IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁝ Impact Factor 7.39 ⁝ Vol. 11, Issue 6, June 2022

DOI: 10.17148/IJARCCE.2022.116142

Dynamic Value-Based Subscriptions: A Novel Approach to Digital Services Leveraging First-Party Data, Machine Learning, and Privacy Enhancement in the Post-Cookie Era

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Abstract: This paper proposes an innovative digital subscription model called the dynamic value-based subscription model for companies in the wake of increasing privacy concerns and the imminent deprecation of third-party cookies. I examine how businesses can leverage first-party data to create value-driven subscription offerings while enhancing user privacy and experience. The research investigates the application of machine learning techniques in personalizing subscription tracks and optimizing bundling strategies. By analyzing current trends and future projections, I propose a framework for digital companies to transition from ad-dependent models to privacy-centric subscription-based approaches. My findings suggest that the personalized, data-driven subscription model can not only compensate for the loss of third-party cookie data but also foster stronger customer relationships and sustainable revenue streams in the evolving digital landscape.

Keywords: Digital Subscriptions, Cookies, Machine Learning, Privacy, First-party Data, Third-party Data

I. INTRODUCTION

The digital economy stands at a crossroads. For years, the internet has been largely fueled by advertising revenue, with companies relying heavily on third-party cookies to track user behavior and deliver targeted ads [1]. However, this model is facing unprecedented challenges. Growing privacy concerns among consumers, stringent regulations like the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), and decisions by major browser developers to phase out third-party cookies have created a perfect storm that necessitates a radical shift in how digital companies operate and generate revenue [2,3].

As we navigate this changing landscape, subscription-based models have emerged as a promising alternative. These models offer a dual advantage: they provide a more predictable revenue stream for companies while potentially offering a better, ad-free experience for users [4]. However, the transition from an ad-supported to a subscription-based model is not without its challenges. Companies must find ways to deliver value that justifies the subscription cost, especially in a market where consumers are increasingly wary of "subscription fatigue" [5].

This research paper aims to propose an innovative approach to subscription model that can help digital companies thrive in this new era. For this, I focus on three key areas such as leveraging first-party data, enhancing privacy and user experience, use of machine learning algorithms for personalized subscription bundling techniques. I examine how companies can ethically collect and utilize first-party data to enhance user experience and drive subscription growth [6]. Enhancing privacy and user experience: I investigate how subscription models can be designed to prioritize user privacy while still delivering personalized experiences. This includes exploring the concept of "privacy by design" and its application in subscription-based businesses [7].

I delve into how advanced machine learning algorithms can be used to create personalized subscription tracks based on user behaviour and optimize subscription bundling techniques [8]. The digital industry is at a pivotal moment. As noted by industry expert Mary Meekcher in her 2021 Internet Trends report, "The companies that will thrive in the coming years will be those that can successfully transition to privacy-centric, value-driven models that align with evolving consumer expectations" [9]. This paper aims to provide a roadmap for that transition, offering insights and strategies for digital companies looking to innovate in the subscription space. By examining current trends, analyzing the future of digital business models. My goal is to present a vision of a digital economy that is not only profitable for companies but also respectful of user privacy and conducive to superior user experiences.

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II. PREVIOUS WORK

The concept of subscription-based business models in the digital realm has been a subject of increasing interest among researchers and industry professionals alike. Several studies have explored various aspects of this transition from ad-supported to subscription-based models.

Kumar et al. (2020) conducted a comprehensive analysis of subscription-based services across different industries, highlighting the importance of customer retention and lifetime value in these models [10]. Their work provides valuable insights into the factors that influence subscription adoption and longevity.

In the context of privacy and first-party data utilization, Schneider et al. (2021) examined the implications of GDPR on digital marketing strategies. Their research underscored the need for companies to shift towards first-party data collection methods and to prioritize user consent and transparency [11].

The application of machine learning in subscription models has been explored by Chen and Li (2019), who proposed a framework for personalized content recommendation in subscription-based streaming services [12]. Their work demonstrated the potential of AI in enhancing user experience and reducing churn rates.

