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Navigating Psychological Boundaries: A Boundary-Aware Interaction Policy for Adaptive Service Robots in Exhibitions

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ABSTRACT

While service robots in exhibition spaces are evolving into social agents that mediate visitor experiences beyond mere information delivery, the service paradox remains a persistent challenge where unsolicited proactive interventions diminish visitor satisfaction. This study proposes the concept of psychological boundaries as a regulatory mechanism for visitors' openness to robotic intervention and develops a boundary-aware interaction policy. Empirical analysis of 164 visitors revealed that service preferences are structured into three latent dimensions: proactive support, adaptive responsiveness, and autonomy-oriented minimal service. Furthermore, the study identifies that hedonic and epistemic visit motivations are key determinants of the permeability of these psychological boundaries. Based on these findings, we established a cost-sensitive decision model optimized for the asymmetric social costs of misclassification. The results demonstrate the efficacy of this policy in accurately classifying visitor types at an early stage and selecting appropriate service intensities with high accuracy. This research suggests that robotic intelligence resides not merely in increasing service quantity but in situational restraint, which involves determining when to withhold intervention to respect visitor autonomy, thereby providing a novel framework for the design of non-intrusive service robots.

Introduction

Service robots play an increasingly diverse role in exhibition spaces by providing guidance, interpretive assistance, and support for safety and convenience¹. As such systems are more widely adopted in museums and exhibitions, robots are no longer limited to delivering functional information but are increasingly positioned as socially interactive agents that actively mediate the visitor experience^{2,3}. However, proactive robot involvement is not consistently nor uniformly welcomed by all visitors⁴. In some cases, a service paradox emerges, whereby the presence of robots hinders rather than enhances visitor satisfaction⁵. This service paradox refers to situations in which increased service provision leads to reduced satisfaction because the manner, timing, or contextual fit of the intervention conflicts with visitors' expectations. Crucially, visitors may interpret identical robot behaviors in qualitatively divergent ways: as supportive facilitation that enhances exploration or as intrusive control that violates experiential autonomy. This qualitative divergence in interpretation suggests that service paradoxes in exhibition contexts are not merely a matter of degree, but of fundamentally different modes of service perception.

This paradox is particularly salient in exhibition contexts. Unlike task-oriented service environments, exhibitions are characterized by voluntary participation, open-ended exploration, and heterogeneous visitor goals. Visitors retain strong autonomy over pacing, attention, and social engagement, which makes them especially sensitive to unwanted or ill-timed interventions⁶. As a result, robotic services that are experienced as interruptions, attentional overload, or unwanted social presence may undermine rather than support the exhibition experience. Nevertheless, many exhibition robots continue to rely on standardized interaction scripts that implicitly assume visitors to be homogeneous users, thereby amplifying the risk of service paradoxes when such assumptions fail to hold.

Existing research in HRI has extensively examined how robots' social and emotional cues influence user experience, trust, and acceptance⁷⁻⁹. Prior studies demonstrate that anthropomorphic behaviors, affective expressions, and proactive communication can positively shape user perceptions in various service contexts. However, much of this work implicitly assumes that increasing the amount or richness of service leads to improved outcomes^{10,11}. Such approaches tend to emphasize service quantity or feature matching, while paying comparatively less attention to the temporal and contextual congruence between users' psychological states and robots' intervention strategies. Empirical research that explicitly examines how heterogeneous users regulate their openness to robotic intervention remains limited, particularly in exhibition environments^{12,13}.

In exhibition contexts, visitors are generally motivated by a combination of hedonic and epistemic goals, seeking enjoyment as well as knowledge acquisition¹⁴. Importantly, these motivations do not directly determine service preferences. Instead, they shape how visitors conceptualize the robot's role within the exhibition environment. For some visitors, enjoyment is associated with social engagement and emotional stimulation, leading them to perceive robots as social companions that may enrich the experience¹⁵. For others, however, hedonic enjoyment is grounded in uninterrupted, low-effort immersion, in which robotic intervention—especially when cognitively demanding—may undermine rather than support the experience. For others, enjoyment is grounded in uninterrupted, self-directed exploration, and robotic intervention may be perceived as competing with immersion rather than enhancing it. These differences in role attribution influence how visitors regulate their openness toward robot services.

Building on prior work in service design and behavioral change^{16,17}, this study conceptualizes psychological boundaries as regulatory processes through which visitors continuously calibrate their desired level of openness toward robots while maintaining control over their exhibition experience. Importantly, expectations regarding robots' higher-order social flexibility and human-like situational responsiveness remain exploratory; visitors may lack stable psychological schemas for interpreting such advanced forms of robotic adaptability, resulting in ambivalent or inconsistent evaluations¹⁸. In this context, psychological boundaries encompass multiple experiential constraints, including perceived autonomy, cognitive load, social distance, experiential flow, and cognitive autonomy—that is, the desire to minimize the depth and complexity of robotic intervention rather than merely maintaining physical distance. This notion of cognitive autonomy later corresponds to the autonomy-oriented minimal service preference identified in the results. When robotic interventions violate these boundaries, they may trigger psychological resistance, resulting in service rejection rather than acceptance^{19,20}.

