INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 5, May 2026 | ISSN: 2456-4184 | IJNRD.ORG

User-Centric Smart Behaviour Adaptive Recommender System

A produvtivity and Digital Wellness Application With Adaptive Recommendations

[1]Aditya Pimpare, [2]Sayali Kale, [3]Bhavesh Chavan, [4]Janhvi Kalore,

[1]Student, [2]Student, [3]Student, [4]Student,
[1]B-Tech CS & E,
[1]Dy Patil Dnyaan Prasad Global University, Pune, India

Abstract: However, most productivity and wellness applications provide generic recommendations without adapting them to individual user behaviour. The proposed Android-based recommender system observes user behaviours such as task performance, phone usage, mood input, and wellness activity to provide more personalized recommendations. The system is built on four major pillars: productivity research-informed rule-based logic, a feedback learning loop based on user actions, community-driven similar-user pattern matching, and a foundation for possible future machine learning integration. The interface is designed with a human-focused approach, using supportive messaging and psychology-informed colours to encourage calmness, motivation, and long-term positive behaviour change. Based on prototype development and testing, users can manage tasks, observe behavioural patterns, receive tailored research-based suggestions, and explore useful solutions shared by community members. By combining productivity support and wellness guidance into a single human-centric platform without requiring wearable devices, the proposed system aims to address major limitations of existing productivity and wellness applications.

I. INTRODUCTION

With smartphone proliferation there is a multitude of productivity and wellness applications today, but most of them operate in isolation without real time integration. People uninstall these apps quickly because the recommendations seem so similar, and really disconnected from what they do in real life. Most existing tools only exist as stand alone task managers or habit trackers and rarely combine productivity with mental and physical wellness. Not a real-time adaptation any change in user behaviour, mood or circumstance. Moreover, these apps depend heavily on manual logging, adding to the friction that hampers long-term adherence. Proposing an integrated, behaviour-adaptive system designed with human-centric principles—facilitating slow and steady improvement without guilt or stress. Instead of learning general patterns, you are only given combined pattern by each user and every possible solution that worked on a similar user to guide through this mechanism instead.

II. Motivation and Objectives:

Motivation

Users behave differently: some are morning people, while others work better in the evening. One pattern works while another fails—most importantly, the system designed for it. Existing apps do not examine the relationship between phone use and incomplete tasks or how stress impacts productivity. Manually tracking generates additional friction, which leads to app churn. Perhaps most importantly, productivity and wellness are separate: you may finish all your tasks while sacrificing sleep and exercise, but that in no way represents achieving wellness! A cohesive platform that tracks these dependencies can offer comprehensive assistance.

Objectives

- Create a complete Android-based productivity tracker, integrated with wellness support.
- Passive task behaviours - track usage patterns and temporal productivity fluctuations
- Track user data related to mood, stress, sleep, energy and health preferences without causing excessive tracking burden.
- Build the rule-based, feedback learning and similar-user based recommendation engine in multiple stages
- Set up user-feedback loops to help refine recommendations and produce a more accurate system.
- Train your model and human-centric UI with calming UX that provides support without guilt.
- Facilitate community learning by allowing users to share and find the solutions that have been validated
- Provides analytics and visualization to deliver actionable insights.
- Lay the groundwork for future machine-learning features.

III. Related Work:

Sr. No.	Author(s)	Year	Title of Paper	Research Focus	Key Contributions	Limitations
1	Pazzani & Billsus	2007	Content-based recommendation	Content-based recommendation system	Foundational filtering Techniques	Cold-start problem
2	Fogg	2003	Persuasive Technology: Using Computers to Change What We Think and Do	Persasive technology design	Framework for behaviour change via tech	Theoretical only
3	Mulder et al.	2016	User engagement and feedback in behaviour change technology	User engagement in behaviour change	Systematic review of feedback	Heterogenous interventions
4	Consolvo, McDonald & Landay	2009	Theory-driven design strategies for behaviour change technologies	Theory-driven design	Integrated psychology into design	Limited Validation
5	Ryan & Deci	2000	Self-determination theory and the facilitation of intrinsic motivation	Self-determination theory	Importance of autonomy in change	Non tech -specific

Summary:

1. **Pazzani & billsus (2007):** Talks about how recommendation systems use content features to recommend items to user. Good base work but have problems with a lack of data about new users (cold-start problem).
2. **Fogg (2003):** Introduces an architecture for technology that convinces people to do things differently. Illustrates the computer from the perspective of design as an editor that alters thought and action.
3. **Mulder et al. (2016):** A research review on how to keep users engaged with behavior-change apps. Shows that user involvement and personalized feedback is vital for app retention in the long term.
4. **Consolvo, McDonald & Landry (2018)**: Combining Psychological and Technological Insights to Design More Effective Systems for Behavioural Change Show that theory-informed design produces more effective apps than trial-and-error approaches.
5. **Ryan & Deci (2000)**: Basic research demonstrating that people are more inclined to change behaviour when they feel autonomous and in control. It proves that autonomy matters more than external pressure for sustainable behavior change.

