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Designing Adaptive Human-Computer Interaction Models with AI Personalization and Mobile Gamification Elements for Pervasive Sustainable Applications

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Abstract

Most mobile interventions use static interfaces and general reward systems that lose effectiveness within weeks, while pervasive sustainable applications require long-term user engagement. This study proposes an adaptive human-computer interaction model named AHCI-PG, which embeds both context-aware interface adaptation and AI-driven personalization features in a closed feedback loop, and introduces the concept of mobile gamification. Proposes a multi-layered

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architecture: a deep engagement predictor and a contextual bandit recommender that optimize a reward function combining engagement, pro-environmental behavior, and sustainability impact by choosing interface configurations and gamification actions. The model is tested on a survey sample of 1053 respondents and traces of their engagement over a period of twelve weeks, and is compared to four baselines in terms of accuracy, precision, recall, F1-score, AUC-ROC, and RMSE. AHCI-PG has a higher accuracy of 93.4% and an F1-score of 92.4%, an AUC-ROC of 0.968, and an RMSE of 0.318, which are 6.3 and 24.5 percentage points more accurate than the best baseline, respectively. The static gamification had a retention rate of 24.9%, while the week-twelve retention was 63.8%. The results of structural equation modeling (SEMs) showed that personalization ($\beta = 0.62$), gamification ($\beta = 0.55$), and engagement ($\beta = 0.75$) were found to be significant at $p < 0.001$, with engagement intervening in the relationship between the other factors and pro-environmental behavior. An ablation study was performed where the personalization using AI was removed, which led to the highest degradation, with an 8.3-point drop in F1-score. The results will guide the design of mobile systems to meet user needs and to be sustainable.

Keywords: Adaptive Human-Computer Interaction, AI Personalization, Mobile Gamification, Pervasive Computing, Sustainable Applications, User Engagement, Pro-Environmental Behavior.

1 Introduction

Human-computer interaction (HCI) has moved beyond command-driven screens to interfaces that watch the user, guess what wants to do, and change themselves at runtime. Initial formalizations treated the problem of generating interfaces as an optimization problem that involved matching layouts to devices, tasks, preferences, and abilities and showed measurable contributions in speed, accuracy, and satisfaction. This is all the more important for ubiquitous applications, which are carried out in everyday life on private mobile devices, especially in the context of achieving sustainability objectives like using less energy, less waste, and less carbon when traveling. Persuasive technology was highlighted as one of several identified genres of mapping sustainable HCI and was found to be a heterogeneous approach with little consensus on the means of measuring success (Janson et al., 2023). A comparative study of eco-feedback technology also revealed the lack of studies that measured behavior changes in HCI, leaving the relationship between interface design and environmental outcomes to be well supported (Zhao et al., 2020; Brăileanu, 2025).

Artificial Intelligence (AI) provides the missing adaptivity. A typical definition of AI is the ability of a system to correctly interpret external data, learn from it, and use it to achieve goals by being flexible in adaptation (Troussas et al., 2025; Padman & Ladhania, 2025). This capability is known as personalization in interactive systems: the constant prediction of user state, prediction of engagement, and the determination of what to show, when, and how. The motivational layer is provided by gamification, which is the use of game design elements in non-game contexts (Lao, 2025). Empirical studies have been reviewed, and the results are overall positive, with results varying significantly depending on the context and the users of the system (Kassenkhan et al., 2026). In the field of sustainability, gamified apps and games have been used in energy reduction, transportation, air quality, waste management, and water conservation, but why some designs work better than others is not well understood (Albarrak, 2024). Data-driven methods have been widely used in different fields to identify patterns, make better decisions, and draw meaningful associations out of complex data structures (Mirdjonovna et al., 2025).

The opportunity and risk of mobile technology are multiplied. Interfaces and rewards that are left open promote novelty decay; always-on sensing, notifications, and short interactions provide just-in-time feedback. Thus, an attitude-behavior gap exists: there is a high awareness of environmental

problems, but a low level of sustained action. Previous studies focus on adaptive interface design, AI personalization, and gamification in isolation, and an integrated model that adapts the interface, personalizes the incentive, and verifies sustainable behavior in one feedback loop is under-researched.

The contribution of this study is fourfold:

- A layered adaptive HCI architecture (AHCI-PG) that integrates context sensing, interface adaptation, AI personalization, and a mobile gamification engine.
- A sustainability-aware reward formulation and a contextual bandit algorithm that jointly select interface configurations and gamification actions.
- An empirical validation on 1,053 respondents using six performance metrics, structural equation modeling with mediation analysis, and an ablation study.
- Design guidance, in the form of benefits, limitations, and best practices, for user-centered sustainable mobile systems.

The rest of the paper is organized as follows. It reviews the literature on adaptive HCI, AI personalization, and mobile gamification in Section 2. Section 3 introduces the proposed model, including the overall flow, model architecture, mathematical model, and algorithm. Section 4 presents the results and discussion on the integration benefits, challenges, and best practices. Section 5 summarizes and specifies the directions for future research.

2 Literature Survey

Adaptive Human-Computer Interaction Models

Adaptive HCI models detect, perceive, and adjust presentation, content, and/or interaction flow automatically based on user, task, and context (Rathnayake et al., 2019). Distinguished by context awareness, learning from the interaction history, run-time reconfiguration, transparent adaptation, and maintained control by the user. A unified set of 18 guidelines for human-AI interaction is suggested, which cover the expectations prior to interaction, the behavior during the interaction, error handling, and learning over time (Cheng et al., 2025). Human-centered AI, as presented in the framework of HCI's ethical alignment and human factors approach to the design of reliable, safe, and trustworthy systems, aims to be the discipline that provides that approach and ethically aligned design to human-centered AI systems.

Adaptations lead to lower cognitive load, increased task efficacy, increased accessibility, and increased satisfaction. Here are a few examples of the benefits: navigation apps change routes based on real-time traffic, fitness trackers customize daily goals based on the wearer's activity, and home-energy companions adapt the timing and context of their recommendations. In each of these cases, it is also shown that the lack of explanation and override when adapting reduces trust, leading to transparency and user control as key design features of the current paradigm.