From this perspective, acceptance or rejection of exhibition robot services is not a static attitudinal judgment but a dynamic process of psychological boundary regulation^{21,22}. Visitors adjust their boundaries depending on their motivations, engagement states, and situational expectations. As a result, identical robotic behaviors may be perceived by some visitors as supportive facilitation, while others interpret them as intrusive control. This boundary-sensitive interpretation explains why a simple more service is better logic fails to account for visitor responses to exhibition robots.

Based on this theoretical background, the present study addresses the following research questions: RQ1. What types of interventions and support do exhibition visitors expect from robot services?, RQ2. Do the identified visitor groups differ merely in the amount of service they prefer, or in the qualitative orientation of preferred services, such as proactive intervention versus minimal support?, and RQ3. Do visit motivations influence service preferences directly, or indirectly through the formation of psychological boundaries that regulate openness to proactive robot intervention?

To address these questions, this study first identifies the core preference dimensions underlying visitors' expectations of robotic services by reducing the dimensionality of multi-item service expectation measures. Service preference is defined as a structured set of expectations that visitors evaluate as desirable, and exhibition robot design is framed as a problem of aligning service strategies with these preference dimensions. Based on the derived dimensions, visitors are classified into psychological segments, and systematic differences are examined not only in the quantity of service they prefer, but in the qualitative orientation of that preference—ranging from proactive intervention to deliberately minimal support—along with associated visit motivations and boundary-regulation tendencies.

Finally, this study advances a boundary-sensitive perspective on adaptive robot services that explicitly accounts for asymmetric misclassification costs. Rather than equating personalization with increased intervention intensity, adaptive exhibition robots are conceptualized as decision-making agents that must balance action and restraint. In environments that privilege autonomy and voluntary engagement, withholding, delaying, or minimizing intervention constitutes a legitimate—and sometimes optimal—service strategy. By formalizing exhibition robot services as processes of adaptive boundary management, this study provides a foundation for designing personalized yet non-intrusive interaction protocols that align visitor motivations, psychological boundaries, and service preferences. In particular, this perspective recognizes that intervening when visitors prefer autonomy may be more detrimental to exhibition experience than failing to intervene when support is potentially desired, thereby justifying conservative intervention strategies as a principled design choice.

Results

Dimensional Structure of Service Preferences for Exhibition Robots

In this study, Principal Component Analysis (PCA) was conducted to identify the service-preference structure of exhibition attendees. Prior to the analysis, the suitability of the data was assessed, revealing a Kaiser-Meyer-Olkin (KMO) sample adequacy index of 0.853. Additionally, the results of Bartlett's test of sphericity indicated an approximate χ^2 value of 1156.08 ($df = 190$, $p < .001$), confirming that the data possessed a suitable correlation structure for dimensionality reduction analysis.

Factor extraction aims to succinctly summarize the covariance of multiple items into a manageable number of interpretable dimensions (data reduction). This study employed Principal Component Analysis (PCA), which is based on the total variance of the data. To enhance the independence and interpretability among the factors (components), the Varimax orthogonal rotation

Table 1. Principal Component Analysis (PCA) of Service Preference Dimensions ($N = 164$)

Factor / Dimension	Item Description	Loading	Var (%)	Cronbach's α
Factor 1: Proactive Support & Intervention	Proactively inquiring if help is needed	0.716	23.95	0.78
	Proactively announcing events/services	0.700		
	Adding entertaining elements to explanations	0.719		
Factor 2: Adaptive Responsiveness	Expressing own thoughts/opinions	0.707	16.19	0.61
	Attempting to persuade through dialogue	0.672		
	Flexible handling via supplementary info	0.718		
Factor 3: Autonomy-Oriented Minimal Service	Providing guidance only upon request	0.774	19.06	0.69
	Allowing visitors to proceed independently	0.792		
	Providing only the location of facilities	0.605		
Total Cumulative Variance Explained			59.20%	

method was applied. By considering the Kaiser criterion of eigenvalues greater than 1.0 and the scree plot together, we ultimately identified three key components (principal components) that balance academic stability and explanatory power. This decision was supported by the pattern observed in the scree plot, where the slope change (elbow) becomes gradual after the third component. It is worth noting that PCA is fundamentally a variance-summarization technique, and the precise estimation of latent factors can be more directly addressed within the framework of exploratory factor analysis (EFA) based on common factors. Therefore, this study interprets the PCA results as an exploratory summary of service preference dimensions, and it also includes the results of common factor estimation for the same data (e.g., PAF or ML-based EFA) in the appendix to assess the robustness of the interpretation.

The structure of these three components accounts for 59.20% of the total variance, indicating that audience service expectations can be summarized and organized into three key dimensions. A cutoff criterion of $|0.40|$ for factor loadings was applied; items identified as social facilitation and safety/convenience, when treated as single items, were excluded but preserved as independent indicators.

Factor 1 (Proactive Support and Intervention) explained 23.95% of the total variance, with a reliability coefficient of Cronbach's $\alpha = .78$. Items loaded onto this factor included “proactively inquiring if assistance is needed” (0.72), “announcing and managing upcoming events in advance” (0.70), and “providing explanations with engaging or entertaining elements” (0.72). These results align with expectations for proactive agency, in which the robot proactively approaches visitors to provide both emotional support and information.

Factor 2 (Adaptive Responsiveness) accounted for 16.19% of the total variance, showing a reliability of Cronbach's $\alpha = .61$. This dimension comprised items such as “expressing its own thoughts or opinions” (0.71), “attempting to persuade through dialogue” (0.67), and “handling situations flexibly through supplementary explanations” (0.72). This represents a psychological dimension in which users expect the robot to exhibit human-like flexibility and to provide contextual interventions beyond pre-programmed responses.

