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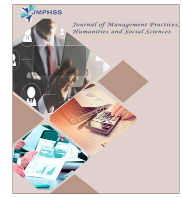

ORIGINAL CONTRIBUTION

Adoption of Web 3.0: Factors Affecting Behavioral Intention

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Abstract— In the present study, we explore the landscape of web 3.0 technology, a pivotal phase in the digital domain. Multiple factors have been identified that influence the behavioral intention of the users and further the adoption of web 3.0 technology. By employing a deductive approach, we collected 200 samples from the IT professionals. To draw the sample, non-probability purposive sampling techniques were used. The PLS-SEM technique was used to predict the causal relationship between the studied variables, as it has the ability to provide meaningful results for complex models with a minimal sample. Results revealed the factors that are influencing the behavioral intention of the users. Among others, digital dexterity plays a crucial role in affecting the behavioral intention of Web 3.0 technology users. In addition, the electronic word of mouth also plays an important in enhancing the behavioral intention of the users which further enhances the adoption of web 3.0 technology. Data privacy security and perceived ease of use both have a positive and significant impact on the user's behavioral intention. Interestingly, performance expectancy was found to be an insignificant element that increases user intention. These findings serve as valuable resources for developers and marketers, allowing them to leverage their potential for strengthening user privacy and data security.

Index Terms— Web 3.0 adoption, Behavioral intention, Digital dexterity, Data privacy security, Performance expectancy

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Introduction

Technology is a cornerstone for revenue generation and expense management in firms. Internet is at the forefront of this evolution due to its transformative impact on global communication (Brynjolfsson and Hitt, 2000; Voshmgir, 2020). This concise exploration delves into the integral role of technology, the evolution of the Internet through Web 1.0 and Web 2.0, and the anticipated advancements with Web 3.0.

The World Wide Web, a realm of significant growth potential for Small- and Medium-Sized Enterprises (SMEs), is marked by over a trillion Uniform Resource Locators (URLs) and a growth rate exceeding 500% in the past decade (Alpert and Hajaj, 2008; Rudman & Bruwer, 2016). Web 1.0, emerging in 1996, laid the initial groundwork for web development but lacked interactivity and user engagement similar to modern web applications (Ahmad, Hussain & Aqil, 2013). The subsequent transition to Web 2.0 brought forth a more dynamic and user-focused digital environment, introducing social media platforms like LinkedIn and Facebook.

Web 2.0, while transformative, introduced challenges such as centralized control, security issues, and privacy breaches. The General Data Protection Regulation (GDPR) in 2018 addressed these concerns, emphasizing the need to balance technological benefits with user

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privacy. The potential solution lies in the concept of Web 3.0, where blockchain technology takes center stage, promising decentralization, elevated privacy, security, and openness (Kasireddy, 2021).

Web 3.0 represents a paradigm shift from Web 2.0's focus on user interface improvements to fundamental changes in infrastructure and back-end technologies (De Choudhury & De, 2014). The integration of blockchain in Web 3.0 facilitates decentralized application processors, peer-to-peer transactions, and computations. This evolution aims to restore user ownership and reduce reliance on centralized servers, presenting decentralized solutions for the World Wide Web (Voshmgir, 2020).

Web 2.0 challenges, including privacy issues exemplified by incidents like the Facebook-cambridge analytica scandal and Edward snowden's leaks, increased awareness and directed attention toward the anticipated evolution of Web 3.0 (Voshmgir, 2020). Based on blockchain, Web 3.0 envisions decentralized application processors supporting peer-to-peer transactions and computations. This development prioritizes privacy, user ownership, and reduced reliance on intermediaries (Voshmgir, 2020; Labadie et al., 2020).

Understanding behavioral patterns and acceptability regarding Web 3.0 is pivotal for academic contributions and empirical research in the realm of human-technology interaction. This study not only aims to define privacy but also investigates factors influencing Web 3.0 adoption, providing insights for developers and marketers. Focusing on the factors affecting behavioral intention towards Web 3.0 adoption and its potential impact on user privacy and data security, the research endeavors to provide a comprehensive understanding.

