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Human-Computer Interaction in Digital Performance: Enhancing Audience Engagement through Technology

Rania Lampou[1*]

[1] Directorate of Educational Technology and Innovation, Greek Ministry of Education, Religious Affairs and Sports, Athens, Greece;

* **Corresponding author:** rania.lampou@gmail.com.

ABSTRACT: Human-computer interaction has become a decisive factor in transforming digital performance into a responsive, participatory, and measurable experience. This paper develops a user-centered human-computer interaction framework to enhance audience engagement in digital performance and supports it with a secondary empirical analysis of open research records. After methodological screening, we retained interactive art records containing 1,400 observations across 21 analytical measures as the primary analytical source. We constructed an Audience Engagement Index on a 0 to 100 scale by combining min-max normalized indicators of attention, interaction count, satisfaction score, and reward, yielding an overall sample mean of 48.175 and a standard deviation of 17.293. Predictive regression modeling demonstrated that movement intensity (standardized beta = 0.753, $p < 0.001$) and crowd density (standardized beta = 0.555, $p < 0.001$) are the most influential predictors of audience engagement, supplemented by pattern coherence (0.174), visual complexity (0.170), and color diversity (0.152). Linear and ridge regression models explained a large proportion of variance in the engagement index ($R^2 = 0.939$, root mean square error = 4.255). Furthermore, one-way analysis of variance revealed statistically significant differences across display patterns ($F = 2.572, $p = 0.036$), with abstract display patterns generating the highest mean engagement score (50.590). The study concludes that digital performance systems must support embodied agency, clear feedback, and collective responsiveness rather than relying on technological novelty or attendance metrics alone.

Keywords: human-computer interaction; digital performance; audience engagement; interactive art; user-centered design; engagement index.

I. INTRODUCTION

Digital performance has become one of the clearest cultural spaces where technology changes the relationship between artistic form and audience experience. In contemporary theatre, interactive installation, museum performance, immersive media, dance, sound art, and public digital environments, computation no longer functions only as a technical support placed behind the event. It increasingly enters the performance itself as a responsive participant that can sense movement, translate bodily action into sound or image, adapt visual rhythm, reorganize spatial attention, and invite spectators to act as co-producers of the experience.

This transformation creates an important research problem. Advanced technology does not automatically create meaningful engagement. A performance can include projection mapping, motion tracking, mobile participation, responsive sound, or immersive screens and still leave the audience passive or unsure how to participate. At the same time, a simple interactive system can produce strong involvement when it gives spectators understandable agency, immediate feedback, emotional resonance, and a clear connection between their action and the artistic structure of the event. The central issue, therefore, is not whether

technology is present, but whether the interaction is designed around human perception, embodied response, usability, social presence, and meaning.

Human-computer interaction offers a strong basis for examining this issue because it studies the relationship between people, interfaces, systems, actions, and experience. In digital performance, the interface may not appear as a conventional screen or menu. It may be a sensor field, light environment, responsive floor, camera-tracked body, wearable device, sound-reactive space, or collective mobile input. The audience may interact deliberately through touch or gesture, or indirectly through movement, proximity, sound, gaze, or group behavior. These conditions make performance engagement more complex than ordinary attendance because the audience not only watches the event but also helps shape its rhythm, atmosphere, and interpretive direction.

Audience engagement is also multidimensional. It includes focused attention, curiosity, emotional involvement, perceived agency, satisfaction, social connection, aesthetic response, and willingness to continue participating. In digital performance, feedback clarity and interaction coherence strongly shape these dimensions. When spectators understand that their action produces a visible, audible, spatial, or narrative response, they can recognize themselves as part of the performance system. When the feedback is delayed, ambiguous, excessive, or disconnected from the artistic purpose, interaction may become decorative noise rather than meaningful participation.

A persistent gap in this field is the separation between artistic interpretation and empirical evaluation. Many discussions of digital performance describe technological form, immersion, or participation, but they do not always specify which interaction conditions increase attention, satisfaction, or continued involvement. Conversely, many quantitative indicators in cultural and performance research, such as attendance, revenue, participation frequency, or recommendation scores, describe reach or popularity but not interaction quality. A digital performance study therefore needs a framework that can interpret artistic meaning while also identifying measurable engagement conditions.

This paper addresses this problem by developing a user-centered framework for understanding and evaluating audience engagement in digital performance. The framework connects five elements: HCI design inputs, interaction processes, engagement outcomes, performance meaning, and design evaluation. It treats audience engagement as both an artistic and measurable phenomenon. This position matters because digital performance requires interpretation of meaning, but it can also be measured through indicators such as attention, interaction count, satisfaction, reward, movement intensity, visual complexity, and pattern coherence.

The study therefore combines conceptual analysis with secondary empirical analysis. The study screened three empirical source groups to assess their relevance to digital performance engagement. The study selected interactive art records as the core analytical source because they include variables related to environmental conditions, interface design, embodied movement, attention, interaction, satisfaction, and reward. We retained cultural engagement and Broadway attendance records as contextual evidence because they describe participation and attendance but do not directly measure HCI interaction quality. This distinction strengthens the paper's methodological logic by separating general audience reach from interactive engagement.

