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GENERATIVE ARTIFICIAL INTELLIGENCE AS A COGNITIVE CO-PILOT: THE IMPACT OF HIERARCHICAL GOAL DECOMPOSITION IN THE BLOCK AI APPLICATION

INTELIGÊNCIA ARTIFICIAL GENERATIVA COMO CO-PILOTO COGNITIVO: O IMPACTO DA DECOMPOSIÇÃO HIERÁRQUICA DE METAS NO APLICATIVO BLOCK AI

INTELIGENCIA ARTIFICIAL GENERATIVA COMO CO-PILOTO COGNITIVO: EL IMPACTO DE LA DESCOMPOSICIÓN JERÁRQUICA DE METAS EN LA APLICACIÓN BLOCK AI

Leonardo de Oliveira[1], Tardelli Ronan Coelho Stekel[2],
Olavo Olimpio de Matos Junior[3]

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ABSTRACT

Managing personal productivity has become increasingly difficult under the pressure of daily information overload. This study presents the design and evaluation of Block AI, a mobile application that links hierarchical goal decomposition with generative artificial intelligence. Grounded in Locke and Latham's (1990) Goal Setting Theory and Allen's (2015) Getting Things Done (GTD) framework, the app uses a three-tier model (Objectives, Goals, and Tasks) to turn abstract ambitions into daily routines. Its generative AI engine runs on large language models (LLMs) through two modes: Creator, which outlines structured action plans from raw text descriptions, and Coach, which processes real-time performance metrics to deliver contextual productivity advice. Methodologically, the work is an applied technological development utilizing React Native, Supabase, and the Gemini model. Practical testing shows that dividing goals into bite-sized tasks, paired with built-in timers and haptic feedback, reduces procrastination and improves daily user engagement. Ultimately, merging traditional time management principles with generative models shows strong promise for next-generation personal productivity systems.

KEYWORDS: *Personal Productivity. Generative Artificial Intelligence. Goal Decomposition. Mobile Application. Task Management.*

RESUMO

Gerenciar a produtividade pessoal tornou-se um desafio complexo frente à crescente sobrecarga de informações cotidiana. Este estudo descreve o desenvolvimento e a avaliação do *Block AI*, um aplicativo móvel projetado para articular a decomposição hierárquica de objetivos à inteligência artificial generativa. Apoiada na Teoria de Fixação de Objetivos de Locke e Latham (1990) e no método *Getting Things Done* (GTD) de Allen (2015), a ferramenta adota uma estrutura em três níveis Objetivos, Metas e Tarefas para converter intenções abstratas em ações práticas. O suporte de inteligência artificial baseia-se em modelos de linguagem (LLMs) operando em duas vertentes: o modo *Creator*, que elabora planos de ação estruturados com base em descrições livres do usuário, e o modo *Coach*, responsável por analisar dados de desempenho em tempo real e sugerir estratégias de produtividade personalizadas. Caracterizada como pesquisa aplicada de desenvolvimento tecnológico, a metodologia empregou *React Native*, Supabase e a API do Gemini. Ensaios com o sistema indicam que a subdivisão de metas em atividades menores, combinada com temporizadores integrados e retorno tátil, reduz a procrastinação e amplia o engajamento diário. A integração entre métodos tradicionais de gestão do tempo e inteligência artificial demonstra forte potencial para a criação de assistentes digitais focados no desenvolvimento pessoal.

[1] Federal Institute of São Paulo (IFSP). Undergraduate student in Systems Analysis and Development (IFSP).
[2] Federal Institute of São Paulo (IFSP). PhD in Space Geophysics from the National Institute for Space Research (INPE).
[3] Federal Institute of São Paulo (IFSP). Master's degree in Computer Science from the Federal University of Amazonas (UFAM).

