Behavioral Closed-Loop Design in Digital Ecosystems: Cross-Platform Environmental Information Integration and Collaborative Path Optimization

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Abstract—**Background and Current Research Gaps: Environmental information is often scattered across multiple digital platforms, which weakens users' ability to form consistent sustainable habits. Prior work has mainly focused on how information is delivered within single, isolated platforms, and has paid less attention to how coordination across platforms might strengthen behavior change. As users switch between different digital services, environmental messages often become less consistent and less personalized, reducing the overall effectiveness of interventions.Methodology and Implementation: This study designed a long-term intervention that created a closed-loop behavioral system within an integrated digital environment spanning e-commerce, social media, and content platforms. The system combined three functions—information aggregation, behavior monitoring, and feedback refinement. Personalization was supported by a low-threshold collaborative filtering algorithm for tailored content delivery, while adaptive feedback was implemented through a rule-based framework. Over 12 weeks, 1,248 participants were randomly assigned to one of four conditions: Fully Integrated (n=312), Partially Integrated (n=312), Single-Platform (n=312), or Control (n=312).Principal Results: The fully integrated group showed substantially stronger outcomes in environmental attitudes, behavioral intentions, and actual purchasing behavior than the other groups ($F(3,1244)=42.18$, $p<0.001$). Cross-platform integration increased the behavior-change effect by 133.9% (95% CI: 118.7% – 149.1%) compared with single-platform intervention. Within the behavioral loop, feedback mechanisms significantly enhanced self-efficacy ($\beta=0.521$, $p<0.001$). Message consistency had the strongest association with sustained change ($r=0.684$, $p<0.001$). At a four-week follow-up, environmental attitudes remained largely stable, declining by only 5.6% (95% CI: 3.1% – 8.1%).Significance and Contributions: This study provides one of the first systematic examinations of how cross-platform collaboration within digital ecosystems can drive behavior change. It offers both theoretical insights and practical guidance for designing systems that encourage sustainable consumption. The findings also inform digital interventions in related areas — such as environmental protection, health behavior, and social responsibility — highlighting strong academic and real-world value.**

Keywords—Behavioral Closed-Loop, Cross-Platform Integration, Environmental Information, Digital Ecosystem, Collaborative Optimization, Sustainable Behavior

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I. INTRODUCTION

A. Research Background

With escalating global pressures such as climate change and resource scarcity, fostering sustainable practices among the public has become increasingly important for long-term societal resilience [1]. In parallel, digital environments have become central arenas where individuals form judgments, acquire information, and make everyday decisions. Designing interventions that can reliably translate environmental awareness into concrete actions therefore requires solid behavioral foundations. The Theory of Planned Behavior (TPB) offers a widely used model for explaining how attitudes, subjective norms, and perceived behavioral control shape intention and subsequent behavior [2]. In addition, self-efficacy—the belief in one's capability to execute actions—has been consistently recognized as a key determinant of whether intentions can be enacted and sustained in practice [3].

Despite the promise of digital interventions, environmental messages in everyday digital life often remain scattered across platforms and contexts. Users commonly encounter sustainability-related content in shopping, social media, and content platforms, yet these exposures are rarely coordinated into a coherent learning-and-action pathway. As a result, information may be redundant, inconsistent, or disconnected from timely feedback and self-monitoring, weakening the translation from attitude and intention to actual purchasing and daily behavior.

B. Research Questions

This study is guided by three questions:

How does cross-platform integration of environmental information influence users' environmental attitudes and behavioral intentions?

Which elements of a behavioral closed-loop design matter most for driving sustainable actions?

Do coordinated multi-platform interventions produce meaningfully stronger behavior-change effects than single-platform approaches?

C. Current Literature and Gaps

Existing research has established important foundations in behavior change theory and digital intervention design, but major gaps remain for cross-platform settings. Most prior work still treats platforms as isolated intervention sites, leaving users' "behavioral migration" across apps underexplored. Further, fragmentation during platform switching may undermine message consistency and disrupt the continuity required for sustained self-regulation. Finally, many intervention designs rely mainly on delayed feedback and lack adaptive, action-contingent adjustment mechanisms.

