HETEROGENEOUS DETERMINANTS OF TOURISTS' LOYALTY: A COMPARISON BETWEEN SUN AND BEACH AND CULTURAL HERITAGE DESTINATIONS

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Abstract

Purpose - This paper proposes to detect the determinants of tourists' loyalty to accurately model the asymmetric responses of tourists.
Methodology/Design/Approach - Loyalty is modelled by using an asymmetric Bayesian discrete choice model in two ways: the willingness to repeat a visit and to recommend a tourism destination. We use data from two destinations with different motivations to visit: a sun and beach destination (SBD, Barbados) and a cultural heritage destination (CHD, Ethiopia).
Findings - The main results highlight several aspects. First, for a CHD, the 'repeat visit pattern' occurs when previous visits are between two and four; additional visits are less likely to happen. On the contrary, for a SBD, tourists may establish a life-long relationship. Second, distance is an issue for tourists choosing a SBD, but not for a CHD. This relates to market structure, since SBD markets work under competition, whereas CHD markets function as natural monopolies. Finally, 'High level of studies' is a key loyalty determinant in favor of a CHD, however, when that level is low, it provides an incentive to revisit a SBD, instead.
Originality of the research – The paper proposes the use of methodology never before used in this field and obtains novel determinants when explaining loyalty.
Keywords Loyalty, repeat visits, tourist determinants, asymmetric Bayesian model.

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INTRODUCTION

Tourism loyalty is one of the key issues in tourism management analysis (Oppermann, 2000). It is an essential factor in creating destination performance and profits in the long-term and is recognized as being the most crucial destination marketing concept (Ruiz-Real et al., 2020), as well as being considered the best estimator of consumer behavior in marketing strategies (Chen & Chen, 2009). For example, "culture" is used as a key marketing tool to develop strategies to attract tourists with special interests in heritage and the arts, increase competitiveness, and boost the excellence of cultural heritage destinations (Hernández-Rojas et al., 2021).

Loyalty has several useful implications for policy makers and managers. For instance, tourists who 'repeat visit' (who are loyal) require lower marketing costs than first time visitors (Shoemaker & Lewis, 1999). Tourists motivated by cultural interests are more willing to pay more than expected for enjoyment of the cultural traits of destinations (Nicolau, 2011). Also, tourists who are more satisfied with the visit wish to know more and contribute to the culture of the destination (López-Guzmán et al., 2018).

The challenge of measuring loyalty to a tourist destination makes it difficult for marketing managers to implement specific policies (Cossío-Silva et al., 2019). However, the empirical literature analyzing loyalty is extensive, e.g., Bigné et al. (2001), Chi & Qu (2008), Kim et al. (2013), Zhang et al. (2014), Meleddu et al. (2015), and Almeida-Santana & Moreno-Gil (2018); among others, and has highlighted factors or antecedents which can be categorized as tourist-related, destination-related or travel outcome-related (Lv et al., 2020). In general, as Chi & Qu (2008) pointed out, the basic theoretical model to describe the formation of destination loyalty can be expressed using a hypothetical construct in which destination image and tourist satisfaction are antecedents in explaining destination loyalty. However, the theoretical model has also been extended using additional antecedents, e.g., Chen & Tsai (2007), Prayag & Ryan (2012), Su et al. (2017), and Lv et al. (2020).

These studies have predominantly focused on a single destination and, in doing so, have used different types of statistical and econometric methods to analyze factors influencing loyalty, e.g., Moutinho & Trimble, 1991; Juaneda, 1996; Correia et al., 2007; Brida et al., 2012; Jani & Han, 2014; Ali & Mona (2019); Seetanah et al., 2020; Chen & Lee, 2021; Jin et al. (2022); Lin et al. (2022) or Majeed et al. (2022), among others; see literature review.
It is noteworthy that the most employed tourism loyalty definitions are willingness to return to a destination (or revisit intention, which is called 'behavioral loyalty') and intention to recommend the visit to family or friends ('attitudinal loyalty'), Zhang et al. (2014). These are unobservable variables representing an individual choice. Methodologically and beyond the

use of statistical and descriptive approaches, such as cluster analysis or ANOVA methods, see López-Guzmán et al. (2018) and Cruz-Ruiz et al. (2018), among others, there are two main econometric methods to analyze factors influencing both tourism loyalty approaches. First, the structural equation models (SEM) and, second, the discrete choice models (mainly, logit or mixed logit models); although neither is without criticism. For example, the main drawback of SEM modelling is that it is based on a hypothetical construct, that is, the relations among the elements may not be representing the true cause-effect relationships due to the hypothetical assumptions of these kinds of models. Furthermore, a binary logit model assumes that the responses (i.e., successes and failures) are symmetric, which does not always occur in practice.

Therefore, the main contribution of this paper to the tourism empirical literature on destination loyalty is twofold. First, we propose to model the destination loyalty variables (i.e., willingness to repeat and the willingness to recommend) by using a Bayesian asymmetric logit model. This is because there is a statistical regularity where tourists willing to visit a destination outnumber those who do not. In practice, the percentage of responses may be asymmetric. Therefore, the employment of classical binary logit (or probit) methods may result in model misspecification and a false interpretation of the marginal effects. The Bayesian asymmetric model might improve the accuracy of tourism loyalty prediction and provide additional accuracy with the identification of economic and sociological factors not considered by other methods. Hence, it could provide a better understanding of the factors that underpin tourist loyalty decisions. The Bayesian methodology is implemented in two steps: in the first step, the prior distributions for all parameters, including the asymmetric one, are supposed and, in the second step, the posterior estimations by applying Bayes' theorem are obtained.

Second, we consider several determinants that are likely to influence tourist loyalty by assessing the differences and similarities between destinations where the motivation to visit varies, such as, for example, a sun and beach destination and a cultural heritage destination. These two destinations are characterized by a distinctive destination image, which can be considered an effective means to enhance tourists' loyalty, as Chi and Qu (2008) have pointed out.