IV. Research Gap:

- Productivity and wellness remain siloed. There are only a few that weigh both task management and mood tracking and well being supporting together.
- Limited adaptation to behaviour change. Most apps use static recommendations that are not updated over time, regardless of how user patterns evolve.
- Minimal community learning. Systems typically do not let users find solutions of peers who acted similarly.
- Design focused on productivity alone. There are few applications that utilize human-centric design which avoids guilt-based messaging.
- Manual tracking becomes burden over time because of system requiring extensive manual input which discourages user for long-term engagement

V. Proposed System:

The system is made up of four cohesive layers:

Data Collection Layer:

Observes task completion Passthrough Overall, tracks phone usage frequencyApp sessions Unlock rate Time interval productivity variations Asks about mood, stress levels, sleep quality, energy levels, exercise preferences and hobbies etc on a regular basis.

Behaviour Analysis Layer:

Spot underperforming hours, the right times of practice and usage, how work gets completed in terms of time (when), type (what), and overcoming stress relate to productivity or how users behaviour clusters.

Recommendation Engine Layer:

It has a four-stage logic: Stage 1 involves rule-based filtering in line with well-known productivity principles. Stage 2: Stage 2 learn from the history feedback. In stage 3 we compare user patterns to identify same-user clusters. Stage 4 – Preparation for Machine Learning

Application Interface Layer:

We are going to present information in soothing design tones, muted teal and soft blues sage greens colors, rounded corners subtle shadows typography that is clean line by line. Supports dark/light modes. Features custom dashboards better preview of the recommendations and community

System Operation Flow

Workflow of the System: The system could be utilized as follows:

Gathering user data through registration, profile setup along with goals, hobbies, health preferences.

Transparent explanation for tracking purposes.

Observation of passive behaviours and explicit periodic inputs regarding wellness.

Personal level pattern checking for inefficiencies and productivity windows.

Detect hidden patterns and personalise recommendations based on what the user wants.

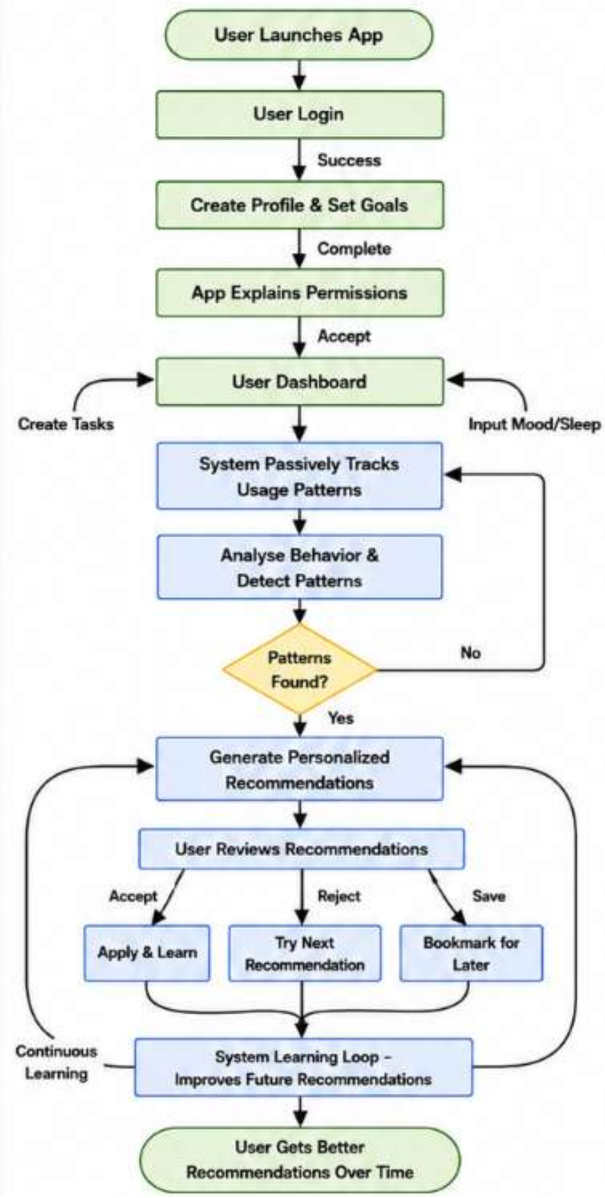
User feedback: accept, reject, save or get alternatives generated?

Learn from feedback and modify the next suggestions you make.

Similar-user matching surfaces community-validated solutions.

