.3% of variance in brand engagement, while materialism dimensions selectively influenced attention toward symbolic status cues. The findings support a gaze-driven Human–Computer Interaction (HCI) framework in which aesthetic salience functions as a primary attentional signal within visually dense digital environments. From a systems-design perspective, the study proposes an attention-adaptive interface model integrating real-time ocular metrics into rendering and layout optimization processes. The research contributes a computational framework linking biometric attention sensing with adaptive interface engineering for mobile commerce, social media, and immersive digital environments.

Keywords: Human–Computer Interaction (HCI); Eye-Tracking; Computational Attention; Adaptive Interfaces; Visual Attention; Luxury Digital Interfaces design.

INTRODUCTION

Managing cognitive load in interactive digital environments requires understanding how users allocate visual attention to interface elements. This study investigates human-system interaction in digital fashion platforms, where high-fidelity images of luxury garments create complex visual networks that challenge usability and engagement. Using eye-tracking, we empirically assess how users prioritize aesthetic details over brand identifiers, and how individual materialist values filter these patterns—offering direct implications for designing intuitive, attention-aware interfaces.

Eye-tracking has transformed HCI research by objectively revealing gaze behaviours in contexts like online advertising, social media, and mobile apps (e.g., De Keyser et al., 2023; Pieters & Wedel, 2008). In digital fashion interfaces, users navigate dense stimuli blending aesthetics, textures, and logos, yet little is known about how these elements compete for attention or influence user experience. We address

this gap through three experiments testing selective attention theory (Yiend, 2010): unbranded images (Exp. 1), branded vs. unbranded comparisons (Exp. 2), and materialism moderation via the Material Values Scale (Richins, 2004; Exp. 3). Results guide interface designers toward usability enhancements, such as optimizing visual hierarchies for faster brand discovery and reduced cognitive strain.

Harnessing the proven value of ocular tracking, this study investigates individual responses to fashion imagery by focusing on the mapping of visual attention and brand recognition. We conducted three experiments to test this model: analyzing fixations on unbranded images, comparing branded versus unbranded stimuli, and uniquely exploring the link between biometric search patterns and personal value systems using the Materialism Values Scale (Richins, 2004). By reframing the fashion environment as a complex network, we aim to refine how digital platforms optimize for human cognitive constraints.

Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Theoretical Background

Attention in Digital Interfaces

Selective Attention Theory (SAT; Yiend, 2010) explains how users filter interface clutter, prioritizing salient elements amid competing stimuli—a core usability concern in HCI. In digital fashion environments (e.g., e-commerce apps, Instagram feeds), eye-tracking metrics like fixations and saccades reveal processing depth, informing design for accessibility and engagement (Rayner, 1998; Pieters & Wedel, 2004). Eye-tracking provides an objective and indispensable method for assessing visual attention and understanding consumer decision-making, outperforming subjective self-reported measures that often misrepresent latent gaze patterns (Aribarg *et al.*, 2010; Chandon *et al.*, 2007, 2009; Valenzuela & Raghuram, 2009, 2010). This empirical objectivity is crucial for discerning phenomena such as the "gaze cascade effect," where attention intensifies on a chosen option before a decision is finalized, profoundly influencing internal preferences (Shimojo *et al.*, 2003; Glaholt & Reingold, 2011; Russo, 2011). Despite its broad utility in general marketing, the application of eye-tracking in mapping the visually dense digital displays of fashion image perception remains under-explored.

The present research utilizes Selective Attention Theory (SAT) (Yiend, 2010) to explore how individuals manage cognitive load and prioritize visual information in luxury fashion. This theory posits that people do not ingest all available data but instead actively prioritize relevant information while filtering out distractions, a process observable through eye-tracking fixation metrics (Reeck & Egner, 2015; Stevens & Bavelier, 2012). For example, longer fixations on complex or emotionally resonant fashion visuals indicate deeper cognitive processing and the strategic deployment of selective attention.

While Attention Engagement Theory (AET) (Duncan and Humphreys, 1989, 1992) has historically provided insights into how visual elements initially capture attention, our study shifts its emphasis. AET explains the initial "pull" of a visual signal, where longer fixations indicate the processing of complexity (Alemdag & Cagiltay, 2018; Kim & Lee, 2021; Sperling & Weichselgartner, 1995). However, this study moves beyond initial capture to focus on the

active filtering and prioritization of information detailed by SAT. By utilizing the principles of selective attention, we aim to better understand how consumers not only notice, but also deeply process specific visual cues in luxury fashion to evoke emotional responses, enhance brand recall, and influence purchase intent.

Eye-tracking directly measures this selective attention, yielding empirical data crucial for understanding the nexus of memory and perception (Kessinger & Corkin, 2023; Ferre, 2002). This provides insight into how attention shapes consumer preferences, particularly concerning materialistic values. As SAT suggests that personally relevant stimuli capture a disproportionate share of attention (Yiend, 2010), individuals with higher materialistic values may focus more intensely on status-associated elements, which the Materialism Values Scale (MVS) quantifies (Richins, 2004, 2017).

