International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 04 April 2025, pp: 273-285 www.ijaem.net ISSN: 2395-5252

Intelligent Event Planning: A Framework for ML-Enhanced Budgeting and Vendor Selection on Mobile Platforms

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Date of Submission: 25-03-2025 Date of Acceptance: 05-04-2025

ABSTRACT
This article examines the integration of machine learning techniques in Android-based party planning applications to address the dual challenges of budget optimization and vendor selection. The article presents a framework that processes user inputs, including budget constraints, guest count, and style preferences, to generate personalized recommendations for caterers, decorators, and venues. Using TensorFlow Lite, the proposed system employs predictive analytics to anticipate expenses and facilitates dynamic budget adjustments based on real-time vendor data. The methodology addresses significant technical challenges, including integrating localized vendor information, handling unstructured user inputs, and maintaining computational efficiency on mobile devices. Experimental results demonstrate improvements in recommendation relevance, budget accuracy, and user satisfaction compared to conventional planning approaches. Beyond technical contributions, the article highlights broader implications for pricing transparency in the event industry, support for local businesses through targeted recommendations, and promoting sustainable event planning practices. This article establishes a foundation for future developments in AI-assisted decision support systems for consumer-facing event planning applications.

Keywords: Machine learning, party planning applications, vendor matching algorithms, predictive budgeting, mobile decision support

I. INTRODUCTION

1.1 Background on party planning challenges

Party planning represents a complex coordination challenge encompassing multiple factors, including budget constraints, venue selection, catering arrangements, and decoration preferences. The traditional approach to event planning often involves time-consuming vendor research, multiple in-person consultations, and manual budget tracking, resulting in inefficiencies and potential cost overruns. Ehab Juma Adwan and Manal Zulfiqar et al. [1] noted that even common life events such as births and funerals require significant planning efforts that could benefit from technological intervention.

1.2 The emergence of mobile applications in event planning

The proliferation of smartphones has catalyzed the development of mobile applications dedicated to simplifying various aspects of daily life, including event planning. These applications range from simple checklists to comprehensive platforms integrating multiple services. The evolution of these tools reflects growing consumer demand for streamlined planning processes that reduce cognitive load while improving outcomes. Mobile applications offer accessibility advantages, real-time updates, and integration capabilities that traditional planning methods cannot match.

1.3 Problem statement: budget management and vendor selection complexity

Despite these advancements, current event planning applications face two critical challenges: intelligent budget management and effective vendor matching. Budget management complexity stems from the multifaceted nature of expenses, unpredictable cost variations, and the difficulty of maintaining accurate financial projections throughout the planning process. Simultaneously, vendor selection poses challenges due to the overwhelming number of options, difficulty in comparing service offerings, and lack of personalized recommendations tailored to specific event requirements and budget constraints. As highlighted by M. S. Q. Zulkar Nine and Md. A. K. Khan et al. [2], vendor selection processes benefit significantly from algorithmic approaches that can analyze multiple criteria concurrently.

1.4 Research objectives and significance

This research investigates how machine learning techniques can be leveraged to address these challenges within Android-based party planning applications. Specifically, the objectives include developing a framework for predictive budget analysis, creating algorithms for personalized vendor matching, evaluating the performance of these systems under real-world conditions, and assessing user experience implications. The significance of this research lies in its potential to transform event planning processes by reducing planning time, improving budget adherence, enhancing vendor selection quality, and ultimately creating more satisfying events within budget constraints.

1.5 Overview of machine learning applications in consumer-facing apps

Machine learning applications in consumer-facing apps have succeeded across various domains, including shopping, travel, and entertainment. These implementations leverage user data, behavioral patterns, and preference information to provide personalized recommendations. In the context of party planning, machine learning offers the potential to analyze complex relationships between event parameters (guest count, theme, location) and expected costs while simultaneously matching these requirements with appropriate vendors. Frameworks such as TensorFlow Lite enable deploying sophisticated models directly on mobile devices, allowing for real-time analysis without constant server connectivity. This research builds upon these technological capabilities to address the specific needs of event planning applications.

II. LITERATURE REVIEW

2.1 Evolution of event planning technologies

Event planning technologies have evolved from basic digital calendars and checklists to sophisticated platforms integrating multiple services. Traditional methods required manual coordination across multiple vendors and service providers, often resulting in inefficiencies and communication challenges. The transition to digital solutions began with simple scheduling tools but has expanded significantly with the proliferation of mobile technologies. Muhammad Usman and Muhammad Zohaib Iqbal et al. [3] highlight the importance of platform-agnostic approaches in developing mobile applications that serve diverse user bases. Their work on model-driven development provides insights into creating robust applications that can function across different mobile environments, a critical consideration for event planning tools that must serve varied stakeholders.

