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The role of blockchain technology in the tourism industry: analyzing the factors affecting its adoption

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Abstract
Blockchain technology (BT) has attracted increasing attention in various research domains in recent years, particularly in the tourism industry where investments in blockchain-based solutions have witnessed remarkable growth. Scholars recognize BT as a disruptive innovation that has the potential to revolutionize the management of tourism processes and enhance traveler experiences. However, despite this growing interest, the literature on BT's application in the tourism sector is still in its early stages compared to other internet-related technologies. This research paper addresses the gap in understanding the challenges and opportunities of implementing and accepting BT within tourism. Specifically, it focuses on the critical aspects of security and trust, as they play pivotal roles in influencing tourists' behavioral intentions towards BT adoption. The study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) model, incorporating security and trust as relevant antecedents, to comprehensively examine the dynamics driving BT adoption within the tourism context. The proposed model and findings contribute to filling the gaps in existing literature and offer valuable information for tourism players and policymakers to formulate strategies promoting BT acceptance in the tourism sector. By advancing understanding of BT adoption factors and end users' perspectives, this research facilitates the industry's transition towards integrated and seamless experiences for travelers, thus shaping the future of tourism through blockchain technology.

Keywords Blockchain · UTAUT · Trust · Security · Structural equation model · Multigroup analysis

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1 Introduction

In recent years, scholars have shown a growing interest in blockchain technology (BT) in a wide range of research domains. With a remarkable increase in investments in blockchain-based solutions within tourism, it is evident that the development of blockchain systems will have a profound impact on the future of the industry, revolutionizing the management of processes and transforming tourist experiences (Erceg et al. 2020). As a disruptive innovation, BT is poised to reshape how the tourism industry will develop providing integrated and seamless experiences for travelers (Khan et al. 2017). Despite the growing interest in BT, the literature on its application in the tourism sector is still in its early stages, especially when compared to other internet-related technologies (Erol et al. 2022). While there is recognition of the potential benefits that BT can offer to the industry, a comprehensive overview explaining and predicting the challenges concerning the implementation and acceptance of BT within tourism is lacking (Irannezhad and Mahadevan 2021). In this regard, academics acknowledge the need for a more thorough investigation into the drivers and drawbacks of adopting BT, as well as the theoretical and managerial implications of its integration in the tourism context (Valeri and Baggio 2021). Previous studies have been criticized for overlooking the end users' perspective, often focusing primarily on the technological architecture of BT (Önder and Gunter 2022; Dadkhah et al. 2022). Specifically, at the heart of the literature gap lies a neglect of understanding tourists' perceptions and their behavioral intentions toward BT adoption (Balasubramanian et al. 2022; Zavolokina et al. 2023; Muharam et al. 2023). At the same time, the potential applications of BT in the tourism industry include enhancing security, improving trust, and optimizing performance (Rashideh 2020). Security stands out as a paramount concern, given the sensitive nature of data involved in tourism transactions, including activities like booking accommodations and managing travel itineraries (Buhalis et al. 2019; Gong and Schroeder 2022). The presence of robust security features in BT plays a crucial role in instilling a sense of confidence among tourists, consequently encouraging them to adopt the technology for their travel needs. However, beyond security, trust forms the bedrock of any transactional relationship (Calvaresi et al. 2019; Shin 2019). Building trust in BT systems becomes crucial for tourists who need assurance that their data and transactions are secure and reliable (Shin 2019). A lack of trust in the technology can be a major deterrent in embracing BT for tourism-related activities. Furthermore, limited research has delved into examining the moderating effects arising from individual differences, as delineated in the original UTAUT model (Venkatesh et al. 2016). Consequently, the exploration of how various personal characteristics, such as demographics or technological expertise, interplay within the UTAUT framework remains relatively unexplored in existing studies (Terblanche and Kidd 2022).

Therefore, the following research questions are proposed:

RQ1: What are the antecedents of tourists' acceptance and use of blockchain technology?
RQ2: How gender affects tourists' acceptance and use of blockchain technology?

Accordingly, based on these premises and by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al. 2003) to include relevant antecedents, namely security and trust, the study seeks to provide a more comprehensive understanding of the dynamics driving BT adoption within the tourism industry. The proposed model and the findings of the study allows to bridge the gaps in existing literature and generate insights that can inform policymakers, organizations, and stakeholders on

strategies to promote BT acceptance in the tourism sector. In order to corroborate our proposal, a survey was conducted. After designing the questionnaire, the data collected were analyzed through a Structural Equation Model and in order to verify the influence of gender, a Multi Group survey was carried out.

The paper is organized as follows: in Sect. 2, a literature review is presented. Section 3, delves into the conceptual model and hypothesis development, outlining the specific relationships between the antecedents and behavioral intentions. In Sect. 4, the methodological approach and results are discussed, providing empirical evidence to support the proposed model. Building on the results, Sect. 5 discusses the empirical findings and explores the theoretical and practical implications. The final Sect. 6 highlights the paper contribution to the field, describes the limitations of the study and proposes future research streams.

2 Literature review

Technological advancements continuously revolutionize entire domains in a cyclical manner (Calvaresi et al. 2019). Most recently, the emergence of blockchain technology (BT) has sparked global interest from both companies and governments due to its revolutionary nature (Rashideh 2020) and, in the last few years, many authors attempted to define it. Risius and Spohrer (2017 p.386) defined BT as a fully distributed system for cryptographically capturing and storing a consistent, immutable, linear event log of transactions between networked actors. Similarly, Monrat et al. (2019) defined BT as a decentralized and distributed network consisting of a series of interconnected blocks. These blocks store information along with digital signatures, ensuring the integrity and security of the data stored within the network. Lafourcade and Lombard-Platet (2020) suggested a more straightforward notion, describing BT as a sequential chain of transactions, in which each block consists of multiple transactions, along with a proof that is essential for achieving consensus. Its fusion with other Industry 4.0 technologies has the potential to be a transformative force that could generate massive impacts on many sectors, including hospitality and tourism (Treiblmaier and Beck 2019; Treiblmaier 2021). The tourism sector can be described as an umbrella industry because of the variety and quantity of stakeholders engaged. These include tour operators, travel agencies and agents, transport companies, hoteliers, insurance and payment service providers, local authorities and institutions, and many others (Rashideh 2020), resulting in complex business relationships and fierce competition. To deal with these challenges and enhance the quality of services provided to tourists, the adoption of BT alongside other technologies proves beneficial (Rana et al. 2022). The role of BT as a catalyst for the forthcoming technological revolution is widely recognized, since this transformative technology holds immense potential to unlock unparalleled opportunities for companies operating in this industry (Calvaresi et al. 2019). Nevertheless, its implementation encompasses a wide range of uses (Antoniadis et al. 2020), for both providers and tourists. According to Irannezhad and Mahadevan's study (2021) BT presents a significant opportunity to challenge established players in the travel industry, including hotels, online travel agencies (OTAs), peer-to-peer providers, travel comparison websites, leading to potential economic growth in destinations. In this regard, Nam et al. (2021) emphasized the main characteristics of BT within the smart city and smart tourism framework and discussed its potential evolution and impact on the industry. Their findings indicate that BT is advancing and smart destinations worldwide are adopting BT solutions for cryptocurrency payments, smart contract automation, and sustainable sourcing.