Studies on Fixations and Visual Imagery

Guided by Selective Attention Theory (SAT), this study explores how clothing design elements function as "attentional anchors." Prior research on web layouts (Hsieh & Chen, 2011) and product-specific features, such as handbag handles (Ho, 2013), demonstrates that specific features draw primary focus. Eye-tracking reveals that complex stimuli necessitate more eye movements and longer fixations for deeper processing (Rayner, 1998; Henderson & Hollingworth, 1999). Furthermore, studies in reading and visual search confirm that intricate visual scenes elicit longer fixations and more saccades to resolve information (Rayner, 1978; Wolfe, 2007), informing the hypotheses below. Longer fixations on complete images, indicating deeper processing, are expected to extend overall viewing times as the user navigates the high-fidelity details of the image. This aligns with research showing that attention is linked to aesthetic preference (Calvo & Lang, 2004), and aesthetically pleasing elements elicit prolonged fixations (Reber, Schwarz, and Winkielman, 2004) and increased fixation counts (Park & Lee, 2016), reflecting heightened engagement.

Hypothesis 1a: *A positive relationship exists between the duration of whole fixations and the number of saccades predict user engagement in fashion interfaces.*

Cumulative research posits that aesthetically appealing luxury fashion imagery elicits prolonged and increased fixations, signaling heightened engagement and deeper processing density (Parkhurst and Niebur, 2002; Leder et al., 2004). Research consistently confirms that visually complex or aesthetically pleasing stimuli drive longer, more frequent fixations (Nummenmaa et al., 2009; Leder et al., 2004).

Hypothesis 1b: *A positive relationship exists between the duration of whole fixations and the average duration of whole fixations predict user engagement in fashion interfaces.*

Interdisciplinary findings support the idea that longer fixations correlate with frequent saccades in complex processing (Rayner, 1998; Wolfe, 2007), and aesthetically pleasing advertisements elicit prolonged fixations (Pieters and Wedel, 2007). Given luxury fashion's inherent visual emphasis, viewers are expected to prioritize aesthetically striking elements as high-value nodes in their search.

Hypothesis 1c: *A positive relationship exists between the duration and number of whole fixations on aesthetics predict user engagement in fashion interfaces.*

Biometric Processing of Brand Nodes and Aesthetic Hierarchy

In visually dense digital displays, brands function as pivotal anchors for identity and self-expression, particularly within materialistic cognitive frameworks (Kim & Kramer, 2015). These brand identifiers act as high-value data points that foster systemic loyalty and drive trend adoption (Ferreira et al., 2019; Kautish & Sharma, 2018; De Mooij, 2011). From an HCI design perspective, the intricate designs inherent in luxury branding necessitate an increase in ocular activity, specifically higher fixation counts and saccadic frequency, signaling deeper engagement with the stimulus (Wedel et al., 2008; Pieters and Wedel, 2004). Eye-tracking thus serves as a sensor for quantifying how these aesthetic nodes modulate user behavior. Gaze patterns, attention, aesthetics, and brand perception are intricately linked and inform the following hypotheses:

Hypothesis 2a: *There is a positive relationship between the number of brand fixations and the number of saccades, highlighting interface salience needs.*

Hypothesis 2b: *There is a positive relationship between the number of brand fixations and the average duration of whole fixations, highlighting interface salience needs.*

Hypothesis 2c: *There is a positive relationship between the number of brand fixations and the number of whole fixations on aesthetics, highlighting interface salience needs.*

Materialism as a Cognitive Filter in Human attention model for digital interfaces

This study integrates the Materialism Values Scale (MVS) (Richins, 2004) with ocular biometrics (Pesa et al., 2024) to explore how internal psychometric states function as filters for visual attention. Guided by Selective Attention Theory, we propose that the user's level of materialism dictates their "attentional priority" within a luxury network. Individuals who internalize materialism as a primary value for self-validation and status (Audrin et al., 2018; O'Cass, 2004; Richins, 2017) are expected to exhibit a specialized ocular "tuning," characterized by heightened sensitivity to brand identifiers and aesthetic luxury cues. This informs the following hypotheses:

Hypothesis 3a: *There is a positive relationship between fixations on aesthetics and materialism associated with happiness, centrality, and success, suggesting interface adaptations.*

Hypothesis 3b: *There is a positive relationship between fixations on brand labels and material preferences linked to happiness, centrality, and success, suggesting personalized interface adaptations.*

The experiments

This research, across three experiments each with sixty participants, explored visual attention, materialism, aesthetics, and brand perception in luxury fashion using eye-tracking. Participants were compensated with a £6.00 Amazon voucher for their involvement. Experiment 1 analyzed fixations on

unbranded images and showed aesthetics drive consumer choice, validating eye-tracking over self-reports and drawing on Selective Attention Theory (Yiend, 2010). Experiment 2 examined brand identity's influence on visual attention using branded images. Experiment 3 investigated materialism's impact, linking higher materialism (Richins, 2004) to

increased focus on luxury cues, aligning with Selective Attention Theory (Audrin *et al.*, 2018). Eye-tracking on diverse imagery (Figure 1a, 1b) revealed how materialism shapes engagement with luxury aesthetics and brands, correlating fixations on brands and aesthetics with materialism dimensions.



Source: Figures taken by Steele and Menkes (2016) and modified by the authors

Figure 1(a). Bespoke Fashion designs



Source: Figures taken by Steele and Menkes (2016) and modified by the authors

Figure 1(b). Bespoke Fashion designs

Methods

Experimental Design and Data Acquisition: Experiment 1

The research architecture was designed to map the intersection of human ocular behavior and digital information networks using a cohort of sixty participants (N=60). This group, primarily composed of London-based professionals and academic researchers, provided a demographic distribution (75% female, 25% male; 73.8% under 34 years old)

optimized for analyzing the cognitive processing of high-fidelity luxury fashion stimuli. To ensure the integrity of the ocular data, the experimental protocol was conducted in a controlled environment designed to minimize external noise and interference. All procedures received formal approval from the London College of Fashion Ethics Review Board (2023-3002023sv), adhering strictly to British Psychological Society (BPS) ethical standards, with all participants providing written informed consent prior to the initialization of the sensor arrays.