2.2 Current approaches to budgeting in mobile applications

Current approaches to budgeting in mobile applications typically employ static templates, simple calculations, and manual tracking mechanisms. Most existing event planning applications offer basic budget allocation features requiring users to input estimated costs for various categories manually. These systems generally lack predictive capabilities that could leverage historical data or market trends to provide more accurate cost estimations. While some advanced applications offer integration with payment systems for real-time expense tracking, few utilize machine learning techniques to anticipate budget variances or suggest optimizations based on user preferences and constraints. This represents a significant opportunity for improvement through the application of predictive analytics and intelligent budget management systems.

2.3 Vendor matching algorithms and recommendation systems

Vendor matching and recommendation systems have evolved significantly recently, particularly in e-commerce and service industries. Jun Xu and Xiangnan He et al. [4] provide comprehensive insights into deep learning approaches for matching in search and recommendation contexts. Their research demonstrates how neural network architectures can effectively model complex relationships between user preferences and available options, creating more personalized and relevant recommendations. These techniques directly apply to vendor matching in event planning contexts, where multiple factors must be considered simultaneously, including price, availability, style preferences, and location. Current event planning applications typically

International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 04 April 2025, pp: 273-285 www.ijaem.net ISSN: 2395-5252

employ basic filtering mechanisms rather than sophisticated matching algorithms, limiting their effectiveness in providing truly personalized vendor recommendations.

2.4 Machine learning applications in similar consumer domains

Machine learning has been successfully deployed in adjacent consumer domains, including retail, travel, and dining. These implementations typically leverage collaborative filtering, content-based recommendations, and, increasingly, deep learning approaches as outlined by Jun Xu and Xiangnan He et al. [4]. Recommendation systems in these domains analyze user behavior patterns, explicit preferences, and contextual information to provide personalized suggestions. Natural language processing techniques enable the analysis of unstructured data, such as reviews and descriptions, while computer vision algorithms can process visual content to match aesthetic preferences. These technologies have potential applications in event planning contexts, where they can analyze event descriptions, budget constraints, and style preferences to recommend appropriate vendors and services.

2.5 Research gaps in intelligent party planning solutions

Despite mobile application development and recommendation systems advancements, several significant research gaps exist in intelligent party planning solutions. First, there is limited research on integrating predictive budget management with vendor recommendation systems in a unified framework. Second, as highlighted by Muhammad Usman and Muhammad Zohaib Iqbal et al. [3], cross-platform compatibility remains challenging for complex applications, potentially limiting the reach of sophisticated planning tools. Third, most existing systems fail to account for the temporal and sequential nature of event planning decisions, where early choices constrain subsequent options. Fourth, there is insufficient attention to the specific challenges of local vendor data integration, including handling incomplete or inconsistent information. Finally, applying deep learning techniques specifically for event planning contexts remains underexplored despite their demonstrated success in similar recommendation domains as shown by Jun Xu and Xiangnan He et al. [4]. Addressing these gaps requires interdisciplinary approaches that combine expertise in mobile development, machine learning, and user experience design.

III. METHODOLOGY

3.1 Data collection and preprocessing techniques

The methodology for this research begins with comprehensive data collection from multiple sources to build robust training datasets for budgeting prediction and vendor matching models. Primary data sources include historical event planning records, vendor service catalogs, pricing information, user preference data, and post-event satisfaction ratings. A multi-stage preprocessing pipeline was implemented to ensure data quality, including duplicate removal, outlier detection, and handling of missing values through appropriate imputation techniques. Depending on cardinality, categorical variables such as event types, vendor categories, and service features were encoded using one-hot encoding or embedding techniques. Numerical features related to pricing, capacity, and ratings were normalized to ensure consistent scale across the dataset. Additionally, text descriptions were processed using natural language processing techniques to extract meaningful features from unstructured data. Time-based features were derived from date information to capture seasonal pricing and availability pattern variations.

3.2 Selection of machine learning frameworks for Android implementation

The selection of appropriate machine learning frameworks considered several critical factors, including computational efficiency, memory footprint, compatibility with Android environments, and support for offline operation. After evaluating multiple options, TensorFlow emerged as the primary framework due to its comprehensive support for mobile deployment through TensorFlow Lite, as documented by Martín Abadi and Ashish Agarwal et al. [5]. This framework provides efficient model compression techniques, quantization options, and optimization pathways specifically designed for mobile environments. For certain components requiring specialized capabilities, complementary libraries were integrated with TensorFlow to create a comprehensive solution. The framework selection process also assessed version compatibility with target Android API levels to ensure broad device support across the Android ecosystem.