This approach is especially useful for performance researchers because it avoids reducing engagement to a single behavioral signal. A high level of interaction may be meaningless if participants do not understand the system, while high satisfaction may conceal low agency if spectators enjoy the visual surface without shaping it. By combining multiple indicators, the study can examine engagement as a relation among body, interface, environment, affect, and evaluation. This also lets the paper connect statistical results to concrete design principles, such as embodied input, immediate feedback, interpretable visual complexity, collective responsiveness, and preserved narrative coherence.

The paper's contribution is both practical and theoretical. It clarifies why digital performance should be designed from the audience's interactional experience rather than from technology novelty alone. It constructs an Audience Engagement Index that combines attention, interaction, satisfaction, and reward into a normalized measure. It also translates statistical findings into design implications for artists, HCI researchers, cultural institutions, and performance designers. By linking interaction design, measurable

engagement, and artistic meaning, the paper offers a structured basis for evaluating digital performance systems that are not only visually impressive but also usable, participatory, and emotionally compelling.

1. STUDY CONTRIBUTION

This study makes three main contributions.

- First, it develops a user-centered HCI framework that links design inputs, interaction processes, engagement outcomes, performance meaning, and design evaluation within one coherent structure.
- Second, it proposes an Audience Engagement Index that combines attention, interaction, satisfaction, and reward into a normalized measure suitable for evaluating digital performance engagement.
- Third, it translates statistical findings into practical implications for the design of interactive performance environments, including embodied input, immediate feedback, collective responsiveness, and coherent visual structure.

The contribution is therefore both theoretical and applied. Theoretically, the paper clarifies how digital performance engagement can be understood as a relationship among body, interface, space, audience agency, and artistic interpretation. Methodologically, it provides a reproducible evaluation logic that theatres, museums, interactive-art designers, cultural institutions, and HCI researchers can adapt to assess whether technology strengthens or weakens the audience experience.

II. LITERATURE REVIEW

Studies on digital performance and HCI increasingly show that audience engagement depends on the relationship among interface, body, space, performer, and spectator rather than on the presence of technology alone. Benford et al. emphasized the need to study performance-led interaction in real settings, where audience behavior, spatial arrangement, and system response shape the event as it unfolds [3]. Svanæs similarly framed interaction as an embodied process grounded in bodily perception, movement, and lived experience [31]. Nam and Nitsche extended this position by treating interactive installations as performance systems in which the spectator, object, interface, and environment operate as one shared structure [21]. In theatre contexts, Cerratto-Pargman et al. and Dima showed that digital systems can prepare, guide, and intensify audience participation when connected to theatrical meaning rather than used as isolated technical additions [4], [7].

A second body of research focuses on participation, agency, and mediated performer-audience exchange. Nelimarkka et al. demonstrated that live participation systems can transform events into responsive exchanges between performers and audiences [22]. Salovaara et al. later showed that such participation becomes stronger when professional event technologies support communication without interrupting the artistic rhythm of performance [29]. Hodl et al. examined large-scale audience participation in live music and highlighted mobile devices' potential for collective input [11]. Lee et al. further showed that social interaction among audience members can increase willingness to participate in live music settings [17]. Together, these studies suggest that audience engagement is not only a private reaction; it is also a social, situated process shaped by feedback, visibility, and collective presence.

Measurement-oriented studies provide important foundations for evaluating engagement in digital performance. O'Brien and Cairns examined the User Engagement Scale and clarified that engagement includes attention, usability, aesthetics, reward, and continued involvement [23]. Wiebe et al. applied engagement measurement in game-based environments, confirming that interactive experiences require multidimensional assessment rather than one simple satisfaction score [33]. O'Brien et al. later refined the User Engagement Scale and provided a practical structure for measuring focused attention, aesthetic appeal, perceived usability, and reward [24]. Miranda et al. adapted the scale across cultural contexts, showing that engagement measures must remain sensitive to language and context [19]. Hassib et al. added another methodological direction by using EEG-based implicit sensing to estimate audience engagement without directly interrupting the viewing experience [10]. Cordeiro et al. also showed that even instructional cues can alter participation in interactive art, confirming that interface clarity is a measurable design factor [5].

Interactive art research contributes directly to the conceptual logic of the present study because it treats interactivity as aesthetic, technical, social, and interpretive at the same time. Ahmed clarified that interaction in digital art installations should not be reduced to input-output mechanics, because spectators also interpret meaning through the way the installation responds [1]. Jeon positioned interactive art as a long-standing site for HCI inquiry because it makes ambiguity, emotion, participation, and non-standard interfaces visible [13]. Lee argued that liveness in interactive systems matters because real-time response changes the spectator's role from observer to collaborator [16]. Rajcic and McCormack showed how affective installations can support human-machine co-construction of emotion [28]. Jung et al. extended the field by connecting HCI to altered states of consciousness, while Stimberg and Brennecke illustrated how interactive light and sound installations can produce sensory engagement through responsive media [14], [30].