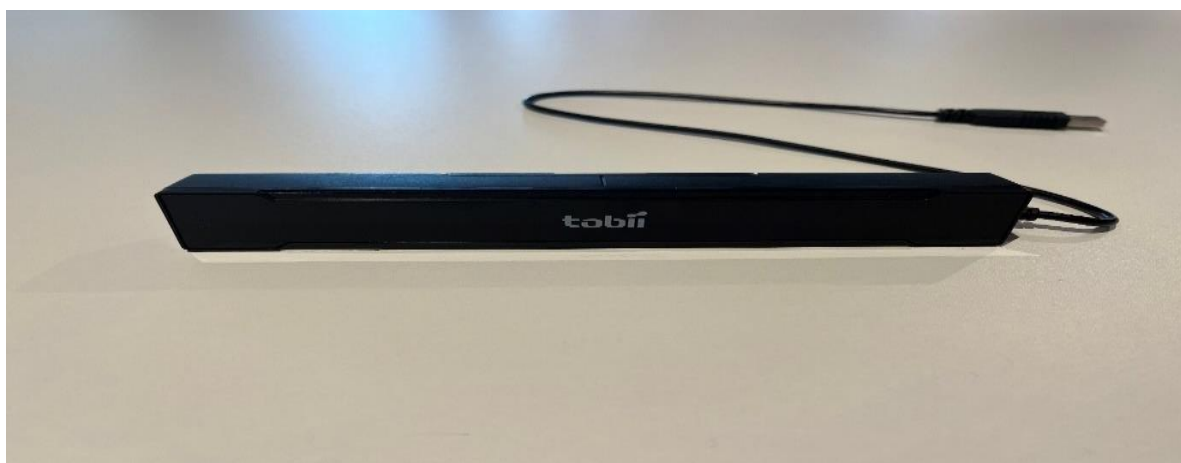


Figure 2. Tobii X2 Experiment set-up Tobii X2-30 Eye-tracker

High-Frequency Infrared Ocular Sensor Array

Experiments used a Tobii Pro X2-30 eye-tracker (figure 2) to capture gaze in controlled settings simulating digital viewing (8 seconds exposures). Tobii Pro X2 is high-frequency infrared ocular sensor, a specialized hardware component utilizing dark-pupil tracking to capture gaze data. Operating at a sampling rate of 30 Hz, the sensor ensures the precise measurement of micro-fixations (with a minimum duration threshold of 0.05s) and rapid saccadic transitions. The specifications of this array allow for a high-accuracy tracking range within a 50 x 36 cm head-motion box, system-validated at a 70 cm viewing distance to maintain the spatial reliability of coordinates within the visual field. Data processing was subsequently executed via Tobii Pro Lab - Full Edition (2023), which translated raw infrared reflections into actionable biometric metrics required for the development of our predictive statistical model.

Stimuli were static luxury images (Steele & Menkes, 2016), defined as Areas of Interest (AOIs) for aesthetics and brands, mirroring real e-commerce layouts.

Stimuli and Materialist Value Orientations

During the testing phase, participants were exposed to nine high-fidelity, static visual stimuli featuring unbranded garments from premier luxury fashion designers including *Chanel, Christian Dior, Dolce and Gabbana, Giorgio Armani, Gucci, Jean Paul Gaultier, Versace, Vivienne Westwood, and Valentino*

for an 8-second exposure cycle (Steele & Menkes, 2016). Within this computational model, the images are framed as visually dense digital displays, while the user's psychometric profile, quantified by the Materialism Values Scale (MVS), is treated as a Materialist Value Orientations Parameter. This parameter functions as a Materialist value orientation that facilitates the categorization of user behavior based on internal value systems. By correlating these Materialism value parameters with ocular data, specifically fixation duration, frequency, and saccadic velocity, this experiment developed a predictive statistical model for visual throughout to determine how different users prioritize specific nodes of information within the digital fashion environment.

To reduce potential confounding influences, brand familiarity was treated as a source of bias because prior exposure to luxury labels may affect fixation behavior independently of the visual properties of the stimuli. In addition, the presentation order of the nine stimuli was randomized across participants to minimize order effects such as habituation, fatigue, and carryover from one image to the next. This procedure increased the likelihood that observed fixation patterns reflected the visual characteristics of each stimulus rather than its position in the sequence. Because each image was presented for a fixed interval, temporal consistency was maintained across trials, supporting comparability across conditions.