Factor 3 (Autonomy-Oriented Minimal Service) explained 19.06% of the total variance, with a Cronbach's $\alpha = .69$. Loading items included “providing guidance only when summoned” (0.77), “allowing visitors to proceed independently” (0.79), and “providing only the location of facilities” (0.61). This factor represents a desire for autonomy, emphasizing minimal robot intervention to maintain an independent viewing environment. Notably, items such as “facility location guidance” imply a preference for functional minimization rather than absolute non-intervention; thus, this factor was interpreted as a dimension of autonomy-oriented minimal service.

Although additional factors (Factors 4–6) were identified based on an eigenvalue criterion of 1.0 or higher, they were excluded because they consisted of single items, which would make it difficult to ensure reliability and could undermine the interpretability of the overall model. To maintain academic rigor and strategic clarity for service development, this study finalized a three-factor model. Significant variables among the excluded items were retained as independent indicators for subsequent analyses.

Psychological Segmentation Based on Service Preference Profiles

To segment the market by visitors' psychological characteristics and service preferences, a K -means clustering analysis was conducted. After entering the three factor scores and key usage behavior variables, the Elbow method and Silhouette coefficient were used to evaluate the clustering results, confirming that a two-cluster model provided the most stable and optimal structure. For consistency of interpretation, Cluster 1 is defined as the “Active-Experiential” group, and Cluster 0 as the

“Passive-Observational” group.

Table 2. Comparison of Service Preferences and Motivations between Clusters ($N = 164$)

Variable	Cluster 1 (Active) ($n = 107$)	Cluster 0 (Passive) ($n = 57$)	p -value
<i>Service Preference Factors</i>			
Factor 1: Proactive Support	0.25	-0.47	< .001***
Factor 2: Adaptive Responsiveness	0.20	-0.38	< .001***
Factor 3: Autonomy-Oriented	-0.47	0.88	< .001***
<i>Visit Motivations</i>			
Hedonic Motivation	5.39	3.53	< .001***
Epistemic Motivation	5.34	3.58	< .001***
Social Motivation	4.75	3.85	< .01**
<i>Interaction Expectations</i>			
Professional Knowledge	6.10	4.52	< .001***
Empathetic Attitude	6.16	4.47	< .001***

Note: * $p < .05$, ** $p < .01$, *** $p < .001$ based on Mann-Whitney U test.

Cluster 1 accounts for 65.2% ($N = 107$) of respondents and is characterized by high levels of both visit motivation and acceptance of robot service interventions. This group exhibited high levels of hedonic motivation ($M = 5.39$) and epistemic motivation ($M = 5.34$), as well as relatively strong social motivation ($M = 4.75$). Regarding service preferences, Cluster 1 recorded positive (+) scores for both Factor 1 (Proactive Support and Intervention, $M = 0.25$) and Factor 2 (Adaptive Responsiveness, $M = 0.20$). Conversely, their preference for Factor 3 (Autonomy-Oriented Minimal Service, $M = -0.47$), which emphasizes independent viewing with minimal robot interference, was relatively low. These traits identify Cluster 1 as an interaction-oriented group that perceives proactive guidance and personalized intervention as core service values, and that highly prioritizes professional information delivery ($M = 6.10$) and empathetic service attitudes ($M = 6.16$).

Cluster 0 represents 34.8% ($N = 57$) of the sample and demonstrates a clear preference for independent viewing experiences with minimal external intervention. Compared to Cluster 1, this group showed significantly lower levels of hedonic ($M = 3.53$) and epistemic ($M = 3.58$) motivations, indicating a general tendency toward lower visit motivation and activity levels. Service preference analysis revealed that Cluster 0 responded negatively to proactive robot intervention, as evidenced by negative scores for Factor 1 ($M = -0.47$) and Factor 2 ($M = -0.38$). In contrast, they exhibited a strong preference for Factor 3 ($M = 0.88$), expecting robots to provide only essential functions rather than engage in direct intervention. These results suggest that Cluster 0 is likely to perceive a robot's proactive approach as disrupting their viewing flow; thus, they are an autonomy-oriented group that prioritizes maintaining psychological and physical distance.

Disparities in Service Preferences and Visit Motivations Across Visitor Segments

To verify whether the two identified clusters—Active-Experiential ($N = 110$) and Passive-Observational ($N = 54$)—exhibit statistically significant differences in terms of psychological characteristics and service preferences, a non-parametric Mann-Whitney U test was conducted. The analysis revealed a significant psychological disparity between the two groups across major service latent factors, visit motivations, and overall interaction expectations.

First, an analysis of the three factors representing service requirements showed that Cluster 1 (Active-Experiential) exhibited significantly higher preferences across all service-intervention factors than Cluster 0 (Passive-Observational). In particular, for Factor 1 (Proactive Support and Intervention), the mean score for Cluster 1 (0.39) was significantly higher than that of Cluster 0 (-0.79) ($U = 915.0$, $p < .001$). This difference represents a large effect size ($r = .56$, Cliff's $\delta = -0.69$), suggesting that active-experiential visitors perceive proactive guidance and support not merely as a matter of personal preference, but as a qualitatively distinct dimension of the service experience.

