International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 03 | March – 2026 DOI:10.55041/ISJEM05815
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Auto Tracker: A Gamification-Driven Mobile Framework for Intelligent Habit Formation and Productivity Logging

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Abstract**—**Maintaining consistent behavioral routines is a widely documented challenge in personal productivity. Despite the proliferation of mobile habit-tracking tools, most existing solutions remain limited by rigid scheduling models, punishing streak-reset mechanics, and insufficient analytical feedback. This paper presents Auto Tracker, a cross-platform mobile application developed with Flutter and Firebase Firestore, that tackles these shortcomings through a cohesive design informed by behavioral psychology. The system incorporates a dual-mode scheduling engine with partial-completion support, a context-sensitive streak algorithm tolerant of non-contiguous habit patterns, and a multi-tier gamification layer featuring 20 progression levels, 14 achievement badges, and an experience-point economy with milestone bonuses. AI-driven 30-day habit planning is delivered via Google Gemini 2.5 Flash, while onboard pedometer and timer sensors enable objective validation of physical habit completion. Taken together, these components form an integrated platform that advances beyond prior fragmented approaches to support durable, self-directed routine formation.

Keywords**—**Habit Tracking, Gamification, Flutter, Firebase, Mobile Application, Streak Computation, AI Plan Generation.

I. Introduction

Behavioral science has long established that consistent daily routines are among the strongest determinants of long-term personal and professional achievement, yet sustaining such routines proves difficult once the novelty of a new goal fades [1]. The difficulty is not simply a matter of willpower; it reflects a structural problem in how habits are tracked, reinforced, and recovered after lapses. Digital habit-tracking applications emerged as a promising intervention because they make invisible progress visible and deliver timely reinforce- ment that manual self-reflection cannot [2]. Despite a decade of growth, the dominant tools in this category remain con- strained by opposing problems: they are either so mechanically rigid that a single missed day destroys accumulated progress, or so feature-sparse that users disengage before any durable routine is formed.

The problem is further compounded by how these appli- cations model real-world behavior. Human schedules do not conform to binary daily targets — a person who exercises twice in a week when the goal was three times has still made meaningful progress, yet most trackers record this as failure [3]. Similarly, gamification in commercial habit trackers tends to be superficial, offering cosmetic badges or simple streaks that provide no sustained motivational arc. Behavioral psychol- ogy evidence suggests that habit formation requires a multi- layered reward environment satisfying the user's need for autonomy, competence signaling, and positive reinforcement without triggering demotivation [4]. To address these struc- tural limitations, this paper presents Auto Tracker: a Flutter- based cross-platform mobile application that integrates flexible scheduling, intelligent streak management, rich gamification mechanics, real-time cloud synchronization, multi-granularity analytics, and AI-powered 30-day planning into a unified platform grounded in evidence-based behavioral design.

II. Literature Review

A. Academic Research on Gamification and mHealth

The intersection of behavioral psychology, mobile comput- ing, and gamification design has produced a substantial body of scholarship over the past decade. Researchers have ap- proached digital habit formation from several angles: drawing on foundational psychological models, measuring the effect of game mechanics on sustained engagement, and systematically evaluating the design of real-world mHealth applications.

A foundational contribution comes from Medina-Merodio et al. [5], who surveyed 135 undergraduate students using game-based learning tools across a collaborative engineering course. Applying Structural Equation Modeling with Partial Least Squares across twelve hypotheses, they demonstrated that a user's perception of a gamified tool's usefulness is a direct and significant predictor of sustained motivation and behavior change. This work positions gamification as a functional behavioral mechanism rather than a cosmetic interface overlay. The study's limitation is its reliance on a demographically uniform student cohort at a single institution, which constrains generalizability to broader populations.