With time, recommendations can get very personalised.

Flowchart:



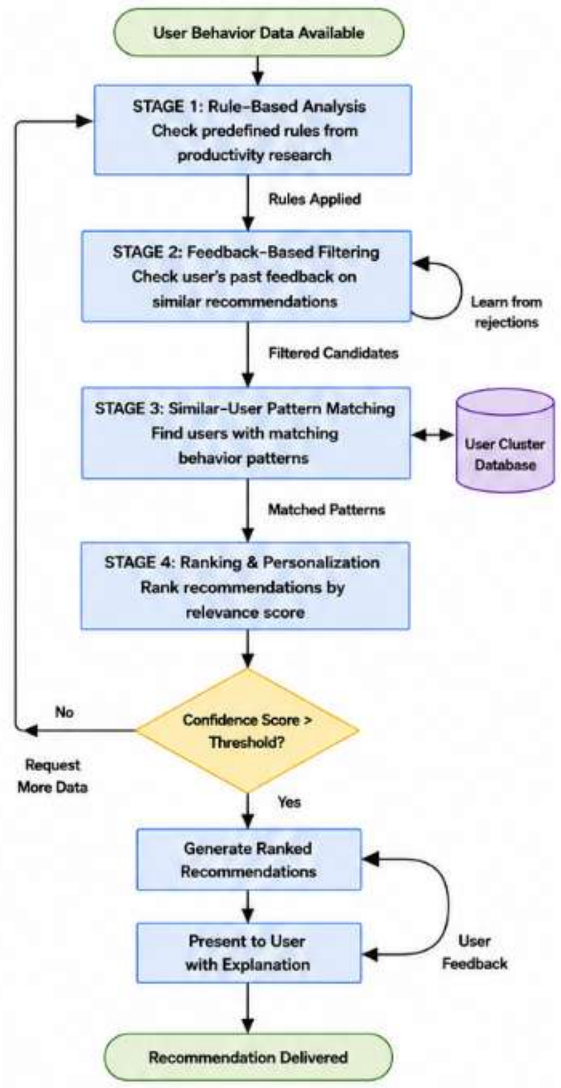
VI. Recommendation Engine:

Stage 1: Rule-Based Logic
Sweeping rules based on productivity science. Examples: evening task fulfilment x use user preferred stress reliving activity. If the sleep quality score is low, recommend sleep optimization.

Stage 2: Feedback-Based Learning
System learns from user interactions. If user regularly agrees to morning focus sessions but is rejecting meditation, recommendations begin adjusting. Feedback in detail based on reasons allows more than just binary accept/reject.

Stage 3: Similar-User Matching
It clusters users based on their behaviour patterns (peak time productivity, task completion style, activity preferences). The system suggests solutions to problems which worked for other users with similar circumstances. This utterance in the learning community allows for peer-validated recommendations.
Stage 4: ML Enhancement Foundation
Architecture designed to be integrated with future ML use cases: user clustering segmentation, behaviour prediction, recommendation ranking optimisation and burnout risk estimation.

Recommendation Engine Flow:



VII. Major Features and Modules:

• Authentication: Login via email/Google, password reset, and secure sessions.
• Task & Goal Management - Create, edit, and complete tasks, organize by priority, track progress of tasks and link them to the goals.
• Monitor Usage: Usage pattern, Per Session Frequency, Unlock behaviour, Productivity windows.
• Mood & Health Input: Log your mood, stress levels, sleep patterns, energy levels and health preferences which may correlate with productivity.
• Recommendation System: Based on rule-based logic and feedback learning, provide appropriate recommendations.
• Dashboard and insights → Productivity score, present working task indicators, mood graph and trend report, focus indicator graphsWeekly Report.
• Community Section: Experience sharing, Solutions posting, Peer-validated recommendations.
• Settings: You can do dark/light mode settings, privacy controls, permission management (who can see whom), profile customization

VIII. UI/UX Design Philosophy:

The design of the interface is calm supported with messaging. Color psychology: muted teal for trust, soft blue for focus, sage green for wellness, off-white will give a sense of comfort. Aesthetically, soft shadows and rounded corners grant the sensation of tenderness. Dark and light modes are gentle on the eye. It does not constantly remind the user, nor any guilt-speech but suggest for improvement. Provides support for long-term behaviour change by making users feel understood and not coerced.