System Performance and Data Output Analysis

Model		B	Stand. Error	β	T	Sig.	Correlations			R^2 adjusted
							Zero-order	partial	part	
1	(Constant)	883.406	1068.895	0.91**	0.826	.412	0.91	0.91	0.91	0.825
	Number of saccades	344.318	20.618		16.7	<.001				
	(Constant)	-7659.088	1404.303		-5.454	<.001				0.908
2	Number of saccades	337.696	14.983	0.892**	22.539	<.001	0.91	0.948	0.891	
	age average duration of whole fixations	20.198	2.768	0.289**	7.296	<.001	0.343	0.695	0.288	
	(Constant)	-8264.664	1383.162		-5.975	<.001				0.914
3	Number of saccades	251.015	41.141	0.663**	6.101	<.001	0.91	0.632	0.233	
	Age average duration of whole fixations	21.22	2.713	0.303**	7.822	<.001	0.343	0.723	0.299	
	Number of whole fixations on aesthetics	85.026	37.775	0.244*	2.251	.028	0.863	0.288	0.086	

Dependent Variable: Total duration of whole fixations

B represents the unstandardized coefficients**Table 1. Stepwise Regression Results Predicting Total Duration of Whole Fixations**

To evaluate the efficiency of the visual information network and validate the predictive capacity of our model, a Stepwise Multiple Regression was executed. Stepwise regression was adopted in the first two experiments as an exploratory variable-selection strategy because the eye-tracking indicators were likely intercorrelated and potentially redundant, a common issue in regression models with multiple related predictors. In particular, fixation-based metrics often overlap conceptually and statistically, making it useful to identify which variable contributes

unique explanatory variance beyond the others. Prior methodological work recognizes that stepwise procedures can be useful for regression model building when the goal is to isolate predictors with incremental value (Babyak, 2004; Harrell, 2015). This analysis functioned as a diagnostic for visual throughout, identifying which biometric variables served as the primary drivers of total system engagement. The regression architecture was developed across three incremental stages,

establishing a high-performance statistical model (see Table 1).

Predictive Modelling for Total Visual Throughput

The first phase of the analysis (Model 1) integrated the "Number of Saccades" as the primary independent variable. The results supported Hypothesis 1a, with the model demonstrating high statistical significance, $F(1, 58) = 276.12, p < .001$. This single variable accounted for 82.5% of the variance ($Adj. R^2 = .825$), confirming that saccadic frequency is a dominant positive predictor of processing time ($\beta = .91, p < .001$). From an HCI standpoint, this validates that more frequent gaze shifts represent the increased computational effort required to map the high-fidelity features of the fashion network.

In the second stage (Model 2), the "Average Duration of Whole Fixations" was introduced to the system, which successfully increased the explained variance to 90.8% ($Adj. R^2 = .908$). This supported Hypothesis 1b, identifying average fixation duration as a significant positive predictor ($\beta = .289, p < .001$) even when controlling for saccade frequency. This indicates that while the system "scans" via saccades, the dwell time on specific data packets substantially extends the overall duration of the processing cycle.

The final iteration (Model 3) incorporated the "Number of Whole Fixations on Aesthetics" as a targeted feature vector. The resulting model was significant and accounted for 91.4% of the total variance ($Adj. R^2 = .914$). Supporting Hypothesis 1c, fixations on aesthetic nodes significantly predicted total throughput duration ($\beta = .244, p = .028$). Although aesthetic focus contributed a smaller portion of unique variance (Part correlation = .086) compared to primary scanning metrics, it represents a critical incremental value in explaining the "stickiness" of the visual stimuli.

The data output demonstrates that visual engagement within a luxury fashion network is a multifaceted computational process. While the frequency of gaze shifts (saccades) remains the most robust technical predictor of total processing time, the temporal length of individual fixations and the specific targeting of aesthetic nodes provide vital insights into the user's cognitive priority. These findings suggest that

aesthetic appeal effectively "hooks" the processor, extending the bandwidth dedicated to resolving the visual network. Having established this baseline for general stimuli, the subsequent phase of our system analysis will investigate visual fixations on branded data nodes to quantify brand-specific interaction.

Experimental Design and Data Acquisition: Branded Node Integration for Experiment 2

Experiment 2 utilized sixty London-based professionals (N=60) 48 females (75%)/12 males (25%); 73.8% under 34 and 30.3% over 35. The visual stimuli were upgraded to test the system's response to Brand Interference within the information network. Participants were exposed to a dual-state stimuli set. Nine high-fidelity unbranded images Chanel, Dior, Dolce and Gabbana, Armani, Gucci, Gaultier, Versace, Westwood, and Valentino (Steele and Menkes, 2016) and nine corresponding images integrated with brand/designer wordmarks.

To minimize potential confounding influences, there was randomization of brand presentation, ensuring each brand appears in both branded and unbranded conditions across participants in balanced order. Stimuli order was counterbalanced across participants to control for order and habituation effects. The data acquisition phase maintained the 30 Hz sampling frequency via the Tobii infrared ocular sensor. To ensure spatial precision in this more complex network, the hardware was validated through a 5-point calibration and 4-point validation protocol. Each visual node was presented for a standard 8-second exposure cycle to monitor the transition of attention between aesthetic features and brand identifiers.

Predictive Modelling for Brand-Specific Data Throughput

A second Stepwise Multiple Regression was executed to determine which biometric features successfully predict the number of fixations on brand-specific nodes (Hypotheses 2a–2c). The results, summarized in Table 2, highlight a significant shift in how the visual system prioritizes branded data.