Tyan et al. (2020) also explored the potential of BT in the context of smart destinations, revealing that its main benefits include improving the tourism experience, encouraging sustainable behaviors, ensuring positive impacts on host communities, and mitigating privacy risks. Jain et al. (2023) claimed that BT enhances the tourist experience, facilitating co-creation and co-promotion of destination-specific attractions and products through features such as traceability, automation, convenience, and affordability. However, they argued that a significant hurdle in the adoption of this technology in tourism is the lack of user confidence and trust. The more innovative the applications, the greater the need for efforts to raise awareness and build trust among users. Therefore, the novelty associated with BT application plays a significant role, alongside the trust in its adoption (Batwa and Norrman 2021). However, the issue of proving BT trustworthiness to end users remains unresolved (Zavolokina et al. 2023).

3 Conceptual model and hypothesis development

Based on scientific literature concerning BT, both trust (e.g., Calvaresi et al. 2019; Rashideh 2020; Nam et al. 2021) and security are important antecedents of its adoption (e.g., Shin 2019; Shin and Bianco 2020). As introduced by Venkatesh et al. (2003), the UTAUT model encompasses four exogenous constructs that can be interpreted as reflecting technology attributes, namely performance expectancy (PE) and effort expectancy (EE), as well as contextual factors, including facilitating conditions (FC) and social influence (SI) (Dwivedi et al. 2019). Starting from this groundbreaking work, other studies attempted to investigate the influence of trust in BT on behavioral intentions (BI). Salem's study (2019) proposed a conceptual model extending the basic UTAUT model by integrating two constructs, namely risk and trust, without testing and validating the proposed model. In the context of secondhand apparel retailing industry, Jain et al. (2022) examined the factors influencing the adoption of BT using theoretical constructs of consumer's buying motives and UTAUT model. The results of the study highlighted that the UTAUT constructs significantly influenced the acceptance of BT within the industry. Similarly, Pham and Nguyet (2023) applied the UTAUT model to examine the antecedents of BT adoption in journalism activities. The findings revealed that EE and FC were among the five factors that positively influenced the intention to apply BT in journalism. Therefore, considering the dearth of studies addressed at examining the adoption of BT and issues related to its trust and security within the tourism industry, this work fills the gap extending the original UTAUT model adding two constructs, namely Trust (T) and Security (S). Moreover, extant literature suggests that gender can significantly influence individuals' perceptions, attitudes, and behaviors towards technology adoption (Chen et al. 2015; Tsourela and Roumeliotis 2015; Lee et al. 2019). Indeed, gender is considered a moderating variable, meaning that the higher its value, the higher the intention the behavioral intention toward technology adoption by end users (Venkatesh et al. 2003; Falwadiya and Dhingra 2022). Therefore, this work investigates the difference between male and female tourists in the acceptance of BT. The proposed model is described in the next subsections.

3.1 UTAUT-based constructs

EE refers to the perceived ease and simplicity of using a technology (Venkatesh et al. 2003). Hence, any new technology should provide a system that makes it easy to operate

(Falwadiya and Dhingra 2022). In this regard, Jain et al. (2023) and Chang et al. (2022) posit that since the utilization of BT demands minimal effort and complexity, users would be satisfied with their overall experience using this particular technology. Therefore, the following hypothesis is proposed:

H1: Effort expectancy has a positive influence on behavioral intention.
H1.a: Gender moderates the effect of effort expectancy on behavioral intention.

The intention to use BT-based systems is not only influenced by the technology itself, but also by the social context in which it is used (Batwa and Norrman 2021). Thus, it is important to consider social influence that is defined as the degree to which individuals perceive that important references (e.g., family and friends) believe they should use a particular technology (Venkatesh et al. 2003). Joa and Magsamen-Conrad (2022) state that the higher the perceived prevalence, the more likely potential consumers are to recognize such conduct as typical or normal. In this regard, Dečman (2020) considers social influence as an extrinsic motivator which provides social recognition for using certain technology. In their study, Lee and Kim (2022) argue that customers choose a certain type of technology according to recommendations and opinions of others in addition to their own motives and personal preferences. Thus, individual behavior is influenced by the usage intention of other people, who will see it as a result of using technology (Rakhmawati and Rusydi 2020; Radic 2022). Hence, it is hypothesized that:

H2: Social influence has a positive influence on behavioral intention.
H2.a: Gender moderates the effect of social influence on behavioral intention.

Venkatesh (2022) states that FCs pertain to an individual's belief in the presence of an organizational and technical infrastructure that supports the use of a given technology. However, these are widely described as resource factors, encompassing aspects such as time and financial resources, as well as technology factors that relate to compatibility issues (Teo 2009). The original model developed by Venkatesh et al. (2003) assumes that FC has not a significant influence on BI, in fact, consistent with the Theory of Planned Behaviour (Ajzen 1988, 1991), FCs are modeled as a direct antecedent of usage. Specifically, as users gain more experience with the technology, the impact is anticipated to grow, as they discover various channels for assistance and support. This will effectively eliminate barriers to continued usage. Nonetheless, based on recent research (Huang and Chueh 2022; Hooda et al. 2022; Cao et al. 2021), FCs contribute to the development of heightened awareness and a close connection with intentions; thus, they are considered predictors to analyzing intentions to use technology. Therefore, the following hypothesis is proposed:

H3: Facilitating conditions have a positive influence on behavioral intention.
H3.a: Gender moderates the effect of facilitating conditions on behavioral intention.

PE is defined as the degree to which the use of a new technology can provide individuals the expected advantages in performing specific activities (Huang and Kao 2015; Chowdhury et al. 2023). Over the years, several studies have confirmed its influence on the adoption of technology across various technological contexts (Wong et al. 2020) and, nowadays, it is considered as a good predictor of technology adoption intention (Chua et al. 2018; Talukder et al. 2019; Al-Saedi et al. 2020). Extant literature on BT adoption has empirically demonstrated that PE is a significant factor positively influencing people's intention to embrace blockchain technology (Falwadiya and Dhingra 2022). Therefore, it is hypothesized that:

H4: Performance expectancy has a positive influence on trust toward the use of Blockchain technology.
H4.a: Gender moderates the effect of performance expectancy on trust toward the use of Blockchain technology.