AI Personalization in Human-Computer Interaction

The technical backbone of personalization is the class of recommender systems that is based on deep learning, which were surveyed here, and is able to model non-linear user-item interactions, as well as combine heterogeneous signals (Awasthi et al., 2025). In the context of gamified environments, he suggested a general framework for coding the users, items, and transactions of a recommender system as players, game elements, and interactions (Wu, 2025). A study of 543 participants showed that the

perceived persuasiveness of ten strategies differs between the different gamification user-types, the results being: players were attracted by competition and reward, while disruptors were discouraged by punishment and goal-setting (Méndez et al., 2023).

There are three ways that user data is gathered. Explicit channels include onboarding questionnaires and preference settings. Interactions are logged, sessions are timed, and sensor streams are created, which are all implicit channels. Location and time, weather, and device state are examples of contextual channels. Analysis usually relies on profile clustering, sequence models for engagement prediction, and bandit or reinforcement learning for action selection, all under the informed consent and data-minimization principles. Common applications include personalized recommendations in streaming services, personalized e-commerce suggestions, adaptive learning apps, and coaching on health and wellness apps.

Mobile Gamification in Human-Computer Interaction

Gamification is a way to make things more fun and relate more to the rewards available through mechanisms like points, badges, levels, leaderboards, quests, and streaks that create dynamics of progress, competition, and cooperation. The study then discussed gamification research as the study of motivational information systems and mapped its most studied domains and design elements (Chen & Zhang, 2026). Social factors and hedonic attitude were pointed out as factors that could be used to explain the continuation of using gamification services (Xiao et al., 2022). That particular game element fulfills different psychological needs, and element-level rather than blanket design is supported in an experimental study (Zamani et al., 2025). Suggested that the field is evolving from considering the question that is "Does gamification work?" to "How does gamification work?" "For whom?" and "Under what conditions?" (Kankanhalli et al., 2021).

Mobile: Push nudges, streak counters, location-based quests, micro-challenges, and social sharing leverage short and frequent sessions. Based on 276 respondents using a gamified mobile app, the results indicated that gamification led to higher engagement, which in turn led to increased satisfaction with competence, autonomy, and relatedness needs, and increased intention to use, word of mouth, and app ratings (Pushpalatha & Duraipandian, 2026). Immediate feedback, attainable objectives, and social visibility are the three elements that all successful commercial cases share, and that is what makes them successful. Successful commercial cases have three elements: immediate feedback, attainable objectives, and social visibility.

Gamification for Wellbeing and Sustainability

A systematic review of gamification for health and wellbeing found that there were overall positive, but inconsistent, research findings and that studies needed better study designs (Cardoso & Rodrigues, 2025). A couple of special-issue editorials about gamification studies summarized trends and future research opportunities, and reiterated the need for rigorous, theory-based, and longitudinal research (Alhasani & Orji, 2026). Overall, these works suggest that sustainability and wellbeing applications could be good targets for gamification, but that there is no consistent evidence of outcomes.

Inference

This survey leads to four inferences. Adaptive HCI research focuses on the behavior and guidelines of the interface and interaction, but rarely includes motivational mechanics. Second, personalization studies typically suggest content or persuasive strategies and are not much concerned with coordinating them with interface adaptation. Third, gamification effects can be context-specific and are mostly short-term.

Fourth, studies about sustainability are seldom verified in terms of behavior change. These gaps inspire a model that evolves the interface, curates the incentive, and proves sustainable behavior within a single closed loop as described in the following section.

3 Proposed Adaptive HCI Model (AHCI-PG)

Overall Flow

The methodology is based on an 8-step closed loop. Data acquisition gathers survey responses, logs interactions, and context signals. Preprocessing involves normalization of Likert items, encoding of categorical attributes, and feature vector construction. The vector of user states incorporates stable preferences, user context, and recent behavior. The layout, content density, and notification timing are determined based on the adaptive interface selection. A contextual bandit then chooses the gamification action in a personalized way via AI. The gamification engine provides points, badges, challenges, or feedback. Rewards are measured and used to update the models when observed, before the next round.

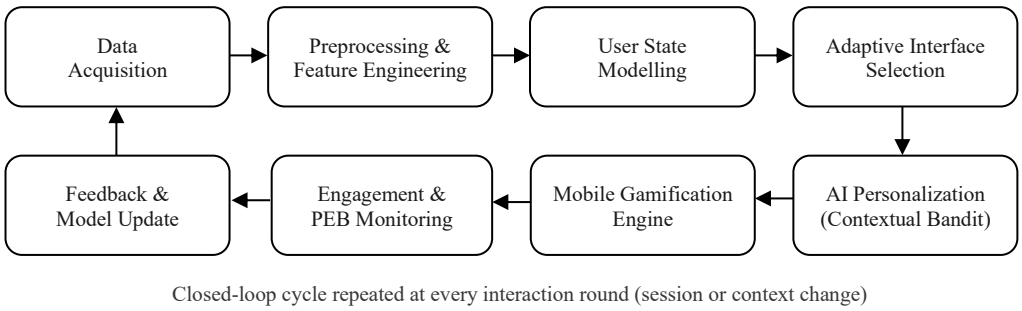


Figure 1: Overall flow of the proposed AHCI-PG methodology

Figure 1 shows the closed loop process is shown as a flowchart in figure 1. The data acquisition then supports the process of preprocessing and user state modeling, and adaptive interface selection and AI personalization determine the presentation and the gamification action. Engagement and pro-environmental behavior monitoring result in a reward signal, which is fed back to the models through updating and feedback. This cycle is repeated with each session or context change, enabling continual refinement without manual redesign.

System Architecture

The architecture is in four layers. On the mobile client, adaptive user-interface components, gamified widgets, and an eco-feedback dashboard are presented on the presentation layer. The adaptive HCI layer is responsible for context sensing, applying interface adaptation rules under an Optimizer, and logging interactions. User profiles are stored in the AI personalization layer, supported by Hexad user-type estimates, engagement prediction using a deep neural network, and action selection using a contextual bandit. The data and sustainability layer consist of behavioral and survey data, verification of sustainable actions, and privacy and consent controls.

Figure 2 shows four stacked layers with bidirectional data flows. The presentation layer presents widgets and an adaptive interface; the adaptive HCI layer detects context and adapts the presentation; the personalization layer models the users and determines what to do; the data layer stores evidence, verifies sustainable actions, and enforces consent. Outputs include the interface state, gamification action, engagement score, and pro-environmental behaviour log.