				β	T	Sig.	Correlations			R ² adjusted
Model	B	Std. Error					Zero order	Partial	Part	
1	(Constant)	0.428	0.127		3.365	.001				0.022
	Number of saccades	0.004	0.002	0.196	1.526	.133	0.196	0.196	0.196	
2	(Constant)	1.092	0.339		3.222	.002				0.076
	Number of saccades	0.004	0.002	0.21	1.679	.099	0.196	0.217	0.21	
	Age average duration of whole fixations for pupil diameter	-0.181	0.086	-0.263**	-2.102	0.04	-0.252	-0.268	-0.263	
3	(Constant)	0.584	0.287		2.035	.047				0.403
	Number of saccades	-0.002	0.002	-0.104	-0.907	.368	0.196	-0.12	-0.091	
	Age average duration of whole fixations for pupil diameter	-0.106	0.07	-0.154	-1.505	.138	-0.252	-0.197	-0.151	
	Number of whole fixations on aesthetics	0.092	0.016	0.658**	5.675	<.001	0.631	0.604	0.571	

Dependent Variable: Number of fixations on brands

B represents the unstandardized coefficients and the β the standardized coefficients, * $p < 0.05$ and ** $p < 0.001$

Table 2. Stepwise Regression Results Predicting the Number of Brand Fixations

Predictive Modeling for Brand-Specific Data

Throughout the initial phase of the predictive analysis, Model 1, tested Hypothesis 2a by entering the "Number of Saccades" as the primary predictor for brand-node engagement. However, the resulting relationship was not statistically significant ($\beta = .196$,

$p = .133$), suggesting that the raw frequency of rapid eye movements, or generalized scanning behavior, does not reliably correlate with brand-specific attention. From an HCI perspective, this implies that high-speed data scanning across the visual field does not automatically translate into the successful

detection of brand-specific nodes. The subsequent iteration, Model 2, incorporated the "Average Duration of Fixations" to test Hypothesis 2b.

This significant negative correlation was observed between the number of brand fixations and the average duration of fixations across stimuli,

$$\beta = -0.263, t(57)$$

$$= -2.10, p$$

$$= .040 \text{ accounting for } 7.6\% \text{ of the system variance}$$

$$(Adjusted R^2 = .076)$$

This result indicates that participants who spent longer viewing general visual features tended to fixate less frequently on branded elements. Conceptually, this reflects a cognitive trade-off in attentional allocation, that is extended dwell time on non-branded or aesthetic details reduces the temporal bandwidth available for detecting brand identifiers. In attentional network terms, prolonged fixation denotes deeper visual processing of perceptual details, which may divert resources from brand wordmarks. Hence, fixation duration inversely predicts engagement with brand-specific nodes, illustrating how sustained aesthetic inspection limits rapid brand detection within complex visual fields.

Model 3, testing Hypothesis 2c, emerged as the most robust architecture for the predictive model by incorporating the "Number of Whole Fixations on Aesthetics" as the primary driver. This final model successfully accounted for 40.3% of the variance in brand fixations ($Adjusted R^2 = .403$), with the aesthetic fixation count functioning as a highly significant positive predictor ($\beta = .658, p < .001$).

A positive correlation was found between aesthetic engagement and brand fixations, ($\beta = 0.658, t(57) = 5.68, p < .001$), explaining approximately 40% of the variance in brand fixations ($R^2_{adj} = .403$). This finding demonstrates that aesthetic processing acts as a primary attentional predictor. When viewers are visually attracted to aesthetic nodes such as composition, color harmony, and design sophistication, those same regions guide the gaze toward associated brand identifiers. Thus, aesthetic appeal does not operate independently of brand processing; rather, it enhances it by spatially and cognitively channeling attention toward brand features embedded within aesthetically pleasing visual contexts. In luxury design networks, aesthetic

salience serves as the key mechanism for brand recognition and engagement.

Crucially, the introduction of the aesthetic feature vector caused the previous variables, saccadic frequency and average duration, to lose their statistical significance ($p > .05$). This indicates that aesthetic engagement serves as the primary driver of brand attention within the luxury information network. The analysis demonstrates that visual appeal is not merely a decorative or secondary factor; rather, it functions as the primary vehicle for directing user attention toward brand-specific elements. Within this Human attention model for digital interfaces, the "aesthetic node" acts as a critical predictor, facilitating the cognitive prioritization and successful processing of brand identifiers.

Experimental Design and Data Acquisition: Experiment 3

Integrating Materialism Value Orientations into the Computational Model

Experiment 3 extends previous behavioral research (Audrin *et al.*, 2018) by investigating how Materialism functions as a cognitive filter, directing attentional priority toward specific brand and aesthetic nodes. While traditional literature suggests that high materialism prioritizes brand signifiers over product quality, this study utilizes the Materialism Values Scale (MVS) (Richins, 2004) in conjunction with high-frequency ocular sensors (Pesa *et al.*, 2024) to generate deeper systemic insights. Building on the data output from Experiment 2, which identified increased brand-node fixations and reduced pupil diameter as indicators of cognitive engagement, this research models the relationship between internal value systems and external brand perception. This is particularly critical given the established link between

materialism and the use of luxury acquisitions as markers of success and fulfillment (Fitzmaurice, 2008; Richins, 2017; Richins and Dawson, 1992).

The pursuit of fashionable attire within a visually dense digital displays is heavily influenced by a user's drive for self-identity and social validation (Dittmar, 2005; Lertwannawit & Mandhachitara, 2012). For users with a high materialistic feature vector, fashion serves as a primary tool for self-expression and social approval (O'Cass, 2000, 2004; Segev *et al.*, 2015). However, the specific biometric mechanics of this dynamic remain largely unexplored in luxury consumption. By employing infrared ocular tracking, this study aims to bridge this research gap, revealing the complex interplay between materialist value systems, brand-node perception, and status-seeking behavior in the luxury market.

Participants and Biometric Setup

The experimental architecture utilized a cohort of sixty participants ($N=60$), maintaining demographic consistency with previous phases (48 females, 12 males; 73.8% under 34 years old). Participants were recruited via targeted digital advertisements and social media campaigns aimed at art and commerce communities to ensure a sample with varied sensitivity to luxury stimuli. The data acquisition process involved the presentation of nine fashion imagery sets, incorporating high-prestige brand identifiers (Figure Plate 1), while synchronized with the 30 Hz Tobii infrared ocular sensor array. This setup allowed for the simultaneous tracking of visual search patterns and the quantification of the user's psychometric parameters.