3.2 Trust in blockchain technology

The absence of public trust is a notable problem arising from the application of innovative technologies in tourism (Caddeo and Pinna 2021) and in relation to BT, people express their greatest concern about the risks associated with its adoption (Albayati et al. 2020). Therefore, the issue of trust is often analyzed and discussed in the context of BT, as it is argued to be its main advantage (Calvaresi et al. 2019; Caddeo and Pinna 2021). However, understanding the concept of trust is a challenging task, and there is no widely agreed-upon definition for this relevant issue (Zavolokina et al. 2023). It is conceived as a multi-faceted topic that involves intricate dynamics and is prone to potential misunderstanding (Whipple et al. 2013). Extant literature provides several definitions of trust. More in general, Mayer et al. (1995) defined trust as the willingness of a party to expose itself to the actions of another party, with the expectation that the other party will perform a specific action that is crucial to the trusting party. Similarly, Chen et al. (2004) claimed that trust is about feeling safe to rely on something or someone. Khezr et al. (2021) stated that trust in BT is established through a transparent and unchangeable process of generating and storing transactions in a ledger. Thus, blockchain embodies a technological breakthrough that facilitates transparent engagements among entities within a highly reliable and fortified network, thereby disseminating data accessibility (Singh et al. 2022). Its capacity for innovation resides in its ability to facilitate transactions between untrusting parties through a computer network devoid of inherent trust, relying on the integration of distributed networks, consensus protocols, cryptographic algorithms, and market processes (Mendling et al. 2018). BT is often lauded for its ability to provide secure and trustworthy transactions without the intermediation of authorities or third-party entities, such as banks or government institutions (Rawat et al. 2020). Furthermore, the implementation of BT in the tourism industry results in enhanced process efficiency, heightened trust levels among business partners, improved personal data protection, and a reduction in the reliance on intermediaries (Rashideh 2020; Irannezhad and Mahadevan 2021). Moreover, BT is considered a promising solution for the issues faced in financial services, such as delays in transactions, fraudulent activities, and operational risks (Guo and Liang 2016). The cryptographic features of BT prevent double spending, effectively tackling the primary challenge of digital transactions without the need for intermediaries (Badidi 2022). These attitudes are confirmed by previous studies (i.e., Joo et al. 2021; Raluca-Florentina 2022). Therefore, by acknowledging trust definitions and understanding the importance of the issue in the technological realm, the present study aims to delve deeper into the factors that influence trust in BT adoption and explore its implications within the tourism industry. To this end, this paper builds upon the assumptions of trust endorsed by McCloskey (2006), Jarvenpaa et al. (2000), Albayati et al. (2020) and Al-Ashmori et al. (2022), according to whom trust refers to a user's sense of comfort, confidence, and security during interactions with technology. As the level of trust associated with a particular technology has a direct impact on how users perceive it and their willingness to adopt it, trust can be conceived as an antecedent factor to attitudes toward blockchain adoption (Wu and Chen 2005; Shin 2019). In line with Gefen (2000) and Khalilzadeh et al. (2017), since trust is a part of expectation, it is

possible to assume that it can affect both the PE and the success of BT adoption. Therefore, the following hypotheses is formulated:

H5: Trust has a positive influence on performance expectancy.
H5.a: Gender moderates the effect of trust on performance expectancy.

3.3 Security in blockchain technology

The security of the underlying BT infrastructure is crucial for establishing and maintaining trust in the adoption of BT within the tourism industry (Rejeb et al. 2021; Erol et al. 2022). Security refers to the state in which a system or technology is deemed safe from forgery, unauthorized disclosure, and infringement of transactional data, including personal information (Chang et al. 2022). In tourism, sensitive information like personal details and financial transactions are exchanged among various stakeholders (Buhalis et al. 2019). The decentralized, open and cryptographic nature of BT elicits trust and generates unprecedented security benefits (Min 2018). The security features of BT have a notable impact on performance expectancy by mitigating risks, improving the reliability of data, promoting transparency, and bolstering defense against potential cyber-attacks (Zhu and Zhou 2016; Falwadiya and Dhingra 2022; Singh et al. 2023). Hence, the following hypotheses is formulated:

H6: Security has a positive influence on performance expectancy in adopting blockchain.
H6.a: Gender moderates the effect of security on performance expectancy in adopting blockchain.

Security and protection of personal data have become key concerns for tourists (Wut et al. 2021). BT-based services grant tourists enhanced security and ownership over data they disclose to tourism providers, providing them with more control over the information (Tyan et al. 2020). Moreover, considering that being protected by the technology can create a sense of reassurance (Balasubramanian et al. 2022), users are more likely to use BT in a certain context. Indeed, when tourists have confidence in the security guaranteed by the technology they are using, they feel safer against intimidating threats that could compromise their personal or financial data in transactions (Tussyadiah 2020; Ruangkanjanases et al. 2023). Therefore, security can be considered as an antecedent of behavioral intention toward the BT usage (Khalilzadeh et al. 2017). Accordingly, the following hypothesis is proposed:

H7: Security has a positive influence on behavioral intention in adopting blockchain.
H7.a: Gender moderates the effect of security on behavioral intention in adopting blockchain.

Due to its security mechanisms, such as cryptographic hashing and consensus algorithms, BT is believed to ensure the integrity of this data, prevent unauthorized modifications (Minoli and Occhiogrosso 2018) and foster trust towards its adoption. Therefore, BT can enhance transparency and accountability in the exchange process (Kshetri 2017, 2018) and it has the potential to foster and strengthen trust among users (Treiblmaier 2020; Nam et al. 2021), by offering a guaranteed level of security in transactions, notwithstanding the intricate nature of trust itself (Antoniadis et al. 2020; Rashideh 2020; Rana et al. 2022). Thus, the following hypotheses has been derived:

H8: Security has a positive influence on trust in adopting blockchain.
H8.a: Gender moderates the effect of security on trust in adopting blockchain.

4 Study design

4.1 Data collection and measures

In order to test the statistical hypotheses set out in the previous paragraph, a survey was carried out. With reference to data collection, a questionnaire has been administered to tourists visiting the city of Naples (Italy) during the period from February 2023 to April 2023. Prior to administering the questionnaires, the authors introduced the topic by way of a short introduction explaining the aims of the study. An autonomously designed seven-Likert scale survey instrument has been employed for the collection of quantitative data. The questionnaire was structured in two parts: the first one consisted of 28 seven-Likert scale items (see Table 1) (1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree nor disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly Agree) relating to various facets of BT adoption. The second part concerned demographic and personal factors including such aspects as gender, age, income and education. Following suggestions from earlier studies (Davis and Venkatesh 1996; Podsakoff et al. 2003; Zhang and Farh 2019), in order to reduce retrieval biases, we intermixed the items from different constructs within the scaled-response questions. The face validity of the questionnaire, conceived as the degree to which a survey is perceived by individuals as effectively capturing the concept it aims to assess (Holden 2010), has been ensured through a pilot test involving 50 respondents from the target segment.

