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# Unraveling the Determinants of Platform Economy Adoption in Developing Countries: An Extended Application of the UTAUT2 Model with a Privacy Calculus Perspective

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**Abstract:** The platform economy has emerged as a transformative force in various industries, reshaping consumer behavior and the way businesses operate in the digital age. Understanding the factors that influence the adoption of these platforms is essential for their continued development and widespread use. This study examines the determinants of economic platform adoption in Tunisia by extending the widely used unified theory of acceptance and use of technology 2 (UTAUT2) model with a privacy calculus model. By applying the partial least squares structural equation modeling (PLS-SEM) technique, the research provides significant insight. The results highlight the critical influence of factors such as performance expectancy, habit formation, trust in technology, perceived risk, privacy concerns, and price value on users' behavioral intentions and actual usage of the platforms. These findings provide a deeper understanding of the dynamics surrounding the adoption of the platform economy in developing countries and offer valuable insight for stakeholders. By leveraging this knowledge, stakeholders can foster an inclusive digital ecosystem, drive economic growth, and create an environment conducive to the widespread adoption and use of the platform economy in developing countries.

**Keywords:** economic platforms; user behavior; UTAUT2 model; privacy calculus model; PLS-SEM; Tunisia



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## 1. Introduction

The platform economy, which marks a significant economic shift in the digital age, has emerged as a powerful driver of economic growth and innovation around the world. By reinventing traditional business models and influencing consumer behavior, these digital platforms have streamlined various industries, increased operational efficiency, and fostered new forms of competition and collaboration. Developing countries, such as Tunisia, are witnessing an increase in the adoption of digital platforms due to the enticing prospects of economic development, job creation, and social inclusion that they offer.

Despite these promising aspects, the adoption trajectory of digital platforms in developing countries is often shaped by a unique set of variables. Understanding these factors is critical for countries like Tunisia to maximize the benefits of the platform economy. Although numerous studies have attempted to understand the mechanisms underlying platform adoption, a comprehensive study specifically focused on Tunisia is rare, creating a research gap that our study aims to fill.

To unravel the complex dynamics of platform economy adoption in Tunisia, this study adopts an extended application of the unified theory of acceptance and use of technology 2 (UTAUT2). This model is widely recognized for its reliability in technology acceptance studies across various contexts [1]. While the insightful extensions of the UTAUT model proposed by [2] and others [3–5] offer valuable frameworks, we identified an opportunity for an even deeper exploration. By integrating the UTAUT2 model with a privacy calculus model, a more in-depth exploration of user behavior towards platforms became possible. This integration proves to be particularly valuable in the unique socio-economic and cultural context of a developing country such as Tunisia, where factors heavily influence technology adoption. This approach not only caters to the intricacies of the Tunisian situation, but also provides a comprehensive understanding of the complex influences that shape the adoption of the platform economy.

This paper is structured in several sections to provide a comprehensive analysis of the adoption of the platform economy in Tunisia. This introduction is followed by an overview of the platform economy from a global and local perspective, highlighting the opportunities and challenges it presents, particularly in the Tunisian context. This is followed by a detailed discussion of the theoretical framework, which combines the UTAUT2 model and the privacy calculus model. This framework forms the basis for the development of hypotheses related to the factors influencing the adoption of platform economy in Tunisia. The next section outlines the research methodology used, including the approach to data collection, sampling procedures, and data analysis techniques. The findings are then presented and thoroughly discussed, highlighting their implications for the development and evolution of the Tunisian platform economy and its broader digital ecosystem. Finally, the paper concludes by highlighting the contributions of the study and providing valuable recommendations for policymakers, businesses, and other stakeholders in the region.

By analyzing the determinants of platform adoption in Tunisia, this study provides valuable insight that can guide policymakers, businesses, and other stakeholders. This insight enables the formulation of targeted strategies that effectively address the prevailing challenges and optimize the opportunities presented by the platform economy. We believe that our research contributes significantly to the growing literature on platform adoption in developing countries and acts as a catalyst for evidence-based decision-making within Tunisia's evolving digital ecosystem.

## 2. Platform Economy: Global and Local Perspectives

### *2.1. Defining the Platform Economy*

The platform economy refers to a digital ecosystem that encompasses a range of digital platforms facilitating interactions and transactions among diverse user groups, such as businesses, consumers, and service providers [6]. These platforms act as intermediaries, leveraging network effects, data-driven algorithms, and innovative business models to create value for all participants. The scope of the platform economy spans diverse sectors, such as e-commerce, social media, ride-hailing, and financial services.

### *2.2. Global Impact of the Platform Economy*

The platform economy has gained significant global traction, driven by major players such as Amazon, Uber, and Airbnb, which have transformed various industries and redefined consumer behavior [7,8]. Enabled by advances in big data, cloud computing, and machine learning technologies, the platform economy represents a new economic model that leverages digital technologies to drive growth, spur innovation, and expand consumer choices [9]. Its financial impact is significant, as evidenced by the fact that the combined market capitalization of the top 70 platform companies surpassed $11 trillion in 2021, representing approximately 30% of global GDP [10]. In addition, the platform economy has created innovative employment opportunities, with more than 60 million active platform workers worldwide in 2020. This underscores the profound influence of the platform economy in reshaping business operations, labor markets, and consumer behavior on a global scale.

### *2.3. The Role of Digital Platforms in Developing Countries*

Digital platforms contribute significantly to economic development and social inclusion in developing countries by providing entrepreneurs with broader market access, facilitating job creation, and promoting digital literacy [11]. For example, platforms such as

Jumia, Grab, and Rappi have transformed local markets and created new opportunities for small businesses and entrepreneurs [12]. In India, the platform economy is projected to contribute $2.3 trillion to the GDP by 2025, with online platforms creating over 20 million livelihood opportunities in the last five years and contributing to about 5% of the country's GDP [13]. However, the adoption and impact of the platform economy depends on various factors, including digital infrastructure, the regulatory environment, and socio-cultural aspects unique to each local context.

### *2.4. Economic Platforms in Tunisia: Context and Challenges*

In Tunisia, the platform economy is gradually gaining traction, driven by factors such as increasing internet penetration, a youthful and technologically savvy population, and government initiatives to promote digital transformation [14]. This is evidenced by the emergence of numerous local platforms, including Tayara, Jumia, and Dabchy, across various sectors, reflecting the country's growing interest in the platform economy. However, Tunisia also faces significant challenges that hinder the widespread adoption of the platform economy. One of the key challenges is the significant digital literacy gap, with only 15% of Tunisians possessing advanced digital skills [15]. This digital literacy gap is an obstacle to effectively participating in and benefiting from the platform economy. In addition, privacy concerns are prevalent among 53% of the country's internet users [14], further hindering platform adoption. Furthermore, regulatory hurdles pose additional barriers to platform adoption in Tunisia.