The study focuses on identifying key factors motivating users' adoption and evaluating the efficacy of Web 3.0 solutions to address privacy and security issues. Ultimately, it aims to offer significant insights into factors affecting behavioral intention, thereby guiding the adoption and use of Web 3.0. By emphasizing the role of blockchain technology, Web 3.0 holds the potential to facilitate peer-to-peer transactions while removing the need for intermediaries that compromise user privacy. The overarching goal of this research is to contribute to a deeper understanding of the factors influencing behavioral intention toward Web 3.0 adoption and to evaluate the effectiveness of various solutions designed to address privacy and security challenges. In doing so, it aims to pave the way for a more decentralized, secure, and user-centric web environment.

Eras of world wide web

Tim Berners-Lee coined the term "Web 1.0" to describe the initial version of the World Wide Web, characterized as a "read-only" web with static content (Berners-Lee, 1998; De Choudhury & De, 2014). This early web focused on delivering information efficiently, limiting user modifications and interactions. Shopping cart applications exemplify Web 1.0, resembling catalog displays and lacking the envisioned interactivity of the "read-write" web proposed by Berners-Lee for Web 2.0.

Web 2.0, introduced by O'Reilly Media in 2004, marked a paradigm shift, emphasizing enhanced collaboration and user engagement (Voshmgir, 2020). This phase allowed users to actively contribute content, transforming web pages into dynamic platforms. Prominent examples include blog posts, YouTube, Twitter, Facebook, and wiki sites, enabling various user activities such as creating, reading, editing, and deleting content (Naik & Shivalingaiah, 2008).

Web 3.0, as envisioned by Berners-Lee, signifies a significant backend infrastructure transformation, focusing on users' ability to engage in activities like reading, writing, and executing actions (Voshmgir, 2020; Naik & Shivalingaiah, 2008). Berners-Lee also introduced the concept of the "semantic web," emphasizing data sharing and reutilization across applications, companies, and communities to transcend current boundaries (De Choudhury & De, 2014). This semantic web aims to understand and respond to complex human requests by considering semantic significance. The evolution of Web 3.0 encompasses various conceptual frameworks and forms the core exploration in this thesis.

Literature Review

Web 2.0, characterized by Alabdulwahab (2018) as a front-end revolution, poses challenges related to data centralization, privacy, and security. Kasireddy (2021) outlines the standard web service architecture with three components: front end, back-end, and database, typically hosted on centralized servers. This setup facilitates peer-to-peer interactions globally, but the intermediary role of trusted third-party platforms raises concerns about data control (Voshmgir, 2020). User engagement in Web 2.0 results in a loss of control over personal data, contributing to the rise of organizations exploiting customer data for their benefit (Voshmgir, 2020).

The advent of Web 3.0 signals a paradigm shift with uncertain implications for web interaction (Knublauch et al., 2004). Investigating the relationship between user behavior and privacy concerns, the study builds on previous research (Lawler and Molluzzo, 2010; Gogolin, 2014). However, research on Web 3.0 is primarily industry-driven, lacking substantial academic studies (Garrigos-Simon et al., 2012). Focusing on Web 3.0's technological foundations, this study emphasizes blockchain's role, particularly in creating decentralized apps and ensuring data security through virtual state machines (Kasireddy, 2021). Unlike Web 2.0's centralized servers, Web 3.0's decentralized network eliminates single points of failure and ensures user data control (Voshmgir, 2020).

Empirical reviews

For this research on the adoption of Web 3.0 and its impact on user data privacy and security, we adapted the UTAUT model, a well-established framework extensively used to study technology adoption behavior. Specifically, we used the independent variables of electronic word-of-mouth, performance expectancy, and digital dexterity because prior research has demonstrated that they have a considerable impact on users' adoption behavior. In addition, we added an additional variable of data privacy security, which is justified by the TAM framework. TAM contends that users' inclination to adopt a technology might be influenced by their perceived privacy and security concerns. Therefore, by adding this variable to the UTAUT model, we aim to investigate how users' concerns about data privacy and security affect their adoption behavior of Web 3.0.