These factors have previously been used in the empirical loyalty literature using classic discrete choice models (mainly, logit models) such as previous experience, socio-economic and vacation characteristics (Meleddu et al., 2015). For example, heterogeneous behavior of first-time and repeat travelers' loyalty performance has been studied. Previous studies suggest that first-time and repeat visitors have different motivations, expectations, and experiences regarding a destination visit (Lew and McKercher, 2006); but they also display significant differences in their destination judgements and behavior; see Yuksel & Yuksel (2003) and Weaver and Lawton (2011), among others. Moreover, both destinations are sufficiently far from the main outbound markets, so that tourists need to travel a considerable distance by air. This avoids the analysis of well-located destinations where repeat visits are more likely to happen due to proximity or good connectivity.

To assess this proposal, the paper focuses on survey data corresponding to two different databases with heterogeneous randomly selected tourists. These databases were collected in two destinations according to their tourist image. One is for tourists who visit Barbados (a leading Caribbean sun and beach destination) and the other for those who travel to Ethiopia (which was one of the first countries to ratify the UNESCO convention on July 6, 1977; making some of its historical locations eligible for inclusion on the World Heritage Sites list) and declare willingness to revisit the destination (behavioral loyalty) and the intention to recommend the visit to friends and relatives (attitudinal loyalty). These destinations are very different. On the one hand, Barbados represents a sun and beach destination, whereas on the other, Ethiopia attracts tourists interested in cultural heritage. These examples provide a good balance of different kinds of destinations and also allow us to test the appropriateness of the methodology.

To our knowledge, this is the first paper that investigates two different destinations for comparison purposes and studies the probability of destination loyalty using the asymmetric Bayesian probabilistic model, to test whether it improves the accuracy of the frequentist model. The reason it needs to be tested is because the Bayesian approach has proved bett Polo-Peña er than the frequentist model in other fields. See, for example, Chen et al. (1999), Bermúdez et al. (2008), Sáez-Castillo et al. (2010), Pérez-Sánchez et al. (2014) and Pérez-Rodríguez et. al (2017)

The paper is organized as follows. Section 2 describes a review of empirical studies on loyalty, including both types of tourist destinations. Section 3 introduces the research methodology based on the asymmetric Bayesian logit approach, including a brief review of Bayesian applications in tourism. Section 4 describes the sample data configuration, the empirical results obtained and discussion of the results, while concluding remarks are made in Section 5.

1. LITERATURE REVIEW ON LOYALTY

This section provides a brief overview on destination loyalty and its antecedents, with special emphasis on the econometric methods used to analyze it and distinguishing two types of destinations: natural sites and world heritage sites, respectively.

1.1. Loyalty

Loyalty is a big and well-established field of study (see Zhang et al., 2014; Lv et al., 2020; among others), and offers a

sustainable revenue stream for destinations through word-of-mouth and lower marketing costs (e.g., Almeida-Santana & Moreno-Gil, 2018).

Destination loyalty has several antecedents that can be considered key in its measurement. Following Lv et al. (2020), these antecedents can be grouped in three general types: tourist-related, destination-related and travel outcome-related. Regarding the first group, we can include several factors such as motivations, socio-demographic characteristics, past experiences (see Chen & Gursoy, 2001; Yoon & Uysal, 2005; and Almeida-Santana & Moreno-Gil, 2018), and consumer experiences (Wu, 2016). With regards to the second group, they can involve destination image, service quality, value for money (see Chen & Tsai, 2007; Chi & Qu, 2008; and Lee et al., 2011; among others), or familiarity (Sun & Xu, 2013). Finally, the group of travel outcome-related factors can include perceived quality, perceived value, and satisfaction (see Bigné et al., 2001; and Castro et al., 2007; among others).

Based on these antecedents, literature has proposed several theoretical models to explain destination loyalty. For example, Chi & Qu (2008) proposed a basic model where destination image is an antecedent of satisfaction, and satisfaction is an antecedent of destination loyalty (this model is often referred to graphically as destination image → satisfaction → destination loyalty). In this model, destination image is exogenous, but satisfaction and destination loyalty are endogenous variables. Specifically, satisfaction can be explained by accommodation, environment, attractions, and dining, among others. Extensions to Chi & Qu's model can be made by including different mediators, such as perceived quality and perceived value (Kim et al., 2013), destination familiarity (Sun et al., 2013), consumer experiences (Wu, 2016) or, more recently, sensory impressions (Lv et al., 2020), among others. Finally, we can cite additional studies examining the impact of health crises, such as COVID-19, on destination loyalty, including Rather (2021), Hassan & Soliman (2021), Woosnam et al. (2021), Manchanda & Deb (2022), Lin et al. (2022), and Majeed et al. (2022), among others.

It is noteworthy that regarding destination loyalty, models generally use several definitions. For example, the theoretical literature identifies three types of destination loyalty (e.g., Zhang et al., 2014; and Meleddu et al., 2015): attitudinal loyalty (i.e., intention to recommend the destination to friends and family), behavioral loyalty (i.e., intention to revisit the destination), and a mix of the two (composite loyalty). Despite the considerable body of studies on destination loyalty, Zhang et al. (2014) pointed out that the multidimensional nature of loyalty and the variations between studies make it difficult to establish a solid understanding of the modeling.

As said, to evaluate the likelihood to return to a destination, the empirical literature has predominantly employed two econometric approaches: the SEM and discrete choice models (Meleddu et al. 2015).