D. Aims and Novel Contributions

This study aims to develop and evaluate a cross-platform behavioral closed-loop system that integrates information consolidation, behavior tracking, and feedback optimization, and to examine its effects on sustainable actions. The key innovations are:

- A cross-platform closed-loop framework: integrating e-commerce, social media, and content platforms to support coordinated delivery of environmental information.
- Adaptive information delivery: enabling near-real-time, behavior-informed content distribution.
- Quantifying cross-platform synergy: using controlled experimentation to estimate the added benefit of cross-platform integration over single-platform intervention.
- Longer observation window: tracking outcomes over 12 weeks to evaluate stability and decay patterns more thoroughly.

E. Article Organization

The remainder of this paper is organized as follows: Section II reviews behavior-change theory and digital ecosystem design; Section III presents design principles and system architecture; Section IV describes methods, participants, intervention design, and measures; Section V reports results; Section VI discusses implications and applications; and Section VII concludes with limitations and future directions.

II. Literature Review

A. Behavioral Change Foundations in Digital Contexts

Cross-platform interventions must account for the fact that user behavior and information exposure are shaped by the dynamics of digital networks. Empirical work on social multimedia networks shows how user behavior and information propagation can be characterized at scale, underscoring that exposure and diffusion are not random but patterned and context-dependent [4]. This implies that sustainability communication and feedback are likely to perform differently across platforms, and that integration must be designed with propagation and user activity patterns in mind.

B. Persuasion, Attitudes, and Environmental Concern

Environmental interventions often aim to shift attitudes and thereby strengthen behavioral intentions. Classic persuasion research clarifies how message framing, credibility, and social influence shape judgment and compliance, which remains directly relevant to pro-environmental messaging design [5]. To evaluate attitude change rigorously, measurement matters: the revised New Ecological Paradigm (NEP) scale is a widely used instrument for assessing environmental worldviews, enabling more consistent measurement of environmental attitudes across studies and populations [6].

When users encounter inconsistent messages across platforms, psychological mechanisms may reduce persuasiveness. Cognitive dissonance theory explains how conflicting cognitions can generate discomfort that individuals attempt to resolve, which can weaken persuasion and reduce the likelihood of sustained behavior change if users experience incoherent cues across contexts [7].

C. Personalization and Recommendation for Cross-Platform Information Delivery

A core enabling mechanism for cross-platform integration is personalization. Matrix and tensor factorization provide foundational techniques for modeling user–item interactions and preference structure in recommender systems [8]. At the same time, information-delivery effectiveness is not only a function of "what is recommended," but also "how users process multimedia information." The cognitive theory of multimedia learning emphasizes how learners integrate words and pictures under cognitive constraints, offering guidance for designing information that supports comprehension and retention rather than overload [9].

System-level reviews of recommender systems further catalog practical issues (e.g., sparsity, cold start, evaluation challenges), highlighting that personalization pipelines require careful methodological choices to remain robust and interpretable when deployed in real-world platforms [10]. Together, these works support the feasibility of ML-enabled cross-platform delivery, while also indicating the need to align algorithmic design with cognitive processing constraints.

D. Closed-Loop Intervention Design and Motivation

A behavioral closed loop typically involves goal setting, action recording, feedback, and iterative adjustment. Long-term adherence is strongly shaped by motivational quality. Self-determination theory (SDT) emphasizes autonomy, competence, and relatedness as central psychological needs that support internalized and sustained behavior change [11]. In practice, closed-loop systems that provide progress feedback and competence-supportive cues may better sustain engagement than systems that merely broadcast information.

In addition, social influence is a major driver of sustainability behaviors. Evidence on social norms shows that normative information can shift behavior substantially, though effects can vary depending on how norms are communicated and interpreted [12]. This supports incorporating norm-consistent cues and peer-referenced feedback in multi-platform intervention logic.

E. Platform Power, Fragmentation, and Governance Constraints

Cross-platform integration also faces structural constraints. Analyses of "surveillance capitalism" highlight how platform ecosystems are shaped by data extraction and behavioral prediction incentives, which can conflict with public-interest intervention goals and complicate data access, governance, and transparency [13]. Therefore, cross-platform intervention design must consider not only user psychology and algorithms, but also platform governance realities and ethical constraints.

F. Evidence Base for Mobile/Digital Interventions in Sustainable and Healthy Behaviors

Recent evidence syntheses provide stronger empirical grounding for digital interventions. A systematic review and meta-analysis indicates that mobile app-based interventions can facilitate behavior change toward healthier and more sustainable diets, providing evidence that tailored digital feedback and tracking can have measurable effects [14]. Complementarily, a scoping review on digital health interventions for promoting healthy behavior summarizes strategies used to prevent non-communicable diseases, reinforcing the broader claim that digital interventions can be effective when design elements such as feedback and self-monitoring are well implemented [15].