After data collection, we made the data wrangling process in order to organize the raw data into a more useful format it for efficient analysis. Particularly we removed from the dataset straight lining patterns, which occur when a respondent marks the same response for almost all survey items. In fact straight lining responses minimise variability and lead to undetected (or detected but underestimated) moderator effects in MGA (see Hair et al. 2017). Smart PLS (ver. 4) software has been used to analyze the data (Ringle et al. 2022). In total, 390 usable questionnaires were received and analysed. G*Power was also used to calculate the sample size based on statistical power (Faul et al. 2009) and therefore to assess whether the sample size is acceptable for the purpose of the study. For a statistical power of 0.95, a sample size of 129 was suggested what means our sample size of 390 respondents is acceptable for model testing.

Even if total sample size is relatively large, unequal sample sizes across the moderator-based subgroups (gender) would decrease statistical power and lead to the underestimation of moderating effects (Hair et al. 2017). However in our case the two subgroups (males and females) had similar sample size (181 vs 209), so that sample variance is maximized (see Aguinis et al. 2017).

According to Cohen (1988), this solution appeared satisfactory for a study in social sciences. In this research, Behavioral Intention (BI) is the dependent variable and the drivers that affect it are unobservable variables called Latent Variables (LVs), each measured by several observed indicators usually defined as Manifest Variables (MVs). Therefore, we considered Structural Equation Modeling (SEM) as the most suitable statistical methodology to carry out the analysis.

Table 1 Measurement items

Variable	Item code	Description of measurement item (indicators)	Source
Performance expectancy (PE)	PE1	BT allows me to improve/enhance the purchasing experience	Adapted from Pham and Nguyet (2023)
	PE2	BT helps me access tourist information more accurately	
	PE3	BT helps me timesaving in researching information, avoiding misinformation	
	PE4	BT allows me to reduce my reservation costs	
Effort expectancy (EE)	EE1	BT is easy to use	Adapted from Jain et al. (2022) and Chang et al. (2022)
	EE2	The use of BT is reliable and saves time in the purchasing process	
	EE3	BT simplifies the decision-making process	
	EE4	BT use is intuitive	
Social influence (SI)	SI1	People who are important to me encourage me to use BT	Adapted from Lin et al. (2020)
	SI2	People whose opinions I appreciate would prefer that I use BT, rather than other innovative technologies	
	SI3	People who can influence my decision motivate me to use BT	
	SI4	If many people in my community or my friends use BT, I will also use this technology	
Facilitating conditions (FC)	FC1	I think I have the resources (technological devices) to use BT	Adapted from Chang et al. (2022)
	FC2	I think I have the required expertise to use BT	
	FC3	I think the other technologies I use are compatible with BT	
	FC4	I believe it is easy to purchase tourism products/services through BT	
Trust (T)	T1	BT is reliable	Adapted from Wong et al. (2020) and Mukherjee et al. (2023)
	T2	I believe that legal regulations adequately protect me from possible problems related to BT	
	T3	I believe in the feasibility of applying BT	
	T4	I believe BT ensures protection of personal data	

Table 1 (continued)

Variable	Item code	Description of measurement item (indicators)	Source
Security (S)	S1	BT allows data to be saved securely	Adapted from Khalilzadeh et al. (2017)
	S2	BT ensures secure transactions and less exposure to fraud	
	S3	Facilities transactions by securely transmitting sensitive information	
	S4	I would feel completely safe in sharing my personal information through BT transactions	
Behavioral intention (BI)	BI1	I intend to adopt BT within 3 years	Adapted from Khalilzadeh et al. (2017)
	BI2	I expect to use the BT	
	BI3	I will recommend the use of BT to friends and acquaintances	
	B14	I will pioneer the use of BT in tourism	

4.2 Method

SEM has emerged as a valuable research technique in the field of social sciences for analyzing the connections among latent variables. Two approaches are commonly employed to estimate relationships within SEM: the covariance-based SEM (Jöreskog 1970) and the variance-based method (Wold 1975), also known as the Partial Least Squares Path Model (PLS-PM).

A very popular method for studying structural equation models with latent variables is Partial least squares path modelling (PLSPM) used as a composite based estimator. PLS-PM was developed in the 1970s as an alternative estimator to covariance-based structural equation modelling (Jöreskog and Wold 1982; Wold 1982). In order to simplify the explanation of the model's relationships, PLSPM maximizes the amount of variance explained in the endogenous constructs of the structural model (Chin and Dibbern 2010).

In the current study, the constructs are defined as composites, so that, a composite-based method like PLS should be used to provide consistent and not bias estimates (Sarstedt et al. 2016; Rigdon et al. 2017; Henseler 2018). PLS-PM is formally defined by two sets of linear equations called inner (or structural) and outer (or measurement) models, respectively. The structural model specifies the relationships between LVs, whereas the measurement model specifies the relationships between an LV and its manifest variables (MVs). A PLS path modelling (PLS-PM) is analysed and interpreted in two stages: (1) evaluating the measurement model; (2) assessing the structural model. This study assessed the measurement model by evaluating the reliability and validity of the composites (Hair et al. 2017). The structural model was evaluated by examining the significance of the path coefficients and by assessing the R^2 as an indication of the explanatory power of the research model.

Often when carrying out business research researchers often assume that data stems from a single homogenous population; on the contrary, in many real-world applications, the assumption of homogeneity is rather unrealistic. Ignoring heterogeneity often leads to questionable conclusions (Chin and Dibbern 2010). In order to address this concern Multigroup analysis (MGA) has been proposed (Hair et al. 2024). It allows testing predefined data groups to determine the existence of significant differences across group-specific parameter estimates. In PLS-PM context, MGA permits testing, efficiently and generally, moderation across multiple relationships (Fig. 1).

4.3 Descriptive statistical results

Some descriptive statistics of the sample are reported in Table 2. In terms of age most respondents are between 18 and 26 years old (50.9%) and between 27 and 34 (15.7%). Next, there are people aged between 45 and 54 years old (12.3%), while just a little part of the sample has an age between 35 and 44 or < 18 or over 55 (respectively 10.7%, 4.8% and 5.6%). Moreover, Table 2 provides the respondents' profile, highlighting a similar distribution between female (50.7%) and male (46.7%) respondents. In addition, 2.6% of the sample did not declare the gender. With respect to respondents' education level, the majority are high school graduates (46%). 26.9% and 14,1% of the sample held bachelor's and master's degrees respectively. They are followed by middle school graduates (8%) and PhD (7%). Regarding the annual gross income (expressed in Euro—€), there is a concentration in the 10.001–29.999 (49.6%), < 10.000 (23.7%) and 30.000–59.999 (18,9%) ranges.