Performance expectancy

The UTAUT model, validated by Venkatesh et al. (2003), underscores Performance Expectancy (PE) as pivotal in predicting behavioral intention toward IT use. In this study, PE is redefined in the context of Web 3.0, signifying users' confidence in enhanced data access, control, ownership, and online privacy (Venkatesh et al., 2003). Web 3.0's potential for user data control aligns with motivation theories emphasizing individual control, such as the control theory of motivation (Deci & Ryan, 2000). Privacy calculus theory supports the idea that perceived control over personal data encourages the adoption of Web 3.0 technologies (PixelPlex, 2021). The implementation of decentralized cloud storage is expected to enhance data security, extending this improved data management to various Web 3.0 applications and services (PixelPlex, 2021).

Voshmgir (2020) highlights the role of blockchain in Web 3.0, functioning as a processor for decentralized applications and supporting smart contracts. Decentralization and blockchain technology empower users, eliminating the need for centralized servers and intermediaries (Voshmgir, 2020). In line with the UTAUT model, Yadegaridehkordi et al. (2018) find a significant impact of Performance Expectancy on Behavioral Intention. UTAUT to identify factors influencing university students' adoption of Web 3.0, revealing the importance of performance and effort expectancy. Chaveesuk et al. (2021) show, based on data from 467 Thai digital payment system users, that PE significantly affects users' intent to use the system. This aligns with previous literature, including Chayomchai et al. (2020), which establishes a strong relationship between PE and online technology use.

H1. Performance Expectancy (PE) positively influences behavioral intention to adopt Web 3.0

Electronic word-of-mouth

Individuals exhibit a preference for user-generated electronic Word-of-Mouth (eWOM) over advertisements, relying on online reviews for insights into technology adoption. eWOM, as defined by Hennig-Thurau et al. (2004), involves users sharing positive or negative feedback online, serving as a reliable information source for potential users. With the rise of social media, consumers seek guidance from close associates and influencers, trusting user-generated eWOM more than firm-provided communication (Jeong, 2015; De Bruyn, 2008).

Research has consistently shown the positive impact of eWOM on purchase intention (He & Bond, 2015; Naujoks & Benkenstein, 2020; Zhang et al., 2021). Positive eWOM influences consumer Attitude Toward the Entity (ATE) (Lien & Cao, 2014) and shapes Perceived Value (PV) (Wang et al., 2018). Customers with a positive opinion of online platforms tend to recommend them to their social network contacts. Studies, including those by Tien et al. (2019) highlight the significant impact of favorable eWOM on consumers' intention to purchase, reaffirmed by meta-analysis (Ismagilova et al., 2019). The positive association between eWOM and purchase intention is robust and supported by empirical analysis (Yuan et al., 2019).

H2. Electronic Word-of-Mouth (eWOM) positively influences Behavioral Intention to adopt Web 3.0

Digital dexterity

Digital Dexterity (DD), encompassing the capacity and willingness to succeed in the digital environment, is crucial for Web 3.0 adoption. The DD funnel identifies Personal innovativeness and technology self-efficacy as key components. Personal innovativeness reflects users' willingness to experiment with Web 3.0, while technology self-efficacy gauges their perception of effectiveness in its use (Agarwal & Prasad, 1998; Venkatesh & Davis, 2000).

Research by Twum et al. (2021) establishes a significant link between creative IT behavior and e-learning intent, with Ahmed et al. (2021) reinforcing Personal innovativeness as a crucial predictor for digital competence. Personal innovativeness is a significant factor in adopting new technology. Conversely, the study by Doan et al. (2021) highlights the impact of users' confidence in technology use on the intention to continue online learning.

Moreover, technology self-efficacy predicts self-directed learning with technology. As digital transformation relies on advanced infrastructures and human adaptability to rapid technological changes, DD serves as a catalyst (Ahmed et al., 2021). The proposed hypothesis posits that Digital Dexterity positively influences individuals' intention to adopt Web 3.0.

H3. Digital Dexterity (DD) positively influences behavioral intention to adopt Web 3.0

Perceived usefulness and Perceived ease of use

Perceived usefulness, as defined by Davis (1989), reflects an individual's subjective evaluation of a technology's potential to enhance productivity, efficiency, and overall well-being. This perception significantly influences the intention to adopt new technologies (Raza et al., 2017). In the context of Web 3.0, perceived usefulness pertains to users' assessment of the value and benefits of Decentralized Applications (dApps) and blockchain technology, aligning with the shift towards decentralization, transparency, and user empowerment.