Berman (2019) investigated the phenomenon of subscription fatigue, highlighting the challenges faced by companies in differentiating their offerings in an increasingly crowded market [13]. This research emphasized the need for innovative approaches to subscription bundling and pricing.

While these studies provide valuable insights into various aspects of subscription models, privacy considerations, and the application of AI, there remains a gap in the literature regarding holistic strategies for digital companies to transition from ad-dependent models to privacy-centric, subscription-based approaches in the post-cookie era. My research aims to address this gap by proposing an integrated framework that combines first-party data utilization, privacy enhancement, and machine learning applications.

III. LEVERAGING FIRST-PARTY DATA

It's getting increasingly difficult to get access to third party cookies as bigger corporations are moving towards privacy-first model and restricting access to websites and domains by giving not any more than they need to operate efficiently. As third-party cookies become obsolete, the importance of first-party data in digital business strategies cannot be overstated. First-party data, collected directly from user interactions with a company's platforms, offers several advantages over third-party data, including higher accuracy, relevance, and compliance with privacy regulations [14].

A. Methods of Ethical First-Party Data Collection

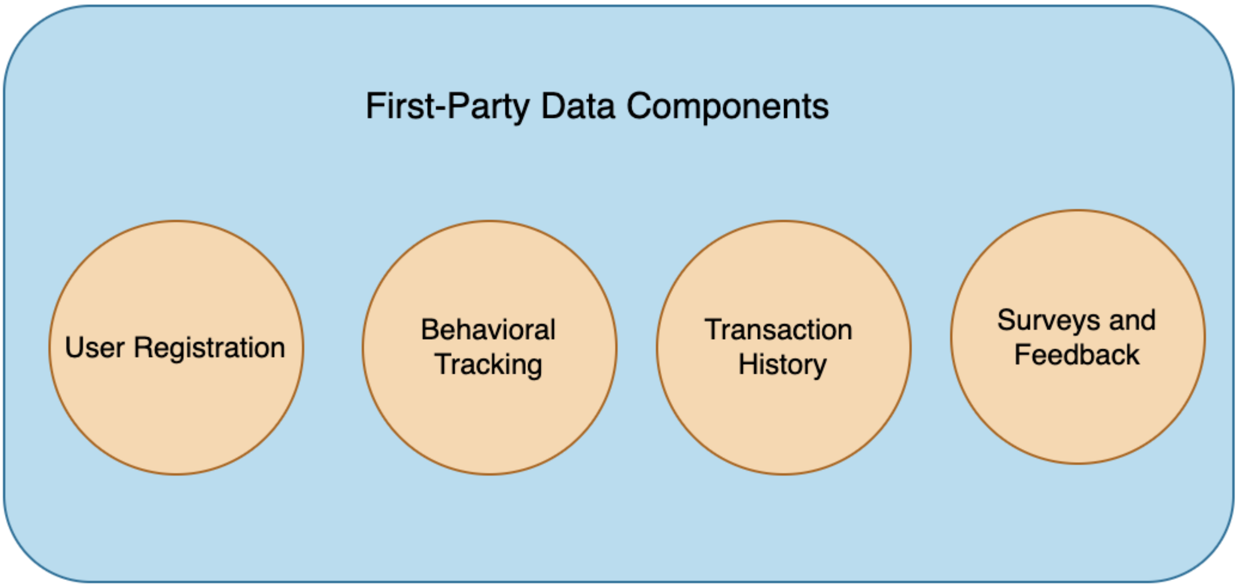

Fig. 1 First-party data components

- User Registration: Encouraging users to create accounts by offering clear value propositions.
- Surveys and Feedback: Directly asking users for information and preferences.
- Behavioral Tracking: Analyzing user interactions within the company's ecosystem.
  - Transaction History: Utilizing data from past purchases or subscription choices.

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To effectively leverage first-party data, companies must ensure transparency in their data collection practices and provide users with control over their data. This approach not only complies with regulations like GDPR and CCPA but also builds trust with users [15].