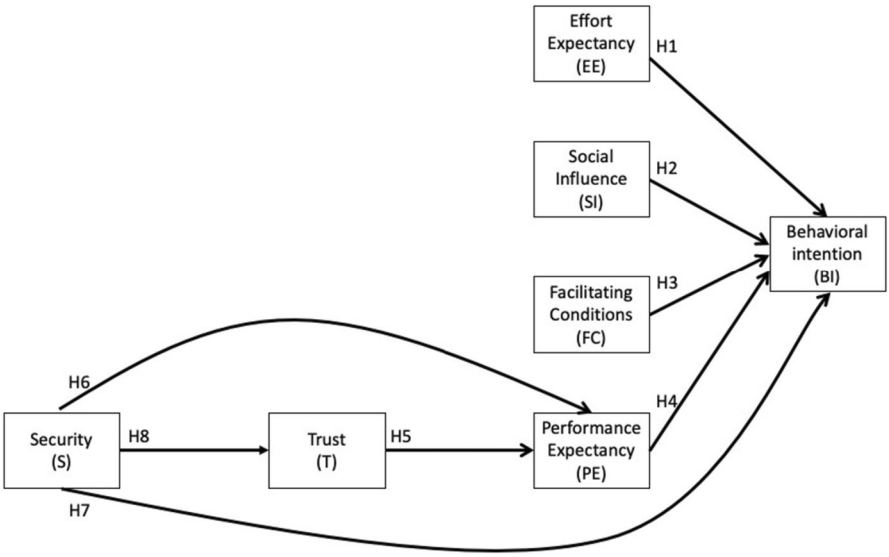

Fig. 1 Conceptual Model and Hypotheses

Finally, with reference to occupation, most of the sample are students (33.9%) and workers involved in the service industry (21.6%).

4.4 Results

A SEM has been elaborated to formalize a scheme for the interpretation of BI and detect the drivers. Starting from the considerations made in the previous sections, we hypothesized that EE, SI, FC, S, T and PE are exogenous LVs, while BI is an endogenous LV. The PLS estimations show that the relationship between BI and FC is not statistically significant, on the contrary all the other coefficients are statistically significant (Fig. 2), as they are for coefficients in the measurement models. Then, the SEM assessment has focused on the measurement models. This evaluation has been performed according to the empirical consideration summarized in Sarnacchiaro and Boccia (2018). For these measurement models, the indicators are evoked by the underlying construct, and have positive, and desirable intercorrelations. In our case, all the manifest variables are strongly correlated for each measurement model. Since indicators have positive intercorrelations, we used Cronbach's alpha to empirically assess the individual and composite reliabilities of the indicators (greater than 0.70), Composite Reliability (greater than 0.70) and the average variance extracted (greater than 0.50). All these measures confirm the suitability of the measurement models (Table 3). When computing the correlation between variables and latent variables, we have checked the correct classification of the MVs by cross loadings (Table 4).

We have considered the correlation between items/factors for the assessment of convergent validity and the Fornell-Larcker Criterion for the evaluation of discriminant validity (Table 5). To complete the convergent validity analysis, we have considered magnitude estimation for each weight, linking the question/item to the relative corresponding LV, and the bootstrapping results to assess the statistical significance. Once the goodness of the

Table 2 Sample description

Measure	Item	*n*	Percentage
Age	< 18	18	4.8
	18–26	191	50.9
	27–34	59	15.7
	35–44	40	10.7
	45–54	46	12.3
	> 55	21	5.6
Gender	Female	190	50.7
	Male	175	46.7
	Not specified	10	2.6
Education	Middle school	30	8
	High school	165	44
	Bachelor's degree	101	26.9
	Master's degree	53	14.1
	PhD	26	7
Annual gross income (€)	< 10.000	89	23.7
	10.001–29.999	186	49.6
	30.000–59.999	71	18.9
	60.000–89.999	19	5.1
	90.000–129.999	1	0.3
	> 130.000	9	2.4
Occupation	Primary sector	21	5.6
	Manufacturing and production	50	13.3
	Service industry	81	21.6
	Public sector	67	17.9
	Student	127	33.9
	Homemaker	10	2.7
	Unemployed	19	5

measurement models has been verified, we have underlined how the inner model goodness of the fit is good in the second step of the evaluation model ($R^2 = 0.576$). As regards the path coefficients, the effect of T on PE is the highest (0.575) and also the impact of SI and S on BI is considerable and very similar (0.334 and 0.267 respectively). Considering the statistical significance, all the coefficients between latent variables are significant except the impact of FC on BI. All the outer loadings for latent variables are statistically significant (Table 6). Therefore, the proposed model represents a practical and solid instrument to interpret the drivers of BI. This model, supported by the large size of the research sample along with the results of the statistical methods is able to conceptualize BI as an endogenous LV (Tables 7 and 8).

In order to deepen our study, we proceeded to carry out a Multigroup Analysis (MGA) that allows to test if pre-defined data groups have significant differences in their group-specific parameter estimates. In particular we considered the gender variable to group the sample data. The model estimated for the group of men and women are substantially statistically similar to each other and to the general model. However, some differences are noteworthy: considering the statistical significance, all the coefficients between latent variables are significant except the impact of FC on BI (for both men and women) and the impact of EE on BI (only for men),

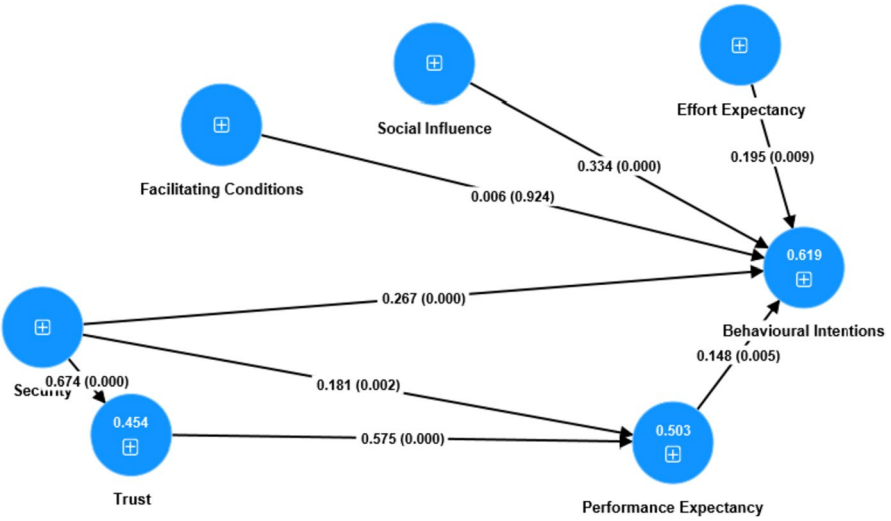

Fig. 2 Model with path coefficients and p-values (in parentheses)

Table 3 Construct reliability and validity—overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavioural Intentions	0.796	0.798	0.880	0.710
Effort Expectancy	0.812	0.812	0.877	0.640
Facilitating Conditions	0.868	0.874	0.910	0.716
Performance Expectancy	0.856	0.857	0.904	0.701
Security	0.825	0.831	0.885	0.660
Social Influence	0.872	0.877	0.922	0.797
Trust	0.822	0.822	0.883	0.654

as regards the coefficients, it is possible to point out that the impact of T on PE is greater for men than for women and, on the contrary, the impact of S on PE is greater for women than for men.