Research on extended reality and cultural heritage expands the discussion toward immersive experience, evaluation, and interface design. Bekele et al. reviewed augmented, virtual, and mixed reality in cultural heritage and showed that immersive technologies can support interpretation when user experience is carefully evaluated [2]. De Bonis et al. reached a similar conclusion in their review of extended-reality user studies for archaeology and heritage, emphasizing the need for systematic evaluation of visitor experience [6]. Merino et al. reviewed mixed- and augmented-reality evaluation methods and stressed the importance of perception, usability, attention, and situated behavior [18]. Grubert synthesized mixed-reality interaction techniques, including gesture, gaze, tangible, and multimodal input [8]. Walker et al. added a taxonomy of virtual, augmented, and mixed-reality design elements, which is useful for classifying digital performance systems that combine human action with virtual or responsive environments [32].

Recent immersive theatre and virtual-performance studies show how digital performance is moving beyond conventional screen-based interaction. Pyae et al. linked immersion, enjoyment, and engagement in virtual reality activity, showing that experiential involvement can be evaluated through both behavioral and user-response indicators [27]. Mulvany mapped immersive theatre affordances into game-engine interaction and argued that digital audiences require carefully designed theatrical cues, spatial logic, and responsive participation [20]. Pietroszek et al. developed a virtual reality theatre play, demonstrating how theatrical presence can be transferred into interactive virtual environments [25]. In a related mixed-reality prototype, Pietroszek et al. used volumetric performance to support participatory theatrical experience [26]. Lakkis and Issa added a technology-continuance perspective by showing that sustained use of interactive mixed reality depends on perceived value, usability, and user intention [15].

Overall, the reviewed literature supports a user-centered approach to digital performance engagement. Collectively, the studies show that meaningful engagement depends on embodied action, interface clarity, real-time feedback, social participation, aesthetic coherence, immersive design, and measurable user response. However, the literature also indicates that engagement should not be treated as attendance, novelty, or technological complexity alone. It requires a framework that links interaction design variables to audience attention, satisfaction, reward, and the meaning of performance. This synthesis provides the basis for the proposed Audience Engagement Index and the later empirical analysis of interactive performance conditions.

Table 1. Comparative summary of reviewed HCI and digital performance studies.

Ref. no	Author, year	Focus	Method/evidence	Contribution to the present paper
[1]	Ahmed, 2018	Interaction in digital art installation	Conceptual analysis	Defines interaction and interactivity in installation contexts.
[2]	Bekele, 2018	XR technologies in cultural heritage	Survey study	Links immersive media to interpretation and visitor experience.
[3]	Benford, 2013	Performance-led HCI in the wild	Field-based performance research	Supports situated analysis of audience, space, and interaction.

[4]	Cerratto-Pargman, 2014	Audience participation in interactive theatre	Empirical performance study	Clarifies audience agency, self-reflection, and contribution.
[5]	Cordeiro, 2017	Instructional cues in interactive art	Public field experiment	Shows that interface clarity affects participation.
[6]	De Bonis, 2022	Extended-reality user studies in heritage	Systematic review	Informs evaluation of cultural and museum experiences.
[7]	Dima, 2014	Mobile engagement before theatre events	Design-led theatre study	Shows how digital systems prepare spectators for participation.
[8]	Grubert, 2021	Mixed-reality interaction techniques	Technical overview	Clarifies gesture, tangible, gaze, and multimodal inputs.
[9]	Haimson, 2017	Engagement in live digital events	Empirical study of live media	Highlights immediacy, liveness, and shared viewing.
[10]	Hassib, 2017	Implicit audience engagement sensing	EEG-based HCI system	Supports non-intrusive engagement measurement.
[11]	Hodl, 2020	Large-scale audience participation in music	Performance technology study	Demonstrates collective input through audience devices.
[12]	Hook, 2016	Somaesthetic appreciation design	Design research in embodied HCI	Links aesthetic response with bodily experience.
[13]	Jeon, 2019	Interactive art and HCI	Review and conceptual synthesis	Positions art as a research site for HCI.
[14]	Jung, 2022	Altered states and HCI experience	Review study	Extends engagement toward affective and immersive states.
[15]	Lakkis, 2022	Continuance in interactive mixed reality	Empirical technology-use study	Links usability, value, and sustained engagement.
[16]	Lee, 2019	Liveness in interactive systems	Conceptual HCI paper	Explains why real-time response matters in performance.
[17]	Lee et al., 2019	Social interaction in live music	Creativity and cognition study	Shows how crowd interaction facilitates participation.
[18]	Merino, 2020	MR/AR evaluation methods	Systematic literature review	Supports rigorous user-centered evaluation procedures.
[19]	Miranda, 2021	Cross-cultural engagement scale adaptation	Psychometric adaptation	Supports engagement measurement across contexts.
[20]	Mulvany, 2022	Digital immersive theatre	Game-engine performance study	Maps theatre affordances to digital interaction design.
[21]	Nam, 2014	Interactive installations as performance	Conceptual HCI framework	Connects installation art, performance, and interface design.
[22]	Nelimarkka, 2016	Live participation in public events	Audience-performer interaction system	Supports mediated performer-audience exchange.
[23]	O'Brien, 2015	User Engagement Scale validation	Quantitative validation study	Strengthens the measurement logic of engagement indicators.
[24]	O'Brien, 2018	Refined User Engagement Scale	Psychometric measurement study	Provides dimensions used to justify the AEI design.
[25]	Pietroszek, 2022a	VR theatre play	Interactive VR performance prototype	Shows how theatrical presence can move into virtual space.
[26]	Pietroszek, 2022b	Volumetric mixed-reality theatre	Mixed-reality prototype	Demonstrates participatory performance with volumetric media.
[27]	Pyae, 2021	Engagement in immersive VR activity	Empirical VR user study	Links immersion, enjoyment, and interaction metrics.
[28]	Rajcic, 2020	Affective interactive installation	Artwork and system study	Connects emotion, interpretation, and responsive media.
[29]	Salovaara, 2021	Performer-audience participation in events	Professional event case study	Shows how live participation systems reshape event communication.
[30]	Stimberg, 2020	Interactive light and sound installation	Installation case study	Supports sensory and responsive environmental design.
[31]	Svanæs, 2013	Embodied interaction and the lived body	Theoretical HCI analysis	Frames bodily movement as a central interaction resource.
[32]	Walker, 2022	Virtual and mixed-reality interface taxonomy	Survey and taxonomy	Supports classification of virtual design elements.
[33]	Wiebe, 2014	Engagement in game-based environments	Scale evaluation	Supports multidimensional engagement measurement.
[34]	Yan, 2016	Adaptive virtual performance with BCI	Experimental engagement system	Demonstrates real-time sensing of performance engagement.