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***PALAVRAS-CHAVE**: Produtividade Pessoal. Inteligência Artificial Generativa. Decomposição de Objetivos. Aplicativo Móvel. Gestão de Tarefas.*

RESUMEN
El control de la productividad personal se ha convertido en un desafío complejo frente a la creciente sobrecarga de información. Este estudio describe el desarrollo y la evaluación de Block AI, una aplicación móvil diseñada para vincular la descomposición jerárquica de objetivos con la inteligencia artificial generativa. Con base en la Teoría de Fijación de Objetivos de Locke y Latham (1990) y en el método Getting Things Done (GTD) de Allen (2015), el sistema estructura el flujo de trabajo en tres niveles Objetivos, Metas y Tareas para transformar ideas abstractas en acciones cotidianas. El motor de inteligencia artificial emplea modelos de lenguaje (LLM) en dos modalidades: el modo Creator, que elabora planes de acción estructurados a partir de descripciones en lenguaje natural, y el modo Coach, que analiza datos de rendimiento en tiempo real para sugerir pautas de productividad personalizadas. La metodología se define como una investigación aplicada de desarrollo tecnológico que utiliza React Native, Supabase y la API de Gemini. Los ensayos preliminares indican que subdividir las metas en tareas simples, junto con temporizadores integrados y respuesta háptica, disminuye la procrastinación y mejora la constancia de los usuarios. Se concluye que integrar metodologías tradicionales de gestión del tiempo con modelos generativos abre un camino prometedor para el diseño de asistentes digitales de apoyo personal.

***PALABRAS CLAVE**: Productividad Personal. Inteligencia Artificial Generativa. Descomposición de Objetivos. Aplicación Móvil. Gestión de Tareas.*

1. INTRODUCTION

In a digital environment saturated with continuous stimulation and information overload, personal productivity has evolved from a simple routine into a complex cognitive challenge. While the widespread adoption of task management software signals a robust demand for organizational tools, conventional systems often fail to bridge the gap between abstract aspirations and actionable daily tasks (Steel, 2012). This misalignment frequently leads users to set ambitious long-term goals only to abandon them when confronted with the friction of immediate, unstructured execution steps.

Goal-Setting Theory establishes that specific, challenging goals yield significantly higher performance than vague or easily attainable objectives (Locke & Latham, 1990). Complementing this perspective, Allen (2015) argues that externalizing tasks into a reliable system reduces cognitive load, thereby freeing mental resources for execution rather than active recall. Consequently, these theoretical frameworks suggest that decomposing high-level objectives into manageable, immediate actions serves as an effective strategy to mitigate procrastination and enhance personal efficacy.

The emergence of generative artificial intelligence (AI) introduces novel mechanisms to automate this decomposition process. Modern AI systems function as cognitive co-pilots, assisting users in planning, structuring, and monitoring complex pursuits (Mollick, 2024).

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Leveraging these agentic capabilities allows system designers to build a direct bridge between abstract goal formulation and concrete task execution through intelligent automation.

Driven by this intersection, this study addresses the following research question: How can a mobile application that integrates generative artificial intelligence and hierarchical goal decomposition enhance personal productivity?

This investigation is prompted by the prevalence of chronic procrastination and the high abandonment rates of traditional productivity software due to excessive complexity or a lack of structured guidance. Approximately twenty percent of the adult population identifies as chronic procrastinators, a figure that intensifies in digitally saturated environments (Steel, 2012). Despite the abundance of productivity applications, few integrate established cognitive psychology principles with generative AI capabilities within a unified interface.

To address this gap, this paper introduces the development and evaluation of Block AI, a mobile productivity application designed to combine hierarchical goal decomposition with generative AI to assist users in structuring and achieving their professional and personal objectives.

The paper is structured as follows: we first outline the three-tier database architecture of Objectives, Goals, and Tasks designed to align with goal-setting theories. Next, we describe the integration of the Gemini Large Language Model into the Creator and Coach modes, explaining how they generate structured plans and analyze user performance metrics. Lastly, we evaluate the application's interface choices, illustrating how glassmorphism, gamified features (such as activity heatmaps and haptic feedback), and Pomodoro-based timers collaborate to sustain long-term user engagement.

2. THEORETICAL FRAMEWORK

This section establishes the theoretical foundations of the Block AI application. We examine Locke and Latham's Goal-Setting Theory, David Allen's Getting Things Done (GTD) methodology, Piers Steel's Temporal Motivation Theory (TMT), and the emerging paradigms of Human-Computer Interaction (HCI) driven by generative artificial intelligence and Self-Determination Theory (SDT). Together, these frameworks provide the conceptual scaffolding for our hierarchical goal-decomposition model and conversational coaching assistant.

2.1. Goal-Setting theory and hierarchical decomposition

The structural architecture of the Block AI application is grounded in Locke and Latham's (1990) Goal-Setting Theory. Empirically, their work establishes that specific, measurable, and challenging goals yield superior performance compared to vague or easily achievable targets.