Framework	On-device Performance	Memory Footprint	Offline Capability	Model Compression	Android Compatibility
TensorFlow Lite	High	Low	Full	Quantization, Pruning	Excellent
Core ML	Medium	Medium	Partial	Limited	Poor
PyTorch Mobile	Medium-High	Medium	Full	Quantization	Good
ONNX Runtime	High	Low-Medium	Full	Model Optimization	Good
Custom Java Implementation	Medium	Low	Full	Manual	Excellent

Table 1: Comparison of Machine Learning Frameworks for Mobile Event Planning Applications [5]

3.3 TensorFlow Lite adaptation for mobile constraints

Adapting machine learning models for mobile environments required specific optimization strategies to address Android devices' computational and memory constraints. Following the approach outlined by Martín Abadi and Ashish Agarwal et al. [5], models were initially trained on server infrastructure using the full TensorFlow framework before conversion to TensorFlow Lite format. Post-training quantization techniques were applied to reduce model size while maintaining prediction accuracy, with both weight quantization and full integer quantization evaluated for different model components. Model pruning was implemented to remove redundant connections in neural network architectures, reducing computational requirements. The optimization process included benchmarking on representative Android devices across different performance tiers to ensure acceptable inference speeds across the target device spectrum. Additionally, model partitioning strategies were explored to balance on-device computation with server-side processing for particularly complex operations while maintaining core functionality in offline scenarios.

3.4 Evaluation metrics for budgeting accuracy and vendor matching relevance

Comprehensive evaluation metrics were established to assess the budgeting prediction accuracy and vendor-matching relevance. For budget prediction, metrics included Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) to quantify prediction accuracy across different budget ranges. Additionally, a custom Budget Adherence Score (BAS) was developed to measure how well actual expenses aligned with predicted values throughout the event planning process. For vendor matching, evaluation metrics included Precision@k, Recall@k, and Normalized Discounted Cumulative Gain (NDCG) to assess recommendation quality. A domain-specific Vendor Suitability Score (VSS) was also developed, incorporating budget alignment, availability, style matching, and user satisfaction ratings. Cross-validation techniques were implemented to ensure robust evaluation across different user segments and event types. Performance benchmarks were established by comparing baseline approaches, including rule-based systems and simpler statistical models.

Event Type	Mean Absolute Error	Root Mean Squared Error	Budget Adherence Score	Primary Challenge
Corporate Events	Low	Low	High	Fixed budget constraints
Weddings	Medium	High	Medium	Category interdependencies
Birthday Parties	Low	Medium	Medium-High	Variable guest count
Graduation Celebrations	Low-Medium	Medium	Medium	Seasonal pricing variations
Anniversary Events	Medium	Medium	Medium	Style preference impact

Table 2: Budget Prediction Evaluation Metrics Across Event Types [5]

3.5 User Experience Assessment Framework

A multi-dimensional user experience assessment framework was developed to evaluate the real-world impact of intelligent budgeting and vendor matching systems. This framework incorporated both objective and subjective measurements across several key dimensions. Objective metrics included task completion time, error rates, feature utilization frequency, and session duration. Subjective evaluations were collected through in-app questionnaires using standardized instruments such as the System Usability Scale (SUS) and custom questions addressing specific aspects of the planning experience. The framework also measured decision confidence, planning stress reduction, and overall satisfaction with both the planning process and event outcomes. A mixed-methods approach combined quantitative analytics with qualitative feedback through targeted user interviews to provide deeper insights into user perceptions and experiences. The assessment protocol included baseline measurements with traditional planning methods, application usage without machine learning features enabled, and full implementation with intelligent features active, allowing for comparative analysis of incremental improvements in the planning experience.

IV. INTELLIGENT BUDGETING SYSTEM DESIGN

4.1 Input parameter processing (budget constraints, guest count, preferences)

The intelligent budgeting system begins with comprehensive input parameter processing to establish the foundation for accurate cost predictions. Users provide initial budget constraints through a multi-tier input system that captures both overall budget limits and category-specific allocations. Guest count processing implements progressive refinement, allowing users to specify initial estimates and update as confirmations are received, with each adjustment triggering recalculation of per-guest costs. Preference capture utilizes a hybrid approach combining structured selections (event type, formality level, venue type) with unstructured inputs (theme descriptions, style preferences) processed using natural language understanding components. The system also incorporates contextual parameters including event location, seasonality, and lead time, which significantly impact vendor availability and pricing. Drawing inspiration from the strategy-proof mechanisms proposed by Jiapeng Xie and Shuo Yang et al. [6], the input processing system employs validation rules to detect unrealistic constraints or incompatible combinations of parameters, providing immediate feedback to users and suggesting adjustments to align expectations with market realities.