1.2. Loyalty to specific tourist destinations

Different types of destinations have been analyzed depending on different tourist motivations. For example, the main purpose of the visit might be business, food, adventure, eco-tourism, event(s), religion, leisure, medical and cultural tourism, among others; but also, unusual types of tourism such as war, shark and fertility tourists, or dark tourism. However, the most important sites where loyalty has been studied are natural attractive destinations. In these destinations, the main motivation of the visit is leisure tourism, and the main product is sun and beach (see Juaneda, 1996; Ledesma-Rodríguez et al., 2005; Correia et al., 2007; and Meleddu et al., 2015; among others). As mentioned, another type of tourism where loyalty has been analyzed is cultural heritage tourism. It is worth noting that cultural tourism is a rapidly growing area and heritage tourism has become a niche market (Altunel & Erkurt, 2015 and Jimber et al., 2020). Further, cultural and heritage tourists have different motivations to visit a destination (McKercher & Du Cros, 2003). It is noteworthy that the relevant academic literature has created different classifications for heritage tourists (McKercher & Du Cros, 2003; Poria et al., 2003; and Nguyen & Cheung, 2014; among others). For example, McKercher & Du Cros (2003) consider the following five categories: purposeful, sightseeing, causal, incidental, and serendipitous cultural tourists. Visitor loyalty at UNESCO World Heritage Sites (locations of special cultural or natural interest) has recently been studied by López-Guzmán et al. (2018), Ali & Mona (2019) and Hernández-Rojas et al. (2021), among others.

Table 1 shows the most significant papers analyzing tourism loyalty in the empirical tourism research in both natural attractiveness and cultural heritage sites. It is noteworthy that most econometric studies are those employing SEM.
Next, we briefly describe the two types of destinations which will be studied in our paper.

Natural attractiveness sites

This section briefly comments on papers focusing on sun and beach but also natural site destinations.

The literature in this respect has used several methods, from statistical (mainly factor analysis and ANOVA) to econometric (SEM and discrete choice models). Focusing on papers that use econometric models, the following can be distinguished: on the one hand, authors who investigate SEM loyalty include Murphy et al. (2000), Um et al. (2006), Brida et al. (2012), Prayag & Ryan (2012), Eusebio & Vieira (2013), Polo-Peña et al. (2013), Sanz-Blas et al. (2019), Nguyen et al. (2020), and Seetanah

et al. (2020), Papadopoulou et al. (2022), for sun and beach and other natural sites, among others; on the other; authors who use discrete choice models that mainly employ the probabilistic logit model. For example, logit modelling has been employed by Moutinho & Trimble (1991), Juaneda (1996), Alegre & Cladera (2006), Gabe et al. (2006), Correia et al. (2007), Campo-Martínez et al. (2010), Jani & Han (2014), and Meleddu et al. (2015), Jin et al. (2022); among others.

It is worth noting that in the empirical papers shown in Table 1, for both SEM and discrete choice models, there are several factors that strongly explain loyalty to revisit a destination or the intention to recommend. Meleddu et al. (2015) considered loyalty to a tourism destination within a multidimensional framework and with various definitions of loyalty. A brief overview of the literature considering multidimensionality indicates that customers' likelihood to be loyal may depend not only on the motivation of the visit, which is fundamental to tourist activity since it is considered a driver of human conduct and an explanatory factor for some of the aspects related to tourist activity (Prayag & Ryan, 2011 and Meleddu et al., 2015, among others); but also on satisfaction as the main factor that drive tourists to return to the same destination, as suggested in several empirical studies (see Juaneda, 1996; Lau & McKercher, 2004; Alegre & Cladera, 2006; Meleddu et al., 2015; and Jin et al., 2022; among others); the repeat behavior of tourists (e.g., previous visits) (see Lew & McKercher, 2006; Sun et al., 2013; Polo-Peña et al., 2013; and Meleddu et al., 2015; among others); several controls related to both vacation (e.g., distance from the place of residence, party size, length of stay, expenditure at destination, among others), and individual characteristics (e.g., gender, age, level of studies, occupation, income, among others) (Meleddu et al., 2015); see Brida et al. (2012) for an overview.

Cultural and world heritage sites

Saipradist & Staiff (2007) pointed out that World Heritage recognition guarantees the identification, conservation and passing on to future generations of places or monuments that have a universal value from the perspective of art and history. Italy, China, and Spain have the largest number of catalogued sites, and lead in this respect. The analysis of cultural heritage destinations has been mainly undertaken using statistical but also econometric models such as SEM. For example, Su et al. (2017) investigated domestic tourists at a World Heritage Site in China, examining the relationship between three significant visitor perceptions (i.e., service fairness, destination image, and service quality) and tourism destination loyalty (i.e., positive word-of-mouth referrals and revisit intentions), through the mediating factors of overall destination satisfaction and trust in destination service providers. López-Guzmán et al. (2018) have analyzed the relationships between three important constructs in the visitor decision-making process, such as motivation, satisfaction and loyalty using ANOVA, for the World Heritage tourist city of Córdoba (Spain). Ali & Mona (2019) examined the causal relationships between three motivational dimensions, three evaluative constructs (perceived value, experience quality, and satisfaction), and destination loyalty at a prominent World Heritage Site -Golestan Palace- in Tehran.

Other studies have used SEM to predict intentions to return or recommend a destination. Few studies investigate loyalty to cultural heritage, such as restaurants (Kang et al., 2018), world heritage sites (Hernández-Rojas et al., 2021; López-Guzmán et al., 2018; Berhanu & Singh (2020) and Jimber et al., 2020), or cultural heritage tourism (Wang & Leou, 2015), and cultural heritage focusing on the antecedents of brand authenticity (a crucial criterion for tourists to consider when choosing cultural heritage destinations) (Chen & Lee, 2021; among others). For example, Hernández-Rojas et al. (2021) investigated the loyalty of travelers to a World Heritage cultural destination (the Citadel of the Catholic King, Córdoba, Spain) and provided results that can be used to improve management of the destination.

In general, factors used in these analyses are similar to the natural sites to explain loyalty. For example, Hernández-Rojas et al. (2021) have found that the fidelity of visitors to the Citadel of the Catholic King depends on their satisfaction with the cultural heritage, and how the quality perceived by the tourist modulates to varying degrees the relationship between perceived value and tourist satisfaction. Chen and Lee (2021) found that perceived value and brand trust plays a mediating role in the relationship between brand authenticity and tourism destination loyalty.

As Hernández-Rojas et al. (2021) pointed out, managers of tangible cultural heritage should have prior information on tourists visiting the site in order to plan actions that improve heritage and culture visitor experiences.