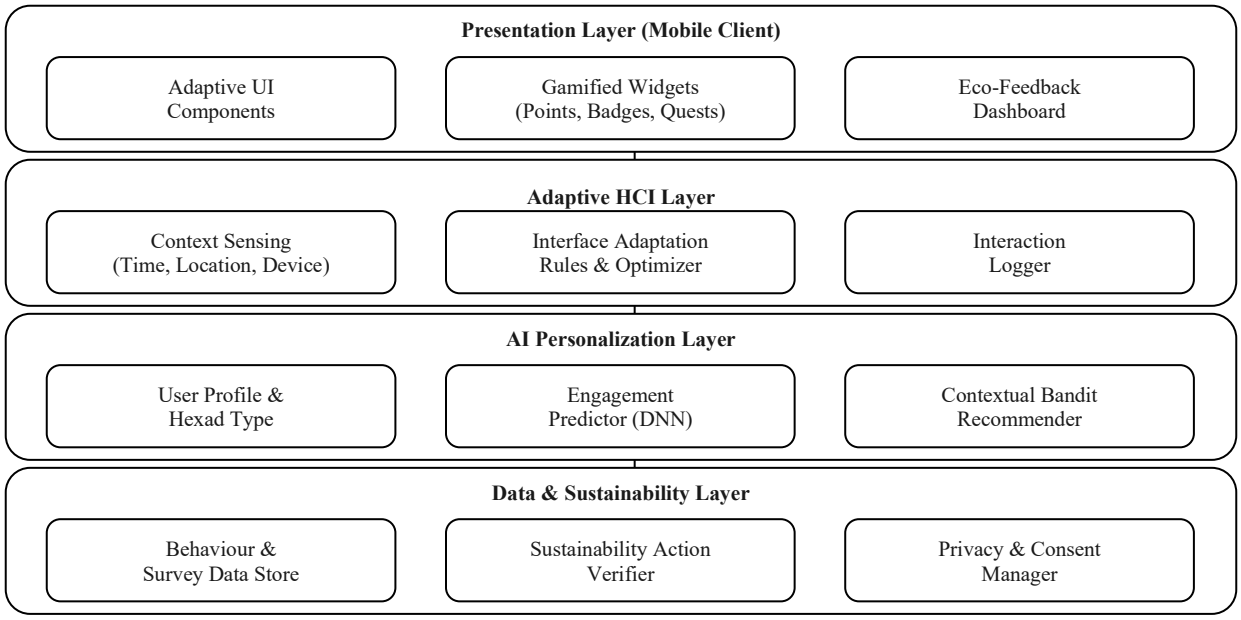


Figure 2: Layered system architecture of AHCI-PG

Conceptual Model and Hypotheses

The conceptual model places user engagement (UE) at the center of the relationship between the technology features and real-world action. The following four hypotheses will be tested:

H1: AI-powered personalization (APP) positively affects UE.

H2: Gamification features (GF) positively affect UE.

H3: UE positively affects pro-environmental behavior (PEB).

H4: UE mediates the relationship between APP/GF and PEB.

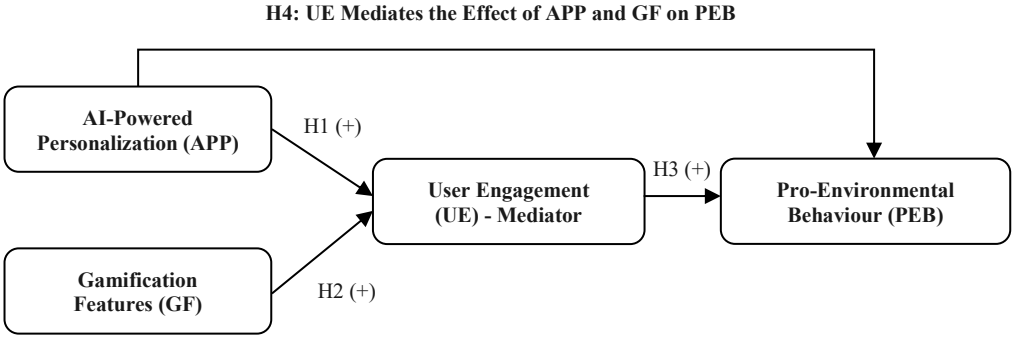


Figure 3: Conceptual model with hypotheses H1 to H4

Figure 3 shows two independent constructs, AI-powered personalization and gamification features, both influencing user engagement through H1 and H2. Engagement then drives pro-environmental behaviour through H3. The dashed arc represents H4, which tests whether engagement transmits the combined effect of personalization and gamification to behaviour. Signs indicate expected positive relationships, later tested with partial least squares structural equation modelling.

Mathematical Description

The mathematical equations of user state modeling, dynamic interface adaptation, reward optimization, and hypothesis testing are presented as equations (1) to (10).

The user state at interaction round t combines a preference vector, a context vector, and a behaviour vector, and the interface configuration is selected by minimizing a weighted cost:

$$\mathrm{x}_t = [\mathrm{p}_u; \mathrm{c}_t; \mathrm{b}_t] \in \mathbb{R}^d \quad (1)$$

$$I^* = \arg\min_I J(I \mid \mathrm{x}_t), \quad J = \sum_k w_k\, c_k(I, \mathrm{x}_t) \quad (2)$$

Engagement is predicted by a feed-forward network trained with regularized binary cross-entropy:

$$\grave{e}_t = \sigma(\mathrm{w}^T \mathrm{h}_l(\mathrm{x}_t) + b) \quad (3)$$

$$L = -\frac{1}{N}\sum_i [e_i \log \grave{e}_i + (1 - e_i)\log(1 - \grave{e}_i)] + \mu\|\mathrm{W}\|^2 \quad (4)$$