The Technology Acceptance Model (TAM) underscores the importance of perceived usefulness and perceived ease of use in shaping users' attitudes and intentions toward technology adoption (Wamba et al., 2020). Davis (1989) defines perceived ease of use as the perceived effort required to understand and integrate technology into daily activities. It plays a pivotal role in technology adoption, with users more inclined to adopt systems perceived as easy to use (Sohaib et al., 2019).

Studies by Teo (2011) and Grover et al. (2019) highlight the correlation between perceived ease of use, perceived usefulness, and users' attitudes towards technology. In the context of Web 3.0, the success of decentralized applications and blockchain technology relies on intuitive and user-friendly designs to encourage mainstream adoption. Perceived ease of use and perceived usefulness exhibit a positive relationship, influencing the intention to adopt new technology, including Web 3.0. Based on this, the proposed hypothesis suggests that both perceived usefulness and perceived ease of use positively influence the intention to use Web 3.0.

H4. Perceived Usefulness (PU) positively influences behavioral intention to adopt Web 3.0

H5. Perceived Ease of Use (PEOU) positively influences behavioral intention to adopt Web 3.0

H6. Perceived Ease of Use (PEOU) positively affects user's perceptions of the perceived usefulness

Data privacy security

Data privacy security, crucial for safeguarding personal and confidential data from unauthorized access, is a prominent concern in the context of Web 3.0 adoption (Davis, 1989). The adoption of Web 3.0 technology has significantly changed user interactions, emphasizing the need for robust data security measures (European Commission, 2022b).

Block chain technology, integral to Web 3.0, enhances data traceability and provenance, reducing costs and protecting data from tampering (Lo et al., 2017). Perceived security is vital in users' acceptance of technology, particularly in the evolving landscape of Web 3.0, where concerns about security, privacy, and legal risks may arise (Atzori et al., 2020).

The decentralization of blockchain contributes to enhanced security and privacy protection, addressing potential risks associated with Web 3.0 technologies (Hassani et al., 2018; Alabdulwahhab, 2018). Decentralized cloud storage solutions are anticipated to enhance privacy protection, aligning with the emphasis on securing users' data (PixelPlex, 2021).

The Technology Acceptance Model (TAM) recognizes the role of perceived security within the perceived usefulness construct, emphasizing that users are more likely to adopt technology perceived as both useful and secure (Davis, 1989). Blockchain's capability for peer-to-peer interactions without revealing personal information contributes significantly to online privacy protection (Liang et al., 2019).

Previous studies within the TAM framework highlight privacy and security as influential factors affecting perceived usefulness (Lallmahamood, 2007). Customers consider security and privacy integral components of e-commerce services, boosting trust within the sector (Udo, 2001; Limbu et al., 2011). Considering the importance of data privacy security, this study incorporates it as an independent variable in the Unified Theory of Acceptance and Use of Technology (UTAUT) model, recognizing its potential impact on Web 3.0 adoption (Venkatesh et al., 2003).

H7. Data Privacy Security (DPS) affects user's perceptions of the Perceived Usefulness

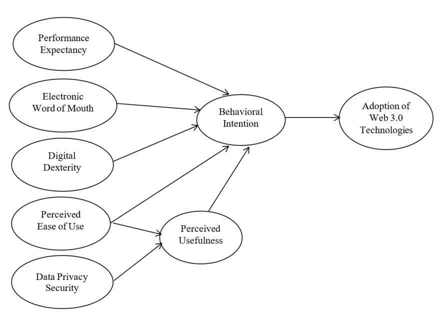

Fig. 1 *Conceptual framework*

Research Methodology

This study employs a quantitative survey design to investigate factors influencing users' behavioral intention to adopt Web 3.0. Utilizing a five-point Likert scale questionnaire, the research aims to collect numerical data from a large sample within the IT/Development field or those familiar with Web 3.0 in Pakistan. The chosen research design facilitates the generalization of findings to the target population. The study employs a causal research approach to explore possible relationships between variables, aiming to identify causes and effects. A total of 200 samples was drawn from the population. As per Sarstedt et al. (2023), PLS-SEM has the ability to obtain meaningful results in complex models having small sizes (<200). Therefore, the study used the PLS-SEM statistical technique to predict the studied causal relationship. To draw the sample, purposive non-probability sampling techniques have been used. This sampling technique is appropriate because the sample possesses unique characteristics.