These challenges contribute to Tunisia lagging behind other developing countries in terms of platform economy adoption. Overcoming these barriers requires a comprehensive understanding of the factors that influence platform adoption in the Tunisian context. The case of Tunisia is of great importance and relevance, not only within its own context, but also for other developing countries in the Middle East and North Africa (MENA) regions. By closely examining the factors that shape platform adoption in Tunisia, valuable lessons can be learned that have implications beyond the country's borders. Tunisia's experience sheds light on the challenges and opportunities associated with platform adoption in similar regional contexts. Understanding the specific challenges faced by Tunisia in terms of digital literacy, privacy concerns, and regulatory barriers can inform the development of strategies and policies to overcome these hurdles in other MENA countries. By leveraging the lessons learned from Tunisia, policymakers, businesses, and stakeholders in the region can formulate targeted approaches to promote the adoption of the platform economy and drive economic growth and digital transformation.

## 3. Theoretical Framework and Hypotheses Development

Successful adoption of new technological systems depends heavily on user acceptance [16]. To understand and predict this acceptance, several theoretical models have been developed in the fields of information systems, psychology, sociology, and economics [3,17]. While the technology acceptance model (TAM) is widely recognized in the field [2,11,18], it has been criticized for its limited depth in understanding individual perspectives on new systems [19–21]. The TAM primarily focuses on external variables, such as perceived usefulness and perceived ease of use, overlooking the links between usage and attitudes or intentions [22]. As a result, there is a growing need for more comprehensive models [23].

In response to this need, the authors of [24] integrated key elements from eight different theories and models, leading to the development of the unified theory of acceptance and use of technology (UTAUT). This theory incorporates variables from diverse theories, such as the theory of reasoned action (TRA), the information diffusion theory (IDT), the theory of planned behavior (TPB), TAM, the combined model of TAM and TPB (C-TAM-TPB), the motivational model (MM), the model of personal computer utilization (MPCU), and the social cognitive theory (SCT) [24].

At the same time, rapid advances in information and communication technology (ICT) have caused significant disruptions in politics, economy, and society [5,25,26]. A notable outcome of this disruption is the emergence of the platform economy, which involves the provision of employment opportunities through online digital platforms for tasks of varying complexity.

With the development of ICT, the gig economy has also undergone significant changes, expanding beyond short-term contracts and freelance work to include high-value jobs and tasks [5]. This evolution necessitates a reassessment of the gig economy in the context of digital literacy and the ability to work in geographically dispersed virtual teams.

Extending the original UTAUT model, the authors of [1] introduced hedonic motivation (HM), price value (PV), and habit (HT) as additional variables to improve the model. These variables complement existing factors, such as performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). The resulting model, UTAUT2, specifically designed for consumer contexts, is recognized as one of the most comprehensive theories for understanding consumer acceptance and use of new technologies [27].

In the Tunisian context, the UTAUT2 model plays a crucial role in examining the factors that influence the adoption of the platform economy. By incorporating variables such as hedonic motivation, price value, and habit, the model provides a deeper understanding of the unique cultural and social nuances that drive technology adoption in Tunisia [28–30].

This study aims to enrich the UTAUT2 model by introducing additional factors that were previously overlooked, such as privacy, perceived credibility, perceived risk, trust, and perceived skill development. These factors are particularly relevant when considering the adoption of the platform economy in Tunisia.

The privacy calculus theory, first introduced by [27] and later extended by [31], examines the impact of individual perceptions, including privacy and risk. The main components of the privacy calculus model include privacy risk, privacy concern, institutional trust (e.g., trust in technology, such as digital platforms), and the propensity to trust.

Originally developed to understand and model users' information sharing behavior, the privacy calculus theory has evolved to include technology platforms, recognizing that information sharing is often a prerequisite for use. Therefore, the willingness to provide personal information has become essential to the adoption and acceptance of intelligent technologies. The acceptance of technology by data owners is critical to the widespread adoption and use of consumer technologies.

Following the methodology of [3], we retain the original UTAUT2 relationships while proposing a new model that combines individual-level technology acceptance concepts with the privacy calculus model. In addition, we include a variable for perceived skill development to increase the relevance of the model in the Tunisian context.

Figure 1 illustrates the proposed model for this study, which combines the extended UTAUT2 model, privacy calculus theory, and the perceived skill development variable. This comprehensive model aims to provide a deeper understanding of the factors driving the adoption of the platform economy in Tunisia while considering the distinctive cultural and social aspects that influence technology adoption behavior.