A significant difference was also observed in Factor 3 (Autonomy-Oriented Minimal Service), which balances independent viewing with the availability of guidance when necessary. Cluster 1 recorded an average of 0.22, whereas Cluster 0 recorded -0.45 , a difference that was statistically significant ($U = 1718.0$, $p < .001$). The effect size was also above a medium level ($r = .34$, Cliff's $\delta = -0.42$), indicating that active-experiential visitors maintain a more open stance toward service interactions in general compared to their passive-observational counterparts.

The primary reasons for the visit also differed markedly between the two clusters. Hedonic motivation ($M = 5.37$ vs. 3.46) and epistemic motivation ($M = 5.34$ vs. 3.48) were both overwhelmingly higher in Cluster 1 ($p < .001$). Social motivation

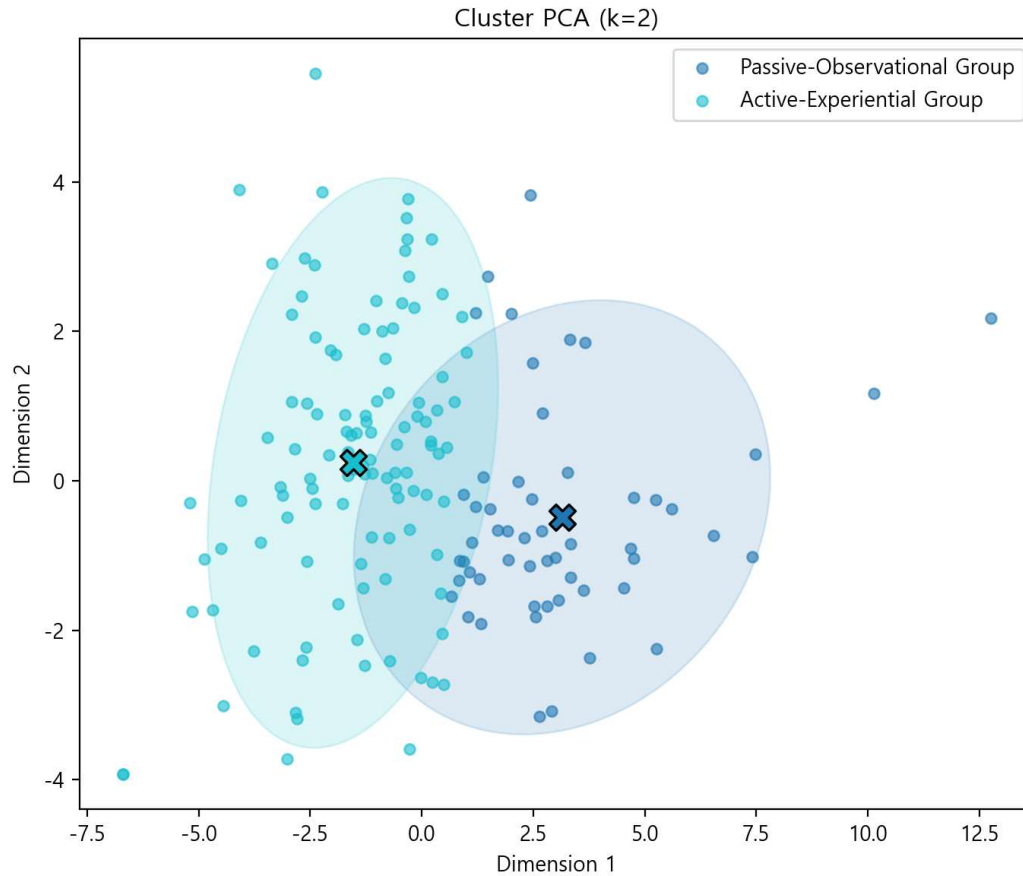


Figure 1. Scatter plot of visitor segmentation based on the first two principal components. The clusters represent the Active-Experiential group (Cluster 1) and the Passive-Observational group (Cluster 0), with 95% confidence ellipses indicating distinct psychological boundaries.

($M = 4.75$ vs. 3.85) also differed significantly, reinforcing Cluster 1's profile as goal-oriented and active visitors. Furthermore, in terms of interaction expectations, Cluster 1 assigned significantly higher scores than Cluster 0 for all items, including the robot's anticipation of their needs ($M = 5.68$), the delivery of professional knowledge ($M = 6.12$), and a kind response attitude ($M = 6.11$). In contrast, Cluster 0 remained below average across all items, maintaining a relatively reserved stance toward interaction with the robot.

The Psychological Mechanism Linking Motivations to Robot Acceptance

To examine the psychological pathways through which visitors' intrinsic motivations translate into service preferences, this study analyzed the explanatory pathways between primary visit motivations and service preference factors. We compared multiple mediation models involving hedonic and epistemic motivations across the three identified service preference factors. Preliminary analysis indicated that social motivation exhibited a weak psychological transition effect toward robots, owing to its inherent focus on human-to-human interaction. Additionally, the pathway in which epistemic motivation influences Factor 2 (Adaptive Responsiveness) (Model A) failed to achieve statistical significance, as the confidence interval for the indirect effect included zero ($ab = 0.022$, 95% $CI [-0.014, 0.065]$). Consequently, this section focuses on Model B, which demonstrated the most robust explanatory power: the pathway in which hedonic motivation (X) influences support service preference (Y) via the mediation of proactive support needs (Factor 1, M).