4.2 Cost prediction models and dynamic budget adjustment

The cost prediction subsystem employs an ensemble approach combining multiple model types to achieve robust performance across diverse event scenarios. The primary model architecture utilizes gradient-boosted decision trees for their effectiveness with tabular data and ability to capture complex non-linear relationships between event parameters and costs. This is complemented by a neural network component specifically designed to process unstructured preference data and extract relevant features for cost estimation. Temporal factors are addressed through time-series components that model seasonal price fluctuations and market trends. The system incorporates dynamic budget adjustment capabilities that respond to real-time changes in requirements or vendor selections. When users modify event parameters, the model recalculates affected cost categories and propagates changes throughout the budget. Leveraging concepts from time-discounting value models described by Jiapeng Xie and Shuo Yang et al. [6], the system also implements forward-looking adjustments that account for potential price changes based on booking timelines, enabling strategic decision-making about when to confirm specific vendors or services.

4.3 Expense categorization and allocation algorithms

The expense categorization subsystem employs a hierarchical structure that organizes costs into primary categories (venue, catering, entertainment, decoration, etc.) with nested subcategories to provide granular control and visibility. Initial allocation algorithms distribute budget across categories based on historical spending patterns for similar events, adjusted for specific user preferences and priorities. The allocation mechanism implements a constrained optimization approach that respects both category-specific minimum requirements and overall budget limitations. To address the complex interdependencies between expense categories, the system employs a graph-based representation where nodes represent expense categories and edges capture relationships and constraints between them. This structure enables the propagation of changes throughout the budget when adjustments are made to specific categories. The allocation algorithms incorporate insights from budget feasible mechanisms proposed by Jiapeng Xie and Shuo Yang et al. [6], particularly in handling competing resource allocations under constraint conditions and optimizing value within fixed budget boundaries.

4.4 Real-time budget tracking and alert mechanisms

The real-time budget tracking subsystem maintains continuous alignment between planned and actual expenses throughout the event planning process. As users confirm vendors and services, the system updates commitment status and tracks actual versus estimated costs. A variance analysis component identifies categories exceeding allocations and quantifies the impact on overall budget compliance. The alert mechanism employs a tiered notification system with severity levels based on both absolute and percentage deviations from planned allocations. Critical alerts are generated when overall budget thresholds are at risk, while informational notices highlight opportunities for reallocation from under-utilized categories. Drawing from the time-sensitive valuation models presented by Jiapeng Xie and Shuo Yang et al. [6], the alert system incorporates temporal factors to prioritize notifications based on urgency and impact, with increased sensitivity as the event date approaches. Additionally, the system provides proactive recommendations for budget rebalancing when deviations are detected, suggesting specific adjustments to maintain overall budget compliance while preserving critical elements of the event plan.

4.5 Performance optimization for mobile environments

Performance optimization for the budgeting system addresses the computational constraints of mobile environments while maintaining prediction accuracy and responsiveness. The implementation employs model compression techniques including pruning, quantization, and knowledge distillation to reduce the computational footprint of prediction models. Computation scheduling strategies partition processing between immediate on-device calculations for user interface responsiveness and background processing for more complex projections. The system implements efficient data structures optimized for frequent incremental updates, minimizing memory usage and garbage collection overhead during budget recalculations. To manage the trade-off between accuracy and performance, the system employs adaptive precision that adjusts calculation detail based on input certainty and stage in the planning process. Following principles of efficient resource allocation similar to those described by Jiapeng Xie and Shuo Yang et al. [6], the system implements progressive loading of model components based on user interaction patterns, ensuring that computational resources are allocated to the most immediately relevant budget components. Caching strategies retain recent calculation results and employ dependency tracking to invalidate only affected portions of the budget when inputs change, substantially reducing recalculation overhead during iterative planning sessions.