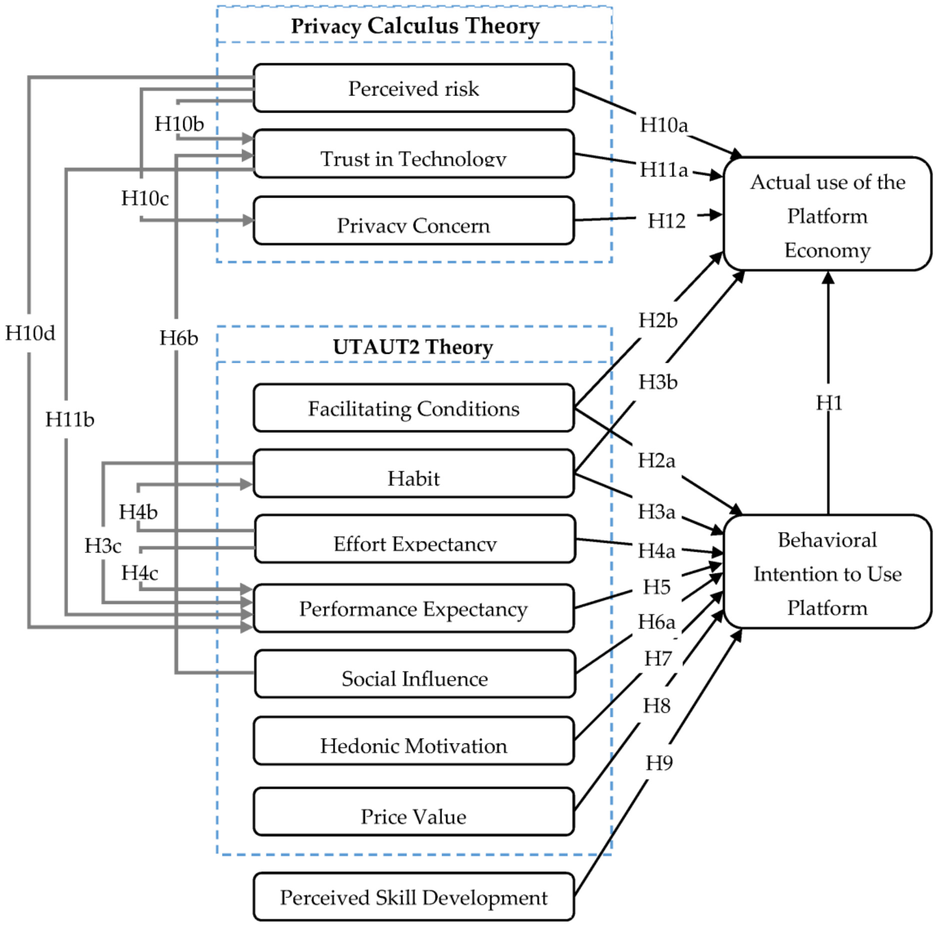


**Figure 1.** Research model.

### *3.1. Behavioral Intention*

Behavioral intention is a critical factor in determining the likelihood of adoption and use of the platform economy. It represents an individual's intention or willingness to engage in a particular behavior, such as using these platforms. In the Tunisian context, behavioral intention has been identified as a significant predictor of technology adoption and use, serving as a precursor to actual usage behavior [30]. Studies conducted in Tunisia have consistently found a positive relationship between behavioral intention and actual use of various platform economy services, including e-commerce, mobile banking, and mobile payment services [28–30]. Behavioral intention has been observed to act as a driving force that promotes actual usage behavior [32]. Therefore, the following hypothesis is posed:

**Hypothesis 1 (H1).** *Users' actual usage behavior will be positively influenced by their intention to use the platform economy.*

### *3.2. Facilitating Conditions*

Facilitating conditions include the organizational and technical infrastructure that supports the adoption of technology, especially platform economy, by individuals [24]. In the Tunisian context, facilitating conditions play an important role in the adoption and use of platform economy services, such as e-commerce, mobile banking, and mobile payment services [28–30]. According to Nasri [30] and other studies, facilitating conditions, such as technological accessibility, technical support, and adequate infrastructure, have a significant impact on the adoption of the platform economy in Tunisia. These conditions increase users' comfort and support in using these platforms, thereby influencing their behavioral intention to adopt and use them. Therefore, the following hypotheses are proposed:

**Hypothesis 2a (H2a)**. *Facilitating conditions positively influence users' behavioral intention to use platform economy*.

**Hypothesis 2b (H2b)**. *Facilitating conditions positively influence users' actual use of the platform economy*.

### 3.3. Habit

Habit, in the context of technology adoption, refers to the automatic and learned behaviors that individuals exhibit when using technology [33]. In Tunisia, habit has been found to play a significant role in the adoption and use of the platform economy, as observed in studies related to e-commerce and mobile banking [29,30]. These studies have shown that a strong habit positively influences behavioral intention, actual usage, and performance expectancy. Habit encompasses two important characteristics: prior usage behavior and the automaticity of the behavior [1]. In the context of mobile systems and digital platforms, habit is a critical factor influencing usage [34]. Research on mobile payment adoption further supports the positive influence of habit and social norms on technology adoption [35,36]. Based on these findings, the following hypotheses are proposed:

**Hypothesis 3a (H3a)**. *Habit will positively influence users' behavioral intention to use platform economy*.

**Hypothesis 3b (H3b)**. *Habit will positively influence users' actual use of platform economy*.

**Hypothesis 3c (H3c)**. *Habit will positively influence users' performance expectancy*.

### 3.4. Effort Expectancy

Effort expectancy refers to the perceived ease of use associated with the system [24]. In the Tunisian context, effort expectancy has been identified as a crucial factor influencing the adoption and use of platform economy. It has a significant impact on behavioral intention, habit formation, and performance expectancy. Previous research on technology adoption has consistently shown a positive relationship between effort expectancy and performance expectancy [37]. This relationship is further supported by studies on mobile banking, remote working platforms, and mobile payment systems [38–41]. Effort expectancy includes the dimension of perceived ease of use, which positively influences users' behavioral intention to adopt and use platform economy [17,42,43]. Thus, we propose the following hypotheses:

**Hypothesis 4a (H4a)**. *Effort expectancy will positively influence users' behavioral intention to use platform economy*.

**Hypothesis 4b (H4b)**. *Effort expectancy will positively influence users' habit formation, as users who perceive platform economy as easy to use are more likely to develop a habit of using it*.

**Hypothesis 4c (H4c)**. *Effort expectancy will positively influence users' performance expectancy, as users who perceive platform economy as easy to use are more likely to expect better performance from these platforms*.

### 3.5. Performance Expectancy

Performance expectancy refers to the extent to which individuals believe that using a particular technology will help them achieve desired outcomes in their daily tasks [24]. In the context of the platform economy, performance expectancy reflects users' perceptions of the usefulness and effectiveness of the technology in providing access to information, enabling communication, and facilitating various tasks without location constraints. Research consistently demonstrates the importance of performance expectancy as a key determinant of users' behavioral intentions to adopt various technologies, including mobile banking, e-commerce platforms, remote work, and cloud computing [28,30,44,45]. In the Tunisian context, the ability of the platform economy to provide continuous innovation and address everyday challenges contributes to users' belief in their benefits [29,30]. According to the innovation diffusion theory, users are more likely to adopt new technological products or services if they perceive them as offering relevant advantages over existing alternatives [46]. Accordingly, we developed the following hypotheses:

**Hypothesis 5 (H5)**. *Performance expectancy significantly influences users' behavioral intention to use platform economy*.