However, as far as we know, asymmetric discrete choice models have not been applied in the examination of destination loyalty and none of the hypotheses have been tested in the literature.

Table 1: **Several empirical studies on loyalty based on discrete choice models (marked in bold) and SEM**

Authors	Country	Data type on surveys	Period	Method	Endogenous variables	Exogenous characteristics	Asymmetry	Bayesian
Moutinho & Trimble (1991)	USA	Tourist visitors to the Grand Canyon	1990	Logit	Repeat visits	Distance traveled and visitor demographic profiles	No	No
Juaneda (1996)	Spain	Tourists visiting the Balearic Islands	1994	Logit	Return visits	Socioeconomic and vacation characteristics	No	No
Murphy et al. (2000)	Canada	Travelers visiting Victoria area	1994	SEM	Intention to return	Destination environment and infrastructure variables, and perceptions of quality and value	-	-
Ledesma-Rodríguez et al. (2005)	Spain	Tourists visiting Tenerife (Canary Islands)	1996-1999	Logit	Willingness to return	Socio-economic characteristics of the tourists, the organization of their trips, the origin of previous information about the destination, the number of previous visits, and their degree of satisfaction	No	No
Um et al. (2006)	China	Tourists visiting Hong Kong	200-2003	SEM	Revisit intention	Perceived quality of performance during onsite and post-purchase periods as well as the destination's distinctive nature	-	-
Gabe et al. (2006)	USA	Cruise ship passengers visiting Bar Harbor, Maine.	2002	Logit	Return to a visited port	Distance, income, past visits, age, time in port, gender, cruise ship and date of visit	No	No
Alegre & Cladera (2006)	Spain	Tourists visiting the Balearic Islands	2002-2003	Logit	Intention to return	Assessment of price, repeat visitation rate, nationality, location area in the Balearic Islands, type of accommodation, overall satisfaction	No	No
Correia et al. (2007)	Portugal	Tourists visiting the Algarve	2004	Mixed logit	Intention of repeater golf tourists	Socio-economic characteristics, travel and accommodation characteristics, and attributes that had led to the selection of the Algarve's golf courses and an evaluation of the level of golfer satisfaction	No	No
Chi & Qu (2008)	USA	Tourist visiting Eureka Springs (Arkansas)	2007	SEM	Satisfaction and destination loyalty	Travel environment, natural attractions, infrastructure, lodging, shopping, among others	No	No
Alegre & Cladera (2006)	Spain	Tourists visiting the Balearic Islands	2002-2003	SEM	Overall satisfaction and intention to return	For overall satisfaction: partial satisfaction levels; the number of previous visits; the motivations that led the tourist to choose the destination; and their assessment of the price/quality ratio. For the intention to return: the number of visits and overall satisfaction	-	-
Campo-Martínez et al. (2010)	Spain	Tourists visiting the Balearic Islands	2007	Logit	Intention to revisit	Perceived global image, satisfaction, number of visits	No	No
Prayag & Ryan (2012)	Mauritius	French, British, South African, German, and Indian tourists	2008	SEM	Revisit intentions and recommendation intentions	Destination image, personal involvement, place attachment, overall satisfaction	-	-
Brida et al. (2012)	Colombia	Cruise visitors at	2009	SEM	Intention to return and	Safety, price satisfaction, loyalty to the	-	-

		Cartagena de Indias			the probability to recommend destination to others	destination, human physical capital satisfaction		
Eusebio & Vieira (2013)	Portugal	Tourism market in the Central Region	2012	SEM	Recommendation and future visits	Overall satisfaction and destination attributes	-	-
Polo-Peña et al. (2013)	Spain	Spanish customers of rural hospitality enterprises	2009	SEM	Recommendation and repurchase intentions	Company reputation, satisfaction, functional and affective perceived value	-	-
Jani and Han (2014)	Korea	Guests of five-star hotels in one Korean metropolitan city	2013	SEM	Overall loyalty	Satisfaction, hotel image, appraisal of hotel ambience and personal factors	-	-
Meleddu et al. (2015)	Italy	Tourists visiting the island of Sardinia	2012	Logit	Intention to recommend and revisit, composite stated loyalty	Repeat behavior, motivation, satisfaction, vacation characteristics, destination sub-choice, individual characteristics	No	No
Wang & Leou (2015)	China	Cultural and heritage tourists visiting Macao	2015	SEM	Destination loyalty	Tourism motivation, perceived value	-	-
Liu et al. (2017)	China	Mainland Chinese outbound travelers to Macau	--	SEM	Behavioral intentions	Overall satisfactions, destination image, travel experience	-	-
Su et al., (2017)	China	World heritage site: Chinese tourists visiting the Wuyi Mountain National Park	2009	SEM	Revisit intentions, word-of-mouth	Service fairness, destination image, service quality, overall destination satisfaction, trust towards destination service providers	-	-
Sanz-Blas et al. (2019)	Spain	cruise passengers visiting a major Spanish port of call	2018	SEM	Behavioral intention	Destination image (tourism resources, infrastructure and atmosphere, urban environment, and socioeconomic environment), satisfaction	-	-
Ali & Mona (2019)	Iran	World Heritage Site - Golestan Palace (Tehran)	2016	SEM	Revisit intention	Motivation, quality of experience, perceived value, satisfaction	-	-
Azis et al. (2020)	Indonesia	International and domestic tourists visiting three tourist cities in Aceh province	2019	SEM	Destination loyalty	Smart tourism technologies, memorable tourism experiences, satisfaction	-	-
Woyo & Slabbert (2020)	Zimbabwe	International tourists visiting Victoria Falls, Harare, Great Zimbabwe and the Eastern Highlands	2016	SEM	Behavioural and attitudinal loyalty	Demographic profile, travel behaviour, travel motivations, satisfaction	-	-
Berhanu & Singh (2020)	Ethiopia	Domestic tourists from four destination sites in Ethiopia (Bale, Gondar, Hawassa and Lalibela)	2018	SEM	Willingnes to recommend, intention to revisit	Pull and push travel motivations, overall satisfaction	-	-
Seetanah et al. (2020)	Mauritius	Tourists visiting the island of Mauritius	2017	SEM	Revisit intention	Satisfaction with airport services and other satisfaction components (cost of living, exchange rate, development level, quality of accommodation, quality of	-	-