Psychometric Materialist Value Orientations

To quantify the internal user parameters, we employed the Material Values Scale - Short Form (Richins, 2004; 2017; Appendix 1). This instrument measures materialism across three distinct sub-dimensions: Success, Centrality, and Happiness, utilizing a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The 18-item scale demonstrated a high level of statistical reliability for measuring the materialism feature vector, yielding a Cronbach's Alpha (α) of .72. This validated psychometric data was then integrated into our predictive model to determine if high scores

in materialistic centrality and success predictably alter the hierarchy of visual attention when navigating branded information networks.

System Performance and Data Output Analysis

Table 3 presents the descriptive statistics and Pearson correlation coefficients for the primary biometric and psychometric variables. The data output indicates a significant divergence in how the visual system allocates bandwidth within the information network. Participants exhibited a substantially higher frequency of fixations on aesthetic nodes ($M = 5.64$, $SD = 2.63$) compared to brand-specific data nodes ($M = 0.61$, $SD = 0.37$). This disparity suggests that while brand identifiers are critical anchors, the vast majority of the "computational load" during visual search is dedicated to resolving the high-fidelity aesthetic features of the garment.

To evaluate the predictive relationship between visual attention and consumer value orientations, a correlation analysis was conducted, treating the sub-dimensions of the Materialism Values Scale Orientations. Regarding Hypothesis 3a, which proposed a link between aesthetic engagement and materialist values, the Pearson correlations analysis revealed no significant correlations with MVQ-Success ($r = .13$), MVQ-Centrality ($r = .08$), or MVQ-Happiness ($r = .22$). Consequently, the data fails to support the hypothesis that a user's internal materialist framework predictably alters their processing of general aesthetic nodes. In contrast, Hypothesis 3b received partial empirical support. Brand fixations were significantly and positively related to the parameters of perceived MVQ-Success ($r = .26$, $p < .05$) and MVQ-Happiness ($r = .33$, $p < .05$), while the association with MVQ-Centrality was not significant, ($r = .07$, $p > .05$).

Aesthetic fixations were strongly correlated with brand fixations, $r = .63$, indicating a robust relationship between aesthetic and brand attention. These effects should be interpreted cautiously because multiple comparisons were tested and the significant associations may not survive correction, and the sample size may have been underpowered for weak correlations.

These findings indicate that the visual processing of brands is not a generic response but is specifically

moderated by the user's internal value system regarding status and achievement. Within our Human attention model for digital interfaces, the "brand node" serves as a high-priority target for users whose parameters emphasize success and happiness. This suggest that visual engagement with branding, rather

than general aesthetic appeal, is the primary biometric marker for status-aligned cognitive processing. This correlation allows us to refine the predictive model, identifying how specific psychological "Materialist Value Orientations" can be used to forecast user interaction with branded information networks.

	M SD		1	2	3	4	5
1.Number of fixations on brands	0.609	0.36703	1				
2.Number of fixations on aesthetics	5.635	2.6308	.631**	1			
3.MVQ_Success	5.753	2.6717	.263*	0.132	1		
4.MVQ_Centrality	4.067	0.7165	0.066	0.076	-0.016	1	
5.MVQ_Happiness	5.831	1.84047	.330*	0.222	.834**	-0.032	1

** . Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 3. Descriptive Statistics and Bivariate Correlations

RESULTS

A hierarchical multiple regression analysis was used to assess whether MVQSuccess, MVQCentrality, and MVQHappiness predicted brand outcomes. The overall model was not statistically significant, $F(3, 52) = 2.416$, $p = .077$ and accounted for 12.2% of the variance in brand fixation outcomes (R^2

$=.122$, $Adjusted R^2 = 0.072$; Table 3). MVQSuccess significantly and positively predicted brand fixations ($\beta = .722$, $p = .012$; Table 4), whereas MVQHappiness significantly and negatively predicted time to first fixation on brand elements ($\beta = -.696$, $p = .013$). MVQCentrality was not significant ($p = .790$). As the overall model did not reach statistical significance, these coefficients should be interpreted cautiously.

Model	R	R Square	Adjusted R Square	Std. Error	Change Statistics	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.350	0.122	0.172	4.35484	0.112	3.316	2	52	0.044	1.933

a Predictors: (Constant), MVQSuccess, MVQCentrality, MVQHappiness.

b Dependent Variable: Time to first events on Brands

Table 4. Hierarchical Multiple Regression Model Summary on Brand Fixations as outcome variable.

Model		Unstand ardized Co efficients		Standard ized Co efficients	T	Sig.	Correlat ions				
		B	Std. Error	Beta			Zero- order	Part ial	Part	Toler ance	VIF
1	(Constant)	24570 .351	45890 .218		0.535	0.595					
	MVQSuccess	13050 .20	4985 .846	0.722	2.618	0.012	0.102	0.341	0.340	0.222	4.511
	MVQCentrality	2604 .693	9735 .112	0.036	0.268	0.790	-0.025	0.037	0.035	0.913	1.096
	MVQHappiness	-17300 .644	6718 .750	-0.696	- 2.575	0.013	-0.071	-0.336	-0.335	0.231	4.333

a Dependent Variable: Time_to_first_events.brands.