### 3.6. Social Influence

Social influence refers to the extent to which individuals adjust their views and behaviors to conform to the expectations of their social group, including friends and family [1]. This concept is related to subjective norms from the theory of reasoned action and the theory of planned behavior [47]. In the context of platform economy, social influence can come from sources such as electronic word of mouth (eWOM) and online reviews [48]. Research conducted in the Tunisian context has highlighted the importance of social influence in the adoption of new technologies, including mobile banking and e-commerce platforms [28,30]. Advances in mobile technology and the proliferation of social media have further amplified the role of social influence in shaping user behavior and adoption decisions [48]. Therefore, we posit the following:

**Hypothesis 6a (H6a)**. *Social influence significantly affects a user's behavioral intention to use platform economy*.

**Hypothesis 6b (H6b)**. *Social influence significantly affects a user's trust in the technology*.

### 3.7. Hedonic Motivation

Hedonic motivation, which refers to the pleasure or enjoyment derived from using technology, has been found to have a significant influence on user trust and behavioral intention in various contexts, including mobile payments, smartphones, e-health applications, e-banking, and e-commerce platforms [1,33,39,49–53]. In the Tunisian context, hedonic motivation has been shown to play a role in the adoption of e-commerce platforms and e-banking applications [29,30]. While some technologies focus primarily on functionality, incorporating hedonic motivation by adding pleasurable features can improve the user experience and increase the likelihood of adoption. Given the importance of hedonic motivation in technology adoption across contexts and technologies, we propose the following hypothesis:

**Hypothesis 7 (H7)**. *Hedonic motivation has a significant positive effect on users' behavioral intention to use the platform economy*.

### 3.8. Price Value

Price value refers to the trade-off that users make between the perceived benefits and the costs of an innovation [1]. In the context of the platform economy, price value includes the costs associated with installing, downloading, and transacting on the platform. It plays a central role in the use of the platform economy, as users are more likely to trust and continue to use a technology if the perceived benefits outweigh the monetary costs [1,54]. The impact of price value on the adoption of new technologies may vary across contexts. While some studies have found that price value is not a determining factor for mobile banking or mobile payment services [51,55], research in the Tunisian context has shown that price value is crucial for users in adopting digital services such as mobile banking and e-commerce platforms [29,30]. Based on these discussions, we propose the following hypothesis:

**Hypothesis 8 (H8)**. *Price value has a significant positive effect on users' behavioral intention to use platform economy.*

### *3.9. Perceived Skill Development*

In this study, we extend the UTAUT2 model by introducing the variable of perceived skill development, which has been identified as a critical factor in technology adoption, particularly in the Tunisian context. By incorporating perceived skill development into the UTAUT2 model, our research aims to provide a more comprehensive understanding of the factors influencing users' behavioral intention to adopt the platform economy in Tunisia. This extension allows us to explore the role of users' belief in their ability to improve and develop their skills while using platform economy [56–58], thereby contributing to the existing literature on technology adoption in developing countries, such as Tunisia. Therefore, we hypothesize the following:

**Hypothesis 9 (H9)**. *Perceived skill development has a significant effect on a user's behavioral intention to use platform economy.*

### *3.10. Perceived Risk*

Perceived risk is a critical factor in the adoption and use of platform economy because it reflects users' beliefs about potential losses and negative consequences associated with using these platforms [59]. Research has consistently shown that perceived risk can hinder users' behavioral intentions to adopt new technologies, especially in online contexts where platform economy is perceived as riskier than traditional offline businesses [60,61]. Several factors contribute to increased perceived risk in the platform economy, including unfamiliarity with products or businesses; privacy concerns; wasted time, money, or effort; and the potential risks associated with customer-to-customer interactions [61,62]. When users perceive higher risks during their decision-making process, the importance of information provided by reference groups, such as family, friends, and colleagues, increases, as users rely on their suggestions to mitigate their perceived risk [60]. Therefore, we propose the following:

**Hypothesis 10a (H10a)**. *Perceived risk will have a significant negative effect on users' actual use of platform economy.*

**Hypothesis 10b (H10b)**. *Perceived risk will have a negative effect on users' trust in technology regarding their actual use of the platform economy.*

**Hypothesis 10c (H10c)**. *Perceived risk will have a positive effect on users' privacy concerns regarding their actual use of platform economy.*

**Hypothesis 10d (H10d)**. *Perceived risk will have a negative effect on users' performance expectancy regarding their behavioral intention to use platform economy.*

### *3.11. Trust in Technology*

Trust in technology plays a crucial role in users' adoption and use of the platform economy, especially in situations of risk and uncertainty [3,33,63]. It includes users' trust in the technology itself, as well as their trust in legal frameworks and service providers to handle their data responsibly. Empirical studies in a variety of contexts, including e-commerce, healthcare, and internet banking, have consistently demonstrated the importance of trust in increasing technology adoption [3,30,64]. Trust also serves as a mitigating factor for privacy concerns [65,66], which further highlights its importance in shaping users' performance expectations [63,67]. In the Tunisian context, trust in technology applications plays a crucial role in users' evaluation of the potential usefulness of embedded services and applications in the platform economy. By fostering trust, users are more likely to feel confident about the benefits they expect to gain from engaging with these platforms. Based on these considerations, we propose the following hypotheses:

**Hypothesis 11a (H11a)**. *Trust in technology will have a positive effect on the performance expectations of users' actual use of the platform economy.*

**Hypothesis 11b (H11b)**. *Trust in technology will have a positive effect on the performance expectancy of users' behavioral intention to use platform economy.*

### 3.12. Privacy Concern

Privacy concerns have become paramount in today's digital world, where technology has permeated every aspect of our lives. The concept of privacy has evolved to encompass the integrity and security of personal information across different platforms, channels, and contexts, as well as the right to determine how personal data are used [3,40,68]. The privacy paradox, which refers to the discrepancy between consumers' expressed privacy concerns and their digital behavior, highlights the trade-off between privacy and innovation [67,69]. Privacy concerns about user information arise from the risks associated with the platform economy, such as the lack of control over information posted by others and the potential for identity theft. Recent research has focused on how privacy concerns affect users' perceptions and behavior in the platform economy [3,66]. Privacy concerns can significantly affect users' acceptance and use of the platform economy [3]. Users value control over their personal information, including determining what data are shared, with whom they are shared, and for what purpose [66]. When users are increasingly concerned about protecting their personal information, they are more likely to have negative attitudes toward adopting platform economy [68]. Based on these findings, we propose the following hypothesis:

**Hypothesis 12 (H12)**. *Privacy concerns will have a negative impact on users' adoption and use of platform economy.*

## 4. Methodology

### 4.1. Data Collection

Data collection for this study involved the distribution of offline questionnaires to the Tunisian population. The questionnaire consisted of 13 constructs adapted from previous studies and related to the extended UTAUT2 model. Each construct was measured using multiple items on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). In addition to measuring the constructs, the questionnaire collected demographic information, such as age, gender, education, occupation, and frequency of use. Prior to the data collection, a pretest was conducted with expert researchers and potential participants to ensure the clarity and understandability of the survey. The data collection period spanned from November to December 2022 and covered all regions of Tunisia, including 12 governorates. The valid response rate was 89%, resulting in a final sample of 893 participants. Data cleaning procedures were carried out prior to data analysis. Table 1 shows the socio-demographic characteristics of the sample.