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This model highlights four key cognitive and motivational pathways: directing focus toward goal relevant tasks, mobilizing physical and mental effort, sustaining persistence over time, and stimulating tactical planning. To translate these principles into application logic, Block AI prompts users to input objectives with measurable criteria, such as deadlines, target workloads, and continuous monitoring metrics. This operational framework guarantees that user objectives are not merely abstract wishes but structured goals that fulfill the theory's specificity demands.

To reduce the cognitive drag of uncompleted tasks, the system incorporates the principles of David Allen's (2015) Getting Things Done (GTD) methodology. Allen stresses that retaining uncommitted items in working memory referred to as 'open loops' imposes an ongoing psychological toll, which impairs concentration. Systematically capturing, clarifying, and organizing these tasks in a trusted external environment relieves this stress and unlocks cognitive capacity. In Block AI, this process is structured as a hierarchical workflow: abstract aspirations are captured as macro-Objectives, clarified as distinct Goals, and ultimately organized into micro-Tasks. This systematic breakdown ensures that no user commitment persists as an unmanaged cognitive burden.

Rather than relying on manual clarification, we address the challenge of structuring these 'open loops' by automating the process using Large Language Models (LLMs). This integration represents the core contribution of this work: the AI does not serve merely as a passive content recommendation engine, but as an active cognitive partner within the goal decomposition pipeline.

2.2. Procrastination and Task Segmentation

Procrastination can be modeled mathematically and behaviorally through Steel's (2012) Temporal Motivation Theory (TMT). TMT posits that individual motivation depends on four primary variables: expectancy, value, delay, and sensitivity to delay. Within this mathematical framework, tasks perceived as highly complex or distant drastically reduce motivation, prompting task avoidance. Empirical evidence suggests that dividing a complex, long-horizon goal into immediate, bite-sized components increases both the expectancy of success and the proximity of perceived rewards, thereby enhancing active motivation.

Block AI mitigates this psychological friction through a strict three-tier schema. Users are required to decompose broad Objectives into intermediate Goals, which are further divided into actionable daily Tasks. Structuring the workflow this way ensures that the user never faces a massive objective without a visible, incremental path of action. Checking off individual daily tasks triggers an immediate reward signal, satisfying the behavioral reinforcement loop that Steel (2012) identifies as crucial to conquering chronic procrastination.

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2.3. Generative artificial intelligence as a cognitive co-pilot

The integration of generative artificial intelligence into personal management tools introduces a distinct paradigm in Human-Computer Interaction (HCI). Rather than aiming for cognitive replacement, Mollick (2024) conceptualizes generative AI as a form of "co-intelligence," acting as a collaborative partner that augments human planning, analysis, and decision-making. This collaborative framework directly targets the initial friction of productivity workflows, where the effort required to define, organize, and schedule goals often prevents users from taking action. Block AI instantiates this partnership by dividing the AI's role into two operational modes: the "Creator" and the "Coach". The Creator mode acts as a planning agent that takes unstructured natural language inputs (such as a user's ambition to learn an instrument) and generates structured plans with explicit objectives, task weights, and timelines. Conversely, the Coach mode evaluates real-time performance indicators, including completion rates and weekly trends, to deliver contextual productivity advice. This guidance is synthesized from established time-management theories, integrating the Pomodoro technique (Cirillo & Fernández, 2020), Time Blocking (George, 2025), and Deep Work principles (Jena & Basu, 2018).

This agentic division of labor is supported by recent advances in agentic AI. Large Language Model (LLM) task decomposition has been shown to significantly improve execution on complex, long-horizon tasks by recursively breaking them down into manageable steps (Prasad et al., 2024). Furthermore, AI-assisted goal setting increases user commitment and progress by establishing clear parameters of accountability (Richins et al., 2025). By deploying the Creator and Coach modes as functional agents, Block AI minimizes the initial executive burden on the user, shifting the primary cognitive effort from planning to execution. The visual flow of this interaction, showcasing conversation initiation, plan generation, and task breakdown, is illustrated in Figure 1.