Table 5. Multiple regression of Time to First events on Brands.

A multiple regression analysis was conducted to examine whether materialism dimensions (success, centrality, and happiness) predict the time to first event on aesthetics. The overall model was not statistically significant, $F(3, 97) = 2.180$, $p = .095$, explaining 6.3% of the variance ($R^2 = .063$; *Adjusted* $R^2 = .034$; Table 7). This indicates that, collectively, materialism variables provide limited explanatory power for predicting initial visual engagement with aesthetic elements.

Despite the non-significant overall model, two predictors made significant individual contributions. MVQ Success emerged as a positive predictor ($\beta =$

.423, $p = .020$; Table 6), suggesting that individuals who associate material possessions with success tend to take longer to fixate on aesthetic elements. This may indicate more deliberate or evaluative processing of visual stimuli among success-oriented individuals.

In contrast, MVQ Happiness was a significant negative predictor ($\beta = -.444$, $p = .015$; Table 6), indicating that participants who associate material possessions with happiness tend to fixate more quickly on aesthetic elements. This suggests a more immediate attentional response to visual appeal among individuals driven by happiness-related material values.

Mo del		Unstandar dized Coefficient s		Standar dized Coefficie nts	t	Sig .	Correlat ions				
		B	Std. Error	Beta			Zero- order	Part ial	Pa rt	Tolera nce	VI F
1	(Constant)	31620.92	22438 .12		1.4 09	0.1 62					

	MVQSuccess	5214.704	2213.188	0.423	2.356	0.02	0.054	0.233	0.232	0.3	3.336
	MVQCentrality	-1869.38	4580.048	-0.04	-0.408	0.684	-0.038	-0.041	-0.04	0.997	1.003
	MVQHappiness	-8178.9	3307.719	-0.444	-2.473	0.015	-0.088	-0.244	-0.243	0.3	3.337

a Dependent Variable: Time_to_first_Event.aesthetics.

Table 6. Regression Coefficients for the Prediction of Time to First Event (Aesthetics) Using MVQ Dimensions.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson	
					R Square Change	F Change	df1	df2	Sig. F Change		
1	.251a	0.063	0.034	33238.127	0.063	2.18	3	97	0.095	2.101	2.101

a Predictors: (Constant), MVQHappiness, MVQCentrality, MVQSuccess .

b Dependent Variable: Time_to_first_Event.aesthetics

Table 7. Multiple Regression Model for MVQ Predictors on aesthetics.

System Synthesis and Discussion

The results indicate that, within visually dense digital displays, visual aesthetics function as the primary driver of attention and often outweigh overt brand focus. Eye-tracking data showed that fixation density and saccadic exploration were directed more toward garment aesthetics than brand logos, consistent with prior work suggesting that aesthetic cues dominate early visual processing in luxury contexts (Nayak & Karmakar, 2018).

This pattern aligns with attention-based accounts in which perceptual salience exogenously guides gaze allocation, including Feature-Based Theory and broader Attention Engagement Theory formulations (Eriksen & Hoffman, 1972; Johnston & Dark, 1986; Joseph & Optican, 1996; Pashler, 1988; Posner, 1980; Theeuwes, 1991a, 1991b). Experiment 1 reinforced this pattern. Increased saccadic activity was

associated with longer fixation duration, suggesting that visual exploration was concentrated on aesthetic detail rather than on brand cues.

From an HCI design perspective, these findings suggest that digital luxury environments should prioritize attention-optimised interfaces, allocating computational and visual resources where attention is most strongly directed. High-resolution textile textures, surface detail, lighting behavior, and material realism are likely to produce greater perceptual engagement than disproportionate emphasis on secondary brand assets. Techniques such as micro-texture mapping, subsurface scattering, and dynamic global illumination are therefore not merely visual enhancements; they represent functional components of attentional design because they support the specific visual features that capture and sustain gaze.

Stepwise regressions further confirmed aesthetic fixations as key predictors of brand attention (Adj. $R^2 = .914$; Table 1), supporting H3 and identifying materialism as an amplifying factor for luxury cue focus. This relationship provides refined insights for HCI practitioners, highlighting how psychological and perceptual inputs can inform interface architecture. In relation to attention guidance, high-aesthetic elements should act as predictors within interactive environments, directing users toward brands and reducing unnecessary visual wandering, particularly valuable in mobile or social media contexts. In relation to cognitive load reduction, visually dense layouts increase fixation duration and signal overload, in line with predictions from Selective Attention Theory (SAT). Reducing clutter through hierarchical visual design supports smoother attentional flow and comprehension. In relation to personalization of experience, interfaces can dynamically adjust for users scoring high in materialism (e.g., those emphasizing success-based values) by emphasizing prominent status cues and refined visual markers, thereby improving interaction satisfaction and UX continuity.

These usability insights extend beyond commercial luxury interfaces to broader digital ecosystems such as social media communities and consumer apps, where user retention depends on balancing perceptual engagement with cognitive efficiency.

Experiment 2 provided additional context by showing no direct link between brand fixations and saccades, alongside a negative relation between increased brand focus and pupil diameter. This suggests that brand visibility alone does not necessarily produce heightened arousal or deeper processing. However, the strong positive association between aesthetic and brand fixations implies that visual appeal acts as a predictor of brand engagement. In an intelligent automation framework, an eye-tracking system can serve as a feedback controller, detecting attention clusters on aesthetic regions and triggering adaptive responses such as interface adjustments, content recommendations, or dynamic attention-optimised interfaces of high-value elements that strengthen the transition from visual interest to brand recognition.