RESEARCH GAP

Across the reviewed studies, three limitations remain visible. First, many digital performance studies describe participation, immersion, or artistic experience without developing a measurable engagement model. Second, many evaluation studies examine general user experience but do not connect engagement metrics to performance meaning, narrative coherence, collective spectatorship, or the artistic purpose of interaction. Third, audience-reach indicators such as attendance, recommendation, frequency, or popularity do not necessarily explain whether interaction was meaningful. This paper addresses these limitations by combining a user-centered HCI framework with an Audience Engagement Index and by distinguishing direct interaction variables from contextual cultural and attendance evidence.

III. PROPOSED FRAMEWORK

The proposed method evaluates digital performance engagement through four connected stages. The first stage identifies interaction-relevant variables and classifies them as environmental conditions, interface and media design features, behavioral engagement indicators, experiential engagement indicators, or composite outcomes. The second stage transforms attention, interaction count, satisfaction, and reward into comparable indicators and combines them into the Audience Engagement Index. The third stage applies descriptive statistics, correlation analysis, variance testing, regression modeling, and random-forest importance analysis to determine which interaction and design conditions are most strongly associated with engagement. The fourth stage interprets the statistical findings through the proposed HCI framework so that numerical results lead to practical performance-design implications rather than remaining isolated measurements.

This method suits digital performance because it treats engagement as both measurable and interpretive. It does not reduce the audience experience to attendance or frequency alone; instead, it connects measurable indicators with agency, feedback clarity, embodied participation, collective presence, and artistic coherence. In this way, the proposed method supports formal evaluation of technology-mediated performance while preserving the field's aesthetic and human-centered nature.

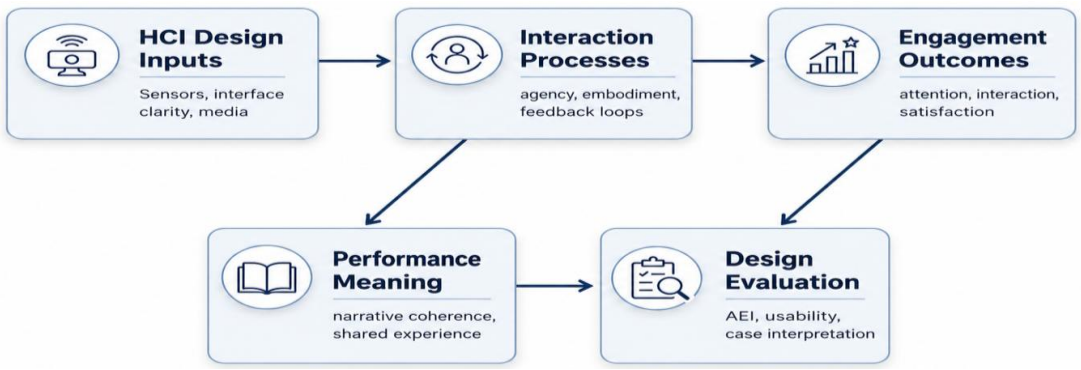


FIGURE 1. User-centered HCI framework for digital performance engagement.

The framework links technological inputs to interaction processes, measurable engagement, artistic meaning, and evaluation. It positions technology as part of the performance's communicative structure rather than a separate visual effect.