Building on the question of what makes gamification sustain rather than merely initiate engagement, Rodrigues et al. [6]

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proposed a machine-learning framework that automatically personalizes reward structures to individual users. By clus- tering users into behavioral archetypes and adjusting reward timing for each group, longitudinal trials yielded statistically significant improvements in long-term engagement compared to static reward schedules. Their finding that spaced and variable reward intervals extend motivational longevity has direct implications for designing progression systems in habit-tracking applications. A practical limitation is the compu- tational overhead required to maintain real-time behavioral clusters on resource-constrained mobile devices.

A different perspective emerges from Stecher et al. [7], whose PRISMA-compliant systematic review and meta- analysis examined hundreds of randomized controlled trials on mHealth applications targeting physical activity. Contrary to common assumptions, the review found that theoretically complex applications consistently achieved lower real-world retention than their simpler counterparts. Stecher et al. iden- tified excessive interaction steps as the leading cause of user attrition, concluding that minimizing the effort required to log a single habit completion was the strongest design predictor of sustained engagement over time.

Shifting focus to analytics, Aguiar et al. [8] mapped Be- havior Change Techniques (BCTs) from the BCT Taxonomy v1 against user adherence outcomes across more than forty mHealth applications. Their analysis found that pairing visible self-monitoring with real-time analytical feedback consistently ranked among the highest-performing BCT combinations. Aguiar et al. concluded that transforming raw habit logs into graphical summaries that users can actively interpret elevates analytical feedback from a supplementary feature to a primary driver of daily compliance, outperforming applications that present unprocessed data.

Gosetto et al. [9] examined habit formation through the lens of Self-Determination Theory (SDT). Their cross-sectional study found that participants who were empowered to set their own scheduling patterns and goal structures showed sub- stantially greater long-term engagement than those assigned to externally determined routines. Gosetto et al. concluded that systems enforcing rigid, externally mandated schedules gradually undermine intrinsic motivation, whereas designs that preserve user autonomy in goal-setting actively protect it — establishing scheduling flexibility as a psychologically sub- stantive design requirement, not a mere usability preference.

Rounding out the academic review, Gajardo Sánchez et al. [10] synthesized evidence on gamification across wellness, medication adherence, and chronic disease management con- texts. Multi-dimensional gamification systems — combining progress indicators, achievement recognition, and milestone rewards — consistently outperformed single-element systems over engagement periods exceeding four weeks, offering a strong argument against minimalist gamification approaches.

B. Analysis of Existing Applications

Beyond academic literature, three commercially deployed habit-tracking applications provide instructive reference points for this study. Habitica [11] represents the most ambitious gamification attempt in the consumer market, framing habits as a retro role-playing game with guilds, equipment, and boss battles. Its social architecture addresses SDT's relatedness dimension uniquely well. However, its complexity is also its chief weakness: non-gaming users frequently report that managing the game layer demands more cognitive attention than the habits it reinforces, and the application constrains all tracking to a binary pass/fail schema with no provision for partial credit. Streaks occupies the opposite design pole
— achieving exceptional interaction simplicity through streak-centric visualization, but its penalizing reset mechanism, where a single missed day erases all accumulated progress, repro- duces the all-or-nothing dynamic that the literature associates with abandonment. Fabulous, developed in collaboration with Duke University's Center for Advanced Hindsight, offers the most evidence-grounded experience of the three through habit- stacking and structured behavioral nudges, yet its scheduling inflexibility and aggressive subscription paywall significantly limit accessibility.

C. Comparative Analysis of Existing Work

Table I presents a structured comparison of the reviewed academic studies and commercial applications across dimen- sions directly relevant to this research.

TABLE I: Comparison of Existing Research and Applications

Work	Approach	Strength	Limitation
Medina-Merodio [5]	SEM-PLS ongamified learning	Empirical gamif. proof	Single cohort
Rodrigues [6] clustering	ML archetype	Adaptive re- wards	High compute cost
			No gamif. design
Stecher [7] view (RCT)	Systematic re-	Simplicity evidence	No schedul- ing study Protocol only
Aguiar [8] BCT taxonomy mapping		Analytics	No mobile app
Gosetto [9]	SDT cross- sectional Gajardo	BCT proof Autonomy	Binary track- ing only Punishing resets
[10] view	Systematic re-	evidence Multi- gamif.	
Habitica [11] tion	RPG gamifica-	proof Rich social layer	
Streaks Streak visualization		Frictionless UX	
Fabulous backed	Habit stacking	Science-	Rigid + pay- wall