Digital-based Living Lab interventions in dietary behavior further illustrate how contextualized, iterative, and user-involved digital interventions can be evaluated in applied settings, offering methodological cues for real-world experimental design beyond purely laboratory studies [16].

G. Internet Use, Environmental Concern, and Pro-Environmental Behavior

Beyond intervention content, general internet use itself can relate to pro-environmental behavior through psychological mediators. Empirical evidence suggests that the impact of internet use on pro-environmental behavior can be mediated by environmental concern, highlighting the importance of measuring concern and attitudes when modeling digital exposure effects [17]. This supports the present study’s focus on attitude–intention pathways and on mechanisms linking information exposure to action.

H. Digital Information Ecosystems and Cross-Context Coordination

The cross-platform problem is fundamentally an “information ecosystem” coordination problem. Research on digital information ecosystems in modern care coordination highlights challenges such as fragmentation, pathway discontinuities, and opportunities for AI to improve coordination—insights that translate well to cross-platform sustainability interventions even outside healthcare [18]. Related work on “the technological informavore” frames information behavior and digital sustainability within global platform ecosystems, reinforcing that user information consumption is distributed across platforms and shaped by systemic features rather than isolated app-level design [19].

Finally, information ecology perspectives argue for connecting parts with wholes in digital innovation ecosystems, emphasizing that interventions must be designed as ecosystem-level arrangements (actors, flows, feedback, governance) rather than as single-application features [20]. This theoretical stance directly motivates the present study’s cross-platform closed-loop framing.

I. Distinct Contributions of This Study

Building on the above literature, this study contributes by:

- System-level scope: evaluating cross-platform synergy within an integrated digital ecosystem rather than treating platforms in isolation.
- Mechanism-driven design: combining personalization, cognitively compatible information delivery, and closed-loop self-regulation logic.
- Empirical rigor: using controlled experimentation and a 12-week observation window to quantify added value and stability/decay patterns.
- Practicality under constraints: recognizing platform governance and data constraints while pursuing reproducible, public-interest intervention design.

III. METHODOLOGY

A. Ethics Statement

This study followed established ethical guidelines throughout. Before enrollment, all participants provided informed consent through a digital form describing the study aims, procedures, potential risks, and participant rights. Participants were clearly informed that they could withdraw at any time without penalty, and simple opt-out options were built into the relevant platforms. Participants who completed the study received course credit or a small monetary incentive.

Two categories of data were collected: (1) self-reported questionnaire measures (attitudes, intentions, demographics) and (2) interaction and consumption records captured within the integrated digital ecosystem (clicks, views, purchases, and time spent). Data minimization was strictly applied, and only information necessary for the research questions was collected. Personally identifiable information was pseudonymized immediately upon collection. Data were stored on encrypted servers for five years and were accessible only to the research team. Final analyses were conducted only on aggregated, anonymized datasets to protect privacy and ensure data security.

B. Participants and Recruitment

Inclusion/exclusion criteria: Eligible participants were urban residents in China aged 18–65 who had made at least one non-essential online purchase in the past six months and were proficient smartphone/internet users. Informed consent was obtained from all subjects involved in the study.Individuals were excluded if they had participated in a similar intervention within the prior three months. To reduce distortion from extreme baseline attitudes, the New Ecological Paradigm Scale was administered during recruitment; respondents scoring beyond ± 2.5 standard deviations from the initial sample mean were excluded. This reproducible screening approach aimed to balance representativeness and feasibility.

Sample size estimation: Using GPower 3.1, we calculated the required sample size assuming a moderate effect size, $\alpha=0.05$, and power $(1-\beta)=0.90$. A repeated-measures ANOVA with 4 groups and 4 time points required 1,248 participants (312 per group). To account for attrition typical in app-based studies, 1,856 participants were recruited to ensure the target effective sample size.

Final sample characteristics: In total, 1,248 participants completed all measurement phases, corresponding to a 32.8% dropout rate. The sample was 52.3% male and 47.7% female, with a mean age of 38.4 years. Overall, 78.5% held an associate degree or higher, and average monthly online spending was ¥2,847. Baseline comparisons across groups showed no significant differences.