To make group comparisons, there are many methods, most of them based on bootstrapping (Hair et al. 2017): Henseler's bootstrap-based MGA (Henseler et al. 2009), the Parametric Test (Keil et al. 2000**), and the Welch-Satterthwait Test (Welch 1947**). Comparing the coefficients of the structural model, all the methods used highlight that, at a level of statistical significance of 5%, the impact of S and T on PE is different between men and women.

5 Discussion and conclusion

This work investigates the antecedents of customers' BT acceptance in the tourism sector. In accordance with the research aim, to address RQ1, our study extends the UTAUT model to include relevant antecedents, namely trust and security, influencing the behavioral

Table 4 Cross-loadings of the indicators

	Behavioural intentions	Effort expectancy	Facilitating conditions	Performance expectancy	Security	Social influence	Trust
BI1	**0.828**	0.537	0.451	0.519	0.597	0.650	0.546
BI2	**0.850**	0.525	0.429	0.498	0.543	0.478	0.512
BI3	**0.851**	0.524	0.413	0.529	0.562	0.543	0.489
EE1	0.522	**0.776**	0.665	0.530	0.505	0.443	0.703
EE3	0.490	**0.789**	0.659	0.594	0.452	0.354	0.658
EE4	0.503	**0.798**	0.518	0.733	0.434	0.353	0.566
EE5	0.494	**0.837**	0.586	0.668	0.420	0.379	0.638
FC1	0.387	0.657	**0.829**	0.570	0.361	0.320	0.642
FC2	0.462	0.655	**0.868**	0.542	0.354	0.369	0.647
FC3	0.391	0.606	**0.860**	0.513	0.375	0.313	0.656
FC4	0.478	0.648	**0.827**	0.604	0.477	0.362	0.746
PE1	0.535	0.539	0.513	**0.749**	0.467	0.414	0.533
PE2	0.497	0.687	0.585	**0.872**	0.454	0.374	0.622
PE3	0.512	0.700	0.524	**0.856**	0.480	0.348	0.570
PE4	0.508	0.709	0.587	**0.867**	0.501	0.414	0.606
S1	0.573	0.483	0.388	0.488	**0.873**	0.573	0.571
S2	0.535	0.412	0.329	0.399	**0.832**	0.566	0.498
S3	0.524	0.509	0.428	0.502	**0.841**	0.444	0.656
S4	0.563	0.427	0.362	0.448	0.692	**0.467**	0.445
SI1	0.548	0.442	0.343	0.402	0.616	**0.867**	0.413
SI2	0.600	0.414	0.356	0.399	0.570	**0.910**	0.407
SI3	0.632	0.429	0.385	0.438	0.508	**0.901**	0.416
T1	0.600	0.538	0.486	0.494	0.695	0.470	**0.758**
T2	0.453	0.677	0.723	0.545	0.475	0.337	**0.855**
T3	0.442	0.628	0.661	0.565	0.545	0.282	**0.847**
T4	0.473	0.755	0.723	0.647	0.440	0.387	**0.769**

Indicators of each latent variable were reported in bold

intentions toward BT usage in the tourism sector. Findings highlight that tourists' willingness to adopt BT depends on a multifaceted process. Specifically, we found support for all the hypotheses, apart for FC on BI (H3). However, this result confirms past research (Venkatesh et al. 2008), according to which FCs have an influence on behavioral expectations rather than intentions. This is because behavioral expectation captures many factors that are external to behavioral intention (Warshaw and Davis 1985). Numerous situations exist where the capability to perform an intended behavior, despite putting in utmost effort, remains ambiguous. This uncertainty can emerge when a behavioral intention is established significantly ahead of the intended behavior, making room for unforeseen occurrences and hindrances to modify the initial intention (Venkatesh et al. 2006). Behavioral expectation acknowledges these potential hindrances, effectively addressing this constraint. As well, it can also effectively overcome this constraint related to FCs, which is linked to an individual's requirement for precise and practical perceptions of his/her tacit sense of control over behavioral enactment in face of uncertainty (Venkatesh et al. 2008). Thus, FCs may not have a substantial impact on the perceived ease of performing the behavior or may

Table 5 Fornell-Larcker criterion

	Behavioral intentions	Effort expectancy	Facilitating conditions	Performance expectancy	Security	Social influence	Trust
Behavioral intentions	0.843						
Effort expectancy	0.628	0.800					
Facilitating conditions	0.512	0.760	0.846				
Performance expectancy	0.613	0.788	0.661	0.838			
Security	0.675	0.567	0.467	0.568	0.812		
Social influence	0.667	0.479	0.405	0.463	0.630	0.893	
Trust	0.614	0.803	0.799	0.697	0.674	0.461	0.809

Table 6 Outer loadings Mean, STDEV, *T* values, *p* values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	*T* statistics (|O/STDEV|)	*P* values
BI1 < -Behavioural intentions	0.828	0.828	0.022	36.950	0.000
BI2 < -Behavioural intentions	0.850	0.849	0.022	39.094	0.000
BI3 < -Behavioural intentions	0.851	0.850	0.021	40.898	0.000
EE1 < -Effort expectancy	0.776	0.775	0.027	28.835	0.000
EE3 < -Effort expectancy	0.789	0.788	0.025	31.208	0.000
EE4 < -Effort expectancy	0.798	0.797	0.031	26.005	0.000
EE5 < -Effort expectancy	0.837	0.836	0.023	36.708	0.000
FC1 < -Facilitating conditions	0.829	0.827	0.024	34.387	0.000
FC2 < -Facilitating conditions	0.868	0.868	0.018	49.529	0.000
FC3 < -Facilitating conditions	0.860	0.859	0.018	47.265	0.000
FC4 < -Facilitating conditions	0.827	0.826	0.024	34.256	0.000
PE1 < -Performance expectancy	0.749	0.748	0.034	22.284	0.000
PE2 < -Performance expectancy	0.872	0.872	0.020	43.957	0.000
PE3 < -Performance expectancy	0.856	0.856	0.023	37.897	0.000
PE4 < -Performance expectancy	0.867	0.866	0.020	44.344	0.000
S1 < -Security	0.873	0.873	0.016	55.846	0.000
S2 < -Security	0.832	0.832	0.024	34.035	0.000
S3 < -Security	0.841	0.840	0.022	37.979	0.000
S4 < -Security	0.692	0.691	0.037	18.570	0.000
SI1 < -Social influence	0.867	0.866	0.022	39.743	0.000
SI2 < -Social influence	0.910	0.909	0.017	54.715	0.000
SI3 < -Social influence	0.901	0.901	0.012	73.225	0.000
T1 < -Trust	0.758	0.758	0.029	26.119	0.000
T2 < -Trust	0.855	0.854	0.018	46.343	0.000
T3 < -Trust	0.847	0.847	0.019	45.606	0.000
T4 < -Trust	0.769	0.769	0.029	26.383	0.000

not be perceived as critical by individuals when forming their intention (Ho et al. 2020). In addition, contextual factors or cultural differences could also influence the relationship between FCs and behavioral intention. Additionally, different cultural norms, societal structures, or environmental factors might affect how individuals perceive and respond to FCs, making the relationship less straightforward or consistent (Bulchand-Gidumal 2022; Rana et al. 2022). At least, other factors, such as personal motivations, or social influences, can play a more dominant role in shaping behavioral intentions compared to FCs. Individuals might prioritize their own intrinsic motivations or the perceived benefits of the behavior over external facilitators, such as FCs. Accordingly, SI has a strong positive impact on BI (H2). This is because since BT is often considered complex and relatively new to many individuals, people tend to rely heavily on social cues and the opinions of others to guide their decision-making (Rakhmawati and Rusydi 2020). The uncertainty and lack of familiarity surrounding BT, above all in the tourism field, can lead individuals to seek guidance from their social networks, experts, or influential figures within their professional or personal circles. As a result, SI becomes a prominent factor in shaping their perceptions and