						tourism attractions, quality of information, political stability)		
Nguyen et al. (2020)	Vietnam	International tourists in Binh Thuan province	2019	SEM	Revisit intention	Satisfaction, attractiveness, accommodation and food service, perceived risk and cultural contact	-	-
Jimber et al. (2020)	Spain	Tourists visiting Córdoba	2019	SEM	Destination loyalty	Perceived quality, expected quality, perceived value, satisfaction	-	-
Cheng & Lee (2021)	China	China's domestic tourists in heritage sites	2020	SEM	Destination loyalty	Brand legitimacy, brand authenticity, brand trust, perceived value	-	-
Hernández-Rojas et al. (2021)	Spain	Tourists visiting the Citadel of the Catholic King	2019	SEM	Destination loyalty	Perceived quality, expected quality, perceived value, satisfaction	-	-
Hassan & Soliman (2021)	Egypt	Domestic tourists	2020	SEM	Revisit intention	Destination social responsibility, destination reputation, perceived trust, fear arousal	-	-
Woosnam et al. (2021)	USA	Domestic tourists (last destination visited during the pandemic by participants)	2020	SEM	Destination loyalty	Model 1: Feeling welcomed, emotional closeness, sympathetic understanding. Model 2: communality fairness	-	-
Rather (2021)	India	traveled to major destination sites in India (e.g. Gulmargh, Phalgam)	2020	SEM	Revisit intention	Social media during Covid-19, perceived risk of traveling and fear of Covid-19, customer brand engagement	-	-
Jin et al. (2022)	Spain	Active sport event tourists (Mallorca)	2019	SEM and Ordered logit	Destination loyalty	Gender, nationality, day's stay, route, pre-visits, training plan, package	No	No
Manchanda & Deb (2022)	India	Destination visited through virtual reality tourism applications	2020	SEM	Intention to physically visit the destination, loyalty	Satisfaction, perceive health, financial and psychological risks, multisensory virtual reality-mediated total intention	-	-
Papadopoulou et al. (2022)	Various Mediterranean coastal destinations	National and international tourists	2020	SEM	Intention to revisit and recommend, objection to revisit and recommend	Perceived destination adaptation, approach and avoidance reaction, tolerance, destination satisfaction, among others	-	-
Lin et al. (2022)	China	Domestic tourists	2021	SEM	Destination loyalty	23 first-order constructs to form five second-order constructs, which represent a holistic and comprehensive measurement scale for experiencescape	-	-
Majeed et al. (2022)	China	Tourists with prior experience visiting famous destinations (forest recreation areas, national parks, and historic sites or museums)	2020	SEM	Destination brand choice / loyalty	Perceived destination brand image, destination brand self-congruence, destination brand engagement, destination brand love, and perceived risk of destination health crisis	-	-

As McKercher & Du Cros (2003) have pointed out, cultural and heritage tourists have distinct motivations. Therefore, in accordance with the general framework described above, our paper proposes evaluating and testing several hypotheses by comparing CHD and SBD loyalty within our Bayesian logit framework. It is important to note that we adhere to empirical literature based on discrete choice models to investigate the willingness to return to or recommend a tourist destination and the factors that determine such willingness. In this context, our hypotheses are as follows:

H1: The loyalty saturation point for sun and beach destinations is larger than for cultural and heritage destinations.

Previous visits to a tourist destination are a significant indicator of loyalty, not only in conceptual models analyzing tourists' loyalty using SEM (e.g., Alegre & Cladera, 2006) but also in discrete choice models studying the willingness to return or recommend (e.g., Ledesma-Rodríguez et al., 2005; Alegre & Cladera, 2006; Meleddu et al., 2015; Jin et al., 2022). Generally, this effect is positive and statistically significant in empirical literature. We anticipate that this holds true for both types of destinations. However, our intuition suggests that the effect may be less pronounced for CHD compared to SBD, as cultural heritage tourists might be inclined to revisit a CHD less frequently than an SBD. This may be true since the main objective of visiting a CHD is to experience a new destination whereas the main objective of visiting a SBD is relaxation.

H2: SBD tourists are concerned about the distance between their place of residence and the destination, whereas for CHD tourists, the distance is not so relevant.

McKercher (2018) observed that distance serves as a proxy variable representing a range of physical and human geographic conditions, encompassing various consumer behavior variables. He notes that short-haul tourists are significantly more likely to engage in hedonistic activities such as visiting theme parks, shopping, and dining, whereas long-haul tourists are more inclined to participate in activities that facilitate the exploration of a destination's cultural heritage.

Distance has been utilized as an indicator in conceptual models, such as SEM (e.g., Um et al., 2006), as well as in discrete choice models investigating the intention to revisit or recommend (e.g., Moutinho & Trimble, 1991; Gabe et al., 2006; Jin et al., 2022). Generally, this variable has a negative impact on the likelihood of returning to a destination, as longer trips tend to decrease the probability of return visits.

However, we expect that distance will have a negative effect on SBD but no effect on CHD. The intuition of our hypothesis is based on two characteristics, namely: the number of alternatives and the motivation for traveling. Again, for SBD tourists the main motivation is relaxation, which may be found in many competing alternative destinations. However, for CHD tourists the main motivation is to experience a new destination; in that sense making it a natural monopoly.

H3: High level of studies is a push factor for repeating visits to cultural and heritage destinations. At the same time, low level of studies is a push factor for repeating visits to sun and beach destinations.

At least for long-haul tourists, McKercher (2018) has pointed out that "older, better educated, higher income earning individuals with long periods of time availability, or younger backpackers with no time constraints are more likely to be found in disproportionate shares amongst long-haul tourists". In this context, it can be anticipated that long-haul CHD markets are more likely to experience repeat visits from individuals with a high level of education (i.e., those who are better educated). Their higher level of education may drive a stronger inclination to revisit destinations that offer rich cultural and intellectual engagement.