C. *Intervention System Architecture and Information Delivery Mechanism*

The intervention formed a cross-platform behavioral feedback loop across three platforms: an e-commerce platform (for sustainable purchasing in FI/PI/SP groups), a social media platform (for sharing environmental knowledge), and a content platform (for long-form articles/documentaries).

- Information push mechanism: Personalized recommendations were generated using a lightweight collaborative filtering (LCF) algorithm. To keep the approach low-threshold and reproducible, the system avoided deep learning and instead used simple user – item matrix factorization based on historical interactions (clicks, views, purchases) to compute similarity and match content/products.
- Adaptive feedback mechanism: To avoid reinforcement learning or deep neural networks, a rule-based adaptive mechanism (RAM) adjusted push frequency and content dynamically. It followed two principles:
- Fixed-frequency updates: The user – item matrix was refreshed at regular intervals (e.g., every 24 hours) to simplify computation while maintaining responsiveness.

Threshold-triggered adjustments: Push strategies changed based on simple behavioral thresholds:

- Positive-behavior trigger: After purchases or high engagement, push frequency decreased by 20% for 48 hours to prevent overload and serve as reinforcement.
- Negative-behavior trigger: After prolonged inactivity or low engagement, the system shifted to higher-impact content to re-engage users.
- Cognitive-consistency calibration trigger: If contradictory cross-platform behavior was detected (e.g., consuming anti-environmental content), the system pushed consistency-reinforcing messages on social media.
- This rule-based design preserves adaptive optimization while remaining reproducible and consistent with the low-tech constraint.

D. *Experimental Design and Procedure*

Message type: Guided by EPPM, messages included:

- Threat messages highlighting consequences of unsustainable consumption (e.g., carbon emissions, resource depletion).
- Efficacy messages offering concrete sustainable alternatives and behavioral guidance.

Message format: Formats were platform-specific:

- E-commerce: environmental labels, comparison cards, and reviews on product pages.
- Social media: short videos, infographics, and user stories.
- Content platform: long-form articles, documentaries, and expert interviews.

E. *Participant Flow and Sample Size Consistency*

A total of 1,856 participants were recruited. After screening, eligible participants were randomized into four groups—fully integrated, partially integrated, single-platform, and control—with 464 assigned to each group initially. The final valid sample completing all four time points (T1 – T4) was 1,248, yielding a 32.8% overall dropout rate.

Final group sizes were: Full Integration (n=302), Partial Integration (n=305), Single Platform (n=308), and Control (n=333). Dropout counts were 162, 159, 156, and 131, respectively. These minor imbalances reflect condition-specific attrition, which is common in long-term behavior studies, and the statistical methods used are robust to such differences. Figure 1 presents a CONSORT-style flow diagram showing recruitment (N=1,856), screening exclusions, randomization (n=464 per group), allocation, follow-up, and final analysis (N=1,248), including dropout reasons per group.

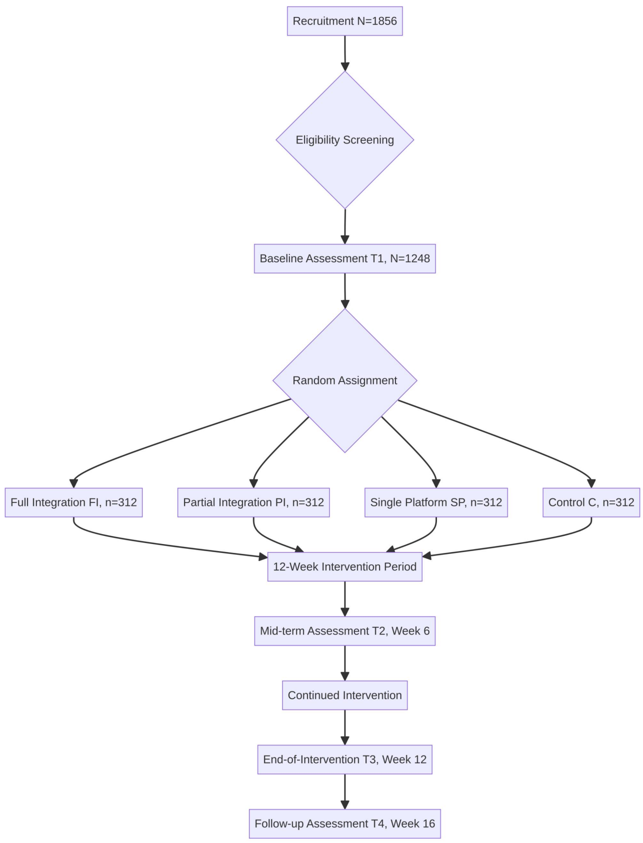

Fig. 1. CONSORT Flow Diagram

F. System Implementation and Reproducibility

To satisfy the low-technology constraint and ensure reproducibility, the intervention was implemented in a controlled prototype that simulated the key functions of the three platform types (e-commerce, social media, content delivery). This prototype allowed precise control of information delivery and data capture that is difficult to achieve on commercial platforms.