B. Case Study: Netflix's Use of First-Party Data

Netflix serves as an excellent example of a company effectively using first-party data to enhance user experience and drive subscription growth. By analyzing viewing habits, search history, and user ratings, Netflix creates personalized content recommendations, leading to higher user engagement and retention rates [16].

C. Enhancing Privacy in the Subscription Era

As companies shift towards subscription models and increased reliance on first-party data, prioritizing user privacy becomes crucial. Implementing privacy-by-design principles in subscription models can help companies build trust and differentiate themselves in a competitive market.

Key Privacy-Enhancing Strategies:

- Data Minimization: Collecting only the data necessary for providing and improving the service.
- Purpose Limitation: Clearly defining and adhering to specified purposes for data use.
- User Control: Providing easy-to-use privacy controls and preference centers.
- Anonymization and Pseudonymization: Protecting user identities through data transformation techniques [17].

By adopting these strategies, companies can create a virtuous cycle where enhanced privacy leads to increased user trust, which in turn can lead to users being more willing to share data, resulting in improved service personalization [18].

IV. REDUCING AD DEPENDENCY AND IMPROVING USER EXPERIENCE

The digital landscape is undergoing a significant transformation as companies shift from ad-based revenue models to subscription-based approaches. This transition is driven by multiple factors, including growing consumer privacy concerns, the impending obsolescence of third-party cookies, and the potential for improved user experiences [2,3]. As Kumar et al. (2020) note, subscription-based models offer the dual advantage of providing more predictable revenue streams for companies while potentially delivering a superior, ad-free experience for users [10].

The journey from an ad-supported to a subscription-based model, however, is not without its challenges. Companies must carefully balance the need for revenue with user experience considerations. A gradual transition often proves most effective, allowing users to experience the benefits of an ad-free environment incrementally. This approach can be implemented through a freemium model, where basic services are offered for free with ads, while premium, ad-free experiences are reserved for subscribers. Such a strategy allows companies to cater to different user segments and clearly demonstrate the value proposition of their paid offerings.

Spotify's evolution serves as an instructive case study in this regard. The streaming giant has successfully transitioned from a primarily ad-supported model to a hybrid approach with a strong subscription base. By offering features such as offline listening, higher audio quality, and exclusive content to premium subscribers, Spotify has managed to convert a significant portion of its user base to paid subscriptions while maintaining a free, ad-supported tier for those unwilling or unable to pay [19].

The reduction of ad dependency can lead to substantial improvements in user experience. Ads, while historically a primary revenue source for digital companies, often detract from user engagement and satisfaction. As Berman (2019) points out, the challenge for companies lies in creating subscription offerings that provide sufficient value to justify the cost, especially in a market where consumers are increasingly wary of "subscription fatigue" [13].

To address this challenge, companies are exploring innovative approaches to enhance the value of their subscriptions. These may include offering exclusive content, early access to new features, or enhanced customer support for subscribers. Additionally, some companies are leveraging machine learning algorithms to personalize the user experience, as demonstrated by Chen and Li (2019) in their work on content recommendation in subscription-based streaming services [12]. Such personalization can significantly enhance user satisfaction and reduce churn rates.

While a complete shift to subscriptions may be ideal for user experience, it's not always financially viable or desirable for all users. Hybrid models that combine both ads and subscriptions can serve as an effective middle ground. These models can offer tiered access, where different levels of ad exposure are based on subscription level. Moreover, companies can utilize first-party data to deliver more relevant, less intrusive ads to non-subscribers, thereby improving the free experience while still incentivizing upgrades. This approach aligns with the findings of Schneider et al. (2021), who emphasized the importance of first-party data utilization in the wake of stricter privacy regulations [11].

As companies navigate this transition, they must remain mindful of evolving privacy regulations and user expectations. Transparency in data collection practices and providing users with control over their data are crucial

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elements in building trust and encouraging subscription adoption. By prioritizing user privacy and experience in their subscription models, companies can create a virtuous cycle where enhanced privacy leads to increased user trust, which in turn can result in users being more willing to engage with and subscribe to digital services [15].