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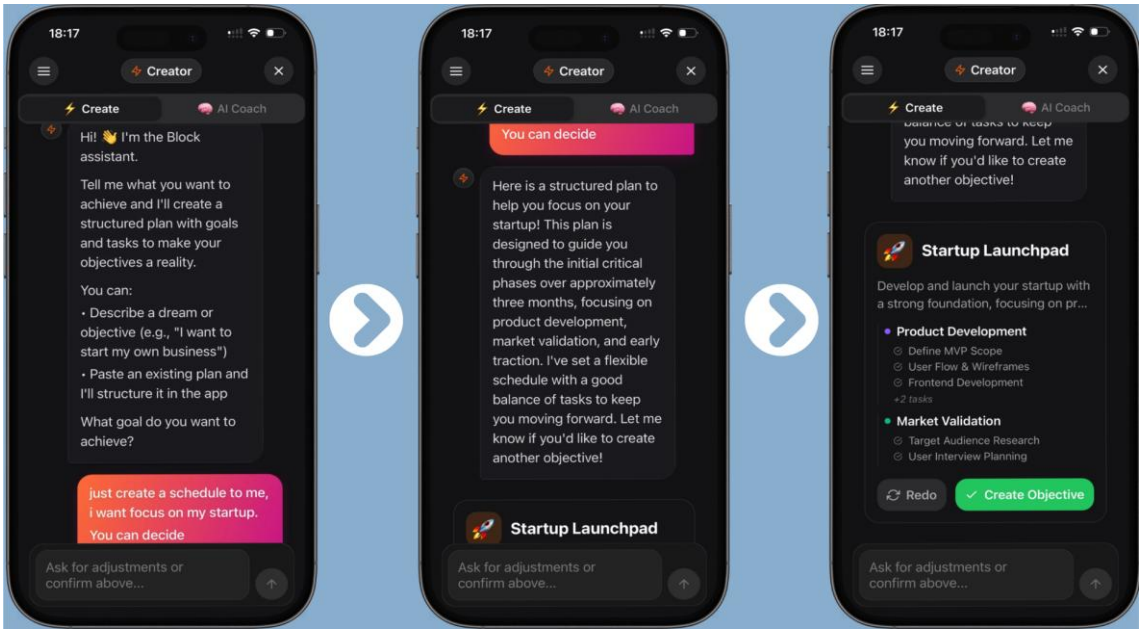
Figure 1. Screens of AI interface. It's a representation of starting conversation, description of plan and component of creation



Source: Authors 2026

2.4. User interface design and engagement mechanisms

The user interface (UI) and user experience (UX) of Block AI are aligned with Ryan and Deci's (2017) Self-Determination Theory (SDT). SDT posits that intrinsic motivation is sustained by satisfying three fundamental psychological needs: autonomy, competence, and relatedness. In behavior-change technologies, these needs can be addressed through custom metrics, progress visualizations, and conversational agents (Alberts et al., 2024).

Block AI implements these principles through specific interface elements:

1. Autonomy: Addressed by offering fully customizable goal hierarchies, allowing users to define their own metrics, target times, and task weights.

2. Competence: Supported through real-time progress indicators, daily completion statistics, and a GitHub-style annual activity heatmap that visually validates user effort.

3. Relatedness: Satisfied via the conversational, empathetic dialogue style of the AI Coach.

To supplement these motivators, the visual layout utilizes a dark-first, minimalist design. By structuring the interface hierarchically, the system minimizes cognitive load, focusing the user's attention on the single next actionable task.