Data analysis

Respondent’s profile

The study included 200 participants, with 80.5% male and 19.5% female. Predominantly aged 21-30 (73%), education varied from Matriculation to postgraduate degrees. Job roles included Web/Software Developers (38%), IT Project Managers (9%), and others. Experience ranged from less than 1 year to over 10 years. Internet use varied, providing diverse participant backgrounds.

Table I
Respondent’s profile

	Frequency	Percentage
Gender		
Male	161	80.5%
Female	39	19.5%
Age		
21-30	146	73.0%
31-40	44	22.0%
41-50	9	4.5%
51 Years and above	1	0.5%
Education		
Matriculation/Intermediate	8	4.0%
Undergraduate	36	18.0%
Graduate	104	52.0%
Postgraduate	52	26.0%
Job Role		
Web/Software Developer	76	38.0%
IT Project Manager	18	9.0%
Network Administrator	8	4.0%
Artificial Intelligence / Machine Learning	6	3.0%
Business Analyst/Business Intelligence	14	7.0%
Other	78	39.0%
Experience		
Less than 1 Year	27	13.5%
1-3 Years	76	38.0%
4-6 Years	63	31.5%
7-10 Years	22	11.0%
Above 10 Years	12	6.0%

Source: Author’s estimation

Measurement model testing

The study assessed construct reliability and validity through various analyses. Cronbach's alpha (α) met the criterion of α> 0.7, and composite reliability (CR) values also exceeded the 0.7 criterion, ensuring the internal consistency of the survey instrument. Convergent validity was confirmed through Average Variance Extracted (AVE) values exceeding 0.50, meeting established guidelines (Hair et al., 2011). See table 2 for detailed results.

Table II
Construct reliability & validity

	Cronbach α	CR	AVE
ADW	0.921	0.941	0.76
BI	0.888	0.922	0.748
DD	0.878	0.911	0.674
DPS	0.903	0.928	0.72
EWOM	0.794	0.879	0.708
PE	0.844	0.889	0.615
PEOU	0.897	0.928	0.764
PU	0.93	0.945	0.741

Source: Author's estimation

The discriminant validity of the variables is checked through different methods. Table 3 employs the Fornell-Larcker Criterion (FLC) to evaluate discriminant validity. Diagonal values, representing square-rooted AVE coefficients, indicate each construct's variance relative to measurement error. Comparing these values to correlation coefficients with other constructs reveals distinct and significant identities. The table demonstrates that the square root of AVE coefficients (diagonally bold) exceeds correlations with other constructs, establishing discriminant validity in the structural model (Ab Hamid et al., 2017; Cheung & Wang, 2017).

Table III
Fornell-Larcker Criterion (FLC)

	ADW	BI	DD	DPS	EWOM	PE	PEOU	PU
ADW	0.872							
BI	0.851	0.865						
DD	0.819	0.781	0.821					
DPS	0.755	0.784	0.772	0.849				
EWOM	0.775	0.765	0.791	0.763	0.841			
PE	0.702	0.669	0.787	0.763	0.729	0.785		
PEOU	0.755	0.687	0.818	0.741	0.706	0.767	0.874	
PU	0.811	0.771	0.849	0.806	0.808	0.833	0.791	0.861

Source: Author's estimation

The HTMT values, all below one for every factor pair in the table, suggest that correlations between these factors are not excessively high. This aligns with the guidelines of Henseler et al. (2016), indicating the measurement model effectively captures distinct aspects of the investigated factors. This supports the validity and reliability of the measurement model and enhances the overall credibility of the research approach.

Table IV
Heterotrait-Monotrait Ratio (HTMT)

	ADW	BI	DD	DPS	EWOM	PE	PEOU	PU
ADW								
BI	0.935							
DD	0.909							
DPS	0.826	0.874	0.865					
EWOM	0.895	0.872	0.936	0.897				
PE	0.784	0.896	0.907	0.864	0.871			
PEOU	0.829	0.752	0.926	0.82	0.828	0.878		
PU	0.876	0.763	0.936	0.877	0.929	0.932	0.866	

Source: Author's estimation

Structural model testing

After ensuring the measurement model testing, the hypotheses were tested using the PLS-SEM technique. Table 5 shows the results that digital dexterity exhibited a positive impact on behavioral intention. Users demonstrating higher digital dexterity were more likely to express a positive inclination toward adopting Web 3.0 technology. This finding aligns with the broader understanding that individuals with advanced digital skills are more receptive to emerging technologies.