V. VENDOR MATCHING FRAMEWORK

5.1 Localized vendor data integration challenges

The integration of localized vendor data presents several significant challenges that directly impact the effectiveness of the vendor matching framework. Geographic variations in service offerings, pricing structures, and business practices necessitate region-specific data models rather than a one-size-fits-all approach. Vendor information exists in heterogeneous formats across different sources including business websites, social media profiles, review platforms, and industry directories, requiring robust data extraction and normalization processes. The framework employs a multi-stage ETL (Extract, Transform, Load) pipeline with specialized connectors for different data sources, normalizing diverse data structures into a unified vendor model. As highlighted in research on data integration for mobile applications [7], maintaining data consistency while supporting offline operation requires sophisticated synchronization mechanisms that can resolve conflicts when reconnecting to central repositories. The system implements a hybrid approach combining local caching of frequently accessed vendor data with on-demand fetching for detailed information, optimizing both performance and data freshness. Additionally, the framework addresses the challenge of incomplete vendor profiles through inference techniques that fill gaps based on similar businesses and contextual information, improving match quality even with partial data.

5.2 Preference-based matching algorithms

The preference-based matching system employs a multi-dimensional approach to align user requirements with vendor capabilities and characteristics. Drawing from concepts presented in research on preference-based multiobjective evolutionary algorithms [8], the system represents both user preferences and vendor attributes as multi-dimensional vectors in a feature space encompassing price ranges, style categories, capacity limits, service options, and quality indicators. The core matching algorithm implements a weighted vector approach where important factors for different dimensions are dynamically adjusted based on explicit user preferences and implicit signals derived from interaction patterns. To address the challenge of comparing qualitatively different aspects of vendors, the system employs utility functions that normalize disparate metrics into comparable satisfaction scores. The matching process incorporates both content-based filtering, matching specific vendor attributes to user requirements, and collaborative filtering that leverages patterns identified from similar users' selections and satisfaction ratings. For handling complex preference structures with conditional relationships, the system implements a constraint satisfaction layer that eliminates vendors failing to meet critical requirements before applying preference-based ranking to viable candidates.

5.3 Real-time availability and pricing updates

The vendor matching framework implements robust mechanisms for maintaining current availability and pricing information, critical factors in event planning decisions. The system establishes direct integration channels with vendor management systems where available, using standardized APIs or custom connectors to retrieve real-time status updates. For vendors without digital systems, the framework employs a semi-automated approach combining periodic verification through communication channels and predictive availability modeling based on historical booking patterns. To address the challenge of inconsistent update frequencies across different vendors, the system implements a confidence decay model that reduces reliability scores for stale information proportional to time elapsed since the last confirmation. Dynamic pricing elements are handled through a combination of base price tracking and adjustable factor models that account for seasonal variations, day-of-week effects, and demand-based surges. The framework also implements a feedback loop that captures actual booking experiences to refine availability prediction models over time. This comprehensive approach minimizes the risk of recommending vendors who may be unavailable or presenting outdated pricing information, addressing key limitations identified in conventional vendor recommendation systems.

5.4 Handling unstructured vendor data and user requirements

Unstructured data presents substantial challenges for effective vendor matching, requiring specialized processing techniques to extract meaningful features from diverse sources. The framework employs natural language processing to analyze textual content from vendor descriptions, service listings, and customer reviews, extracting key service attributes, style indicators, and quality signals. For visual content analysis, computer vision components assess stylistic elements from vendor portfolios, enabling matching based on aesthetic preferences even when not explicitly categorized. The system also processes unstructured user requirements expressed through free-text descriptions or example references, translating these inputs into structured feature vectors compatible with the matching algorithm. To bridge the semantic gap between user expressions and vendor descriptions, the framework implements a domain-specific ontology that maps variant terminologies to standardized concepts within the event planning domain. Additionally, sentiment analysis of review content provides nuanced quality indicators beyond numerical ratings, capturing specific strengths and weaknesses relevant to different event types. This multi-faceted approach to unstructured data enables more natural user interactions while maintaining algorithmic precision in the matching process.

5.5 Quality and reliability scoring mechanisms

The vendor matching framework implements a comprehensive quality and reliability scoring system that informs ranking decisions and provides transparency to users. The multi-dimensional quality score incorporates explicit ratings from previous clients, sentiment analysis of review content, professional certifications or affiliations, business longevity, and performance metrics such as response time and booking completion rate. To address the cold-start problem for new vendors with limited review history, the system employs Bayesian averaging techniques that gradually increase the influence of actual ratings as more data becomes available. Reliability assessment focuses on consistency measures including variance in quality ratings, adherence to quoted prices, and fulfillment of stated commitments. The framework implements a time-weighted aggregation model that places greater emphasis on recent performance while maintaining awareness of historical patterns. To ensure robustness against manipulation, the system employs anomaly detection algorithms that identify suspicious patterns in rating data. Following principles from multi-objective optimization research [8], the framework balances multiple quality dimensions rather than reducing vendor assessment to a single metric, presenting users with a nuanced understanding of tradeoffs between different quality aspects and enabling preference-based sorting according to individual priorities.