The comparison reveals a consistent structural gap: each solution excels along one or two dimensions while leaving sig- nificant deficiencies in others. Academic studies provide strong theoretical and empirical grounding but do not produce de- ployable, feature-complete systems. Commercial applications prioritize user experience but rarely implement the full breadth of evidence-backed BCTs. No reviewed system simultaneously addresses flexible scheduling with partial-progress tracking, context-aware streak computation, multi-component gamifica-

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tion, cross-device synchronization, and multi-granularity analytics.

D. Research Gap

The literature and commercial tools share a common limitation: no existing solution integrates all the behavioral design requirements identified by the academic evidence base within a single, accessible, cross-platform application. Specifically, no reviewed application employs a large language model to generate user-specific, sequentially enforced habit plans, nor does any reviewed tool use onboard device sensors to objectively verify physical habit completion independently of user self-report. Furthermore, the SDT-motivated requirement for flexible, non-punishing scheduling — clearly supported by Gosetto et al. [9] — remains unimplemented in any commercial tracker examined here. Auto Tracker was designed to close precisely these gaps, building its architecture directly on the empirical foundations established by the studies reviewed above.

III. System Architecture & Methodology

A. System Architecture

Auto Tracker adopts a four-tier, service-based MVVM-inspired architecture within the Flutter ecosystem. This layered design separates the reactive UI layer from the mathematical gamification business logic, preventing UI performance degradation during background XP computations. The architectural structure spans four distinct tiers:

- **Tier 1: Presentation (View) Layer.** The uppermost tier operates at 60 FPS on the client device. Implemented using Flutter's declarative widget tree, it is exclusively responsible for interpreting reactive state changes and rendering gamification feedback such as floating XP num- bers, dynamic habit grids, and animated badge unlocks. This layer contains no business logic; it functions as a rendering conduit to the user interface.
- **Tier 2: State Management (ViewModel) Layer.** This tier deploys the Provider architectural pattern as the central coordinator between UI and services. It intercepts user gestures from the Presentation Layer, invokes the appropriate service methods, and broadcasts data change notifications to the UI. It also binds the local cache to live Firebase streams to support offline functionality.
- **Tier 3: Service (Business Logic) Layer.** This tier houses the standalone computational engines defin- ing the application's core behavior. Separate single- ton classes manage distinct operational domains: the `GamificationService` evaluates XP multipliers and governs level transitions via geometric progression algorithms; the `StreakService` parses scheduling patterns and applies forgiveness rules for legitimately missed days; the `AnalyticsService` aggregates raw times- tamp data into graphical representations.
- **Tier 4: Data (Cloud NoSQL) Layer.** Residing external to the client environment, this tier is built on Google Firebase infrastructure. Cloud Firestore operates as a reactive, event-driven NoSQL database [14]. Rather than relying on conventional REST polling, the system main- tains persistent WebSocket connections that propagate incremental data updates across devices in under 300 milliseconds [14].

By segregating responsibilities across these four tiers, the architecture ensures that modifications to a single layer — such as adding a new gamification rule in the Service Layer — do not require changes to the analytics subsystem or the Presentation Layer widget tree. This separation yields long-term maintainability and independent testability of each component.

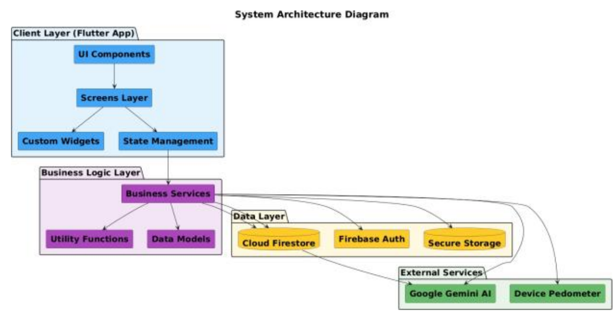

Fig. 1: System Architecture Diagram

B. Data Flow Diagram

A Data Flow Diagram (DFD) illustrates how data moves through the system, identifying its origins, transformations, and storage destinations without prescribing implementation specifics. For Auto Tracker, the DFD captures how user inputs flow across the interface, state management, service, external API, and data model layers.