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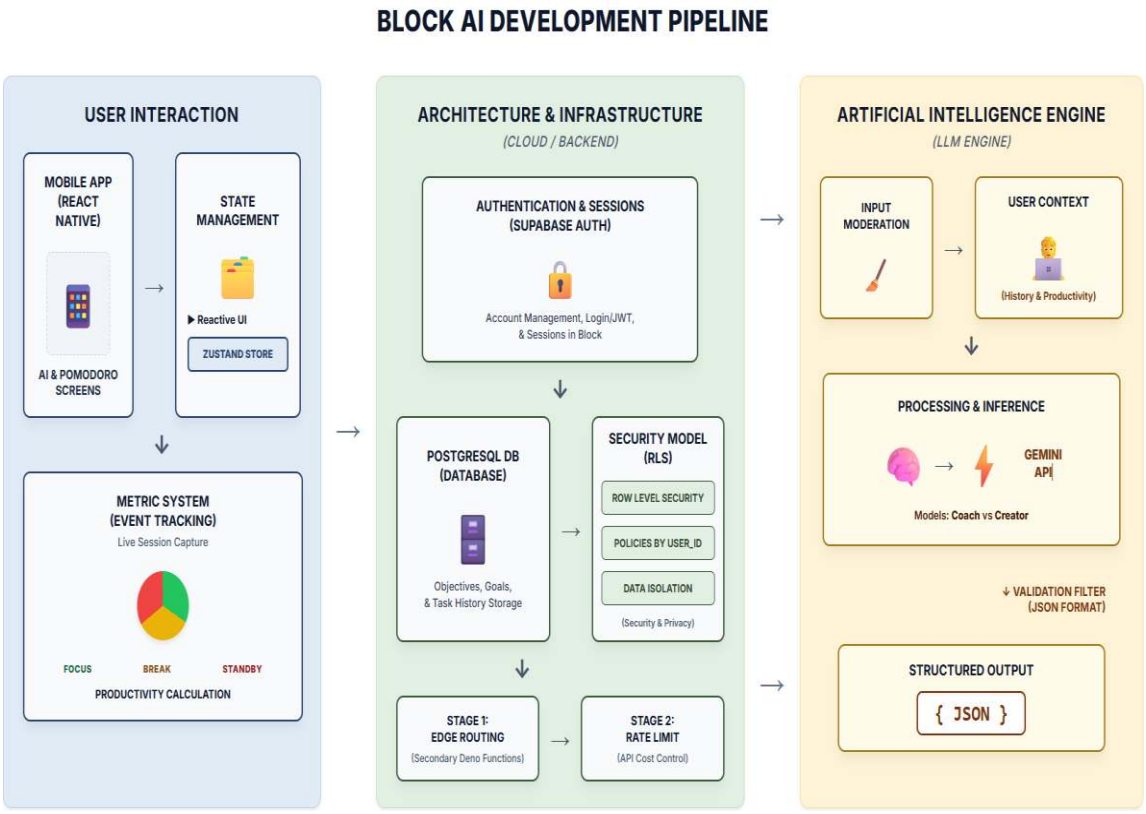
3. METHODOLOGY

This section details the methodology adopted to build, deploy, and evaluate the Block AI application. We outline the iterative prototyping development lifecycle, detail the frontend and backend technologies comprising our software stack, and describe the database schema supporting our hierarchical model. Finally, we explain the integration architecture of the Gemini large language model and the user interface design process that guides user engagement.

3.1. Research type and approach

This study is classified as applied research with a technological development approach, focusing on constructing and functionally validating a software prototype, the Block AI application, grounded in established theoretical frameworks. To develop the platform, we adopted an iterative prototyping methodology, which involved successive cycles of architectural design, system implementation, schema integration testing, and interface refinement, as structured in the development pipeline (Figure 2).

Figure 2. Development pipeline adopted



Source: Authors (2026).

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3.2. Technology Stack

Ensuring scalability, security, and a clean architecture required structuring the software environment across three distinct layers: frontend, backend, and interface. The frontend layer employs React Native and the Expo software development kit (SDK) (Expo, 2024), enabling cross-platform mobile deployment for iOS and Android from a single codebase. TypeScript (Microsoft, 2026) serves as the primary language, providing type safety and compile-time error detection to minimize runtime exceptions. For state management, we implemented Zustand (Zustand, 2024) to maintain a lightweight, centralized store without the boilerplate code typical of heavier frameworks.

The backend infrastructure utilizes Supabase (Supabase, 2026) as a Backend as a Service (BaaS). This platform handles user authentication, stores relational records in a PostgreSQL database, and executes custom server-side logic through Edge Functions. Google Gemini models

(Google, 2024) connect through these Edge Functions, establishing a secure middleware layer that supports the Creator and Coach modes. RevenueCat (RevenueCat, 2026) processes subscription flows and paywalls, while Expo Notifications manages task reminders. To implement the visual layout, the interface layer utilizes Expo BlurView, Expo Haptics, and Expo Linear Gradient to deliver glassmorphism effects, tactile haptic feedback, and smooth gradient styling (Table 1).