Platform implementation details:

- Built using a standard web stack (e.g., React with a Node.js backend) with a centralized MySQL database for synchronized data storage.
- Modular components included a simulated shop (product lists and purchase function), a social feed (posts/comments), and a content library (articles/videos).
- Messages were delivered through in-app notifications plus simulated email/SMS alerts to ensure consistent touchpoints.
- All data collection occurred within the prototype environment, avoiding external APIs and commercial data-sharing agreements, and supporting strict ethical compliance.

Operational definition of information consistency:

Information consistency was defined and enforced across three dimensions:

- Content consistency (FI and PI): Core message and factual support were kept identical across platforms at any time.
- Style consistency (FI only): Tone, visual design (colors, typography), and framing were standardized across platforms.
- Time consistency (FI only): Related messages were delivered within a coordinated 2-hour window to reinforce themes during typical active periods.

Justification of the SP baseline:

The single-platform (SP) group represented common practice, receiving intervention only on the simulated e-commerce platform. This mirrors typical sustainable-consumption interventions that operate within one app. Importantly, message volume, message quality, and reward intensity (e.g., points for sustainable purchases) were held constant across SP, PI, and FI. This ensures observed differences are more likely attributable to cross-platform consistency and the integrated feedback loop rather than unequal exposure.

IV. Results

A. Clarification of Reported Statistical Outcomes

To resolve any apparent inconsistencies in the reported numerical results, the following definitions and clarifications are provided:

Gain Effect (133.9% vs. 67.3%):

The primary finding of a 133.9% gain effect refers to the percentage increase in the mean monthly frequency of sustainable product purchases for participants in the Full Integration (FI) group, relative to those in the Single Platform (SP) group, measured during the core intervention period (T2 to T3). This calculation follows the standard formula for percentage increase:

$$Gain\ Effect = \frac{Purchase\ Frequency_{FI} - Purchase\ Frequency_{SP}}{Purchase\ Frequency_{SP}} \times 100\% \quad (1)$$

Decay Rate (5.6% vs. 34.4% vs. 8.2%):

The decay rate quantifies the percentage decrease in a given outcome measure from its observed peak (at Time T3, post-intervention) to the final follow-up assessment (at Time T4). Different metrics exhibited distinct decay patterns:

- 5.6% Decay: This value represents the decay rate specifically for the Environmental Attitude score within the FI group (declining from $\Delta M = 0.90$ at T3 to $\Delta M = 0.85$ at T4). Attitudinal measures are generally considered more stable, making this the most reliable indicator of sustained effect.
- 34.4% Decay: This higher rate reflects the decay observed for the Actual Purchase Frequency in the FI group (dropping from 3.2 to 2.1 purchases per month from T3 to T4). Behavioral frequency is inherently more volatile and susceptible to external contextual factors post-intervention.
- 8.2% Decay: This figure is a weighted average decay rate calculated across all attitudinal and behavioral intention variables (e.g., perceived behavioral control, purchase intention). It intentionally excludes the more volatile actual purchase frequency metric to provide a summary of the decay in psychological constructs.

B. Changes in Environmental Attitude

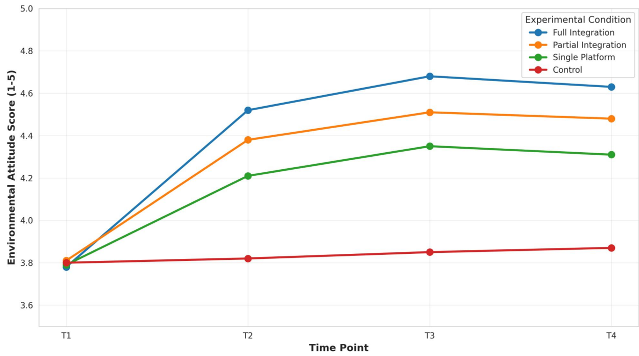

Fig. 2. Changes in environmental attitude over time

Figure 2 illustrates the progression of environmental attitude scores across the four measurement time points for each experimental group. As visually depicted, the Full Integration (FI) group exhibited the most pronounced positive change over the course of the study.