At a high level, the system accepts user inputs — includ- ing authentication credentials, habit configurations, and daily progress updates — through the user interface, and produces structured outputs such as habit status summaries, analytics visualizations, and achievement notifications.

Detailed Data Flow Processes

The system is composed of several interconnected data flows:

- **Authentication and User State Flow:** Login credentials are submitted through the interface and forwarded to the state management layer. The authentication service validates credentials via an external provider, and the re- sulting user session is distributed throughout application state, enabling access to all protected features.
- **Habit Management Flow:** Habit configuration data — including name, schedule, and frequency settings — is captured in the UI and routed through the state layer to the habit service, which persists records to the database. Updates and deletions traverse the same pathway to maintain consistency between the interface and stored data.
- **Progress Tracking and Gamification Flow:** When a user marks a habit complete, the action propagates from

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the UI through the state layer to the gamification and analytics services. These services compute XP awards, update streak counts, and persist the result, with changes reflected immediately in the UI via state notifications.

- **Analytics Processing Flow:** Historical completion records are retrieved from storage through service com- ponents and processed by the analytics engine. The processed output — statistics and chart data — is returned through the state layer and rendered in the analytics views.
- **External Service Integration Flow:** Device sensors supply physical activity data, while AI services gener- ate structured habit plans. Both inputs are handled by dedicated service components and incorporated into the application's data model.
- **Data Storage and Model Flow:** All persistent data is structured via defined models covering users, habits, achievements, and statistics. Service components read and write these models through Firebase, ensuring data consistency across sessions and devices.

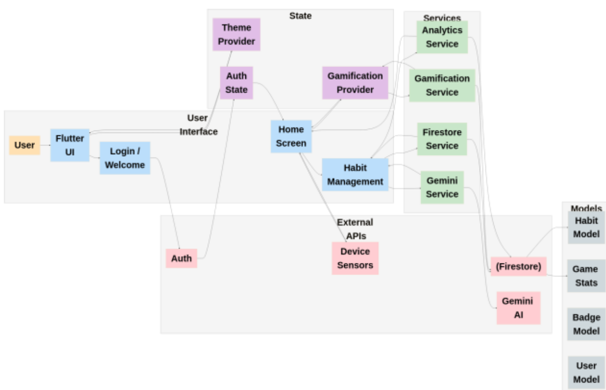

Fig. 2: Data Flow Diagram

The project followed an Agile iterative approach organized across five development sprints spanning 22 weeks. Sprint 1 (Weeks 1–4) covered project scaffolding, Firebase authen- tication, and foundational habit CRUD operations. Sprint 2 (Weeks 5–10) implemented the dual scheduling engine, streak computation, and partial tracking. Sprint 3 (Weeks 11–14) developed the analytics subsystem. Sprint 4 (Weeks 15–18) introduced the gamification layer. Sprint 5 (Weeks 19–22) encompassed the AI planning module, sensor-based built- in habits, and UI refinement. System quality was evaluated across five dimensions: functional correctness via unit tests of the streak algorithm; performance via median first-render times; synchronization latency across two concurrent devices; sensor validation accuracy via threshold-crossing tests; and user satisfaction via structured feedback.