The analysis confirmed a significant explanatory mechanism linking psychological motivations to service needs. Specifically, hedonic motivation—the pursuit of enjoyment and emotional fulfillment—significantly predicted the need for proactive support, reflecting expectations for empathetic interaction from the robot ($a = 0.406$, $p < .001$). This suggests that visitors who prioritize hedonic experiences are more likely to seek proactive, emotionally engaging interventions from robots beyond simple information provision. This need for proactive support, in turn, significantly increased the preference for support services

Table 3. Differences in Latent Factors and Key Preferences between Visitor Clusters

Variable	Active-Exp. (n = 110)	Passive-Obs. (n = 54)	U / Z	p-value	Effect (r)
<i>Latent Factor Scores</i>					
Factor 1: Proactive Support	0.39	-0.79	-7.19	< .001***	0.56 (L)
Factor 2: Adaptive Resp.	0.04	-0.09	-1.65	.099	0.13 (S)
Factor 3: Autonomy-Oriented	0.22	-0.45	-4.38	< .001***	0.34 (M)
<i>Visit Motivations</i>					
Hedonic Motivation	5.37	3.46	-	< .001***	-
Epistemic Motivation	5.34	3.48	-	< .001***	-
<i>Service Expectations</i>					
Exhibition Quality	5.99	4.13	-	< .001***	-
Staff Knowledge	6.12	4.15	-	< .001***	-
Empathetic Attitude	5.68	3.98	-	< .001***	-

Note: * $p < .05$, *** $p < .001$. Effect size (r) interpreted as Small (S), Medium (M), and Large (L).

Table 4. Results of Mediation Analysis (PROCESS Macro Model 4)

Model	Path	Coeff.	SE	t	Indirect Effect		
					Effect	BootLLCI	BootULCI
Model B (Significant)	Hedonic → Factor 1 (a)	0.406	-	-			
	Factor 1 → Preference (b)	0.364	-	-	0.148	0.061	0.252
	Direct Effect (c')	0.406	-	-			
Model A (Non-Sig.)	Epistemic → Factor 2 (a)	0.241	-	-			
	Factor 2 → Preference (b)	0.090	-	-	0.022	-0.014	0.065
	Direct Effect (c')	0.453	-	-			

Note: Factor 1 = Proactive Support, Factor 2 = Adaptive Responsiveness. Confidence intervals based on 5,000 bootstrap samples.

($b = 0.364$, $p < .001$).

The indirect effect, estimated via 5,000 bootstrap resamples, was 0.148, with a 95% confidence interval (CI) of [0.061, 0.252], indicating statistical significance as the interval excludes zero. Moreover, the direct effect remained significant ($c' = 0.406$, $p < .05$), indicating that the need for proactive support partially mediates the relationship between hedonic motivation and support service preference. This implies that while hedonic motivation directly influences service preference, its effect is further reinforced through expectations of proactive and emotional robot intervention, supporting the premise that the acceptance of exhibition robot services is structured around emotional interaction.

To verify the validity of this explanatory pathway, alternative models were analyzed; however, none reached statistical significance because their confidence intervals for the indirect effects included zero. This confirms that Model B is the most consistently supported explanatory pathway within the data. To address potential common method bias (CMB), Harman's single-factor test was conducted. The variance explained by the first unrotated factor was 31.54%, indicating that no single factor accounted for the majority of the variance. Meanwhile, interest in knowledge acquisition (e.g., prior media engagement), identified as a key variable in the prediction model, was found to be a distinct concept from hedonic motivation; it is interpreted as an initial marker variable reflecting the visitor's overall involvement level. Conversely, the preference for a communicative atmosphere was directly linked to the need for proactive support, consistent with the psychological mechanisms identified earlier.

Predictive Modeling for Early Classification of Visitor Types Using Minimal Inputs

In the final stage of this study, predictive modeling was performed to assess the feasibility of early estimation of visitor service preference types using minimal survey inputs collected during brief initial interactions with an intelligent exhibition robot. To ensure model stability and reproducibility, stratified 5-fold cross-validation was employed, accounting for the dataset's class distribution.

The total sample of 164 visitors consisted of 110 Active-Experiential visitors (67.1%) and 54 Passive-Observational visitors

Table 5. Top 10 Feature Importance for Predicting Visitor Segments

Rank	Variable (Feature)	Importance Score
1	Solo Visit Preference	0.071
2	Factor 1: Proactive Support Needs	0.063
3	Interest in History	0.057
4	Preference for Exhibit Labels	0.055
5	Factor 2: Adaptive Responsiveness	0.054
6	Preference for New Exhibits	0.053
7	Hedonic Motivation	0.051
8	Pref: Quiet and Contemplative Atmosphere	0.047
9	Pref: Previously Viewed Exhibits	0.047
10	Pref: Any Exhibit	0.044

Table 6. Performance Comparison of Visitor Type Prediction Models

Model	Accuracy	Weighted F1-score	Cross-Validation Std.
Logistic Regression	0.958	0.958	±0.008
Random Forest	0.896	0.889	±0.021

Note: Based on stratified 5-fold cross-validation ($N = 164$).