The sustainability-aware reward and the LinUCB action-selection rule, with per-action statistics updated after every round, are defined as:

$$r_t = \lambda_1 e_t + \lambda_2 p_t + \lambda_3 s_t, \quad \lambda_1 + \lambda_2 + \lambda_3 = 1 \quad (5)$$

$$a_t = \arg\max_{a \in A} \left[\theta_a^T \mathrm{x}_t + \alpha\sqrt{\mathrm{x}_t^T \mathrm{A}_a^{-1} \mathrm{x}_t}\right] \quad (6)$$

$$\mathrm{A}_a \leftarrow \mathrm{A}_a + \mathrm{x}_t \mathrm{x}_t^T, \quad \mathrm{b}_a \leftarrow \mathrm{b}_a + r_t \mathrm{x}_t, \quad \theta_a = \mathrm{A}_a^{-1} \mathrm{b}_a \quad (7)$$

Here, e is observed engagement, p is a verified pro-environmental action indicator, s is the estimated sustainability impact of the action, and α controls exploration. Challenge difficulty is adapted toward a target engagement level e^* so that challenge remains matched to skill:

$$d_{t+1} = d_t + \eta(e^* - \grave{e}_t) \quad (8)$$

The structural relationships tested through PLS-SEM, together with the indirect effect used for the mediation test, are expressed as:

$$\mathrm{UE} = \beta_1 \mathrm{APP} + \beta_2 \mathrm{GF} + \zeta_1, \quad \mathrm{PEB} = \beta_3 \mathrm{UE} + \zeta_2 \quad (9)$$

$$\mathrm{IE}_{\mathrm{APP}} = \beta_1 \times \beta_3, \quad \mathrm{IE}_{\mathrm{GF}} = \beta_2 \times \beta_3 \quad (10)$$

Algorithm

Algorithm 1. Adaptive personalized gamification loop (AHCI-PG)

Input: user profile p_u, action set A, parameters α, η, λ_1--λ_3, target engagement e^*

Output: interface configuration I^* and gamification action a_t for each round t

1. Initialize $\mathrm{A_a} \leftarrow \mathrm{I}$ (identity matrix) and $\mathrm{b_a} \leftarrow 0$ for every action $\mathrm{a} \in \mathrm{A}$; pre-train the engagement predictor on historical data.
2. for each interaction round $\mathrm{t} = 1,2,\ldots$ do
3. Sense context $\mathrm{c_t}$ and read behaviour $\mathrm{b_t}$; build $\mathrm{x_t} = [\mathrm{p_u}; \mathrm{c_t}; \mathrm{b_t}]$.
4. Compute $\mathrm{I}^* = \arg\min_{\mathrm{I}} \mathrm{J}(\mathrm{I} \mid \mathrm{x_t})$ and render the adaptive interface.
5. Predict engagement $\grave{\mathrm{e}}_\mathrm{t}$ and adjust difficulty $\mathrm{d_{t+1}} = \mathrm{d_t} + \eta(\mathrm{e}^* - \grave{\mathrm{e}}_\mathrm{t})$.

6. For each $a \in A$, compute $\theta_a = A_a^{-1} b_a$ and the score $\theta_a^T x_t + \alpha \sqrt{x_t^T A_a^{-1} x_t}$; select a_t with the highest score.
7. Deliver the gamification action a_t; log observed engagement e_t and verified action p_t.
8. Compute $r_t = \lambda_1 e_t + \lambda_2 p_t + \lambda_3 s_t$; update $A_a \leftarrow A_a + x_t x_t^T$ and $b_a \leftarrow b_a + r_t x_t$.
9. Retrain the engagement predictor every K rounds with the accumulated logs.
10. end for

Algorithm 1 explains the |A| linear solves of the bandit takes the dominant runtime for each round, at a cost of $O(|A|d^2)$ with incremental matrix updates, suggesting that it can be efficiently deployed on-device or in the edge, which is commonplace on modern smartphones.

4 Results and Discussion

Software and Hardware Details

Model development used Python 3.11 with PyTorch, scikit-learn, pandas, and NumPy. SmartPLS 4 was used for structural equation modeling with 5,000 bootstrap subsamples, and Matplotlib was used to create plots. A prototype client was created for Android with Kotlin and Jetpack Compose, and it hosted a cloud-based event store. The experiments were conducted on an 8-core CPU workstation with 32 GB of memory and 1 12 GB GPU.

Dataset Details

The data comes from a cross-sectional survey of 1,053 consumers that was conducted online via social media and in-app prompts. There are 12 Likert-scale indicators (three for each of the four constructs: APP, GF, UE, PEB), three usage attributes (Age band, App usage frequency, AI-recommendation interaction frequency), and 9 encoded contextual variables (Time of day, Device type, Location type), which results in 24 model features. Of those that responded, 58% were aged 25-40 years, 61% said often saw AI recommendations on e-commerce platforms, and 73% found sustainability claims relevant to their pro-environmental actions. The binary target is set to 1 if the composite UE score is 50% or greater, and to 0 if it is less than 50%. The engagement score is normalized between 0 and 1, and the RMSE is used as a metric. A profile-conditioned response simulation was calibrated to the survey constructs and was used to generate 12-week engagement traces to perform a retention analysis.

Table 1: Parameter settings used in the experiments

Parameter	Value	Additional setting
Engagement predictor	Layers 128-64-32, ReLU	Sigmoid output
Optimizer / learning rate	Adam / 0.001	Batch size 64
Epochs / dropout	100 / 0.3	Early stopping, patience 10
L2 penalty (μ)	0.0001	Embedding size 32
Bandit exploration (α)	0.25	Retrain interval K = 50
Reward weights (λ_1, λ_2, λ_3)	0.5, 0.3, 0.2	Difficulty rate η = 0.05
Target engagement (e*)	0.70	Seed 42
Validation protocol	Stratified 5-fold CV	PLS-SEM: 5,000 bootstraps

Table 1 lists the hyperparameters and evaluation settings applied uniformly to all compared models, except where a parameter is specific to the bandit or the reward. Network depth, regularization, and

optimizer choices were fixed before evaluation, and stratified five-fold cross-validation with a fixed random seed was used so that differences in reported metrics reflect model design instead of tuning effort.