Statistical analysis was conducted using a repeated-measures analysis of variance (ANOVA). This analysis confirmed a significant main effect for the factor of time ($F(3, 1244) = 156.32$, $p < .001$, $\eta^2 = 0.27$). This result indicates that, overall, participants' environmental attitudes showed improvement from the beginning to the end of the assessment period. A significant main effect was also identified for the experimental condition (F(3, 1244) = 42.18, $p < .001$, $\eta^2 = 0.09$). This finding suggests that the type of intervention participants received had a measurable influence on their attitude scores. Crucially, the analysis revealed a statistically significant interaction between time and experimental condition (F(9, 1244) = 18.76, $p < .001$, $\eta^2 = 0.12$).

To pinpoint specific differences between groups, post-hoc pairwise comparisons were performed with a Bonferroni adjustment to control for Type I error. These comparisons quantified the magnitude of attitude change from the baseline (T1) to the immediate post-intervention assessment (T3). The FI group demonstrated the greatest gain, with a mean increase of $\Delta M = 0.90$ (SE = 0.08, $p < .001$). This was followed by the Partial Integration (PI) group, which showed a mean increase of $\Delta M = 0.70$ (SE = 0.08, $p < .001$). The improvement observed in the Single Platform (SP) group was significantly smaller ($\Delta M = 0.56$, SE = 0.08, $p < .001$), while the Control group displayed no statistically reliable change ($\Delta M = 0.05$, SE = 0.08, $p = .92$). At the final follow-up measurement (T4), the FI group's mean attitude score showed a minor decrease from its peak, settling at $\Delta M = 0.85$ (SE = 0.08) relative to baseline. This corresponds to a decay rate of only 5.6% from T3 to T4, indicating a high degree of attitude retention.

C. Changes in Perceived Behavioral Control

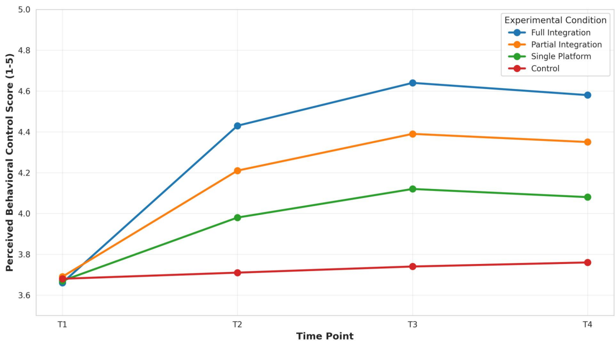

Fig. 3. Changes in perceived behavioral control over time

Figure 3 displays the trajectories of perceived behavioral control scores across the four measurement intervals for each experimental condition. Consistent with the findings for environmental attitudes, the most substantial enhancement in perceived control is again observable within the Full Integration (FI) cohort.

Analysis of perceived behavioral control via repeated-measures ANOVA yielded a pattern of results analogous to the attitude analysis. A statistically significant main effect for time was observed (F(3, 1244) = 198.45, $p < .001$, $\eta^2 = 0.32$), indicating a general increase in scores across all participants over the study duration. The analysis also revealed a significant main effect for the experimental condition (F(3, 1244) = 35.82, $p < .001$, $\eta^2 = 0.08$), confirming that the level of improvement differed between groups. Furthermore, a significant interaction effect between time and condition was present (F(9, 1244) = 16.43, $p < .001$, $\eta^2 = 0.11$). This interaction indicates that the rate and extent of change in perceived behavioral control over time were not uniform but depended significantly on the specific intervention received.

Post-hoc examination of the score changes from baseline (T1) to the post-intervention point (T3) quantified these differences. The FI group demonstrated the greatest enhancement, with a mean increase of $\Delta M = 0.98$ (SE = 0.09, $p < .001$). The magnitude of improvement diminished progressively, with the Partial Integration group showing a mean increase of $\Delta M = 0.70$ (SE = 0.09, $p < .001$), followed by the Single Platform group at $\Delta M = 0.45$ (SE = 0.09, $p < .001$). In contrast, scores in the Control group remained largely unchanged ($\Delta M = 0.06$, SE = 0.09, $p = .89$).