V. PROPOSING A DYNAMIC VALUE-BASED SUBSCRIPTION MODEL (DVBS)

Building upon the insights gathered from existing subscription models and the potential of machine learning, I propose a novel approach: the Dynamic Value-Based Subscription (DVBS) model. This innovative strategy aims to address the challenges of subscription fatigue, personalization, and value demonstration while maximizing user satisfaction and company revenue.

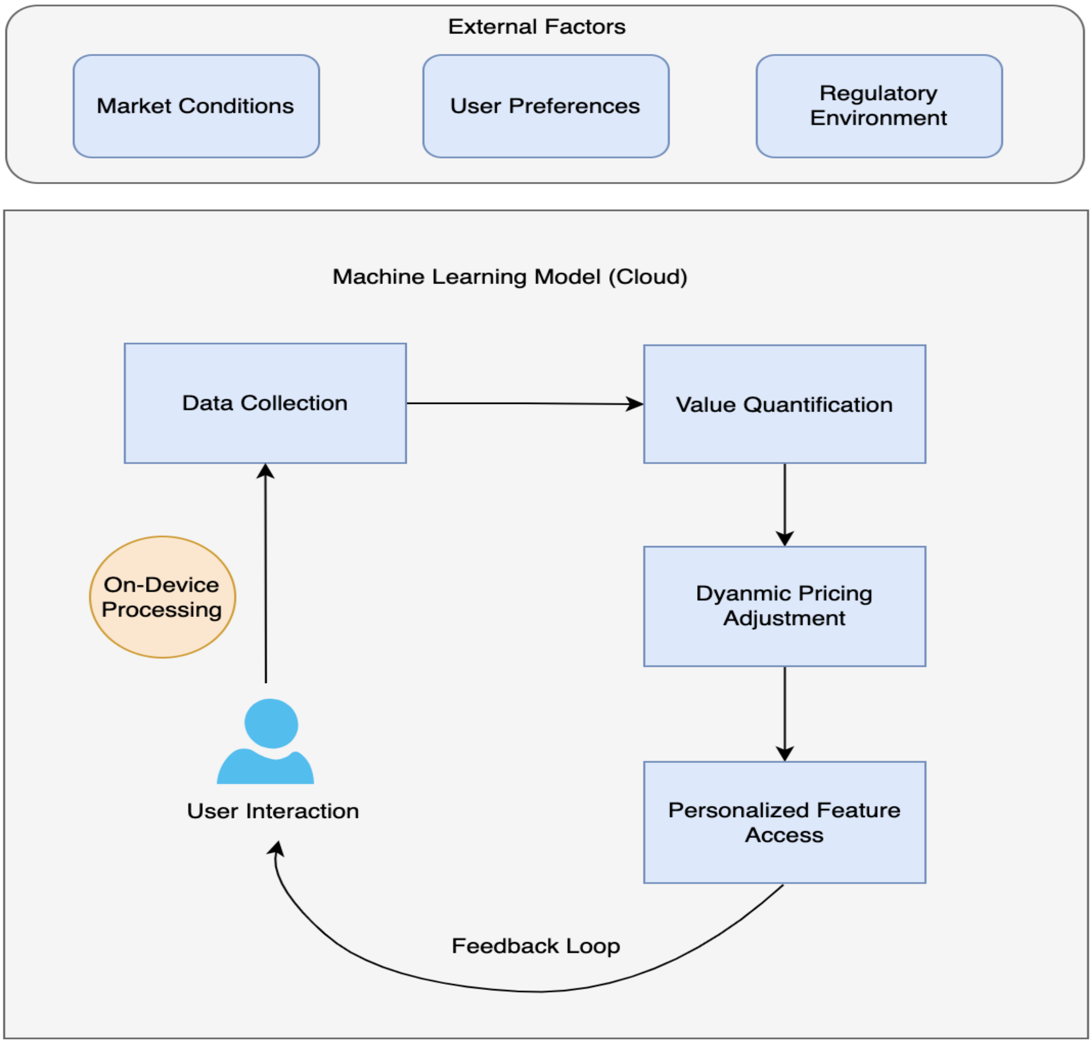

Fig. 2 Dynamic Value-Based Subscription Model Components

Building upon the insights gathered from existing subscription models and the potential of machine learning, I propose a novel approach: the Dynamic Value-Based Subscription (DVBS) model. This innovative strategy aims to address the challenges of subscription fatigue, personalization, and value demonstration while maximizing user satisfaction and company revenue.