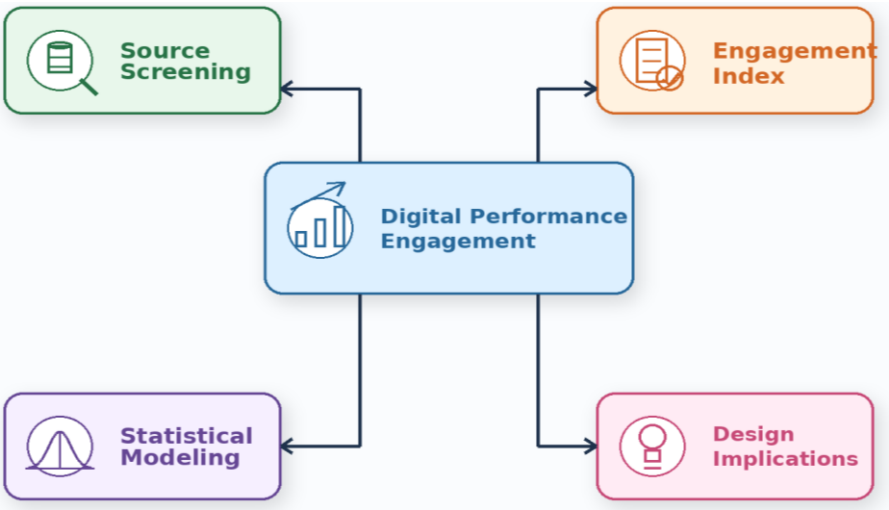


FIGURE 2. Analytical mind map for the empirical study.

The mind map summarizes how the paper moves from source screening to engagement-index construction, statistical modeling, and design implications.

IV. METHODOLOGY

1. RESEARCH DESIGN

The study uses a mixed analytical design that combines qualitative interpretation with quantitative secondary empirical analysis. The qualitative component develops a user-centered HCI framework for digital performance. The quantitative component evaluates engagement-related variables from open empirical records. This design is suitable because digital performance is both an artistic experience and an interaction system that can be partially measured through behavioral and evaluative indicators.

2. VARIABLES AND ENGAGEMENT INDICATORS

Table 2. Variable groups and analytical meaning.

Variable group	Variables	Analytical meaning
Environmental conditions	light level, sound level, temperature, crowd density	Contextual factors surrounding the interaction environment
Interface and media design	light color, animation speed, sound reactivity, display pattern, visual complexity, color diversity, pattern coherence	Design features that shape perception, feedback, and aesthetic response
Behavioral engagement	movement intensity, interaction count	Observable indicators of audience participation and embodied response
Experiential engagement	Audience attention, satisfaction score, reward	Indicators of attention, evaluation, and perceived experience
Composite outcome	Audience Engagement Index	Normalized index combining attention, interaction, satisfaction, and reward

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Variables were organized into design inputs, interaction processes, and engagement outcomes so that the statistical model follows the conceptual framework.

3. AUDIENCE ENGAGEMENT INDEX

The Audience Engagement Index combines multiple engagement indicators into a single, interpretable score. Because the original variables are on different scales, we first normalized each outcome variable using a min-max transformation. The index was then calculated as the average of normalized audience attention, interaction count, satisfaction score, and reward, multiplied by 100.

$$X_i^* = \frac{X_i - \min(X)}{\max(X) - \min(X)}$$

Equation 1. Min-max normalization transforms each variable into a comparable 0 to 1 scale.

$$\mathrm{AEI}_i = 25(A_i^* + I_i^* + S_i^* + R_i^*)$$

Equation 2. AEI combines normalized audience attention (A*), interaction count (I*), satisfaction score (S*), and reward (R*) into a 0 to 100 engagement score.

$$\widehat{\mathrm{AEI}}_i = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ki} + \varepsilon_i$$

Equation 3. The regression model estimates how environmental and interface-design predictors explain the Audience Engagement Index.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Equation 4. Root mean square error evaluates the predictive distance between observed and estimated engagement values.

4. STATISTICAL PROCEDURE

The statistical procedure included descriptive statistics, correlation analysis, one-way analysis of variance for categorical design variables, regression modeling, and random-forest feature importance. The regression models estimated the predictive relationship between environmental/interface variables and the Audience Engagement Index. We added a random forest as a non-linear robustness model to identify predictor importance without assuming a strictly linear relationship. The modeling procedure used a 75/25 train-test split and five-fold cross-validation.

Algorithm 1. Empirical engagement-analysis workflow.

Step	Procedure
1	Inspect the three empirical source groups and assess structure, missing values, and variable relevance.
2	Use the interactive art records as the core HCI source and retain the other empirical sources for contextual interpretation.
3	Normalize attention, interaction count, satisfaction, and reward using min-max transformation.
4	Construct the Audience Engagement Index on a 0 to 100 scale.
5	Estimate correlations, group differences, regression models, and random-forest importance.
6	Interpret the statistical findings through the user-centered HCI performance framework.

The workflow makes the study reproducible and shows how secondary empirical sources were organized into a coherent HCI performance analysis.

V. RESULTS

1. SOURCE QUALITY AND DESCRIPTIVE STATISTICS

We inspected three secondary empirical sources for structure, completeness, and relevance. The interactive art records contained 1,400 observations and 16 original variables; after index construction, the analytical matrix contained 21 measures with no missing values in the variables used for analysis. The cultural engagement records contained 8,737 observations and 16 variables; we derived one duration measure for contextual interpretation. The Broadway attendance records contained 31,296 observations and 12 variables covering the period from 1990-08-26 to 2016-08-14. Because the Broadway attendance source does not contain interaction, usability, attention, satisfaction, or interface-response variables, it was not used for predictive HCI modeling.