Evaluation Metrics and Formulae

Six predictive metrics and one behavioural metric were used. With TP, TN, FP, and FN denoting true positives, true negatives, false positives, and false negatives:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (11)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (12)$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (13)$$

$$\text{AUC} = \int_0^1 \text{TPR}\,(\text{FPR})\, d(\text{FPR}) \quad (14)$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_i (y_i - \hat{y}_i)^2} \quad (15)$$

$$\text{Retention}_w = \left(\frac{\text{Active users in week } w}{\text{Active users in week } 1}\right) \times 100 \quad (16)$$

Measurement Model Assessment

Table 2: Reliability and convergent validity of the constructs

Construct	Indicators	Loading range	Cronbach's α	CR / AVE
APP	APP1–3	0.79–0.88	0.84	0.89 / 0.71
GF	GF1–3	0.80–0.87	0.85	0.90 / 0.73
UE	UE1–3	0.76–0.85	0.81	0.88 / 0.70
PEB	PEB1–3	0.77–0.88	0.83	0.89 / 0.72

Table 2 presents a summary of the outer model of each of the four constructs, with each construct being measured by three indicators. The loadings range from 0.76 to 0.88, the Cronbach's alpha is 0.81 to 0.85, the composite reliability is 0.88 to 0.90 and the average variance extracted is 0.70 to 0.73. All values are above the conventional limits, suggesting internal consistency and convergent validity prior to the assessment of structural relationships.

Performance Comparison

Four baselines were used to compare AHCI-PG: static rule-based gamification, collaborative filtering personalization, a deep neural recommender, and Hexad user-type personalized gamification. The six metrics are presented in table 3, and the results are shown in Figs. The grouped and radar views show that AHCI-PG achieved the highest accuracy (93.4%), precision (92.7%), recall (92.1%), F1-score (92.4%), and AUC-ROC (0.968), and the lowest RMSE (0.318). Compared to the best baseline, accuracy rose by 6.3 percentage points, and RMSE decreased by 24.5%. Compared to static gamification, accuracy increased by 21.6 percentage points, and the RMSE decreased by 48.0%.

Table 3: Performance comparison of AHCI-PG with baseline models

Model	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)	AUC-ROC	RMSE
Static Gamification	71.8	70.4	69.2	69.8	0.768	0.612
CF Personalization	78.6	77.3	76.1	76.7	0.835	0.538
Deep Recommender	84.2	83.5	82.3	82.9	0.893	0.467
Hexad Personalized	87.1	86.4	85.3	85.8	0.921	0.421
Proposed AHCI-PG	**93.4**	**92.7**	**92.1**	**92.4**	**0.968**	**0.318**

Table 3 shows an average performance of the five models over stratified 5-fold cross validation on accuracy, precision, recall, F1-score, AUC-ROC and RMSE. The larger the number, the better the results are for all but the RMSE. The proposed model, shown in the last row, leads on every metric. The gains in performance gradually get better from static gamification to collaborative filtering, deep recommendation, and Hexad personalization, reflecting the incremental benefits of the depth of personalization and adaptive coordination.

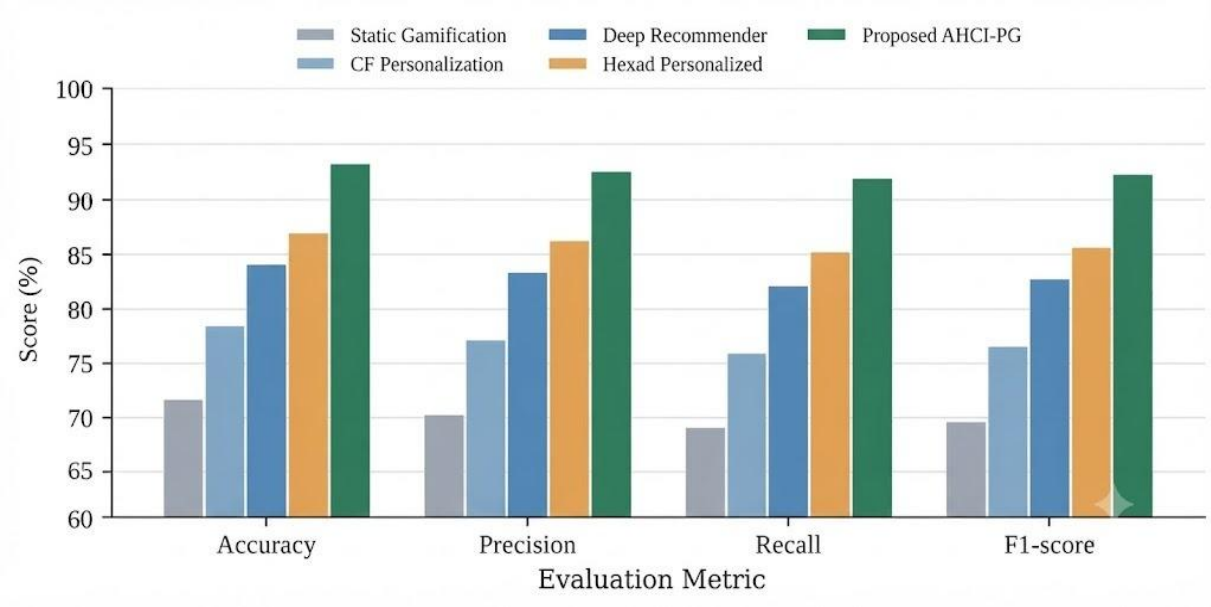


Figure 4: Comparison of Classification Metrics

Figure 4 compares accuracy, precision, recall, and F1-score for the five models. Bars steadily progress from static gamification to the proposed AHCI-PG, which is over 92% on all four measures. The difference between the baseline Hexad and the proposed model is greatest for recall, indicating the combined interface adaptation + reward personalization is more effective than personalization alone to reduce the number of high-engagement users missed.

Figure 5 presents the accuracy, precision, recall, F1 score, AUC/ROC, and 1-RMSE scaled to a 0–100 range across 4 models.

The proposed model would have the largest area and would have the most balanced polygon, while static gamification would have the smallest area with a clear deficiency on the error side. The graphics verify that the improvements are widespread, not just limited to a single measure.