IX. Technology Stack:

1. Frontend: Kotlin, Jetpack compose, android studio
2. Database Firebase Firestore (cloud), Room (local storage)

3. Authenticating: Firebase Authentication
4. Charts: MPAndroidChart library
5. Recommendations logic: You can implement your own recommendations using Kotlin
6. Results and Discussion

X. Advantages and Disadvantages:

Advantages:

• Personalisation: Identify individual patterns and offer tailored recommendations.
• Integrated Wellness: This one combines productivity, mood, stress and physical wellness under a unified platform.
• Designed by and for Humans: Messaging that provides support plus a calm interface motivates sustainable behaviour changes.
• Passive Data Collection: Monitors important signals automatically, which encourages user engagement.
• Feedback Loop: Users interacting with the app can help it to improve and results in a virtuous circle of providing relevant content
• Community-based Learning: People learn from solutions provided by people with similar validation.
• Privacy-First: Sensitive data is stored on the local machine and synced only as aggregated insights to the cloud.
• So this architecture can also support various machine learning and advanced analytics as they can scale.

Disadvantages:

• Currently Android only: The current implementation is targeted for android and it will require additional development to run it on iOS.
• Permission Issues: Behaviour tracking needs a lot of device permissions that might worry privacy-thinking users.
• The Linked Dependency on Data Quality: Recommendations are only as good as how accurately users input preferences and how well they are tracked.
• Cold Start Problem: People are new with little to no historical data, so it is difficult for the recommendation system to make any relevant recommendations at first.
• NEEDS DATA OVER MONTHS NOT DAYS Because installation is only the launch point in a long-term study.
• Individual Differences: Human behaviour is complicated; not all citizens benefit from the same suggestions in the same way.
• Not Medical Treatment: The system cannot provide diagnoses or replace professional medical care. It simply identifies patterns and suggests wellness activities.

XI. Applications:

• Not Medical Treatment: The system cannot provide diagnoses or replace professional medical care. It simply identifies patterns and suggests wellness activities.
• iOS Platform — Build an iOS application to explore the unsaturated Apple ecosystem.
• Wearable integration: Data from fitness trackers & smartwatches for sleep, activity, heart rate.
• Machine Learning Models: Advanced clustering, behaviour prediction and burnout detection
• AI Chat Interface: A conversational assistant to provide answers for wellness questions and guidance tailored to every individual's case.
• Calendar Integration: Integrate with your Google Calendar to make recommendations that consider your schedule.
• Enterprise Edition: Organizational edition, team dashboards, and aggregate wellness analytics.

XII. Conclusion

In this paper, we propose a behaviour-adaptive recommender system to resolve two major shortcomings of existing approaches on productivity and wellness applications. Through the use of passive behaviour tracking, dynamic multi-stage intelligent recommendations based on user behaviours, and optional feedback & human-centric preferences as a help frontend: it allows for personalised support to adapt to the changing users. It is not new algorithms but integrating adaptation, wellness support, community learning in a calm design that makes the core innovation.

All high-level components are implemented successfully in prototype evaluation. It allows users to follow up on tasks, input wellness data and get tailored recommendations along with advice from community solutions. Calm interface design is one that provokes desire for long term engagement rather than abandonment.

There are many open issues—platform scaling, degree of long-term validation in a more diverse population over multiple timescales, integration into wearables—but the architecture does support these improvements in time. The inclusion of machine learning and cross-platform capabilities comes as a logical development. This research advances acknowledgement that technology can support human flourishing when it is built with a deep understanding of user needs, respect for privacy as well as ethically aligned purpose wherever design decisions impact change in behavior.

References

[1] M. J. Pazzani and D. Billsus, "Content-based recommendation systems," The Adaptive Web, Springer, 2007.
[2] B. J. Fogg, "Persuasive Technology: Using Computers to Change What We Think and Do," Morgan Kaufmann, 2003.
[3] C. M. Mulder et al., "User engagement and feedback in behaviour change technology," Journal of Medical Internet Research, vol. 18, no. 7, 2016.
[4] S. Consolvo, D. W. McDonald, and J. A. Landay, "Theory-driven design strategies for behaviour change technologies," Proc. SIGCHI, pp. 405-414, 2009.
[5] R. Ryan and E. Deci, "Self-determination theory and the facilitation of intrinsic motivation," American Psychologist, vol. 55, no. 1, pp. 68-78, 2000.
[6] T. L. Webb et al., "Using the internet to promote health behaviour change," Journal of Medical Internet Research, vol. 12, no. 1, 2010.
[7] A. Pinder, A. Flood, and M. De Angeli, "Digital wellbeing in the age of information overload," Communications of the ACM, vol. 58, no. 8, pp. 55-56, 2015.
[8] E. Karapanos et al., "Personalization and evaluation of mood-based mobile recommender systems," Information Technology & Tourism, vol. 14, no. 4, pp. 349-371, 2014.
[9] N. Calvo, "Affective Computing for Behaviour Change," Building Systems for Behaviour Change, pp. 122-138, 2015.
[10] S. Chatterjee and J. Price, "Healthy living with persuasive wearables," IEEE Pervasive Computing, vol. 8, no. 3, pp. 30-37, 2009.