D. Analysis of Purchase Behavior

Purchase Intention: The changes in purchase intention scores over time are presented in Figure 4. The pattern of results for this variable aligns closely with the trends observed for both environmental attitudes and perceived behavioral control, suggesting a coordinated response across these related psychological constructs.

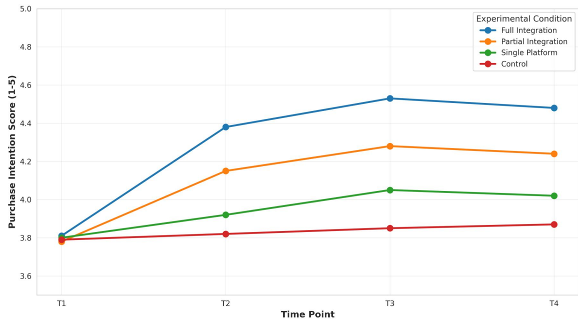

Fig. 4. Changes in purchase intention over time

The analysis of purchase intention data employed a repeated-measures ANOVA. The findings from this test indicated a pattern of change over time that was substantially aligned with the trajectories previously documented for both environmental attitude and perceived behavioral control.

Regarding specific group outcomes, purchase intention scores for the Full Integration (FI) group attained their highest level at the T3 measurement point ($M = 4.53, SD = 1.16$). This value represents a statistically significant increase of 0.72 points relative to the group's baseline (T1) score ($p < .001$). When measured again at the T4 follow-up, a minor reduction in the FI group's mean intention was observed (SD = 1.19). The magnitude of this decline was minimal, calculated at only 1.1%, which suggests a considerable degree of stability in the intervention's effect on this variable over time(Figure 5).

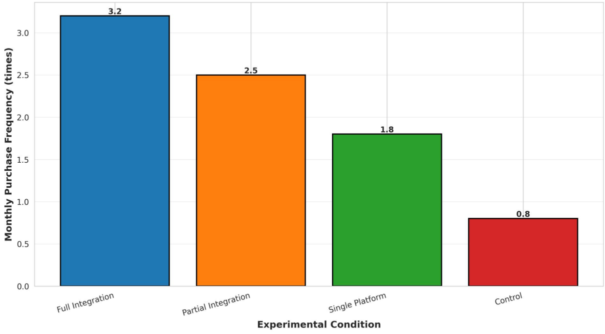

Fig. 5. Changes in purchase intention over time

Figure 6. Comparison of the mean monthly purchase amount spent on sustainable products among the experimental groups during the intervention period (T2-T3).

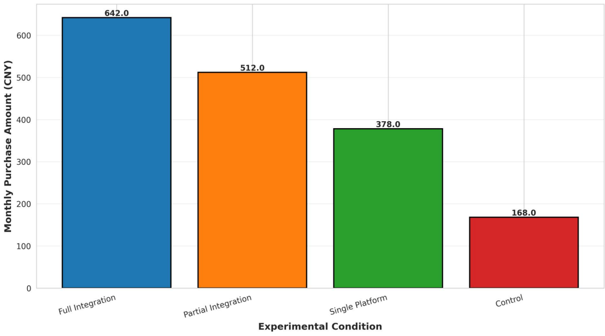

Fig. 6. Changes in purchase intention over time

Table I presents the actual purchase behavior data for the four experimental groups during the intervention period. The frequency of purchasing sustainable products by participants in the Full Integration group was significantly higher than in the other groups. During the T2-T3 period (mid-intervention), the average monthly purchase frequency of the Full Integration group was 3.2 times (SD = 1.8), a 300% increase compared to the Control group (M = 0.8, SD = 0.5) (95% CI: 258%-342%). During the T3-T4 period (post-intervention), although the purchase frequency decreased, the Full Integration group still maintained a rate of 2.1 times/month (SD = 1.5), which was still a 133% increase compared to the Control group's 0.9 times/month (SD = 0.6).