**Table 1.** Demographic characteristics of participants ($n$ = 893).

| Demographic | Characteristics | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 448 | 50.17 |
| | Female | 445 | 49.83 |
| Age | Less than 20 years | 61 | 6.82% |
| | 20–29 years | 324 | 36.24% |
| | 30–39 years | 253 | 28.30% |
| | 40–49 years | 211 | 23.60% |
| | 50 years and above | 45 | 5.03% |

**Table 1.** *Cont.*

| Demographic | Characteristics | Frequency | Percentage |
|---|---|---|---|
| Education level | No formal education | 28 | 3.14% |
| | Primary education | 111 | 12.43% |
| | Secondary education | 298 | 33.37% |
| | Tertiary education | 456 | 51.06% |
| Employment status | Student | 302 | 33.82% |
| | Employee | 212 | 23.74% |
| | Self-employed | 245 | 27.44% |
| | Retired | 17 | 1.90% |
| | Unemployed | 117 | 13.10% |
| Use frequency | Less than 1 h per week | 13 | 1.46% |
| | 1–5 h | 171 | 19.15% |
| | 6–9 h | 244 | 27.32% |
| | 10–14 h | 203 | 22.73% |
| | More than 15 h | 262 | 29.34% |

### *4.2. Modeling Analysis*

In this study, PLS structural equation modeling (PLS-SEM) was used to analyze the data and evaluate the model using SmartPLS 4.0 [70]. PLS-SEM is a method within the broader framework of structural equation modeling that is particularly useful for analyzing complex models with numerous dependent and independent variables. It allows for simultaneous testing of both measurement and structural models, making it well suited for research aimed at explaining a specific phenomenon [71].

While covariance-based structural equation modeling is commonly used to support or test existing theories, PLS-SEM, as advocated by [72], is particularly useful for developing new models with complex relationships. PLS-SEM has gained recognition in various fields and has been widely used in studies focusing on the adoption of new technologies [72].

Given the objectives of this study, which aimed to explain behavioral intention by identifying the influential factors in economic platform adoption rather than validating a specific theory, PLS-SEM was considered an appropriate methodological choice.

## 5. Results

The results of the PLS-based structural equation modeling are divided into two stages: measurement model evaluation and structural model evaluation. In the measurement model evaluation stage, the reliability and validity of the constructs are assessed through internal consistency, composite validity, and discriminant validity. In the second stage, the hypotheses are tested by analyzing the path coefficients for magnitude and significance [73]. Table 2 shows the reliability values for the constructs, indicating that both the composite reliability and Cronbach's alpha exceed the threshold of 0.70.

**Table 2.** Loadings, collinearity, and convergent validity.

| Constructs | Items | Loadings | Cronbach's Alpha | rho_A | CR | AVE | VIF |
|---|---|---|---|---|---|---|---|
| Actual use of economic platforms (AU) | | | 0.821 | 0.897 | 0.873 | 0.580 | |
| | AU1 | 0.715 | | | | | 1.528 |
| | AU2 | 0.706 | | | | | 1.519 |
| | AU3 | 0.770 | | | | | 1.728 |
| | AU4 | 0.729 | | | | | 1.551 |
| | AU5 | 0.876 | | | | | 1.972 |

**Table 2.** *Cont.*

| Constructs | Items | Loadings | Cronbach's Alpha | rho_A | CR | AVE | VIF |
|---|---|---|---|---|---|---|---|
| Behavioral intention to use economic platforms (BI) | | | 0.744 | 0.754 | 0.837 | 0.563 | |
| | BI1 | 0.701 | | | | | 1.479 |
| | BI2 | 0.739 | | | | | 1.459 |
| | BI3 | 0.808 | | | | | 1.610 |
| | BI4 | 0.747 | | | | | 1.297 |
| Effort expectancy (EE) | | | 0.757 | 0.761 | 0.845 | 0.576 | |
| | EE1 | 0.729 | | | | | 1.225 |
| | EE2 | 0.779 | | | | | 1.953 |
| | EE3 | 0.804 | | | | | 2.045 |
| | EE4 | 0.723 | | | | | 1.381 |
| Facilitating conditions (FC) | | | 0.790 | 0.910 | 0.850 | 0.587 | |
| | FC1 | 0.763 | | | | | 2.111 |
| | FC2 | 0.718 | | | | | 1.567 |
| | FC3 | 0.748 | | | | | 1.962 |
| | FC4 | 0.831 | | | | | 1.297 |
| Hedonic motivation (HM) | | | 0.732 | 0.735 | 0.849 | 0.652 | |
| | HM1 | 0.770 | | | | | 1.391 |
| | HM2 | 0.842 | | | | | 1.638 |
| | HM3 | 0.808 | | | | | 1.429 |
| Habit (HT) | | | 0.792 | 0.795 | 0.878 | 0.707 | |
| | HT1 | 0.793 | | | | | 1.484 |
| | HT2 | 0.871 | | | | | 1.924 |
| | HT3 | 0.856 | | | | | 1.806 |
| Privacy concern (PC) | | | 0.719 | 0.736 | 0.876 | 0.779 | |
| | PC1 | 0.860 | | | | | 1.461 |
| | PC2 | 0.906 | | | | | 1.461 |
| Performance expectancy (PE) | | | 0.801 | 0.817 | 0.869 | 0.625 | |
| | PE1 | 0.707 | | | | | 1.669 |
| | PE2 | 0.850 | | | | | 2.047 |
| | PE3 | 0.793 | | | | | 1.625 |
| | PE4 | 0.806 | | | | | 1.742 |
| Perceived risk (PR) | | | 0.742 | 0.753 | 0.885 | 0.794 | |
| | PR1 | 0.874 | | | | | 1.534 |
| | PR2 | 0.908 | | | | | 1.534 |
| Perceived skill development (PSD) | | | 0.819 | 0.887 | 0.887 | 0.726 | |
| | PSD1 | 0.901 | | | | | 2.041 |
| | PSD2 | 0.895 | | | | | 1.921 |
| | PSD3 | 0.751 | | | | | 1.649 |
| Price value (PV) | | | 0.747 | 0.753 | 0.856 | 0.665 | |
| | PV1 | 0.817 | | | | | 1.585 |
| | PV2 | 0.776 | | | | | 1.367 |
| | PV3 | 0.851 | | | | | 1.617 |
| Social influence (SI) | | | 0.771 | 0.773 | 0.854 | 0.594 | |
| | SI1 | 0.775 | | | | | 2.090 |
| | SI2 | 0.823 | | | | | 2.253 |
| | SI3 | 0.745 | | | | | 1.516 |
| | SI4 | 0.736 | | | | | 1.534 |
| Trust in technology (TT) | | | 0.836 | 0.836 | 0.901 | 0.753 | |
| | TT1 | 0.835 | | | | | 1.623 |
| | TT2 | 0.883 | | | | | 2.316 |
| | TT3 | 0.884 | | | | | 2.396 |

Notes: CR = composite reliability, AVE = average variance extracted, and VIF = variance inflation factor.