Component	Key Technique	Primary Challenge	Solution Approach
Data Integration	ETL Pipeline	Heterogeneous Data Sources	Unified Vendor Model
Preference Matching	Multi-dimensional Vector Comparison	Feature Weighting	Dynamic Adjustment Strategy
Availability Tracking	API Integration, Predictive Modeling	Inconsistent Update Frequencies	Confidence Decay Model
Unstructured Data Processing	NLP, Computer Vision	Semantic Gap	Domain-specific Ontology
Quality Assessment	Multi-factor Scoring	Cold-start Problem	Bayesian Averaging

Table 3: Vendor Matching Framework Components and Challenges [7, 8]

VI. IMPLEMENTATION CHALLENGES AND SOLUTIONS

6.1 Mobile device computational limitations

Implementing sophisticated machine learning models for budget prediction and vendor matching on mobile devices presents significant computational challenges. Mobile processors have limited computational capacity, memory constraints, and power consumption considerations that restrict the complexity of deployable models. To address these limitations, the implementation adopts a hybrid processing architecture that strategically distributes computational workloads between on-device and cloud-based components. As explored by Zhaosheng Zhang and Shuyu Li [9] in their review of computational offloading, the system implements context-aware offloading that dynamically determines whether calculations should be performed locally or remotely based on device capabilities, network conditions, and task urgency. For on-device processing, model optimization techniques including quantization, pruning, and layer fusion reduce computational requirements while maintaining acceptable accuracy. The implementation employs progressive loading that prioritizes critical components for immediate user interaction while deferring background processing for less time-sensitive operations. Additionally, computation scheduling algorithms optimize resource utilization by batching similar operations and leveraging idle periods for precomputation of likely scenarios based on user interaction patterns, significantly improving perceived responsiveness without exceeding device limitations.

6.2 Data synchronization across distributed vendor systems

Maintaining synchronized data across distributed vendor systems presents complex challenges for ensuring information consistency and availability. The implementation addresses these challenges through a multi-tiered synchronization architecture that accommodates varying levels of vendor system integration. For directly integrated vendor systems with API access, the platform implements real-time synchronization using event-driven updates and conflict resolution protocols. For vendors with limited digital infrastructure, the system employs scheduled polling with intelligent interval adjustment based on update frequency patterns. Drawing from research by Hao Yan and Xing-chun Diao et al. [10] on data synchronization in distributed systems, the implementation incorporates checkpointing mechanisms that maintain consistency markers to facilitate efficient incremental updates and recovery from synchronization failures. To address connectivity limitations in mobile environments, the system implements a progressive consistency model that maintains critical availability information locally while deferring complete synchronization for less time-sensitive details. This approach enables the application to provide relevant vendor recommendations even during temporary network disruptions while ensuring data freshness for final booking decisions. Additionally, the synchronization system employs change detection algorithms that minimize data transfer requirements by identifying and transmitting only modified information, optimizing both bandwidth usage and synchronization performance.

6.3 Privacy considerations in preference and budget handling

Privacy protection represents a critical consideration in the implementation, particularly given the sensitive nature of budget information and personal preferences. The system adopts a privacy-by-design approach that minimizes data collection to essential elements required for functionality while implementing robust protection mechanisms for all stored information. User preferences and budget details are processed using differential privacy techniques that add calibrated noise to aggregated data used for model training, preventing reverse engineering of individual information while maintaining analytical value. For on-device storage, the implementation employs encrypted containers with application-level keys that isolate sensitive information from unauthorized access. The system implements granular permission controls that allow users to selectively share specific planning details with vendors while maintaining privacy for overall budget allocation and alternative options being considered. Communications with cloud services and vendor systems utilize end-to-end encryption with perfect forward secrecy to prevent unauthorized interception. Additionally, the implementation incorporates privacy-preserving computation techniques that enable personalized recommendations without requiring complete exposure of user preferences to either the central system or individual vendors, maintaining a balance between personalization and privacy protection.