Table 7 Bootstrapping Results for multi-group analysis. Mean, Standard Deviation (STDEV), t value and p value for Female e Male (in parentheses)

Path coefficient	Original Female (Male)	Mean Female (Male)	STDEV Female (Male)	*t* value Female(Male)	*p* value Female (Male)
Effort expectancy -> Behavior intentions	0.140 (−0.005)	0.137 (−0.008)	0.080 (0.116)	1.737 (0.047)	0.083 (0.962)
Facilitating conditions -> Behavior intentions	−0.105 (0.025)	−0.093 (0.031)	0.070 (0.104)	1.507 (0.236)	0.132 (0.814)
Performance expectancy -> Behavior intentions	0.162 (0.316)	0.160 (0.310)	0.077 (0.109)	2.101 (2.894)	0.036 (0.004)
Security -> Behavior intentions	0.221 (0.210)	0.219 (0.213)	0.067 (0.087)	3.296 (2.416)	0.001 (0.016)
Security -> Performance expectancy	0.443 (0.245)	0.444 (0.248)	0.064 (0.053)	6.958 (4.585)	0.000 (0.000)
Security -> Trust	0.581 (0.655)	0.587 (0.658)	0.048 (0.051)	11.993 (12.798)	0.000 (0.000)
Social Influence -> Behavior intentions	0.473 (0.338)	0.474 (0.339)	0.060 (0.079)	7.945 (4.303)	0.000 (0.000)
Trust -> Performance expectancy	0.397 (0.595)	0.398 (0.592)	0.077 (0.052)	5.163 (11.342)	0.000 (0.000)

Table 8 Bootstrapping results for multi-group analysis. Test of MGA Comparisons. (* p<0.05)

	Difference (Male–Female)	Bootstrap MGA 2-tailed (Male vs Female) *p* value	Parametric test *p* value (Male vs Female)	Welch-Satterthwaite test v value (Male vs Female)
Effort expectancy -> Behavior Intentions	−0.145	0.303	0.294	0.304
Facilitating conditions -> behavior intentions	0.130	0.304	0.289	0.301
Performance expectancy -> behavior intentions	0.154	0.248	0.241	0.251
Security -> behavior intentions	−0.011	0.918	0.918	0.919
Security -> Performance Expectancy	−0.198	0.018*	0.019*	0.018*
Security -> Trust	0.075	0.290	0.290	0.290
Social Influence -> Behavior Intentions	−0.135	0.171	0.165	0.173
Trust -> Performance Expectancy	0.197	0.034*	0.040*	0.035*

* means that p-value<0.05

intentions towards adopting BT. The opinions and decisions of peers, and/or industry leaders can carry significant weight in such contexts. If influential individuals or organizations endorse and promote BT adoption, it can create a ripple effect, encouraging others to align their intentions with the perceived consensus within their professional community (Clohessy and Acton 2019). On the same page, also both effort (H1) and performance expectancy (H4) are positively related to behavioral intention. Particularly, in the context of BT adoption, if individuals perceive BT as user-friendly, intuitive, and uncomplicated, they are more likely to believe that adopting and using this tool in the tourism industry would not require excessive mental or physical effort. This perception of ease of use can create a positive attitude towards the technology, leading to a higher intention to adopt it. Moreover, BT is renowned for its complexity and technical intricacies (Singh et al. 2023). However, efforts by developers and stakeholders to simplify user interfaces and provide user-friendly applications can significantly influence individuals' perceptions of effort expectancy (Falwadiya and Dhingra 2022). When potential users find that interacting with BT systems requires minimal effort, it increases their confidence in their ability to use the technology effectively, thereby boosting their intention to adopt it. As for H4, when individuals believe that using BT will lead to improved outcomes, enhanced processes, and better results in their tourism operations, they are more likely to perceive the technology as valuable and worthwhile. Specifically, the alignment of BT features with individuals' specific needs and goals in the tourism context contributes to a positive PE. When individuals perceive that BT can cater to their unique requirements, such as secure transactions, enhanced customer experiences, or simplified record-keeping, they are more motivated to adopt it (Falwadiya and Dhingra 2022). This positive assessment of PE motivates individuals to express a higher intention to incorporate BT into their professional practices within the tourism sector. This study also figures out a noteworthy relationship between T and PE (H5) in the context of BT adoption within the tourism industry. This relationship highlights how T plays a crucial role in shaping individuals' expectations and perceptions regarding the performance benefits associated with the use of BT in tourism operations (Calvaresi et al. 2019). The study reveals that when individuals have a high level of trust in the capabilities, security, and reliability of BT, they are more likely to anticipate positive outcomes and improved performance from its adoption. Trust acts as a foundation upon which individuals base their beliefs that BT can deliver on its promises, leading to enhanced efficiency, transparency, and effectiveness in tourism-related processes. More in depth, the positive impact of T on PE is manifested through various mechanisms. Firstly, a high level of T in BT reduces uncertainty and skepticism among individuals. This reduction in uncertainty allows individuals to have a more positive and confident outlook on the potential benefits that BT can offer to their tourism operations. Secondly, trust enhances individuals' confidence in the accuracy and reliability of BT-based solutions (Shin 2019). When individuals trust that BT can securely and accurately handle transactions, data sharing, and record-keeping, they are more inclined to expect improved performance outcomes, such as streamlined processes and reduced errors. Furthermore, trust in BT fosters a sense of credibility and legitimacy. Individuals who trust the technology perceive it as a credible solution with the potential to enhance performance in tourism activities. This perception of credibility positively influences their PE by reinforcing the belief that BT adoption will lead to favorable results. This work also confirms H6 that is the positive relationship between S and PE. Accordingly, this study reveals that when individuals perceive BT as secure and resistant to unauthorized access, tampering, and fraud, their confidence in its ability to deliver improved performance outcomes is heightened. The sense of security provided by BT's inherent cryptographic features contributes to a positive anticipation of enhanced