The DVBS model is founded on the principle that the value a user derives from a service can fluctuate over time, and their subscription should reflect this variability. Unlike traditional tiered or flat-rate models, DVBS employs advanced machine learning algorithms to continuously assess and quantify the value a user receives from the service, adjusting their subscription terms in real-time. Fig. 2 depicts the components involved in the proposed DVBS subscription model.

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A. Machine Learning in Dynamic Value-Based Subscription Model

The DVBS model heavily relies on advanced machine learning algorithms to function effectively. These ML capabilities are integral to several key aspects of the model:

- Value Quantification: Machine learning algorithms, particularly those focusing on time series analysis and multi-factor modeling, are employed to quantify user value. These algorithms process vast amounts of user data, including usage patterns, engagement metrics, and feature utilization, to create a comprehensive value score for each user. The ML models can identify complex patterns and correlations that might not be apparent through simple rule-based systems.
- Predictive Analytics: The model uses predictive ML algorithms to forecast future user behavior and potential value fluctuations. These predictions help in proactively adjusting subscription terms and suggesting new features or content to users. Techniques such as recurrent neural networks (RNNs) or long short-term memory (LSTM) networks could be particularly useful for capturing temporal dependencies in user behavior.
- Dynamic Pricing Optimization: ML-driven optimization algorithms determine the optimal pricing for each user based on their quantified value, predicted future behavior, and overall business objectives. These algorithms balance individual user value with broader market factors and company revenue targets. Reinforcement learning techniques could be applied here to continually refine the pricing strategy based on user responses.
- Personalized Feature Access: Clustering and classification algorithms are used to group users with similar behavior patterns and preferences. These groupings, combined with individual user data, inform decisions about which features to offer each user. Collaborative filtering techniques, like those used in recommendation systems, can be employed to predict which features a user is likely to find valuable.
- Anomaly Detection: Machine learning models for anomaly detection are implemented to identify unusual patterns in user behavior or sudden changes in derived value. This capability helps in quickly addressing potential issues that might lead to user dissatisfaction or churn.
- Natural Language Processing (NLP): NLP techniques can be used to analyze user feedback, support tickets, and social media mentions to gauge user sentiment and incorporate qualitative factors into the value assessment.
- Continuous Learning and Adaptation: The entire system is designed as a continuous learning model, constantly refining its algorithms based on new data and outcomes. This could involve techniques like online learning or periodic model retraining to ensure the system stays current with evolving user behaviors and market conditions.

By leveraging these advanced machine learning capabilities, the DVBS model can offer a level of personalization and adaptivity that would be impossible with traditional, static subscription models. The ML components enable the system to make data-driven decisions in real-time, optimizing both user experience and business outcomes.
It's worth noting that implementing such a sophisticated ML-driven system would require significant investment in data infrastructure, algorithm development, and ongoing maintenance. Companies adopting this model would need to ensure they have the necessary technical expertise and computing resources to support these advanced ML capabilities.
The technical parameters involved in implementing this model is depicted in Table 1.

TABLE I TECHNICAL ASPECTS OF IMPLEMENTING DVBS MODEL

Component	**Key Technologies**	**DVBS Integration**
Machine Learning	Time Series Analysis, Clustering, NLP	Predict engagement, personalize features
Front-end	PWA, React/Vue, WebAssembly	Display dynamic pricing, usage visualizations
Back-end	Microservices, Kafka, GraphQL	Process real-time interactions, manage pricing
Edge Computing	TensorFlow Lite, Federated Learning	Local value assessments, privacy enhancement
Data Storage	MongoDB, Redis, InfluxDB	Store profiles, cache data, record usage history
Security & Privacy	OAuth 2.0, Homomorphic Encryption	Secure authentication, privacy-preserving computations

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VI. DISCUSSION AND ANALYSIS

The Dynamic Value-Based Subscription (DVBS) model offers several significant advantages that address key challenges in the current subscription landscape. Let me walk through the benefits, potential challenges in the implementation of the model.