Table 7. Confusion Matrix and Classification Performance of the Predictive Model

		Predicted Class		Metric
		Passive-Obs. (0)	Active-Exp. (1)	
Actual Class	Passive-Obs. ($n = 54$)	50 (TN)	4 (FP)	Precision: 0.943
	Active-Exp. ($n = 110$)	3 (FN)	107 (TP)	Recall: 0.926
Overall Performance		Accuracy: 95.7%		Weighted F1: 0.957

(32.9%). Although there was a difference in proportions between the two groups, it was not considered excessively skewed. To control for potential data bias during training, a stratified sampling method was used to preserve this distribution.

The results of the logistic regression model utilizing the full set of variables showed an average accuracy of 95.8% and a weighted F1-score of 0.958. The standard deviation of performance across the 5-fold cross-validation was remarkably low (within $\pm 0.8\%$), confirming the stability of the model for in-depth analysis aimed at the precise post-hoc classification of service preference types. However, as these results are based on a sample collected within a specific exhibition context, the high classification performance should be interpreted with the caveat that further validation is required for generalization to different exhibition types or environments.

An analysis of the confusion matrix revealed that instances of misclassifying passive-observational visitors as active-experiential were less frequent than the reverse. This pattern can be interpreted as supporting a conservative operational strategy that aims to minimize unnecessary robot intervention for visitors who prefer independent, passive viewing.

Feature importance analysis identified preference for information acquisition methods—specifically a preference for “Guided tours”—and “Factor 1 (Proactive Support Needs)” as the most significant contributors to cluster discrimination. A preference for guided tours reflects a behavioral tendency to accept active explanations for knowledge acquisition. Simultaneously, the need for proactive support aligns with the psychological pathway identified in the previous mediation analysis, linking hedonic motivation to service preference. Furthermore, a preference for a communicative atmosphere was identified as a key predictor, suggesting that expectations for emotional connection with the robot are crucial in distinguishing visitor types. While these findings demonstrate the feasibility of early, high-accuracy identification of psychological response types using limited initial inputs, external validity must be further established across diverse exhibition contexts and visitor demographics.

The high importance of “Solo Visit Preference” and “Factor 1 (Proactive Support Needs)” underscores that service preference is not merely a matter of information demand, but a reflection of the visitor’s desired social distance. The predictive power of these features suggests that early cues regarding a visitor’s social orientation—such as their preference for solitary exploration or their explicit need for proactive guidance—are the most reliable predictors of their psychological boundary

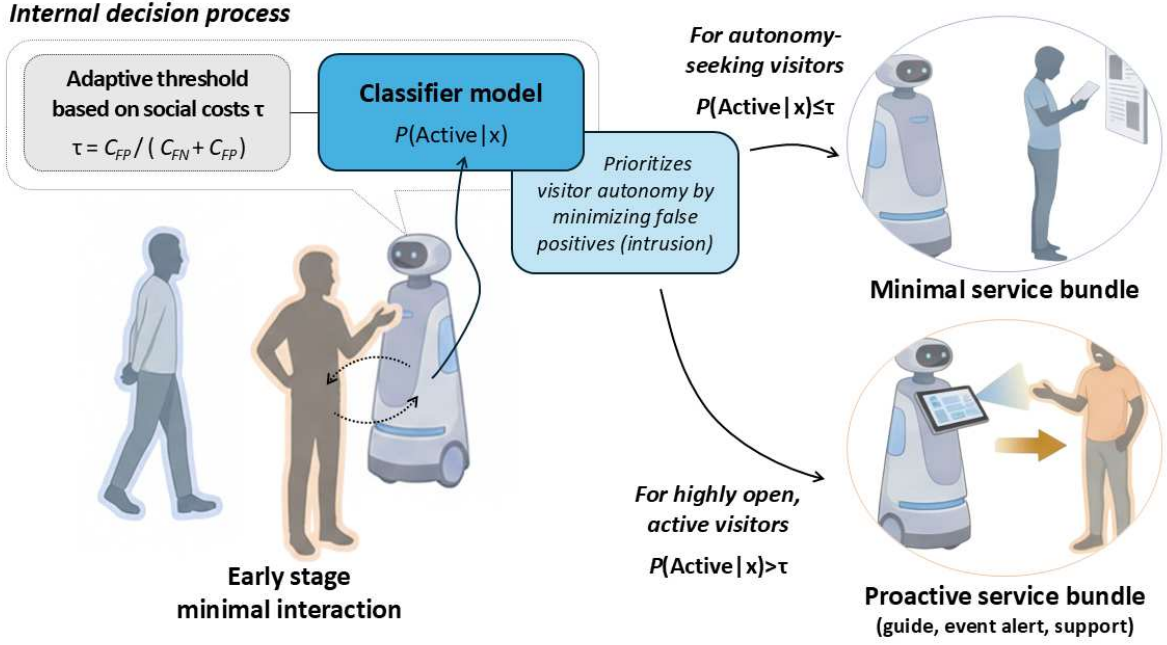


Figure 2. System architecture of the boundary-aware interaction policy. The diagram illustrates the internal decision process where the robot’s perception of visitor motivation is processed through a cost-sensitive classifier to bifurcate service modes based on the adaptive threshold τ .

permeability. This aligns with the mediation analysis, reinforcing that visitors’ hedonic and epistemic goals manifest early in their behavioral preferences, allowing the robot to calibrate its interaction intensity almost immediately upon the visitor’s entry.