Table 1. Core technology stack layers, development frameworks, and architectural components of Block AI

Layer	Technology	Purpose
Frontend Framework	React Native (Expo SDK)	Cross-platform mobile development (iOS and Android)
Programming Language	TypeScript	Type-safe development with compile-time error detection
State Management	Zustand	Lightweight, centralized application state

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Backend as a Service	Supabase	Authentication, database (PostgreSQL), and Edge Functions
AI Integration	Google Gemini (via Supabase Edge Functions)	Generative AI for plan creation and coaching
Monetization	RevenueCat	Subscription management and paywall
Notifications	Expo Notifications	Push notifications for task reminders
UI Components	Expo BlurView, Haptics, Linear Gradient	Glassmorphism effects, haptic feedback, gradient styling

Source: Authors (2026).

3.3. Data Architecture

The application database is structured around a hierarchical data model consisting of three primary entities: Objectives, Goals, and Tasks. An Objective represents a high-level, long-term aspiration (e.g., learning mobile development) and contains one or more Goals, which serve as measurable milestones (e.g., building a portfolio project). Each Goal is decomposed into multiple Tasks, which represent the atomic units of daily action (e.g., studying a library for thirty minutes). We implemented this three-tier architecture using nested TypeScript interfaces with strongly typed properties, ensuring data consistency throughout the application lifecycle.

Each Task supports two productivity paradigms: Timer Mode, which tracks progress using Pomodoro style intervals (Cirillo & Fernández, 2020) with customizable focus and break periods, and Weight Mode, which assigns a specific time weight to tasks to measure their contribution to the goal's overall workload. This dual mode design accommodates both time-intensive deep work sessions and checklist-based daily routines.

Data persistence follows a dual storage strategy. Local state is maintained using AsyncStorage through Zustand, while cloud synchronization is managed by the Supabase PostgreSQL database. A custom conflict resolution merge algorithm prioritizes local edits, ensuring that offline changes are not overwritten by older server data.

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3.4. Artificial intelligence integration architecture

The AI integration is deployed as a Supabase Edge Function, acting as a secure intermediary between the mobile application and the Google Gemini API. This serverless approach provides three key operational advantages: securing API credentials by keeping them off client devices, enabling pre-request input moderation, and allowing post-response schema validation (ensuring each generated plan structurally contains valid objectives, goals, and tasks before client delivery).

In Creator mode, the system's prompt engineering incorporates historical performance data (such as daily task completion rates and active timelines) to calibrate workload complexity. For instance, if a user averages three completed tasks per day, the AI caps new daily requirements accordingly to prevent user fatigue. For Coach mode, the system aggregates a real-time data dashboard tracking completion rates, focused time, time-of-day productivity patterns, and progress metrics to deliver contextually personalized advice.

3.5. User interface design process

The user interface follows a dark-first design philosophy defined by a glassmorphism aesthetic. The color palette centers on a near-black background (`#0D0D0F`) paired with translucent card elements rendered via Expo BlurView. The unified design system enforces a consistent border radius palette, a structured layout spacing scale, and dynamic accent colors derived from user-assigned goal colors to enable interface personalization. Micro animations, such as pulse effects on active timers and smooth transitions between screen states, are integrated to improve the responsiveness and visual feedback of the application. The primary screens of the mobile application, displaying this visual identity and the hierarchical structure of objectives, goals, and tasks, are shown in Figure 3.

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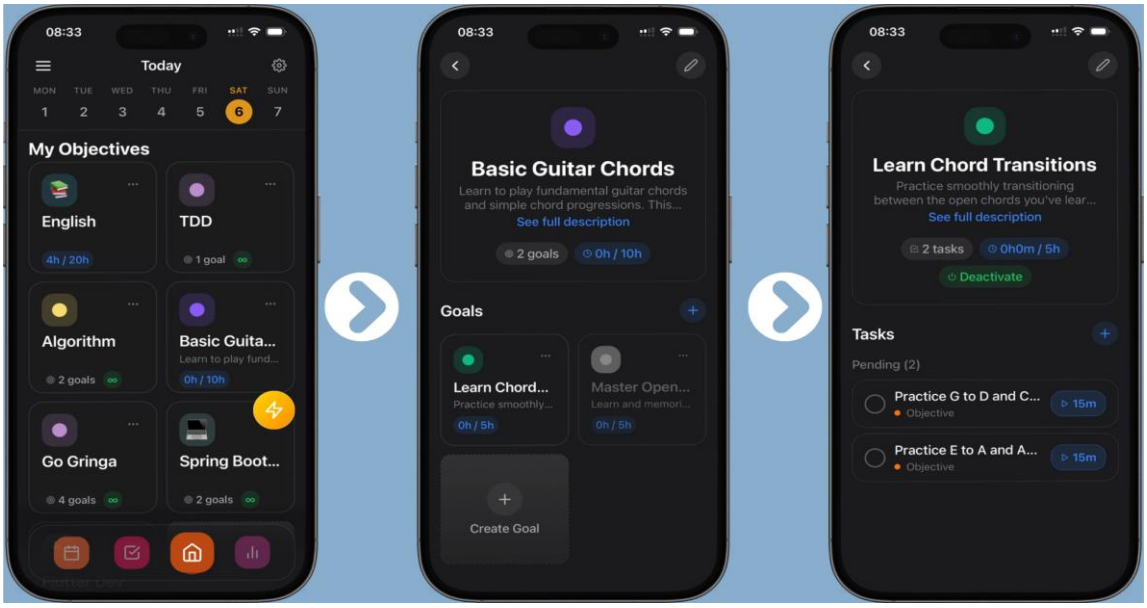
Figure 3. Screens of application, showing the design and the sequence of objectives, goals and tasks