Table 3. Descriptive statistics for the core interactive art variables.

Variable	Mean	SD	Min	Max
crowd_density	0.493	0.287	0.000	1.000
movement_intensity	0.497	0.290	0.000	1.000
visual_complexity	0.751	0.146	0.500	1.000
color_diversity	0.752	0.142	0.500	1.000
pattern_coherence	0.750	0.143	0.500	1.000
audience_attention	0.594	0.211	0.090	1.000
interaction_count	9.901	5.216	0.000	30.000
satisfaction_score	7.194	0.777	4.900	9.300
reward	0.663	0.124	0.350	0.950
AEI_100	48.175	17.293	6.004	93.750

The Audience Engagement Index has a mean of 48.175 and a standard deviation of 17.293 on a 0 to 100 scale. This variation is sufficient to model engagement differences across interaction and design conditions.



FIGURE 3. Correlation structure of interaction and engagement variables.

The correlation map shows that the composite engagement index is closely related to attention, interaction count, satisfaction, and reward, while movement intensity and crowd density are the strongest external predictors among the design-relevant variables.

2. ENGAGEMENT DIFFERENCES BY DISPLAY PATTERN AND LIGHT COLOR

Table 4. Audience Engagement Index by display pattern.

Display pattern	Mean AEI	SD	N
abstract	50.590	17.110	269
pulse	48.730	17.830	294
fractal	48.350	16.250	298
wave	46.620	17.230	286
swirl	46.510	17.890	253

Display pattern differences were statistically significant at the conventional 0.05 level ($F = 2.572$, $p = 0.036$). Abstract patterns produced the highest mean AEI, while swirl and wave patterns were lower in the analyzed source.

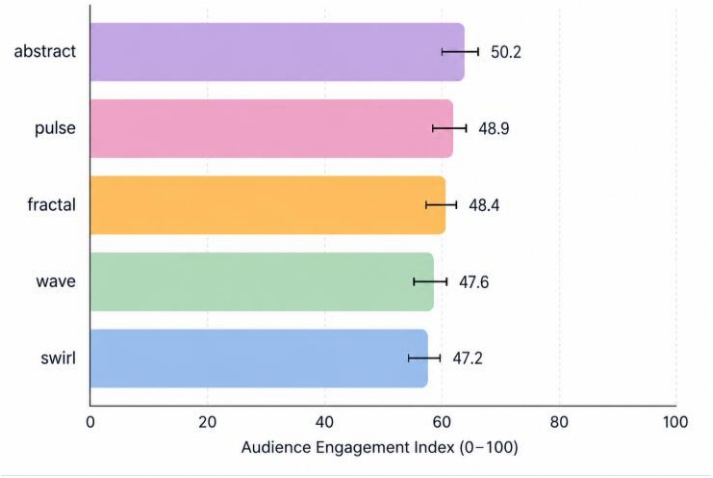


FIGURE 4. Mean Audience Engagement Index by display pattern.

The figure shows group-level engagement differences and supports the interpretation that visual form relates to engagement when it contributes to coherence and clarity.

Table 5. Audience Engagement Index by light color.

Light color	Mean AEI	SD	N
red	50.440	17.290	325
white	48.280	17.910	262
blue	47.860	16.540	257
green	47.440	18.230	286
dynamic	46.410	16.170	270

Light-color differences approached but did not reach the conventional 0.05 threshold, $F = 2.254$, $p = 0.061$. This suggests that color may influence engagement, but its effect is weaker than movement intensity, crowd density, and visual pattern features.

3. PREDICTIVE MODELING OF ENGAGEMENT

Table 6. Predictive performance of engagement models.

Model	Test R2	MAE	RMSE	CV R2 mean	CV R2 SD
Linear regression	0.939	3.425	4.255	0.934	0.007
Ridge regression	0.939	3.424	4.255	0.934	0.007
Random forest	0.902	4.209	5.398	0.900	0.009

Linear and ridge regression produced the strongest test performance in the analyzed material, while random forest showed a slightly lower but still strong result. The high predictive values indicate that the constructed engagement index is strongly structured by the available interaction and design variables.

Table 7. Main standardized regression predictors of AEI.

Predictor	Std. beta	p-value
movement_intensity	0.753	<0.001
crowd_density	0.555	<0.001
pattern_coherence	0.174	<0.001
visual_complexity	0.170	<0.001
color_diversity	0.152	<0.001
light_color_green	-0.045	0.039
display_pattern_swirl	-0.041	0.064
display_pattern_wave	-0.035	0.102
light_color_white	-0.029	0.199
light_color_dynamic	-0.028	0.211

Movement intensity and crowd density are the strongest standardized predictors of engagement. Visual complexity, color diversity, and pattern coherence are also meaningful, confirming that engagement is shaped by both embodied participation and aesthetic-interface structure.