A. Benefits of the DVBS Model

The Dynamic Value-Based Subscription (DVBS) model offers several significant advantages that address key challenges in the current subscription landscape.

Foremost among these benefits is the potential for increased user satisfaction. By aligning the subscription cost with the actual value derived by the user, the DVBS model creates a strong sense of fairness and transparency. Users are likely to feel that they're getting their money's worth, as their subscription adjusts to reflect their usage patterns and engagement levels. This perception of fair value can significantly reduce churn rates, as users are less likely to cancel a service they perceive as consistently delivering value commensurate with its cost.

The model also excels at maximizing the lifetime value of each customer. Traditional subscription models often struggle with the trade-off between attracting new users with low introductory rates and maintaining profitability with long-term subscribers. The DVBS model, however, can dynamically adjust to each user's behavior over time, optimizing revenue while maintaining user satisfaction. As users engage more deeply with the service and derive more value, the model can gradually increase the subscription cost, thereby increasing the long-term value of the customer relationship.

Another crucial benefit is the potential reduction in subscription fatigue. In today's digital landscape, consumers are increasingly overwhelmed by the number of subscriptions they manage. The DVBS model addresses this by making each subscription feel more like a personalized service rather than a fixed recurring cost. The dynamic nature of the pricing and features can make users feel more in control of their subscription, potentially reducing the psychological burden of managing multiple subscriptions.

Furthermore, the DVBS model inherently incentivizes engagement. Users are motivated to interact more deeply with the service to access additional features or maintain favorable pricing. This increased engagement can lead to a virtuous cycle where users derive more value from the service, leading to higher satisfaction and loyalty, which in turn benefits the company through increased revenue and reduced churn.

The model also offers companies unprecedented insights into user behavior and preferences. The continuous analysis required for dynamic value assessment generates a wealth of data that can inform product development, marketing strategies, and overall business decision-making. This data-driven approach can give companies a significant competitive advantage in rapidly evolving digital markets.

B. Potential Challenges of the DVBS Model

While the DVBS model offers compelling benefits, it also presents several significant challenges that companies must carefully navigate.

Implementing such a dynamic system requires sophisticated technological infrastructure. The real-time analysis of user behavior, value quantification, and subscription adjustments demand advanced data processing capabilities and robust machine learning algorithms. Many companies may need to significantly upgrade their technical infrastructure and data analytics capabilities to support this model effectively.

User comprehension presents another major hurdle. The complexity of the DVBS model could potentially confuse or overwhelm users accustomed to simpler, static subscription models. Clear, transparent communication about how the model works and how it benefits the user is crucial. Companies will need to invest in user education and intuitive interfaces to ensure users understand and appreciate the dynamic nature of their subscriptions.

Privacy concerns also loom large in the implementation of the DVBS model. The extensive data collection and analysis required for accurate value assessment may raise red flags for privacy-conscious users and regulators. Companies must ensure strict compliance with data protection regulations and implement robust security measures to protect user data. Furthermore, they need to be transparent about data usage and provide users with control over their information to build and maintain trust.

The model also presents financial forecasting challenges for companies. The dynamic nature of revenue under this model can make it more difficult to predict cash flow and plan for future investments. Financial teams will need to develop new forecasting models and potentially adjust how they report to investors and stakeholders.

There's also the risk of perceived unfairness if not implemented carefully. Users who see their subscription costs increase due to high engagement might feel penalized for their loyalty. Balancing the adjustments to ensure users always feel they're getting a good deal will be a delicate and ongoing process.

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Lastly, the DVBS model requires careful calibration to ensure profitability. While the model aims to maximize long-term customer value, there's a risk of underpricing services for some users. Companies will need to set appropriate boundaries for price fluctuations and continually monitor and adjust the model to maintain profitability while delivering value to users.