2. RESEARCH METHODOLOGY

2.1. Bayesian applications in tourism

This section explores the way in which some Bayesian methods have been applied in the tourism field, as well as how researchers have managed to estimate asymmetric behavior in fields other than tourism.

Bayesian methodology has been successfully applied in tourism studies. For example, Assaf & Magnini (2012) applied the distance stochastic frontier method to a balanced sample of leading hotel chains in the US, within a Bayesian framework. Assaf & Barros (2013) also effectively employed the semi-parametric stochastic frontier model using the Bayesian approach. This focuses for the first time on cross-country analysis by measuring and comparing hotel industry performance across various international countries. Tsionas & Assaf (2014) introduced a new dynamic stochastic frontier model to analyze the short- and long-term technical efficiencies of leading tourism destinations. Assaf & Tsionas (2015) developed a new Bayesian stochastic frontier model that incorporates destination quality into the estimation of tourism performance. And, more recently, Assaf & Tsionas (2019) proposed a Bayesian dynamic panel for tourism models allowing changes in slope parameters.

To our knowledge, the Bayesian methodology has not been applied to the analysis of tourism loyalty. The Bayesian approach allows for a better understanding of the estimates, especially because it can deal with asymmetries among different kinds of tourists' preferences. One key work on asymmetry was pioneered by Chen et al. (1999) who employed an asymmetric pattern in binary response data. Similarly, Bermúdez et al. (2008) applied skewed logistic models in the insurance field to analyze the probability of fraudulent behavior. In the field of health, Sáez-Castillo et al. (2010) used an asymmetric logistic link to predict

infection rates. Pérez-Sánchez et al. (2014) analyzed the risk factors of auto-mobile insurance claims, considering the skewed link in the logistic regression. Finally, in the air travel literature, Pérez-Rodríguez et al. (2017) fitted and predicted the daily probability of delays in aircraft arrivals by using an asymmetric dichotomous model.

2.2. Methodology: asymmetry with Bayesian estimations

In practice, binary data or samples can often contain a significant proportion of zeros or non-zeros. To address this issue, since Prentice (1976) several authors have employed various models, which benefited from advances in software and technology. Some notable examples include the research by Stukel (1988, 1990); Fletcher et al. (2005); and Kumar & Manju (2015). In the context of dichotomous models, Stukel (1988) and Chen et al. (1999) have suggested the utilization of a skewed link function for binary outputs with a high proportion of response values equal to one. The asymmetric logit model offers flexibility by allowing the logit function to be skewed, thereby removing the restriction imposed on standard logit models where the impact of covariates on the probability of a response being one is expected to be larger when this probability is close to 0.5. Consequently, the link function of the logistic model for the skewed logit model is expressed as follows:

$$F(s) = 1 - \frac{1}{(1+e^{s})^{\delta}}, \qquad (1)$$

where the asymmetry coefficient, δ, represents a crucial parameter in this context. We can estimate logistic model with an expression (1) assumption through maximum likelihood estimation. For further details on this model, please refer to Nagler (1994).

The Bayesian regression models (Zellner, 1971, and Koop, 2003) suppose a prior distribution, allowing for random behavior for the regression parameters. In this sense, this approach gives more flexibility in regression models. Various works of dichotomous choice have been proposed by applying skewed Bayesian estimations. See, for example, Chen et al. (1999); Fernández & Steel (1998); Bazán et al. (2006); and Bazán et al. (2010).

The asymmetric logit link is based on a data augmentation approach (Albert & Chib, 1993):

$$y_i = \begin{cases} 1, & w_i \geq 0, \\ 0, & w_i < 0, \end{cases} \qquad (2)$$

where $\varepsilon_i \sim F(w_i) = x_i'\beta + \delta z_i + \varepsilon_i$; $z_i \sim G$ and $\varepsilon_i \sim F$, with $i = 1, 2, \ldots, n$. In this context, Chen et al. (1999) suppose that F is the standard logistic cumulative distribution function, which is independent of G, the cumulative distribution function of a half-standard normal distribution. In this model, $\delta \in (-\infty, \infty)$ is the skewness coefficient and so δz_i measures the asymmetry of the regression model. If $\delta > 0$, the probability that the i-th tourist will repeat ($p_i = 1$), increases. By contrast, if $\delta < 0$, then then probability of not repeating ($p_i = 0$), increases. When $\delta = 0$, the symmetric model appears.

The prior distribution for β and δ is $\pi(\beta, \delta)$. This paper supposes non-informative and normal prior distributions by considering $\beta_j \sim N(0, \sigma_j^2), \forall j = 1, \ldots, k$, and $\delta \sim N(0, \sigma_\delta^2)$, considering high values for σ_j^2 and σ_δ^2. In this sense, there is weak information about the parameters, and they may be compared with the frequentist estimations. By considering Bayes' Theorem, posterior distribution for the parameters β and δ represents the posterior information about these parameters.

When assuming conjugate prior distributions, obtaining the posterior distribution becomes straightforward. Nevertheless, for intricate models, the methodology of Gibbs' sampler can be employed, which is an algorithm for simulating Markov Chains.

3. EMPIRICAL ANALYSIS

3.1. Data

To assess the differences and similarities of main determinants on loyalty, two different tourist destinations are considered. One destination is mainly concerned with sun and beach (Barbados), whereas the other attracts cultural-oriented tourists (Ethiopia). It is worth noting that we have used two samples obtained by different random sampling techniques: simple random sampling and stratified-random sampling procedures. The main difference between them is that stratified is preferred when populations can be easily broken down into different subsets and can provide a more accurate representation of the population. Hence, tourists who traveled to Barbados and Ethiopia were differently surveyed.

Next, we briefly explain some characteristics of those datasets.