Formalization of a Boundary-Aware Interaction Policy

While the predictive models demonstrated high statistical performance, the practical deployment of exhibition robots requires a robust decision-making framework to navigate the “Service Paradox”—the phenomenon where unsolicited proactive interventions lead to social friction. To address this, we translated the classification results into a formal interaction policy based on a cost-sensitive decision framework.

To prioritize visitor autonomy, the robot’s decision rule was optimized to account for the asymmetric social costs associated with misclassification. We defined the Intrusion Cost (C_{FP}), representing the social cost of disrupting a passive visitor’s experiential flow, as being significantly higher than the Opportunity Loss (C_{FN}), the cost of missing a proactive service opportunity. The optimal decision threshold (τ) was formulated as:

$$\tau = \frac{C_{FP}}{C_{FN} + C_{FP}} \quad (1)$$

By assigning a higher weight to C_{FP} ($C_{FP} > C_{FN}$), the threshold τ shifts above the default 0.5. This mathematical constraint ensures that the robot initiates proactive engagement only when the model’s confidence in the visitor’s “Active-Experiential” trait is sufficiently high, thereby minimizing the risk of unwanted intrusion.

The practical implication of this threshold adjustment can be illustrated through a scenario: If the cost of interrupting a visitor who values solitude (C_{FP}) is perceived as three times higher than the cost of missing an interaction opportunity (C_{FN}), the threshold τ becomes 0.75. In this case, even if the robot is 60% certain that a visitor might want help, it will deliberately choose to remain in the “Minimal Service Bundle” because its confidence has not reached the stringent requirement of the “Conservative Intervention Strategy.”

The resulting policy bifurcates the robot’s operational behavior into two distinct modes based on the predicted probability $P(\text{Active}|\mathbf{x})$ relative to the threshold τ , as shown in Figure 2. Specifically, when the probability exceeds the threshold ($P(\text{Active}|\mathbf{x}) > \tau$), the robot initiates the “Proactive Service Bundle.” In this mode, the agent adopts a high-permeability

stance, actively approaching visitors to provide interactive guides, real-time event announcements, and emotional support. This proactive engagement is specifically designed for visitors whose underlying motivations—such as hedonic or epistemic goals—manifest as a high psychological openness to social intervention.

Conversely, when the predicted probability falls at or below the threshold ($P(\text{Active}|\mathbf{x}) \leq \tau$), the robot operates within the “Minimal Service Bundle.” In this mode, the robot maintains a respectful distance to prioritize the visitor’s autonomy and the continuity of their experiential flow. Service delivery is strictly limited to on-demand information, such as facility maps or independent exploration support, thereby ensuring that the robot functions as a non-intrusive observer that respects the visitor’s established psychological boundaries.

The effectiveness of this policy is empirically supported by the confusion matrix analysis (Table 7). The model achieved a remarkably high precision of 94.3% for the “Passive-Observational” group. This signifies that in nearly all instances where the robot predicted a visitor’s preference for autonomy, it correctly withheld proactive intervention. Such a low False Positive rate demonstrates that the proposed mathematical framework successfully operationalizes a “Conservative Intervention Strategy,” allowing the robot to function as a boundary-aware coordinator that balances helpfulness with non-intrusiveness.

Discussion

The three-factor structure of service preferences—Proactive Support, Adaptive Responsiveness, and Autonomy—elucidated in this study illustrates the psychological boundary regulation mechanisms at work when visitors interact with robots as social entities. This aligns with the boundary mechanism framework proposed by²³. Specifically, Factor 3 (Autonomy) can be interpreted as an expression of territorial boundaries, aimed at protecting one’s psychological and spatial domain by minimizing robot intervention. In contrast, Factor 1 (Proactive Support) reflects a willingness to adjust interaction boundaries by engaging emotionally with the robot. These findings support²⁴ assertion that psychologically perceived boundaries, rather than physical barriers, are the primary determinants of the nature of a relationship.

Furthermore, Factor 2 (Adaptive Responsiveness) suggests that boundary regulation is not a binary choice between opening and closing, but rather a dimension in which visitors expect the boundary’s permeability and flexibility to be adjusted according to the situational context. Scott defined personal boundaries as dynamic borders that separate the internal and external worlds, characterized by permeability (the degree of openness) and flexibility²⁵. The expectation of context-based explanations and persuasion—rather than standardized responses—reflects a psychological demand that the robot function as an interaction partner capable of fine-tuning the intensity of intervention, rather than as a rigid rule enforcer.

The Active-Experiential (Cluster 1) and Passive-Observational (Cluster 0) groups identified by cluster analysis exhibited statistically significant differences in social interaction rules and information exchange. While respecting privacy is a universal rule in interpersonal relations²⁶, the criteria for accepting rewards or control vary depending on the purpose and context of the relationship. Cluster 1 perceived proactive guidance ($M = 5.68$) as a beneficial service reward that enriches the exhibition experience, thus demonstrating a tendency to open their interaction boundaries. Conversely, Cluster 0 was more likely to experience the same intervention as a form of control or infringement on their autonomy, reacting by maintaining or closing their boundaries. The medium-to-large effect sizes indicate that these boundary regulation strategies reflect distinct psychological patterns rather than merely differences in preference.