Electronic Word of Mouth (eWOM) was identified as another significant factor positively impacting behavioral intention, highlighting the crucial role of peer recommendations and online reviews in shaping users' perceptions and intentions regarding technological adoption. Data privacy security and perceived usefulness also emerged as influential factors with positive and significant impacts on behavioral intention. This underscores the importance of addressing users' concerns about data security and emphasizing the practical utility of Web 3.0 technology in driving adoption. Surprisingly, performance expectancy exhibited a negative and insignificant impact on behavioral intention. While unexpected, this finding underscores the importance of delving deeper into the specific aspects of performance expectations that may affect users' decisions.

Table V
Path analysis

	Beta Coefficients	*T* Stats	*P*-Values
PE -> BI	-0.072	0.772	0.44
EWOM -> BI	0.313	4.106	0.000
DD -> BI	0.333	3.396	0.001
PEOU -> BI	0.040	0.475	0.635
PEOU -> PU	0.431	6.767	0.000
DPS -> PU	0.486	7.467	0.000
PU -> BI	0.264	2.315	0.021
BI -> ADW	0.851	36.989	0.000

Source: Author's estimation

Overall, behavioral intention was identified as a key driver of Web 3.0 technology adoption. Among the factors examined, digital dexterity emerged as the most impactful, emphasizing the significance of users' proficiency in navigating and utilizing digital technologies. These insights provide valuable guidance for policymakers and technology developers, emphasizing the need to enhance digital skills and address key concerns related to security and perceived usefulness to foster greater adoption of Web 3.0 technology.

Conclusion

This study extensively investigated factors influencing users' intent to adopt Web 3.0, exploring its potential for enhancing privacy and data management. Crucial predictors include digital dexterity, data privacy security, electronic word-of-mouth, perceived ease of use, and perceived usefulness. Behavioral intention positively influences Web 3.0 adoption, emphasizing users' pivotal role. Smart PLS-SEM analysis highlighted the impacts of various factors on behavioral intention, aligning with prior research. Notably, performance expectancy and perceived ease of use were found to be insignificant.

Findings supported perceived usefulness's significant influence on behavioral intention, diverging from performance expectancy. Interestingly, perceived ease of use and data privacy security influenced Web 3.0 usefulness perception, with perceived ease of use indirectly impacting adoption intention through perceived usefulness. This research adds insights to Web 3.0 adoption dynamics, emphasizing the need for ongoing exploration in the rapidly evolving landscape of emerging technologies.

This study enriches the understanding of user adoption behavior in the context of emerging technologies like Web 3.0, expanding established models like UTAUT and TAM. Integrating factors such as data privacy security, the research establishes a comprehensive theoretical framework. Key insights into digital dexterity, data privacy security, and electronic word-of-mouth contribute significantly to technology adoption research, deepening our comprehension of user behavior amid the Web 3.0 era.

Practical implications

This study holds practical implications for developers, marketers, and policymakers shaping Web 3.0 applications and services. Emphasizing digital dexterity, organizations should invest in user education for smoother transitions. Robust security measures are crucial, given the highlighted importance of data privacy security. Fostering electronic word-of-mouth can boost adoption, urging developers to build strong user communities. Insights on performance expectancy and perceived usefulness stress the need for refining these factors to align with user expectations, prompting developers to enhance the performance and usefulness of Web 3.0 technologies.

Recommendations for future research

Future research should extend the exploration of Web 3.0 adoption by investigating factors such as perceived authenticity and value, expanding the understanding of its drivers. Additionally, exploring adoption from diverse demographic perspectives, considering cultural nuances and regulatory environments, could offer valuable insights into the complexities of user behavior in the evolving Web3 landscape.

Investigating the dynamics of performance expectancy and perceived usefulness in the context of Web 3.0 and optimizing these factors for increased adoption rates represents a promising avenue for further inquiry. Addressing identified study limitations will establish a robust foundation for advancing knowledge in this dynamic field, contributing to the continuous evolution of Web3 and its transformative potential.

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