The average variance extracted (AVE) values used for composite validity are higher than the 0.5 threshold recommended by [74]. This indicates that the constructs in the proposed model are reliable.

To address issues of collinearity and potential method bias, variance inflation factors (VIF) were calculated. The VIF values, around two and below the conservative thresholds of 3.3 and 5, indicate that collinearity and common method bias are not significant concerns in this study.

Furthermore, a cross-loadings analysis was conducted to ensure that the loadings of each variable are higher than the cross-loadings of other variables. The results confirm that this criterion is met, further supporting the validity of the measurement model.

Discriminant validity is an important aspect of the analysis that confirms that each variable measures different concepts. It includes evaluation of the Fornell–Larcker criterion, cross-loadings, and the HTMT ratio. According to the Fornell–Larcker criterion, the square root of the AVE values for each construct should exceed its correlations with other constructs [75]. For instance, in Table 3, the square root of the AVE value for the HT variable is 0.841, which is higher than its correlations with other variables. This indicates that the Fornell–Larcker criterion is met, and similar observations can be made for the other variables, further confirming discriminant validity.

**Table 3.** Discriminant validity: Fornell–Larcker criterion.

| | AU | EE | FC | HT | HM | BI | PR | PSD | PE | PV | PC | SI | TT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AU | 0.762 | | | | | | | | | | | | |
| EE | 0.345 | 0.759 | | | | | | | | | | | |
| FC | 0.077 | 0.159 | 0.766 | | | | | | | | | | |
| HT | 0.411 | 0.646 | 0.106 | 0.841 | | | | | | | | | |
| HM | 0.192 | 0.145 | −0.015 | 0.171 | 0.807 | | | | | | | | |
| BI | 0.386 | 0.416 | 0.110 | 0.458 | 0.136 | 0.750 | | | | | | | |
| PR | 0.418 | 0.430 | 0.066 | 0.547 | 0.138 | 0.394 | 0.891 | | | | | | |
| PSD | 0.506 | 0.192 | 0.098 | 0.189 | 0.137 | 0.223 | 0.169 | 0.852 | | | | | |
| PE | 0.372 | 0.313 | 0.053 | 0.328 | 0.197 | 0.643 | 0.302 | 0.153 | 0.791 | | | | |
| PV | 0.321 | 0.339 | 0.096 | 0.330 | −0.013 | 0.480 | 0.312 | 0.123 | 0.456 | 0.815 | | | |
| PC | 0.271 | 0.194 | 0.021 | 0.225 | 0.193 | 0.431 | 0.255 | 0.108 | 0.703 | 0.315 | 0.883 | | |
| SI | 0.462 | 0.308 | 0.073 | 0.271 | 0.330 | 0.278 | 0.283 | 0.265 | 0.330 | 0.205 | 0.289 | 0.770 | |
| TT | 0.310 | 0.297 | 0.092 | 0.254 | 0.371 | 0.230 | 0.256 | 0.148 | 0.281 | 0.149 | 0.231 | 0.593 | 0.868 |

Notes: Actual use = AU, effort expectancy = EE, facilitating conditions = FC, habit = HT, hedonic motivation = HM, behavioral intention = BI, perceived risk = PR, perceived skill development = PSD, performance expectancy = PE, price value = PV, privacy concern = PC, social influence = SI, trust in technology = TT.

The HTMT criterion compares the average correlations between the variables with item-level correlations within each variable. In Table 4, the HTMT values are below the threshold, indicating construct validity. For example, the relationship between SI and TT is 0.735, which is relatively close to the threshold, but still acceptable. The authors of [75] suggest that a threshold of 0.9 can be used for conceptually close relationships. Overall, the HTMT criterion is met, supporting the validity of the model [73].

The last step in testing the structural model is to test the hypotheses. To accomplish this, the 5000-sample bootstrapping method was used to test the hypotheses, and the results are based on the standard errors obtained, as described by [73]. By considering t-values greater than 1.96 and $p$-values less than 0.05, the predicted relationships were evaluated to determine whether they were supported. The analysis of the structural model results is based on the total effects.

The structural model was evaluated by calculating the path coefficients and explained variance ($R^2$) between the constructs. Table 5 shows the results for predicting behavioral intentions and usage behavior using UTAUT2 and UTAUT2 extended with a privacy calculus model. New relationships added to the baseline UTAUT2 model are also shown.

Two separate models were executed to assess the support for the original UTAUT2 and the extended UTAUT2 with the privacy calculus model.

**Table 4.** Discriminant validity: heterotrait–monotrait ratio (HTMT).

| | AU | EE | FC | HT | HM | BI | PR | PSD | PE | PV | PC | SI | TT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AU | | | | | | | | | | | | | |
| EE | 0.375 | | | | | | | | | | | | |
| FC | 0.074 | 0.182 | | | | | | | | | | | |
| HT | 0.459 | 0.811 | 0.113 | | | | | | | | | | |
| HM | 0.234 | 0.211 | 0.053 | 0.224 | | | | | | | | | |
| BI | 0.462 | 0.538 | 0.142 | 0.595 | 0.184 | | | | | | | | |
| PR | 0.501 | 0.563 | 0.073 | 0.722 | 0.180 | 0.525 | | | | | | | |
| PSD | 0.604 | 0.231 | 0.111 | 0.221 | 0.179 | 0.266 | 0.214 | | | | | | |
| PE | 0.440 | 0.382 | 0.065 | 0.403 | 0.260 | 0.778 | 0.386 | 0.168 | | | | | |
| PV | 0.392 | 0.433 | 0.119 | 0.428 | 0.079 | 0.636 | 0.421 | 0.153 | 0.575 | | | | |
| PC | 0.341 | 0.268 | 0.040 | 0.299 | 0.258 | 0.564 | 0.346 | 0.133 | 0.458 | 0.427 | | | |
| SI | 0.562 | 0.408 | 0.081 | 0.347 | 0.437 | 0.359 | 0.369 | 0.334 | 0.421 | 0.270 | 0.385 | | |
| TT | 0.355 | 0.377 | 0.087 | 0.313 | 0.471 | 0.290 | 0.322 | 0.180 | 0.342 | 0.188 | 0.295 | 0.735 | |