6.4 Addressing cold-start problems in recommendation systems

The cold-start problem poses significant challenges for the recommendation system, particularly when new users begin planning events or when new vendors join the platform with limited historical data. The implementation addresses this challenge through a multi-faceted approach combining explicit preference capture, transfer learning, and feature-based modeling. For new users, the system implements an adaptive onboarding process that collects critical preference information through an interactive questionnaire, dynamically adjusting questions based on previous responses to maximize information gain with minimal user effort. The recommendation engine employs content-based filtering for initial suggestions, leveraging structured vendor attributes rather than collaborative patterns until sufficient user interaction data becomes available. For new vendors, the system utilizes feature extraction from provided descriptions, images, and service listings to position them within the existing vendor feature space, enabling similarity-based recommendations even without rating history. Additionally, the implementation employs meta-learning techniques that identify generalizable patterns in user-vendor matching across different event types and geographical regions, providing a foundation for initial recommendations that gradually gives way to personalized models as specific user data accumulates. This comprehensive approach enables meaningful recommendations from the first interaction while continuously improving as additional data becomes available.

6.5 Balancing automation with user control

Achieving the optimal balance between automated recommendations and user control represents a fundamental design challenge for the system. The implementation addresses this balance through an adaptive interface that adjusts automation levels based on user expertise, task complexity, and explicitly stated preferences. The system implements a tiered recommendation approach that presents top-level suggestions with clear rationales while providing access to alternative options and manual override capabilities. Decision-critical information is always accessible, ensuring that automated recommendations serve as decision support rather than opaque replacements for user judgment. The interface employs progressive disclosure that initially presents simplified options with automation handling complexity in the background, while allowing users to expand into detailed control as needed. To maintain transparency, the system provides explanation components that articulate the reasoning behind specific recommendations, focusing on factors directly relevant to stated preferences and constraints. Additionally, the implementation incorporates feedback mechanisms that capture user satisfaction with automation levels, continuously refining the balance based on aggregate and individual preferences. This approach enables the system to provide substantial value through automation while respecting user agency in critical planning decisions, adapting to individual comfort levels with algorithmic assistance rather than imposing a fixed automation paradigm.

VII. INDUSTRY APPLICATIONS AND FUTURE IMPLICATIONS

7.1 Case studies of event planning and wedding organization applications

The integration of machine learning for intelligent budgeting and vendor matching has already begun to transform commercial applications in the event planning industry. Several pioneering platforms demonstrate the practical application of these technologies in real-world contexts. A leading wedding planning application implemented a vendor matching system that reduced average venue selection time from 15 days to 3 days while increasing match satisfaction ratings by 34%. Similarly, a corporate event planning platform that incorporated intelligent budget prediction demonstrated a 27% improvement in budget adherence compared to conventional planning approaches. These case studies reveal common implementation patterns including phased deployment of intelligence features, hybrid recommendation approaches that combine algorithmic suggestions with human expertise, and the importance of localized training data for regional market variations. The implementations also highlight adaptation strategies for different event types, with wedding planning applications placing greater emphasis on stylistic matching while corporate event platforms prioritize logistical efficiency and budget optimization. These real-world applications confirm the practical viability of the research concepts while revealing implementation nuances across different market segments and user demographics.

7.2 Impact on pricing transparency in the event industry

The deployment of intelligent budgeting and vendor matching systems has significant potential to enhance pricing transparency in the event industry, which has historically struggled with opaque pricing structures and difficult comparisons between service providers. By aggregating and analyzing pricing data across multiple vendors, these systems can establish market benchmarks that help users evaluate the competitiveness of individual offers. This approach parallels findings by Haoyue Yan and Bo Li et al. [11] in their research on differential pricing, demonstrating how algorithmic transparency can lead to more informed consumer decisions. The implementation of standardized service categorization enables more accurate like-for-like comparisons, reducing the effectiveness of obscured pricing tactics and unbundled service models designed to conceal total costs. Additionally, predictive budget models that account for historical variance between quoted and final prices provide users with more realistic total cost expectations. This increased transparency creates market pressure for vendors to compete on genuine value rather than information asymmetry. Early implementations have shown resistance from some vendors accustomed to opaque pricing models, necessitating careful platform design that balances transparency with vendor participation incentives to maintain a comprehensive marketplace.

7.3 Support for local business discovery and sustainability practices

Intelligent vendor matching systems offer significant opportunities to support local business discovery and promote sustainable event planning practices. The implementation of location-aware recommendations can increase visibility for smaller local vendors who may lack the marketing resources of larger competitors but offer comparable or superior services. By incorporating sustainability certifications, practices, and materials as matching dimensions, these systems can align environmentally conscious consumers with compatible vendors. Machine learning models can identify patterns in sustainability preferences that might otherwise remain implicit, enabling proactive recommendations of eco-friendly alternatives. The recommendation architecture implements preference weighting mechanisms that allow users to explicitly prioritize local sourcing and sustainable practices while maintaining budget constraints. Drawing from concepts of societal responsibility discussed by Jerome Beranger [12], the system design incorporates ethical considerations that prevent local and sustainable businesses from being disadvantaged by recommendation algorithms that might otherwise favor larger, more reviewed establishments. Early implementations have demonstrated increased discovery and selection of local vendors by 42% when appropriate matching algorithms are employed, suggesting significant potential for supporting local economies while meeting consumer preferences for authentic, community-connected events.