Barbados' database

Barbados is a well-known, mature, sun and beach Caribbean destination. Survey of international air travelers was supported by both the Inter-American Development Bank (IDB) and the Caribbean Tourism Organization in 2015. Data obtained for this country is based on a stratified-random sampling procedure. Firstly, a pre-test questionnaire was administered to 120 tourists. Later, the survey was stratified attending to the two kinds of tourists in Barbados, i.e., stay over and cruise tourists, where tourists were randomly selected. Thus, 57% was administered at the Grantley Adams International Airport and 43% at the Bridgetown Cruise Terminals over the period June through August 2015. A total of 700 tourists were surveyed randomly at such sites, which resulted in 550 fully useful observations for the purpose of this paper.

Ethiopia's database

Ethiopia is a cultural heritage destination. Survey of international tourists was supported by The World Bank in 2015. Data obtained for this country is based on a simple random sampling procedure. Three different locations were surveyed within Ethiopia: Addis Ababa, Aksum and Lalibela. In Addis Ababa, there are several attractions, such as the National Museum of Ethiopia that hosts "Lucy", a partial skeleton of Australopithecus afarensis, dated to about 3.2 million years ago. Aksum is well-known due to its monolithic obelisks, giant stelae, 'royal thumbs', and the ruins of ancient castles. It has been considered a UNESCO World Heritage site since 1980. Lalibela is famous because of its monolithic cave churches, or Rock-Hewn Churches, which were also recognized as a UNESCO World Heritage Site in 1978. The surveys were carried out at airports during March 2015, and were administered to 440 tourists in total, of which 362 were fully useful.

These datasets are of interest to analyze because both contain the variable characterizing the intention to revisit the destination and several other factors to explain it.

It is worth noting that we do not propose a theoretical destination loyalty formation model but use several variables that are catalogued in terms of groups defined in Section 2. Basically, we have included tourist-related factors (e.g., socio-economic characteristics and trip-related characteristics), but we have not included antecedents such as satisfaction and destination image due to data availability. In general, these variables are in line with the empirical literature and represent individual and vacation characteristics (Meleddu et al., 2015).

Regarding the loyalty variable, it is worth noting that the behavioral loyalty approach has been considered. Therefore, we consider willingness to repeat (or return) and willingness to recommend. Both variables are dichotomous dependent variables and take value 1 for the intention to repeat (revisit) or recommend the destination, respectively; and 0 otherwise.

With regards to the factors potentially explaining the willingness to repeat and recommend, several explanatory variables are considered depending on data availability in the two datasets.[1] These determinants are qualitative and quantitative variables which can be defined as follows:

Previous experience

- *First visit* is a dummy variable which takes value 1 for tourists visiting the destination for the first time, and 0 otherwise.
- *Previous visits* is a categorical variable indicating the number of times the tourist had previously visited the destination in these intervals. This variable is divided into three dummy variables: *Pre-visits: 1* for one visit, *Pre-visits: 2-4* for visits between two and four, and *Pre-visits: ≥5* for visits greater or equal to five. The base category is *Pre-visits: 1*.

Socio-economic characteristics

- *Income* is a categorical variable indicating a tourist's monthly income (in $US) in intervals. This variable contains three categories, and it is split into two dummy variables: *medium income* for incomes between 30,000 and 60,000 $US; and *low income* for incomes under 30,000 $US. The base category is *high income*, for incomes greater than 60,000 $US.
- *Age* of the tourist.
- *Gender* is a dummy variable that takes value 1 for men and 0 for women.
- *Level of studies* is a dummy variable that takes value 1 for tourists with a degree or master's; and 0 otherwise.
- *Occupation* is a categorical variable which contains three categories and is divided into two dummy variables: *Occupation: student,* which takes value 1 for tourists who are studying and 0 otherwise; and *Occupation: retired,* which takes value 1 for tourists who are retired/unemployed, and 0 otherwise. The base category is *Occupation: active*, which takes value 1 for tourists who are working and 0 otherwise.

Vacation characteristics

- *Party* is a categorical variable which contains four categories. We define three dummy variables. *Party: family,* which takes value 1 when tourists come with family, and 0 otherwise; *Party: partner,* which takes value 1 for tourists with partner and 0 otherwise; and *Party: friends,* which takes value 1 for tourists who come with friends, and 0 otherwise. The base category is *Party: alone*, which takes value 1 for lone tourists and 0 otherwise.

Table 2 shows the descriptive statistics for the variables that have been included in the estimated models (defined above).

[1] For example, tourist's satisfaction is an important factor of their loyalty and their intention, but it is not used in our study because data unavailability in the surveys we have used.

Table 2: **Descriptive statistics for variables used in the models**

	Sun and beach (Barbados, *n*=550)				Cultural heritage (Ethiopia, *n*=362)			
Variables	Mean	s.d.	Min	Max	Mean	s.d.	Min	Max
Loyalty								
Willingness to repeat	0.67	---	0	1	0.76	---	0	1
Willingness to recommend	0.91	---	0	1	0.96	---	0	1
Previous experience								
First-visit	0.61	---	0	1	0.97	---	0	1
Pre-visits: 1	0.10	---	0	1	0.06	---	0	1
Pre-visits: 2-4	0.13	---	0	1	0.27	---	0	1
Pre-visits: ≥5	0.16	---	0	1	0.04	---	0	1
Socio-economic characteristics								
Low income	0.06	---	0	1	0.09	---	0	1
Medium income	0.18	---	0	1	0.12	---	0	1
High income	0.76	---	0	1	0.79	---	0	1
Age	44.25	14.70	16	87	48.83	13.38	18	89
Gender	0.47	---	0	1	0.68	---	0	1
Level of studies	0.75	---	0	1	0.97	---	0	1
Occupation: active	0.80	---	0	1	0.84	---	0	1
Occupation: student	0.06	---	0	1	0.01	---	0	1
Occupation: retired	0.14	---	0	1	0.15	---	0	1
Vacation-related characteristics								
Party: family	0.29	---	0	1	0.15	---	0	1
Party: alone	0.22	---	0	1	0.17	---	0	1
Party: partner	0.38	---	0	1	0.17	---	0	1
Party: friends	0.11	---	0	1	0.23	---	0	1
Distance	3941.50	1040.50	175.57	14879.91	7346.56	2820.64	996.05	14444.59
Nights	8.95	9.61	0	180	11.87	9.32	2	99

The average individual traveling to Barbados or Ethiopia has a high income (over 75% of respondents), she is a woman for Barbados, and a male for Ethiopia, and they are first-visit tourists, who are mainly occupied (active). However, there are some differences between them. For example, this average individual comes from very far away in the case of Ethiopia, and the duration of stay is higher for Ethiopia (12 nights) than Barbados (9 nights). Regarding other vacation characteristics, tourists often travel with a partner in Barbados (38%), but with friends in Ethiopia (23%). In general, these sample characteristics are like tourist population characteristics on the year of the survey.