**Table 5.** Structural model results.

| | | **Original UTAUT2** | | **UTAUT2 with Privacy Calculus Model** | | |
|---|---|---|---|---|---|---|
| **Hyp.** | **Structural Path** | **Path Coef. (β)** | **T Statistics** | **Path Coef. (β)** | **T Statistics** | **Results** |
| | **Dependent variable: Behavioral intention** | | | | | |
| | $\mathbb{R}^2$ | 0.227 | | 0.290 | | |
| | Adj. $\mathbb{R}^2$ | 0.226 | | 0.287 | | |
| H2a | Facilitating conditions | 0.031 | 1.398 (0.021) | 0.031 | 1.447 (0.020) | Not Supported |
| H3a | Habit | 0.183 *** | 6.604 (0.028) | 0.183 *** | 6.745 (0.027) | Supported |
| H4a | Effort expectancy | 0.078 *** | 2.917 (0.027) | 0.076 *** | 2.823 (0.027) | Supported |
| H5 | Performance expectancy | 0.472 *** | 19.854 (0.024) | 0.472 *** | 19.996 (0.024) | Supported |
| H6a | Social influence | −0.007 | 0.350 (0.022) | −0.007 | 0.333 (0.022) | Not Supported |
| H7 | Hedonic motivation | −0.004 | 0.250 (0.019) | −0.004 | 0.280 (0.019) | Not Supported |
| H8 | Price value | 0.167 *** | 7.122 (0.023) | 0.167 *** | 7.078 (0.024) | Supported |
| | **Dependent variable: Actual Use** | | | | | |
| | $\mathbb{R}^2$ | 0.518 | | 0.521 | | |
| | Adj. $\mathbb{R}^2$ | 0.516 | | 0.519 | | |
| H1 | Behavioral intention | 0.250 *** | 9.540 (0.026) | 0.159 *** | 5.563 (0.029) | Supported |
| H2b | Facilitating conditions | 0.019 | 0.722 (0.027) | 0.011 | 0.471 (0.024) | Not Supported |
| H3b | Habit | 0.304 *** | 11.288 (0.027) | 0.168 *** | 5.624 (0.030) | Supported |
| H10a | Perceived risk | | | 0.203 *** | 7.416 (0.027) | Supported |
| H11a | Trust in technology | | | 0.160 *** | 6.539 (0.025) | Supported |
| H12 | Privacy concern | | | 0.075 *** | 2.875 (0.026) | Supported |
| | **New relationships incorporated into UTAUT2** | | | | | |
| H3c | Habit→performance expectancy | | | 0.136 *** | 3.805 (0.036) | Supported |
| H4c | Effort expectancy→performance expectancy | | | 0.115 *** | 3.285 (0.035) | Supported |
| H4b | Effort expectancy→habit | | | 0.646 *** | 42.755 (0.015) | Supported |
| H6b | Social influence→trust in technology | | | 0.567 *** | 26.935 (0.021) | Supported |
| H9 | Perceived skill development→actual use | | | 0.082 *** | 4.080 (0.020) | Supported |

**Table 5.** *Cont.*

| | | Original UTAUT2 | | UTAUT2 with Privacy Calculus Model | | |
|---|---|---|---|---|---|---|
| **Hyp.** | **Structural Path** | **Path Coef. (β)** | **T Statistics** | **Path Coef. (β)** | **T Statistics** | **Results** |
| H10b | Perceived risk→trust in technology | | | 0.096 *** | 4.341 (0.022) | Supported |
| H10c | Perceived risk→ privacy concern | | | 0.256 *** | 10.024 (0.025) | Supported |
| H10d | Perceived risk→ performance expectancy | | | 0.133 *** | 4.402 (0.030) | Supported |
| H11b | Trust in technology→ performance expectancy | | | 0.178 *** | 6.912 (0.026) | Supported |

Notes: The path coefficients marked with (***) are statistically significant at a 1% level. Standard deviations are shown in parentheses.

Chin [76] provides guidelines for interpreting the $R^2$ values, suggesting that values around 0.670 indicate substantial explanatory power, values around 0.333 indicate an average level, and values of 0.190 or lower are considered weak. However, Hair et al. [73] argues that the interpretation of $R^2$ values depends on the specific research discipline. For example, in the field of user behavior, such as user acceptance and use of technology, an $R^2$ value of 0.20 is considered high.

In our study, focusing on platform economy usage behaviors, our integrated model explained 52.1% of the variance, indicating a substantial level of explanatory power. The most influential predictor of this variance was habit, which accounted for 41.7% of its own variance. In addition, the UTAUT2 model accounted for 36% of the variance in trust in technology and 29% of the variance in behavioral intentions. Performance expectancy and privacy concerns accounted for 17.1% and 16.5% of the variance, respectively.

Within the UTAUT2 model with privacy calculus, performance expectancy had the highest positive influence on behavioral intention (β = 0.472, $p < 0.001$), supporting Hypothesis H5. Habit (β = 0.183, $p < 0.001$) and price value (β = 0.167, $p < 0.001$) also positively influenced behavioral intention, supporting Hypotheses H3a and H8. However, effort expectancy's impact (β = 0.076, $p < 0.01$) was less than expected, partially supporting Hypothesis H4a. Facilitating conditions, social influence, and hedonic motivation did not significantly affect behavioral intention, failing to support Hypotheses H2a, H6a, and H7.

When the UTAUT2 model was extended to include a privacy calculus to predict users' platform economy use, perceived risk (β = 0.203, $p < 0.001$) had the most significant positive influence on the actual platform economy use, supporting Hypothesis H10a. Both trust in technology (β = 0.160, $p < 0.001$) and privacy concern (β = 0.075, $p < 0.01$) also positively influenced actual use, supporting Hypotheses H11a and H12.