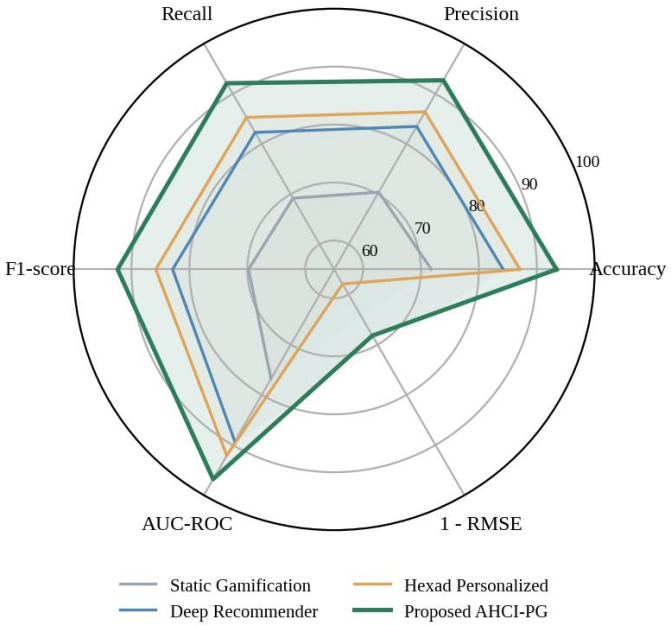


Figure 5: Radar comparison across six normalized metrics

Engagement Dynamics over Twelve Weeks

All models lose users after signing them up, with varying degrees of decay. The retention rates for AHCI-PG were 82.5% for week 4 and 63.8% for week 12, while static gamification was at 53.7% and 24.9% respectively. The curve for AHCI-PG levels off at week eight, a sign of the point at which habit is formed, and the baseline Hexad score hit 49.0% at week twelve, as did the deep recommender at 42.4%.

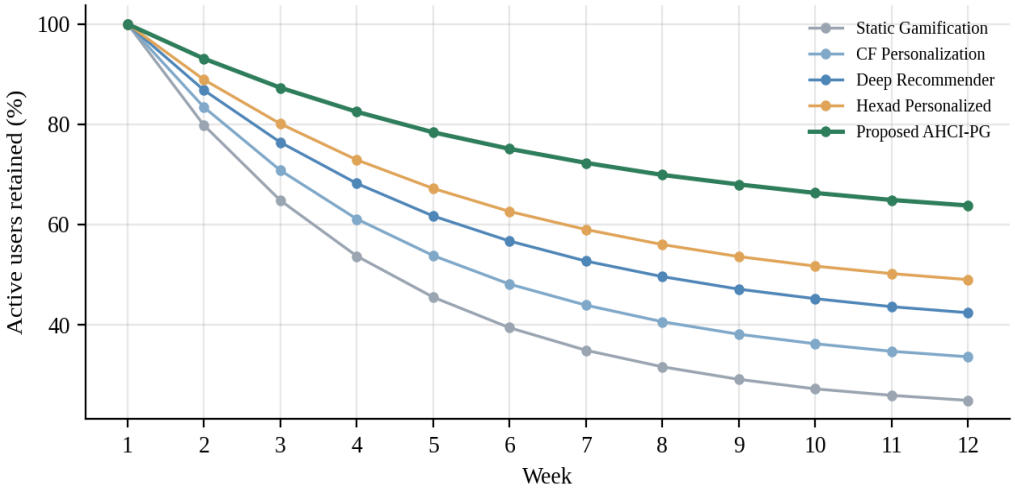


Figure 6: Retention of active users across twelve weeks

Figure 6 chart traces the percentage of active users from week one to week twelve for all five models. All curves went down, but the proposed AHCI-PG curve dropped the least and leveled off around 64% in the last week, and static gamification dropped below 25%. The increasing distance over time demonstrates the power of adaptive coordination of the interface and incentives, which is the primary problem of generic reward mechanisms.

Structural Model and Hypothesis Testing

The correlations between the constructs were positive and significant ($p < 0.001$), and the strongest correlation was observed between UE and PEB (0.66), as shown in figure 7. As indicated in table 4, there is support for all four hypotheses. For both of these trends, personalization and gamification, there was a strong positive relationship with engagement, and engagement was found to strongly predict pro-environmental behavior ($\beta = 0.75$, $t = 12.01$). The indirect effect of gamification via engagement was 0.4125 ($t = 7.55$), whereas the indirect effect of personalization via engagement was 0.62 x 0.75 = 0.465. The personalization and gamification elements are not considered to be fully expected, and thus the mediation can be seen as partial.

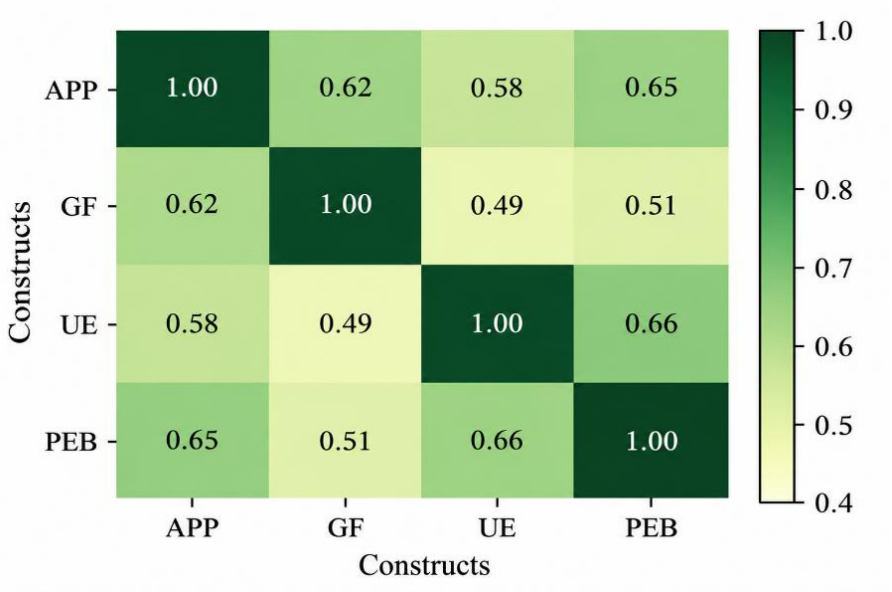


Figure 7: Correlation matrix of the four constructs

Figure 7 shows pairwise correlations among AI-powered personalization, gamification features, user engagement, and pro-environmental behavior. All of the coefficients are significant at $p < 0.001$ and range from 0.49 to 0.66. Personalization has the highest path coefficient in the structural model for both engagement and behavior, and the highest path coefficient for engagement among all constructs, followed by behavior; engagement is also the highest path coefficient among all constructs in the correlation matrix, as is behavior with respect to the other constructs.