The mediation analysis, which revealed a path from hedonic motivation to service preference via Factor 1 ($ab = 0.148, p < .01$), provides a theoretical basis for interpretation through interpersonal emotion regulation framework²⁷. Visitors with strong hedonic motivation expect the robot to serve as an interactional resource that can modulate their emotional state, rather than merely as an information provider. In this process, visitors perceive proactive support as a form of extrinsic regulation, preferring interventions that adjust emotional responses to the exhibition context. This supports Rimé’s theory that emotional sharing strengthens social cohesion and cognitive satisfaction²⁸, demonstrating that interaction with exhibition robots can function as an emotion-based mediating mechanism to achieve psychological goals.

The predictive model proposed in this study should be interpreted not merely as a tool for increasing service delivery but as a decision-support mechanism to avoid unnecessary intervention during the early stages of entry. Considering the psychological cost of boundary violations—particularly the intrinsically higher cost of misclassifying a passive visitor as active—the model serves as a conservative threshold for intervention restraint. This redefines the role of the exhibition robot from a persuasive agent to a coordinator that explores interaction possibilities while respecting the visitor’s psychological boundary state, aligning with the boundary-based interpretive framework of this study.

From a design perspective, this high-accuracy early classification supports a conservative intervention strategy. In exhibition contexts where experiential flow is paramount, the negative impact of an ill-timed intervention often outweighs the benefit of a missed service opportunity. Our results demonstrate that an AI-driven approach can effectively manage these asymmetric misclassification costs, allowing the robot to adopt a supportive yet non-intrusive stance for visitors sensitive to social overstimulation. By formalizing robot services as a process of adaptive boundary management, this study provides a foundation for designing personalized interaction protocols that align visitor motivations with their situational psychological boundaries.

Despite these contributions, this study has limitations in capturing the complex layers of social emotion regulation mentioned by Kappas²⁹, partly due to the exclusion of single-item variables. Psychological boundaries are dynamic and influenced by spatial and environmental conditions as well as individual traits. Future research should incorporate Dixon's theory of spatial boundary regulation to quantify environmental factors such as crowding, movement constraints, and stay density³⁰. Verifying how these factors influence boundary permeability and service acceptance thresholds will allow for the expansion of this boundary-based robot service model into a more sophisticated and generalizable framework.

Methods

To empirically analyze the psychological determinants of visitors' preferences for exhibition robots, an online survey was conducted with 164 participants recruited through online communities and social media platforms. Data collection was managed via Google Forms. The final sample size ($N = 164$) was deemed sufficient for performing multivariate analysis and machine learning modeling. All data were anonymized in accordance with research ethics and privacy protection principles. The survey instrument comprised multidimensional items including visit motivations (hedonic, epistemic, and social), service preferences (proactive support, flexibility, and autonomy), and expectations for robot interaction. Internal consistency was verified using Cronbach's α coefficients, which yielded values of .78 for Factor 1, .61 for Factor 2, and .69 for Factor 3, demonstrating an acceptable level of reliability for an exploratory study.

All methods were carried out in accordance with relevant guidelines and regulations. The experimental protocols and all procedures involving human participants were approved by the Institutional Review Board (IRB) of the Korea Institute of Robot and Technology Convergence (KIRO-2021-IRB-03 on 29 March 2021). Informed consent was obtained from all subjects and/or their legal guardians prior to their participation in the study.

To ensure a systematic investigation of the data, a multi-stage statistical analysis pipeline was established. Initially, an exploratory factor analysis (EFA) based on Principal Component Analysis (PCA) was performed to identify the latent dimensions underlying visitor service expectations. To ensure the independence and interpretability of the identified factors, a Varimax orthogonal rotation was applied.

Following the structural analysis, psychological segmentation was conducted via K-means cluster analysis using the derived factor scores as input variables. The optimal number of clusters (k) was determined through a comprehensive review of the Elbow method and the Silhouette coefficient. To verify the disparities in psychological characteristics and service preferences between the classified visitor segments, a non-parametric Mann-Whitney U test was performed with a significance level set at $p < .05$.

To identify the psychological pathways through which visit motivations translate into service preferences, a path analysis was conducted using the PROCESS Macro (Model 4). The statistical significance of the indirect effects was assessed using 5,000 bootstrap resamples, yielding a 95% confidence interval. Finally, to evaluate the feasibility of real-time visitor classification based on initial information, predictive models—including Logistic Regression and Random Forest—were constructed. Model stability and performance were rigorously evaluated using stratified 5-fold cross-validation.

All data preprocessing and statistical analyses were performed using Python (version 3.12.0). Key libraries utilized for this study included Pandas for data handling, FactorAnalyzer for exploratory structural analysis, SciPy and Statsmodels for rigorous statistical testing and mediation analysis, and Scikit-learn for predictive modeling. To ensure computational stability and precise metric evaluation, the K-means clustering and its associated validation indices, such as Silhouette and Calinski-Harabasz scores, were implemented using optimized NumPy-based routines rather than standard library calls. Model stability and classification performance were rigorously evaluated using stratified 5-fold cross-validation, which accounted for the dataset's class distribution.

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Author contributions statement

H.Y. contributed to the methodology, investigation, visualization, project administration, and writing of the original draft. M.-G.K. served as the principal investigator, providing supervision, conceptualization, and funding acquisition. C.P. contributed to formal analysis, data curation, and validation of the statistical models. H.-N.A. contributed to the final version of the manuscript. All authors reviewed the manuscript.

Data availability

All data are available upon request.