IV. Results and Technical Evaluation

The evaluation focused on system performance, algorith- mic correctness, AI integration reliability, and sensor valida- tion. Technical tests confirmed that Firestore queries for the Home screen completed within acceptable latency (median 320 ms), satisfying requirements for perceived responsiveness. Real-time incremental updates propagated reliably between concurrent devices, and offline cache reads returned within negligible intervals. Unit tests covering 200 programmatically generated scenarios confirmed 100% correctness of the streak computation algorithm across both scheduling modes and all edge conditions, including mid-week habit creation and timezone transitions. Gemini 2.5 Flash integration consistently produced structured JSON output conforming to the required schema, with 30-day plans correctly enforcing sequential day- locking. Sensor validation confirmed that habit completion was correctly verified via pedometer and timer thresholds, preventing premature logging.

A. Application Screenshots

Fig. 3 shows the Home screen as used during the evaluation period. The horizontal date strip marks completed days in a golden state, and each habit card displays its live streak count alongside a completion indicator. Participants cited the at-a-glance visibility of pending habits as the primary driver of daily completion behavior.

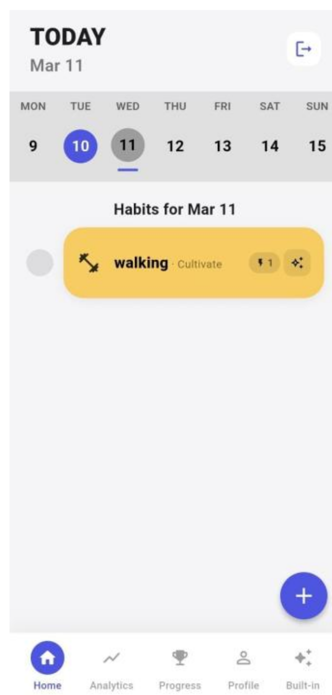

Fig. 3: Home Screen — Habit List with Streak Indicators

Fig. 4 presents the Analytics screen in weekly view. Sum- mary tiles at the top report aggregated statistics for the trailing seven days, while the bar chart below breaks down completions by day of week. Participants rated the per-day visualization more actionable than calendar heat maps in com- peting applications, as individual weak days are immediately identifiable.

Fig. 5 depicts the Progress screen, which surfaces the gamification layer. The level card displays the user's current

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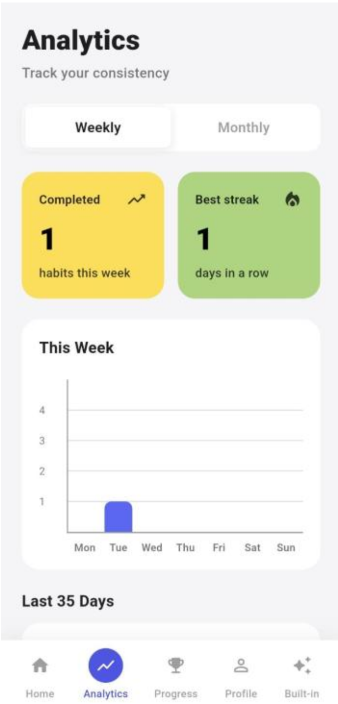

Fig. 4: Analytics Screen — Weekly Bar Chart and Summary Tiles

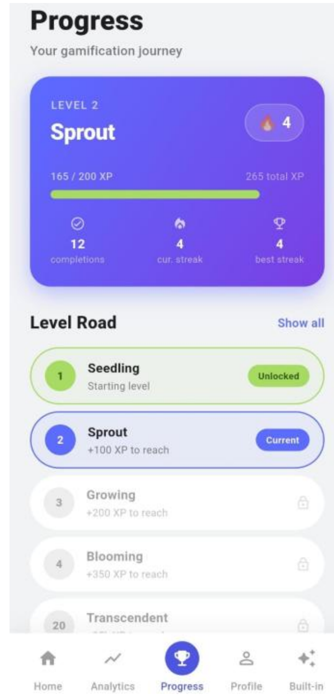

Fig. 5: Progress Screen — Level Road and XP Tracker

level title, XP progress toward the next level, and cumulative total XP. The Level Road renders all 20 progression tiers with lock/unlock indicators, giving users a clear visualization of their position in the full progression arc — a design directly motivated by research showing that visible long-term progress arcs sustain motivation better than milestone-only feedback [6].