Source: Authors (2026).

4. RESULTS AND DISCUSSION

The evaluation of the Block AI application analyzed both the effectiveness of hierarchical goal decomposition and the user engagement generated by the interface design and behavioral coaching mechanisms. The observed results focus on the system's structural planning and user interactions.

Regarding system performance and goal structure, validation testing evaluated the planning interface using unstructured, natural language inputs, such as user aspirations to learn mobile development within a specific timeframe. The integration pipeline processed these requests through a serverless execution environment, using a large language model to map free-form text to the system's hierarchical schema. The resulting structure decomposed high-level intent into three distinct levels: a macro-level Objective, measurable intermediate Goals, and atomic daily Tasks. A key mechanism of this planning phase is the dynamic calibration of daily workload. Instead of generating unrealistic schedules, the system retrieves user completion history from local state and remote database to cap the generated daily workload (e.g., at three tasks). This empirical adaptation to actual user pace prevents cognitive fatigue and premature abandonment, aligning with Steel's (2012) assertion that realistic sub-goals enhance the expectancy of success and reduce procrastination.

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To evaluate engagement, retention, and behavioral response, the analysis examined how combining generative intelligence with human-centered design addresses core behavioral bottlenecks in personal development. Human potential is vast across multiple domains, yet individuals frequently fail to realize their goals due to cognitive overload and the friction of turning abstract ambitions into immediate actions. Block AI addresses this challenge by pairing AI-driven cognitive offloading with intuitive visual architecture. The artificial intelligence component automates the executive burden of goal breakdown (Locke & Latham, 1990; Allen, 2015), allowing users to clearly visualize their progress. Concurrently, the minimalist glassmorphic interface, Pomodoro focus timers, and haptic feedback satisfy the psychological need for competence (Ryan & Deci, 2017) by providing immediate sensory cues that reinforce execution without adding visual noise. This synergy ensures that technology functions not as a substitute for human effort, but as a catalyst to make personal growth visible, structured, and achievable.

5. CONCLUSION

The development of Block AI highlights how traditional time-management frameworks can merge with the adaptive capabilities of generative large language models. By automating hierarchical goal decomposition, the system bridges the gap between abstract ambitions and concrete daily execution. Within this architecture, the generative model operates as an active cognitive co-pilot. Connecting directly to the user's historical performance metrics allows the system to tailor the planning phase to individual capacity, moving past static template generation.

Key psychological and organizational theories support this approach. First, systematic externalization of complex objectives reduces the cognitive load associated with unresolved goals, or "open loops" (Allen, 2015). Second, by offering customizable structures and tracking features such as the yearly activity heatmap the platform satisfies the core needs for autonomy and competence established by Self-Determination Theory (Ryan & Deci, 2017).

Despite these positive outcomes, the application faces two primary limitations. First, planning and coaching capabilities require active network connectivity. Although core tracking features remain functional offline through local storage, the personalized AI remains unavailable without a connection. Second, relying on external model APIs introduces recurring transaction costs, which presents a scalability challenge for the subscription monetization model.

Future research should explore integrating small, on-device language models to enable offline execution of planning features and eliminate server transaction costs. Additionally, longitudinal studies exceeding six months are necessary to evaluate the long-term impact of personalized goal decomposition on student and professional populations.

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