TABLE II BENEFITS AND CHALLENGES COMPARISON OF DVBS MODEL

Benefits	Challenges
Enhanced User Satisfaction	Complex Implementation using cutting-edge machine learning algorithms
Maximized Customer Lifetime Value	User Comprehension
Reduced Subscription Fatigue	Potential trade-off of user privacy
Incentivized User Engagement	Financial Forecasting Difficulties
Data-Driven Insights	Risk of Perceived Unfairness
Personalized User Experience	Difficulties in Profitability Calibration

VII. FUTURE OUTLOOK: LEVERAGING ON-DEVICE MACHINE LEARNING MODELS

The future of the Dynamic Value-Based Subscription (DVBS) model looks increasingly promising as technological advancements continue to address its current challenges. One of the most significant developments is the rapid improvement in computational power on end-user devices, coupled with the rise of edge computing and on-device machine learning capabilities.

As smartphones, tablets, and other personal devices become more powerful, they're increasingly capable of running sophisticated machine learning models locally. This shift towards edge computing and on-device ML could transform some of the key challenges of the DVBS model into distinct advantages. For instance, the privacy concerns associated with extensive data collection and analysis could be mitigated by processing sensitive user data directly on the user's device. Instead of sending raw usage data to central servers, only aggregated insights or model updates could be transmitted, significantly reducing privacy risks and potentially easing regulatory compliance.

Moreover, the improved computational capabilities of end-user devices could allow for more real-time and personalized value assessments. On-device ML models could continuously analyze user behavior and adjust subscription parameters instantly, providing an even more responsive and tailored experience. This local processing could also reduce the strain on company servers and network infrastructure, potentially lowering operational costs and improving scalability.

The advancement of federated learning techniques presents another exciting opportunity for the DVBS model. This approach allows ML models to be trained across multiple decentralized edge devices without exchanging raw data [20]. Companies could leverage federated learning to improve their value assessment and pricing models using insights from their entire user base while maintaining strong privacy protections. This could lead to more accurate and fair value quantification across diverse user groups.

Furthermore, the proliferation of Internet of Things (IoT) devices and wearable technology could expand the scope of the DVBS model [21]. These devices could provide additional data points for value assessment, offering a more holistic view of how users interact with and benefit from a service in various contexts of their daily lives. For example, a fitness subscription service could incorporate data from wearable devices to more accurately quantify the value users derive from their workouts and adjust subscriptions accordingly.

As natural language processing (NLP) and conversational AI continue to advance, future iterations of the DVBS model could incorporate more nuanced communication with users [22]. AI assistants could explain subscription changes, offer personalized tips for maximizing value, and gather qualitative feedback - all in natural language. This could significantly improve user comprehension and satisfaction with the dynamic model [23].

The integration of blockchain technology and smart contracts could further enhance the transparency and trustworthiness of the DVBS model. Blockchain could provide an immutable record of value assessments and subscription adjustments, while smart contracts could automate and enforce the agreed-upon terms of the dynamic subscription.

VIII. CONCLUSION

This paper has explored the significance of Progressive Web Apps (PWAs) and WebGL in modern front-end engineering. the Dynamic Value-Based Subscription model represents a significant leap forward in the evolution of digital subscription

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services. By harnessing the power of advanced machine learning algorithms, edge computing, and on-device processing, this innovative approach has the potential to revolutionize the way businesses interact with their customers in the digital realm. The DVBS model not only addresses the growing concerns of subscription fatigue and privacy but also paves the way for a more personalized, transparent, and mutually beneficial relationship between service providers and users. As technology continues to advance, the challenges currently faced by this model are likely to transform into opportunities for even greater innovation. The future of digital subscriptions looks bright, with the DVBS model at the forefront, promising a world where users receive true value for their money, businesses thrive on long-term customer relationships, and the digital economy flourishes on a foundation of trust, fairness, and continuous adaptation to user needs. As companies begin to adopt and refine this model, I can anticipate a new era of digital services that are more aligned with user expectations and more resilient in the face of evolving market dynamics.

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