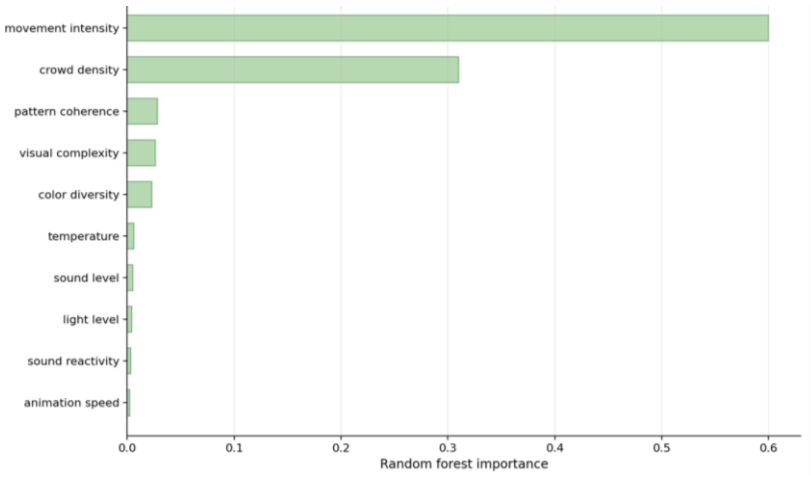


FIGURE 5. Random-forest feature importance for engagement prediction.

The non-linear model confirms the regression pattern: movement intensity and crowd density dominate prediction, while visual coherence variables provide additional explanatory value.

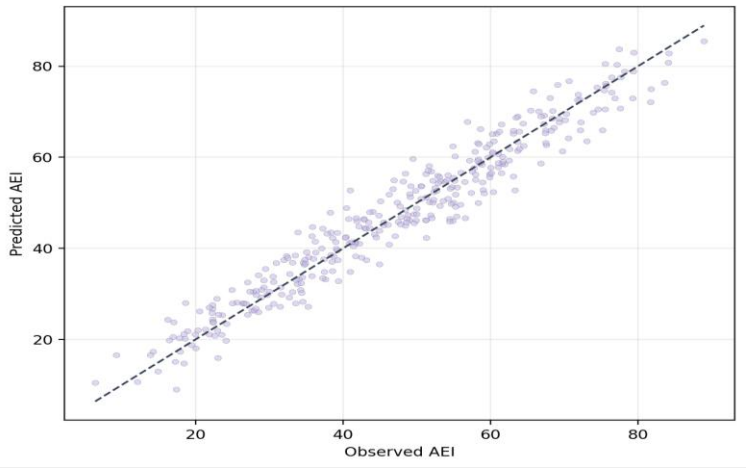


FIGURE 6. Observed and predicted Audience Engagement Index values.

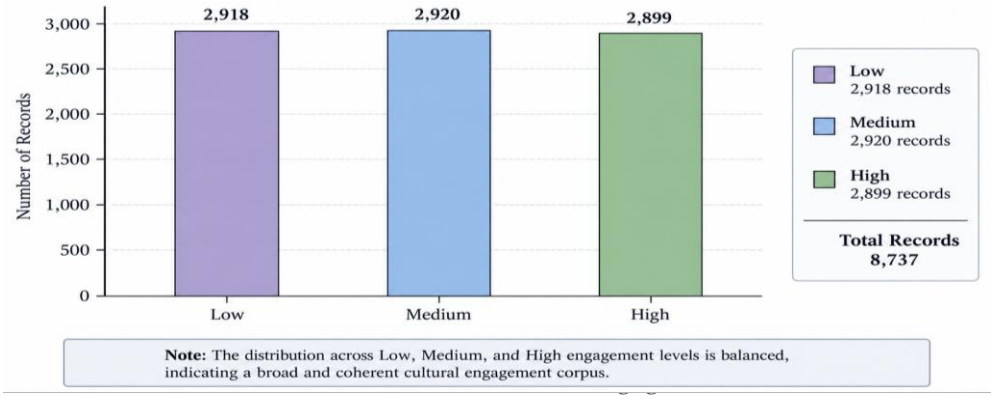
The scatterplot shows that the ridge model estimates observed engagement values with relatively small prediction error, supporting the usefulness of the engagement-index approach for applied evaluation.

4. SUPPLEMENTARY CULTURAL AND PERFORMANCE-CONTEXT RESULTS

Table 8. Supplementary cultural engagement indicators.

Engagement level	Participation freq. mean	Social interaction mean	Recommendation score mean	Duration hours mean	N
High	10.418	5.514	0.552	10.668	2899
Low	10.387	5.561	0.553	10.412	2918
Medium	10.405	5.527	0.553	11.361	2920

The cultural engagement records are balanced across low, medium, and high categories. The association between event type and engagement level was not statistically significant ($\chi^2 = 10.706$, $p = 0.219$). Therefore, these records are better used as contextual support rather than as a direct performance-interaction model.



The cultural engagement records remind us that engagement categories can be measured, but they lack the HCI-specific interaction features needed for digital performance modeling.

Table 9. Broadway attendance context by show type.