Experiment 3 suggests that materialism does not operate as a single, unified predictor of attentional

behaviour. Rather, its influence on brand processing appears to be selective and dimension-specific, with success beliefs emerging as more behaviourally consequential than centrality or happiness. This pattern indicates that the motivational significance of brands may be more important than materialism as a general construct, and it supports the view that future research should examine materialism at the level of its distinct subdimensions rather than treating it as homogeneous. In particular, the findings suggest that success-oriented material values may play a stronger role in directing visual attention to brands, consistent with prior research linking materialism to status signalling and symbolic consumption (Razmus et al., 2024; Audrin et al., 2018; O’Cass, 2004).

When considering aesthetic engagement, materialism showed limited overall explanatory power; however, distinct and opposing effects emerged at the individual level. Success-oriented individuals exhibited delayed initial fixation on aesthetic elements, consistent with more deliberate or evaluative visual processing, whereas happiness-oriented individuals fixated more rapidly, indicating a more immediate, affect-driven response to visual appeal. These findings suggest that attentional reward is differentially structured across motivational dimensions: brand-focused attention is more strongly linked to success-related materialism, whereas aesthetic attention reflects both cognitive evaluation and hedonic responsiveness.

Aesthetic attraction therefore operates as a parallel yet partially independent dimension of engagement, meaning that digital luxury design should combine status signalling with aesthetic richness rather than relying solely on branding cues. Demographic patterns further highlight that younger participants and women favoured aesthetics over branding, reinforcing the need for visually curated, demographically responsive interfaces that adapt visual density, contrast, and chromatic detailing for diverse audiences (Djamasbi et al., 2010; Munoz-Leiva et al., 2024; Yu et al., 2021).

CONCLUSION

This research establishes that visual aesthetic engagement is a dominant predictor of brand-specific attention in digital luxury environments. Explicit

branding serves as a functional anchor but not as the primary activator of gaze behaviour. As luxury interaction design transitions into augmented and virtual reality contexts, aesthetic coherence becomes a technical requirement, not a stylistic embellishment (Boardman & McCormick, 2022).

From an HCI perspective, attention-optimise interfaces systems should prioritize GPU and computational resources around high-aesthetic regions, the areas most likely to sustain fixation and influence brand encoding. Attention-optimise interfaces can detect aesthetic “hotspots” and elevate fidelity in real time, ensuring perceptual continuity while minimizing unnecessary processing.

Integrating gaze data within intelligent automation workflows enables adaptive luxury systems that respond dynamically to user attention. By translating fixation metrics into design triggers, platforms can develop responsive visualization protocols that adjust layout density, symbolic prominence, and sensory realism according to real-time engagement data.

Together, these insights reveal a human-centered design paradigm in which aesthetic engagement actively drives brand recognition, emotional resonance, and sustained digital interaction. This synthesis extends HCI usability principles to the domain of luxury experience design—demonstrating that high-aesthetic presentation, cognitive streamlining, and personalized symbolic reinforcement jointly enhance digital accessibility, user satisfaction, and interactive brand communication.

Limitations and Future Research Directions

While the study provides a strong theoretical and empirical foundation for attention-guided interface design, several limitations warrant acknowledgement. The recommendations drawn from fixation and saccade patterns remain inferential rather than experimentally optimized. Because the study did not manipulate interface parameters such as logo placement, element size, color saturation, or attention-optimised interfaces fidelity, the proposed guidelines should be interpreted as attentional indicators rather than prescriptive threshold values. Future research should systematically vary these parameters within controlled interface simulations to identify optimal

visual ratios, spatial positioning, and contrast boundaries that maximize attentional efficiency and brand engagement.

Generalizability is also constrained by sample composition, which was primarily composed of younger, London-based professionals and women. This demographic configuration likely reflects digital luxury consumption patterns but restricts broader applicability. Subsequent work should evaluate whether these attentional architectures persist across age-diverse, gender-balanced, and cross-cultural populations, since cultural semiotics and value orientations can modulate preferences for aesthetic versus branding prominence.

A further limitation lies in the static nature of the stimuli. Although still imagery allows precise measurement of fixation dynamics, it overlooks interactivity, an essential dimension of modern digital ecosystems such as e-commerce, social media, and augmented reality interfaces. Future designs should incorporate more immersive, temporally continuous environments using dynamic product rotations, try-on simulations, and responsive feedback layers. Longitudinal protocols may clarify whether aesthetic engagement translates into memory encoding, affective recall, and behavioral outcomes like purchase intent or brand loyalty.

Finally, these conceptual and analytical implications should be validated through experimental prototyping. Implementing adaptive attention - optimised interfaces engines or gaze-responsive recommender systems would allow direct evaluation of whether attentional modeling improves engagement without increasing cognitive load. Such applied studies would close the gap between theoretical framework and interactive deployment, transforming fixation-based metrics into scalable design principles for digital luxury interfaces. By testing attentional optimization within live systems, future research can integrate human perception, real-time data processing, and aesthetic algorithmic control into next-generation commercial and experiential HCI platforms.

Author Contribution Statement

Dr Zoi Zoupanou involved in the conception and design, conducted the experiment in the lab, data

acquisition, data analysis and interpretation; the drafting of the paper; revising it for critically intellectual content ; the final approval of the version to be published; was accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. Dr Max Tookey contributed to the data analysis and interpretation, revising the paper for intellectual content, and the final approval of the version to be published.

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