When examining the effects on platform economy usage behavior, behavioral intention (β = 0.159, $p < 0.001$) and habit (β = 0.168, $p < 0.001$) both had a significant impact, supporting Hypotheses H1 and H3b. However, facilitating conditions did not have a significant effect on actual use, which does not support Hypothesis H2b.

For the newly included relationships in the UTAUT2 model, effort expectancy had a significant positive influence on habit (β = 0.646; $p < 0.001$), supporting Hypothesis H4b. Perceived risk positively influenced privacy concern (β = 0.256; $p < 0.001$) and performance expectancy (β = 0.133; $p < 0.001$), supporting Hypotheses H10c and H10d. The newly introduced variable, perceived skill development, positively influenced actual platform economy use (β = 0.082; $p < 0.001$), supporting Hypothesis H9. Trust in technology (β = 0.178; $p < 0.001$) significantly predicted performance expectancy, supporting Hypothesis H11b. Finally, social influence (β = 0.567; $p < 0.001$) and perceived risk (β = 0.096; $p < 0.001$) were significantly related to trust in technology, providing empirical support for Hypotheses H6b and H10b.

Habit, performance expectancy, trust in technology, and perceived risk emerge as the most influential variables in the integrated model, significantly shaping users' intentions and actual behaviors toward the platform economy.

## 6. Discussion

By integrating the UTAUT2 framework with the privacy calculus model, our study uncovers the critical factors driving user adoption of the platform economy in Tunisia, providing significant theoretical and practical implications. The applied extended UTAUT2 model has proven effective for studying platform economy adoption, in line with previous technology acceptance research [1,28]. This detailed analysis of user behavior not only strengthens the existing literature, but also outlines potential avenues for future research.

Our study emphasizes performance expectancy as the primary determinant of behavioral intention, confirming recent research [1,30]. This finding suggests that user adoption is highly dependent on the platform's ability to deliver on its promises and provide tangible benefits. Therefore, the primary focus of platform developers and operators should be on refining the user experience, with particular attention to performance improvements and user satisfaction. This practical implication suggests that a customer-centric approach and a commitment to delivering value can enhance user engagement and increase adoption of the platform economy.

Habit formation is another determinant identified in the adoption process, suggesting that users who are familiar with the platform economy are more likely to sustain their use [24,46]. This finding is consistent with previous research highlighting the importance of habitual behavior in technology adoption [28]. As such, platforms should aim to foster user habits through seamless integration into daily routines and reliable, superior service delivery.

Trust in technology has also been identified as a key determinant of user adoption [3,61]. Consistent with previous research, this finding suggests that user trust can be established by addressing concerns related to the technology and the organization managing the platform [67,77]. Therefore, platform operators should prioritize transparent communication, strong security measures, and effective privacy policies. These strategic investments can foster trust and improve the overall user experience.

Our study found that perceived risk and privacy concerns significantly influence users' intentions and actual use of the platform economy [3,59]. This supports existing research on technology adoption and highlights the need to explore users' perceptions of risk management and the role of privacy concerns in shaping user behavior [60,62]. This theoretical implication underscores that future research should examine strategies to mitigate these risks and address privacy concerns in order to maximize user adoption.

Social influence has been found to significantly affect trust in technology, but not directly affect behavioral intention [54,78,79]. Consistent with previous studies, our research suggests that social influence indirectly affects platform adoption through its effect on trust [28,55]. Therefore, leveraging influential individuals and opinion leaders could potentially promote trust and increase platform adoption.

Price value positively influences behavioral intention, indicating that users consider the cost of using the platform economy when considering adoption [38,40]. This observation is in line with previous research on platform economy adoption, which highlights the importance of understanding users' value perceptions in technology adoption [29,53]. As a result, platform operators should seek to offer competitive pricing and emphasize the value of their offerings to potential users.

Focusing on the context of Tunisia, the findings of our study have significant regional and global implications, particularly for developing countries. Tunisia, as part of the broader MENA region, represents an emerging market where the digital economy is poised for significant growth. Understanding the key factors influencing platform adoption in Tunisia can provide insight applicable to similar economies within the MENA region and beyond.

This study identifies several key factors, including performance expectation, habit, trust in technology, perceived risk, privacy concerns, social influence, and price value, that influence user behavior in platform economy adoption. These findings are consistent with recent studies [3,33,37,40,61,80] and provide valuable insight for both researchers and practitioners. By understanding and addressing these determinants, platform operators can increase user adoption and satisfaction, thereby contributing to Tunisia's economic development and setting a precedent for similar emerging economies.

## 7. Conclusions and Implications

This research represents a pioneering effort to understand user behavior with respect to the adoption of the platform economy in Tunisia. The integration of the UTAUT2 model with a privacy calculus model has provided meaningful insight into the determinants influencing platform adoption in an emerging market, such as Tunisia. This study not only extends the existing literature, but also paves the way for future research and provides practical implications for platform operators, policy makers, and researchers.

Using PLS-SEM, the research revealed several influential factors in user adoption of the platform economy. Critical among these was performance expectancy, highlighting the need for users to perceive platforms as beneficial and effective. Habit formation emerged as another significant factor, suggesting that users who are familiar with the platform economy are more likely to continue using it. Trust in technology also emerged as an important determinant, highlighting the importance of security and reliability within platforms. In addition, perceived risk and privacy concerns significantly influenced users' intentions and actual use of the platform economy. Social influence was found to shape trust in the technology, although it did not directly influence behavioral intentions. Finally, perceived value positively influenced behavioral intention, suggesting that users consider the cost of using the platform economy in their adoption decisions.

These findings have significant implications for various stakeholders. For example, platform operators should improve the user experience by developing user-friendly, secure platforms and investing in initiatives that promote skill development and training. Successful marketing strategies and partnerships with local influencers can highlight the benefits of platforms and build trust among potential users.

Policymakers, on the other hand, are essential to creating an environment conducive to the growth of the digital economy. They should prioritize improving digital infrastructure, establishing transparent regulatory frameworks, and enforcing policies that protect user privacy and data security. Ensuring fair wages and working conditions for platform workers, addressing the digital divide, promoting affordable internet services, and providing targeted support to marginalized groups will be critical for inclusive growth.

The study also opens up avenues for further research. Subsequent research could explore the interaction between the determinants in different cultural and economic contexts, examine the long-term impact of platform adoption on economic development, and explore the role of skills development initiatives in fostering platform adoption.

By addressing these considerations and collaborating effectively, platform operators, policymakers, and researchers can cultivate a thriving digital ecosystem in Tunisia that meets users' needs and drives inclusive economic growth.

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