Table 4: Path Coefficients and Hypothesis Status

Path	Hypothesis	β	t-value	p-value	Decision
APP → UE	H1	0.62	9.15	< 0.001	Supported
GF → UE	H2	0.55	10.02	< 0.001	Supported
UE → PEB	H3	0.75	12.01	< 0.001	Supported
GF → UE → PEB	H4	0.4125	7.55	< 0.001	Supported (partial mediation)

Table 4 lists standardized path coefficients, t-values, and decisions for the structural model. All paths are significant at the .001 level. All direct and indirect (through 'engagement') pathways are positive and large, and some support partial mediation, with the direct pathway from 'personalization' to 'engagement' and from 'engagement' to 'behavior' being large. The results validate the conceptual model.

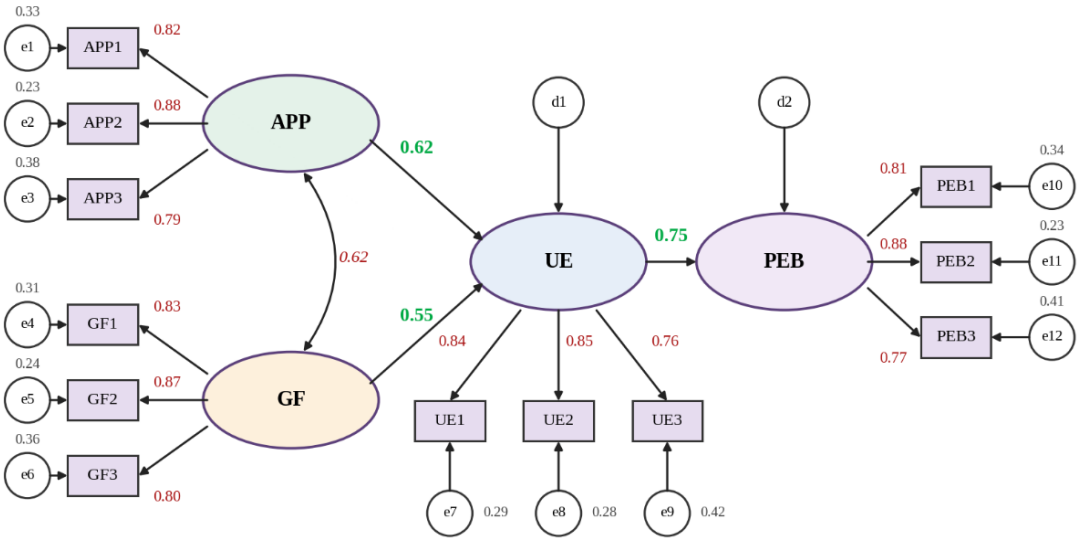


Figure 8: Structural equation model path diagram with standardized estimates

Figure 8 presents the standardized structural equation model for the four constructs. The ellipses represent latent variables, rectangles represent indicators, and circles represent measurement errors. The loadings of the indicators range from 0.76 to 0.88. There is a strong positive link between personalization (0.62) and gamification (0.55) with engagement, which strongly predicts pro-environmental behavior (0.75). The correlation between personalization and gamification is estimated at 0.62 and shown in the curved double-headed arrow.

Ablation Study

Five components were successively subtracted to determine their contributions. The gamification engine (-5.5 points), feedback loop (-3.9 points), sustainability-aware reward (-2.2 points), and adaptive interface layer (-3.1 points) contributed to this largest drop in performance. All of the above, thus, play a material part, and the sequence here indicates that personalization serves as a base upon which gamification and the adaptation of the interface add additional value.

Table 5: Ablation study of AHCI-PG components

Configuration	Acc. (%)	F1 (%)	AUC-ROC	RMSE	ΔF1
Full model	**93.4**	**92.4**	**0.968**	**0.318**	NA
w/o adaptive interface layer	90.1	89.3	0.946	0.361	−3.1
w/o AI personalization	85.2	84.1	0.903	0.452	−8.3
w/o gamification engine	88.0	86.9	0.925	0.405	−5.5
w/o sustainability-aware reward	91.0	90.2	0.953	0.348	−2.2
w/o feedback loop	89.4	88.5	0.938	0.375	−3.9

Table 5 reports accuracy, F1-score, AUC-ROC, RMSE, and the F1 along with the change in F1 score from the full model. All settings are held constant, and only one component is different in each variant. Removing any of the reduced configurations from the model results in a degradation of the performance of the model, and removing AI personalization results in the largest degradation, which validates the complementary nature of the components and the value of a combined design.

Discussion on Integration Benefits, Challenges, and Best Practices

By combining both personalization and gamification, the incentives could be tailored to motivational profiles and the interface adapted to minimize friction at the point of interaction. This led to greater predictive accuracy, decreased attrition, and a strong engagement-mediated path to pro-environmental behavior. The actions also get verified within the reward function, which prevents reward hacking, where points can be scored without any rewarding action to the environment.

The issues with integration are: (i) cold start uncertainty for new users, which cannot be fully overcome by exploration but requires consent management and on-device processing; (ii) unfairness, as engagement-optimized policies may benefit already active user groups; (iii) over-adaptation, which can lead to lower predictability and trust; and (iv) evidence limits, due to the longitudinal traces being simulated using profiles calibrated with surveys, and the surveys being cross-sectional. External validity has to be confirmed in field trials with genuine logs of interaction.

Based on the results, the design principles are: (a) implement personalization first, and add game mechanics selectively, as personalization created the greatest ablation effect; (b) keep users in control with visible settings and reasons for the challenge and/or layout selection; (c) link rewards to sustainable actions that have been verified; (d) adjust difficulty levels towards a target engagement level to maintain flow; (e) collect the minimum data needed and process it locally if possible; and (f) validate using predictive measures and behavioral measures. The results suggest for developers and policymakers that funding and design should be given to adaptive, evidence-validated systems over generic points-and-badges systems.