Show type	Mean attendance	Mean capacity (%)	Mean gross	Mean performances	N
Musical	9,130.85	83.470	700,312.19	7.560	22551
Play	5,122.09	73.570	325,717.98	6.410	8406
Special	5,106.70	76.880	365,321.94	5.060	339

Broadway attendance records are valuable for understanding attendance performance and capacity, but they do not measure interface use, interactive response, or audience agency. We therefore excluded them from the engagement-prediction model.

VI. DISCUSSION

In the analyzed interactive material, movement intensity is the strongest predictor of engagement, which suggests that embodied participation is a key mechanism in digital performance. This aligns with HCI theories of embodied interaction, where meaning emerges through bodily action, spatial relation, and system response rather than through passive observation.

Crowd density also emerges as a major predictor. This does not mean that more people always produce better engagement. Instead, it suggests designing digital performance for collective interaction. Audience members often interpret their own participation through others' behavior. When a system responds to collective movement or group presence, participants may feel that the event is socially shared. This has important implications for interactive theatre, museum installations, festival performances, and immersive public art.

The visual-design variables also matter. Pattern coherence, visual complexity, and color diversity explain a significant portion of the variance. This result matters because it avoids the simplistic view that more complexity automatically produces stronger engagement. Instead, the findings suggest that complexity must remain coherent. In performance terms, the audience should perceive that visual change is connected to interaction and artistic purpose. If complexity is disconnected from action, it may become decorative noise rather than engagement support.

The categorical results show that display pattern is statistically significantly related to engagement, while light color alone has a weaker effect. This supports a design interpretation: structural media behavior is more important than isolated aesthetic choices. A color palette may affect mood, but how visual patterns respond to audience action matters more for HCI-based engagement. Therefore, digital performance design should prioritize interaction logic, feedback clarity, and expressive coherence over purely ornamental technical effects.

The supplementary empirical sources reinforce the methodological argument. Cultural engagement records provide useful categories and behavioral indicators, but they do not directly measure performance interaction. Broadway attendance records describe scale, attendance, and revenue, but they cannot explain whether spectators were interactively engaged. This distinction is crucial for future research. A digital performance study should not treat attendance, recommendation, or participation frequency as sufficient evidence of HCI engagement unless the evidence also includes interaction quality, interface response, attention, agency, or satisfaction.

Future research should strengthen this design through live audience evaluation. A strong follow-up study could combine sensor logs, observation checklists, short user-engagement surveys, and post-performance interviews. It could also compare two versions of the same performance: one with passive digital media and another with audience-responsive interaction. Such a design would allow stronger causal claims about the effect of HCI design on audience engagement.

VII. DESIGN IMPLICATIONS

Table 10. Practical design implications for digital performance.

Implication	Practical meaning
Design for embodied action	Use motion, proximity, gesture, or spatial behavior as meaningful input rather than background detection.
Make feedback immediate	Audience action should produce visible, audible, or spatial response quickly enough to be understood.
Balance complexity and coherence	Visual richness should remain interpretable and connected to narrative or performative purpose.
Support collective participation	Interactive systems should let group behavior shape the performance environment.
Measure engagement multidimensionally	Combine attention, interaction, satisfaction, and reward instead of relying only on attendance or applause.
Preserve artistic meaning	Technology should serve the performance structure and not become an unrelated technical demonstration.

The implications translate statistical findings into actionable recommendations for artists, designers, HCI researchers, and cultural institutions.

VIII. CONCLUSION

This paper examined how human-computer interaction can strengthen audience engagement in digital performance by connecting interaction design, measurable audience response, and artistic meaning. The study argued that technology becomes valuable in performance only when it supports agency, feedback clarity, embodied participation, and coherent interpretation. Digital tools such as sensors, responsive projection, adaptive sound, mobile interfaces, and spatial media should therefore be evaluated not only as technical devices, but as communicative structures that shape how audiences attend, act, feel, and participate.

The empirical analysis confirmed that engagement is strongly associated with embodied and interface-related variables. Movement intensity and crowd density were the strongest predictors of the Audience Engagement Index, showing that digital performance benefits when audiences can act physically and when collective presence becomes part of the event. Pattern coherence, visual complexity, and color diversity also contributed to engagement, indicating that visual richness works best when it remains organized and interpretable. The predictive models further showed that attention, interaction count, satisfaction, and reward can be combined into a useful engagement index for applied evaluation.

The study also clarified an important methodological distinction. Cultural participation and attendance records provide valuable contextual evidence, but they cannot replace direct measures of interaction quality. A full evaluation of digital performance should include variables related to audience agency, interface response, usability, affective involvement, and perceived meaning. The proposed framework and index therefore offer a practical foundation for artists, HCI researchers, museums, theatres, and cultural institutions seeking to design participatory experiences that are both technologically sophisticated and human-centered. Future research should strengthen this framework through live audience studies, sensor-based observation, post-performance interviews, and comparative testing of passive and responsive performance designs.

Author Contributions

The author conducted the conceptualization, methodology, data analysis, investigation, writing, review, editing, and final approval of the manuscript.

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Data Availability

The dataset will be available from the author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

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