efficiency, reliability, and transparency in tourism-related processes. The positive influence of S on PE is driven by different factors. First, a high level of S instills a sense of confidence among individuals in the integrity of data and transactions facilitated by BT. This confidence, in turn, fosters positive expectations of accurate and reliable performance outcomes, such as reduced data breaches and errors (Chang et al. 2022). Secondly, perceptions of S contribute to the perceived credibility and legitimacy of BT. When individuals perceive BT as a secure and trustworthy solution, they are more likely to associate it with positive performance attributes, such as improved data management and enhanced transactional integrity (Tyan et al. 2020). On the same page, also H7 (*Security has a positive influence on behavioral intention in adopting blockchain*) has been confirmed. The positive influence of S on BI is due to a strong sense of security that instills a belief in the reliability and integrity of transactions facilitated by BT. This belief translates into a greater willingness to utilize BT for various tourism-related interactions, such as booking accommodations, managing travel itineraries, and ensuring the privacy of personal information. In addition, security perceptions are closely tied to individuals' concerns about data protection and privacy. The study finds that when individuals perceive BT as a secure solution for managing and safeguarding their personal data, they are more likely to express an intention to adopt the technology. This is particularly pertinent in an era marked by heightened concerns over data breaches and unauthorized access (Balasubramanian et al. 2022). To conclude, this study also confirms the positive relationship between S and T in adopting BT (H8). This result is consistent with past research (Minoli and Occhiogrosso 2018; Rana et al. 2022) according to which securityperceptions serve as a foundation for trust-building in BT adoption. Individuals who view the technology as capable of safeguarding sensitive data and ensuring the privacy of transactions are more inclined to place trust in the entire system. More precisely, the positive relationship demonstrates that security perceptions act as an intermediary factor that influences individuals' initial judgments of BTs reliability and subsequently contributes to the development of overall trust. This suggests that individuals' perceptions of security significantly contribute to the psychological process through which trust in BT is established.

As for the RQ2, the study reveals that the general model is validated for both males and females, with some exceptions. First, regarding the effort expectancy concerning the intention to adopt blockchain technology (H1.a), a noteworthy observation emerges: the impact of this variable seems to be significantly related to females. In fact, they show greater sensitivity (0.140) to the expectation of effort required to use blockchain, unlike males who perceive the usability of blockchain to be within their reach (−0.005). These results are consistent with those of Venkatesh et al. (2003), who argue that effort expectancy is more relevant for females than for males. Therefore, as highlighted by previous research (Wang and Wang 2010; Chen et al. 2015; Strebinger and Treiblmaier 2022), male travelers are more open to BT. Furthermore, facilitating conditions is confirmed as a non-significant antecedent in the intention to use blockchain in the tourism sector (H3.a) (Venkatesh et al. 2008). With reference to the influence of gender on performance expectancy, different attitudes emerge between males and females regarding security (H6.a) and trust (H8.a). In detail, security affects both genders, but females (0.443) are impacted more than males (0.245). In contrast, with respect to trust, males (0.595) are influenced more than females (0.397). These results confirm those of Lee et al. (2019). Implications arising from these findings are significant for both academics and practitioners, including policymakers operating in the tourism industry.

5.1 Theoretical implications

From a theoretical point of view, this study represents a first attempt to advance our comprehension of the underlying factors that shape tourists' behavioral intentions regarding the adoption of BT within the tourism sector. By investigating the antecedents that influence these intentions, this research sheds light on the intricate interplay between motivations and objections, contributing to a deeper understanding of how technology adoption decisions are made in the context of tourism. This exploration could offer insights into strategies that could enhance the acceptance and utilization of BT, leading to more informed policy-making and effective implementation strategies for promoting technological innovation in the tourism industry.

5.2 Practical implications

Specifically, with regard to practical implications, recognizing the pivotal role of trust in shaping performance expectancy, organizations and stakeholders can prioritize building trust among potential users of BT. This could involve transparent communication, education, and the establishment of safeguards to address any concerns related to the technology's reliability and security. Additionally, policymakers can consider initiatives that promote trust-building efforts within the BT ecosystem. By fostering an environment of trust and credibility, policymakers can contribute to enhancing performance expectancy among tourism professionals, thereby encouraging wider adoption of BT. On the same page, also the role of security is of paramount relevance in shaping trust, and in promoting BT adoption, as well. Based on this, organizations can prioritize enhancing security measures and communicating the robustness of BT's security features to potential users. By ensuring that BTs adhere to rigorous security protocols, policymakers may contribute to enhancing individuals' perceptions of security and, consequently, their performance expectancy. Furthermore, by emphasizing the technology's security features and addressing potential concerns, businesses can enhance individuals' confidence and intentions to embrace BT for various tourism-related activities.

6 Conclusion, limits and future directions

The main contribution of this work is to examine the antecedents influencing the behavioral intentions toward BT usage from the tourists' side, with the aim of better understanding the main motivations and objections to its adoption. Therefore, it fills an important research gap and contributes to a more holistic understanding of BT adoption process. This research reveals that both security and trust are two critical constructs, and their inclusion in the UTAUT model provides a comprehensive framework for analyzing and predicting the factors that shape tourists' intentions to adopt BT. More in detail, the findings underscore the essentiality of trust-building measures for the successful integration and widespread acceptance of emerging technologies, such as BT, within the tourism sector. As demonstrated by the analysis, both security and trust acts as a linchpin that can bolster the intention to adopt such technologies. This holds profound implications not only for businesses seeking to implement these innovations but also for policymakers, industry stakeholders, and researchers aiming to decipher the multifaceted dynamics between consumer behavior,

trust, and technology adoption. Nevertheless, this work is not without limitations. First, as BT adoption is in its early stages, the respondents' lack of understanding on how it works may hinder generalizing the survey results. Future studies can undertake surveys based on a better understanding of the respondents' knowledge and awareness levels on BT, also introducing an experimental design research. Second, although the sample size did not compromise the analysis, it poses a limitation in terms of generalizing the results. Large-scale studies are, therefore, recommended in the future. Lastly, the current study does not include UTAUT moderators (e.g., gender, age, income, education and occupation) that may help to understand nuances in the sample. However, there remains a plethora of avenues for future research to delve into. The dynamic and ever-evolving landscape of technology and its application in the tourism industry demands continuous inquiry. Future studies could delve deeper into the mechanisms through which trust is established, exploring the role of various factors such as user experience, perceived control, and transparency. Additionally, a longitudinal examination could provide insights into the evolving nature of consumer perceptions as their familiarity with the technology grows over time. Furthermore, cross-cultural investigations could illuminate how trust dynamics vary across different regions and societies, given the potential influence of cultural norms, values, and socio-economic factors. This could provide valuable insights for businesses seeking to tailor their strategies to diverse consumer markets. In conclusion, as we stand at the precipice of an era marked by unprecedented technological advancements, the continued exploration of trust's impact on consumer behavior and its implications for the industry is paramount. Through rigorous and comprehensive future research, we can unlock a deeper understanding of these dynamics, paving the way for informed strategies, enhanced consumer experiences, and the responsible integration of BT into the tourism realm.

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Declarations

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