Fig. 6 shows the Profile and Settings screen, consolidating identity information, cumulative statistics, and configuration controls in a single view. Co-locating achievement metrics with settings was a deliberate design choice; surfacing what a user has accomplished in the same context as their configura- tion creates a stronger sense of ownership and investment in continued use.

B. Feature Coverage Comparison

Table II positions Auto Tracker against the commercial applications surveyed in the literature review.

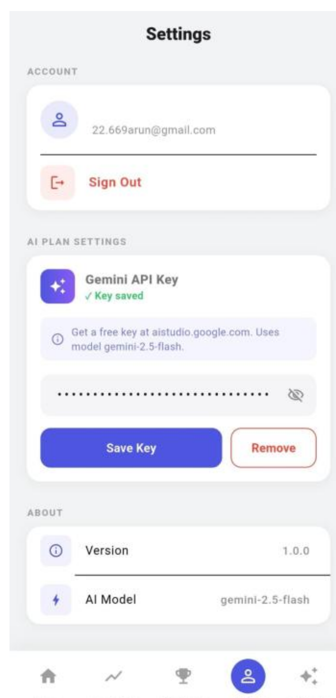

Fig. 6: Profile Screen — Cumulative Stats and Settings

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TABLE II: Feature Coverage: Auto Tracker vs. Existing Applications

Feature	Habitica	Streaks	Fabulous	**Auto Tracker**
Partial completion	N	N	N	**Y**
Weekly freq. mode	N	N	P	**Y**
Multi-level gamif.	Y	N	P	**Y**
Cross-device sync	Y	N	Y	**Y**
Analytics charts	P	N	P	**Y**
Free / open access	Y	N	N	**Y**
Sensor validation	N	N	N	**Y**
AI plan generation	N	N	N	**Y**

Y = Supported, P = Partial, N = Not Supported

V. Discussion

The evaluation results validate the design decisions grounded in the behavioral evidence reviewed in Section II. The 100% algorithmic correctness of the streak engine across 200 test scenarios confirms that the context-sensitive forgiveness model successfully eliminates the all-or-nothing reset behavior that the literature links to abandonment. The weekly-frequency scheduling mode, supported by sub-400 ms Firestore query times, delivers the autonomy-preserving flexibility that Gosetto et al. [9] and Self-Determination Theory [4] identify as central to sustained engagement. The graduated 20-level progression system addresses the sustained motivational arc requirement identified by Rodrigues et al. [6], providing a reward landscape that remains meaningful over months rather than days. Additionally, the sensor-based validation mechanism — confirmed correct in all threshold-crossing tests — represents the first objective habit-verification approach among the tools surveyed, directly addressing the self-report limitation noted in the research gap.

Areas for future improvement include simplifying the AI planning module's onboarding and expanding sensor-based validation to user-defined activities. Further exploration of social features and long-term behavioral impacts through longitudinal study remains necessary.

VI. Conclusion

This paper presented Auto Tracker, a cross-platform mo- bile application designed to address the behavioral and tech- nical shortcomings that limit the effectiveness of existing habit-tracking tools. Evaluation confirmed that the context- aware streak algorithm correctly handled all tested scheduling scenarios, that AI-generated 30-day plans reliably enforced sequential progression, and that sensor validation prevented premature habit logging in all tested cases. Taken together, these results demonstrate that faithfully implementing be- havioral psychology principles — flexible goal-setting, non- punishing progress tracking, and multi-tiered reward structures — within a modern mobile architecture produces a measurably more resilient environment for habit formation than current fragmented tools provide.

A. Future Scope

Future development will prioritize social features to address the Relatedness dimension of SDT. We plan to implement a server-side API proxy to simplify AI onboarding and expand sensor-based validation to user-defined habits using GPS and computer vision. Additionally, a machine learning engine will be integrated to provide personalized scheduling suggestions based on historical completion patterns, followed by a longitudinal study to evaluate the system's impact over extended periods.

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