5 Conclusion

This study proposed an adaptive human-computer interaction model called AHCI-PG, which is based on two key concepts: context-aware interface adaptation and AI personalization, combined with mobile gamification for pervasive sustainable applications. The layered architecture and the sustainability-aware contextual bandit were able to leverage heterogeneous user signals to make both interface and incentive choices in one feedback loop. Evaluation on 12-week engagement and 1,053 respondents revealed consistent superiority against four baselines. The model achieved a 93.4% accuracy rate, 92.4% F1 score, AUC-ROC of 0.968, and an RMSE of 0.318, which are 92.4% accuracy and 24.5% RMSE improvements over the best baseline. This was achieved at 12 weeks with a 63.8% improvement in retention compared to 24.9% for the static gamification. All 4 hypotheses were supported by structural analysis, with path coefficients of 0.62, 0.55, and 0.75, and an indirect effect of 0.4125 with regard to engagement; the ablation study identified AI personalization as the most influential component. The practical implications are: to make personalization the first rule and not overcomplicate with more game mechanics, to check sustainable actions to keep the reward integrity, and to allow users to control the adaptation. The studies hope to see future studies that continue to move towards field deployments that involve real interaction logs, federated and privacy-preserving learning, fairness auditing for user groups, explainable adaptation, and integration of wearable and IoT sensing for automatic verification of the actions performed in the environment. Social dynamics may be explored further in the context of extension to multi-user and/or community challenges; to better understand how social dynamics influence long-term habit formation.

References

[1] Albarrak, A. M. (2024). Integration of cybersecurity, usability, and human-computer interaction for securing energy management systems. *Sustainability*, *16*(18), 8144.

[2] Alhasani, M., & Orji, R. (2026). Personalizing gamified stress management application: the impact of gamification user types on persuasive strategies. *User Modeling and User-Adapted Interaction*, *36*(3), 12.

[3] Awasthi, G. K., Tewari, S., S, N., P, G., Mallick, S., & S, S. (2025). Human-Computer Interaction Design Principles for Enhancing User Experience in Mobile Applications. In *ITM Web of Conferences* (Vol. 76, p. 05003). EDP Sciences.

[4] Brăileanu, P. I. (2025). Human–computer interaction in smart greenhouses: a review of interfaces, technologies, and user-centered approaches. *Computers*, *14*(12), 553.

[5] Cardoso, P. J., & Rodrigues, J. M. (2025). Human-centered AI in placemaking: A review of technologies, practices, and impacts. *Applied Sciences*, *15*(17), 9245.

[6] Chen, R., & Zhang, J. (2026). Modelling the impact of interactive interface features on user experience in artificial intelligence driven digital learning systems. *Scientific Reports*, *16*(1), 14619.

[7] Cheng, N., Yang, L., Zhu, X., & Gomes, R. (2025, May). The role and future applications of human-computer interaction in enhancing residential energy efficiency. In *International Conference on Human-Computer Interaction* (pp. 202-215). Cham: Springer Nature Switzerland.

[8] Janson, A., Schmidt-Kraepelin, M., Schöbel, S., & Sunyaev, A. (2023). Special issue editorial: Adaptive and intelligent gamification design. *AIS Transactions on Human-Computer Interaction*, *15*(2), 136-145.

[9] Kankanhalli, A., Xia, Q., Ai, P., & Zhao, X. (2021). Understanding personalization for health behavior change applications: a review and future directions. *AIS Transactions on Human-Computer Interaction*, *13*(3), 316-349.

[10] Kassenkhan, A., Serbin, V., Beisembekova, R., Abshukirova, A., & Mendekina, B. (2026). AI-supported gamification in e-learning: A systematic review of adaptive architectures and cognitive outcomes. *Information*, *17*(3), 282.

[11] Lao, Q. (2025). A Systematic Review of AI-Driven Game Design and User Experience Research. *Humanities and Social Science Research*, *8*(4), p229-p229.

[12] Méndez, J. I., Ponce, P., Meier, A., Peffer, T., Mata, O., & Molina, A. (2023). Empower saving energy into smart communities using social products with a gamification structure for tailored Human–Machine Interfaces within smart homes. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *17*(3), 1363-1387.

[13] Mirdjonovna, K. S., Kakhramonovna, G. S., Allamuradovich, E. A., Dilshodovna, A. D., Djumaniyozovna, R. S., Abdulhakimovna, K. M., & Abdurasulovich, K. R. (2025, September). 80/20 Principle in Phonetics, Lexis and Word Formation. In *2025 10th International Conference on Computer Science and Engineering (UBMK)* (pp. 433-438). IEEE.

[14] Padman, R., & Ladhania, R. (2025). Artificial Intelligence and gamification for health. In *Artificial Intelligence for Ecology, Health, and Education* (pp. 92-111). Edward Elgar Publishing.

[15] Pushpalatha, S., & Duraipandian, R. (2026). Gamifying Loyalty and AI as a Catalyst for Customer Engagement and Retention. In *Revolutionizing Quick Commerce with AI Tools and Technologies* (pp. 165-194). IGI Global Scientific Publishing.

[16] Rathnayake, N., Meedeniya, D., Perera, I., & Welivita, A. (2019, July). A framework for adaptive user interface generation based on user behavioural patterns. In *2019 Moratuwa Engineering Research Conference (MERCon)* (pp. 698-703). IEEE.

[17] Troussas, C., Krouska, A., & Sgouropoulou, C. (2025). A novel framework of human–computer interaction and human-centered artificial intelligence in learning technology. In *Human-computer interaction and augmented intelligence: the paradigm of interactive machine learning in educational software* (pp. 387-431). Cham: Springer Nature Switzerland.
[18] Wu, J. H. (2025). Design and development of artificial intelligence dynamic physical education teaching resources in human-computer interaction mode. *Journal of Educational Computing Research*, *63*(5), 1219-1248.
[19] Xiao, R., Wu, Z., & Hamari, J. (2022). Internet-of-gamification: A review of literature on IoT-enabled gamification for user engagement. *International Journal of Human–Computer Interaction*, *38*(12), 1113-1137.
[20] Zamani, S., Rostami, A., Nguyen, M., Sinha, R., & Madanian, S. (2025). A gamified AI-driven system for depression monitoring and management. *Applied Sciences*, *15*(13), 7088.
[21] Zhao, Z., Arya, A., Orji, R., & Chan, G. (2020). Effects of a personalized fitness recommender system using gamification and continuous player modeling: system design and long-term validation study. *JMIR serious games*, *8*(4), e19968.

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