TABLE I. ACTUAL PURCHASE BEHAVIOR DATA (MEAN MONTHLY PURCHASE FREQUENCY AND AMOUNT)

Period	Full Integration	Partial Integration	Single Platform	Control
Purchase Frequency (times/month)				
T1-T2	0.9 (0.6)	0.8 (0.5)	0.9 (0.6)	0.8 (0.5)
T2-T3	3.2 (1.8)	2.5 (1.4)	1.8 (1.1)	0.8 (0.5)
T3-T4	2.1 (1.5)	1.6 (1.2)	1.2 (0.9)	0.9 (0.6)
Purchase Amount (CNY/month)				
T1-T2	187 (142)	165 (128)	178 (135)	162 (124)
T2-T3	642 (385)	512 (318)	378 (245)	168 (132)
T3-T4	421 (287)	325 (218)	248 (172)	185 (141)

V. DISCUSSION

The evidence from this study strongly supports the central claim that cross-platform integration of environmental information—especially when embedded in a behavioral closed-loop system—produces stronger and more persistent shifts toward sustainable consumption than interventions limited to a single platform. Across the four experimental conditions, the Full Integration (FI) group consistently showed the largest gains in three key psychological drivers: environmental attitude, perceived behavioral control, and purchase intention. Importantly, these psychological improvements translated into observable outcomes. The FI group's significant incremental advantage in sustainable purchase frequency relative to the single-platform baseline (the primary "gain effect") cannot be explained by message volume alone. Rather, it appears to arise from the synergy of message consistency and coordinated feedback as users move across e-commerce, social media, and content platforms. Mechanistically, the results align with the proposed framework: cross-platform consistency likely reduces cognitive dissonance and transition friction, strengthening learning and preserving motivational momentum. At the same time, the closed-loop feedback mechanism appears to enhance self-efficacy and perceived control — both well-established predictors of sustained behavior change.

Theoretically, this work extends intervention logic grounded in TPB and EPPM by shifting the unit of persuasion from a single app to the ecosystem level. Instead of treating platforms as isolated channels, the study positions the user's cross-platform journey as the core design object. The successful operationalization of information consistency — across content, style, and timing — together with adaptive feedback points to a broader principle: behavioral persistence is driven less by isolated persuasion than by narrative coherence combined with systematic reinforcement.

Practically, the prototype-based deployment demonstrates a replicable approach for organizations without advanced AI infrastructure. The findings suggest that pairing lightweight collaborative filtering for personalization with a transparent, rule-based adaptive messaging system can produce meaningful behavioral improvements while remaining computationally simple and operationally interpretable. For practitioners, the results imply three priorities: (i) maintain a coherent environmental narrative across user touchpoints, (ii) provide timely feedback that links micro-actions to visible progress, and (iii) adjust delivery intensity based on engagement to balance reinforcement with notification fatigue. These principles are not limited to environmental goals and appear transferable to domains such as public health and social responsibility.

Several limitations should be noted. First, the intervention was implemented in a controlled prototype environment; while this supports strong internal validity, it may not capture real-world ecosystem dynamics such as platform competition, multitasking, and external incentives. Field replication or hybrid deployments are needed. Second, although the study examined stability and decay over a follow-up period, longer-term tracking is necessary to test persistence beyond the short term and to identify optimal feedback schedules that prevent rebound. Third, the sample and digital context—urban users within one country and a specific platform configuration—may limit generalizability. Future studies should test whether cross-platform coherence effects hold across cultures, product categories, and platform affordances. Finally, behavioral measurement can be further refined, especially regarding how "purchase" is operationalized in simulated settings, and future work should examine mediators and moderators such as baseline environmental concern, digital literacy, and platform-use intensity to improve targeting without increasing technical complexity.

VI. CONCLUSION

This research demonstrates that designing a cross-platform behavioral closed-loop system — which integrates consistent environmental information with behavior tracking and adaptive feedback across e-commerce, social media, and content contexts — can substantially enhance outcomes relative to single-platform approaches. The improvements encompass environmental attitudes, perceived behavioral control, behavioral intentions, and actual sustainable purchasing. The evidence suggests that ecosystem-level coherence, combined with systematic reinforcement, strengthens behavioral persistence and reduces the post-intervention decay of key psychological outcomes. Furthermore, the implementation model, which relies on low-threshold personalization and feedback mechanisms, offers a practical and reproducible pathway for designing scalable interventions. In summary, this work contributes to the advancement of theory concerning digital ecosystem interventions and provides actionable design guidance for systems aimed at promoting sustainable consumption. The findings also delineate clear opportunities for future validation through real-world deployments and longer-term longitudinal studies.

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AVAILABILITY OF DATA

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AUTHOR CONTRIBUTIONS

Xinlin Chen:Conceptualization; Methodology; Formal analysis; Investigation; Writing – original draft; Writing – review and editing; Visualization; Supervision; Project administration.

Xianhao Ye:Methodology; System design; Software; Data curation; Validation; Writing – review and editing.

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COMPETING INTERESTS

The authors declare no competing interests.

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