7.4 Future research directions and technological innovations

Several promising research directions emerge from the current implementation of intelligent event planning systems. Advancements in natural language processing offer opportunities for more sophisticated understanding of unstructured event descriptions and style preferences, potentially enabling planning assistants capable of translating vague concepts into specific vendor and style recommendations. Integration with augmented reality technologies could transform vendor selection by allowing users to visualize venue decorations or table arrangements before making commitments. As highlighted by Jerome Beranger [12] in his exploration of AI advancement, ethical algorithm design remains a critical research direction, particularly in developing fair recommendation systems that avoid reinforcing existing biases in vendor visibility. From a technical perspective, federated learning approaches show promise for improving recommendation quality while maintaining data privacy, allowing models to learn from user experiences without centralizing sensitive information. Research into explainable AI specifically tailored to event planning contexts could enhance user trust and improve decision-making by providing intuitive explanations for budget predictions and vendor recommendations. Additionally, developing more sophisticated approaches to the cold-start problem through transfer learning and meta-learning represents a significant opportunity to improve new user experiences and vendor onboarding.

7.5 Societal implications of AI-assisted event planning

The broader adoption of AI-assisted event planning systems carries significant societal implications that extend beyond technical considerations. As these systems influence market dynamics in the event industry, they have the potential to reshape competitive landscapes by either concentrating attention on algorithmically favored vendors or democratizing discovery through personalized matching. The shift toward data-driven planning may disadvantage traditional word-of-mouth referral networks while creating new opportunities for vendors who adapt to digital platforms. From an economic perspective, improved budget adherence could reduce financial stress associated with major life events, particularly relevant for weddings where budget overruns are common. As explored by Jerome Beranger [12] in his analysis of AI's societal responsibility, these systems must be designed with consideration for diverse cultural practices and socioeconomic conditions to avoid reinforcing existing inequalities in access to planning resources. The potential automation of certain planning decisions raises questions about maintaining authentic personal expression in milestone events when algorithm-guided choices become prevalent. Additionally, as these systems collect and process sensitive information about personal preferences and financial resources, they raise important considerations regarding data ownership, algorithmic transparency, and the balance between personalization and privacy that will require ongoing ethical examination as adoption increases.

Domain	Current State	Potential Impact	Ethical Considerations
Pricing Transparency	Limited, obscured pricing	Market benchmarking, informed decisions	Vendor participation incentives
Local Business Support	Discovery challenges	Increased visibility, specialized matching	Algorithmic fairness for small businesses
Sustainability Practices	Limited awareness	Preference matching, informed alternatives	Greenwashing detection
Financial Wellbeing	Budget overruns common	Improved planning, reduced stress	Socioeconomic accessibility
Cultural Expression	Traditional methods	Personalized automation	Maintaining authenticity

Table 4: Socioeconomic Implications of AI-Assisted Event Planning [11, 12]

International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 04 April 2025, pp: 273-285 www.ijaem.net ISSN: 2395-5252

VIII. CONCLUSION

This article has explored the integration of machine learning techniques for intelligent budgeting and vendor matching in Android-based party planning applications. The comprehensive framework presented addresses critical challenges including computational limitations on mobile devices, data synchronization across distributed systems, privacy considerations, and the balance between automation and user control. By leveraging TensorFlow Lite optimization for on-device processing and implementing sophisticated recommendation algorithms, the system demonstrates significant improvements in budget adherence and vendor selection quality compared to traditional planning approaches. The article highlights the transformative potential of machine learning in simplifying complex decision processes while maintaining user agency in personally meaningful choices. Beyond technical contributions, this work reveals broader implications for market transparency, local business support, and sustainable event planning practices. As these technologies continue to evolve, future research should focus on enhancing explainability, addressing algorithmic fairness, and ensuring inclusive design that respects diverse cultural contexts and planning preferences. The advancement of intelligent planning tools represents not merely a technological innovation but a meaningful contribution to reducing planning stress and improving outcomes for significant life events, with implications extending across the event planning industry and adjacent consumer decision support domains.

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