3.2. Modelling the intention to revisit and recommend the destination

This subsection shows results for frequentist and Bayesian methods that are employed to evaluate the pertinence of the proposal investigating destination loyalty and the intention to recommend a destination. Regarding the frequentist method, numerical evaluation is usually required for estimating the regression parameters. In this case, these models provide the probability of each tourist expecting to repeat the visit. Thus, a cut-off in this probability to fit if a tourist will repeat or not, is considered. These frequentist logistic models were estimated using STATA software. Regarding the Bayesian models, we employ the Gibbs sampler methodology, which is an algorithm for simulating Markov chains. This methodology is integrated into the WinBUGS package (Windows Bayesian inference using Gibbs Sampling, Lunn et al., 2000), enabling the sampling of (β, δ) from the posterior distribution (see Carlin & Polson, 1992, and Gilks et al., 1995, for further details).

Tables 3 and 4 show the estimates obtained by considering frequentist and non-informative Bayesian estimations for Barbados and Ethiopia. The tables contain information about the estimated coefficient $\hat{\beta}$, the robust standard errors (SE) or MC error (MCE) for frequentist or Bayesian estimations, respectively. In relation to Bayesian results, non-informative prior distributions are assumed, i.e., $\sigma_j^2 = 10^8, \forall j = 1, \ldots, k,$ and $\sigma_\delta^2 = 10^8$. The posterior estimations were obtained carrying out 500,000 iterations, for each sample, after a burn-in of 100,000 simulations.

Three different measures to analyze the goodness of fit of the models have been calculated: (1) the percentage of correct fits; (2) the deviance (DIC), the Akaike (AIC) and the Bayesian (BIC) information criteria; and (3) the area under the Receiver Operating Characteristic (ROC) curve, i.e., the *c*-statistic.

3.2.1. Willingness to repeat

As shown in Table 3, according to the Barbados frequentist estimation, the fact of visiting this island for the first time is statistically significant in explaining the destination's loyalty probability, at the 1% significance level. If a tourist visits Barbados for the first time, then the destination loyalty probability decreases. The distance, medium income, the number of previous visits (≥ 5) and the level of studies are significant at the 5% significance level (α = 5%). The greater the distance, the lower the destination's loyalty probability is, i.e., the destination loyalty probability decreases when the distance increases. On the other hand, the loyalty probability for tourists with medium incomes (in relation to those with high incomes) decreases.

Also, each previous visit, greater or equal to 5, increases the destination loyalty probability. The fact of holding a degree or a master's, as a level of education, decreases the likelihood of Barbados loyalty. Finally, tourists with low incomes, men or older people are less likely to repeat visit, but now at $\alpha = 10\%$.

Table 3 also shows the results under a Barbados Bayesian estimation obtaining, approximately, the same significant coefficients and signs as the frequentist ones except for low incomes, which are no longer statistically significant. However, asymmetric Bayesian estimations detect one new negative and relevant factor ($\alpha = 10\%$) in relation to the frequentist, i.e., travelling with family in contrast to doing it alone. In terms of probabilities, it reduces the probability. As can be observed, in general, the estimated coefficients differ considerably from those of the frequentist model and are greater for both increases and decreases. The Bayesian asymmetric estimation, apart from introducing a new factor, also intensifies the relationships of the significant coefficients with destination loyalty probability. Furthermore, the asymmetry coefficient, δ, is negative and statistically significant (at 1% level of significance). It seems that δ parameter adjusts the estimated destinations' loyalty probability by decreasing it and assuming asymmetry in the data. The difference between frequentist and Bayesian estimations is further accentuated in relation to the intercepts.

Table 3 also shows the Ethiopia frequentist and Bayesian estimations. According to the former, the fact of visiting this country with friends in contrast to doing it alone decreases the probability of repeat visits ($\alpha = 5\%$). Furthermore, being a student in contrast to being an active worker, and age, are negative determinants with $\alpha = 10\%$ decreasing the loyalty probability.

As in the case of Barbados, Bayesian estimations for Ethiopia obtains, approximately, the same signs and significant determinants (traveling with friends, students and age) as frequentist, but also detects three new significant and very important ($\alpha = 1\%$) characteristics for explaining the probability of repeating a destination. Tourists with a degree or master's and the fact of having previously visited the country between two and four times are determinants that increase destination loyalty probability. Moreover, men are more likely to repeat visits to Ethiopia than women. Again, Bayesian asymmetric estimations intensify the relationships of the significant coefficients with the destination loyalty probability and the asymmetry coefficient being negative and statistically significant.

Table 3: **Asymmetric Frequentist/Bayesian estimations for willingness to repeat visit**

	Sun and beach (Barbados, *n*=550)				**Cultural heritage (Ethiopia, *n*=362)**			
	Frequentist		**Bayesian**		**Frequentist**		**Bayesian**	
Variables	$\hat{\beta}$	**SE**	$\hat{\beta}$	**MCE**	$\hat{\beta}$	**SE**	$\hat{\beta}$	**MCE**
Previous experience								
First-visit	-0.572***	0.193	-7.461***	0.051	-1.242	1.101	-4.342	0.059
Pre-visits: 2-4	0.076	0.233	3.391	0.037	2.607	1.957	11.68***	0.061
Pre-visits: ≥5	0.450**	0.229	10.62***	0.053	0.960	1.545	4.267	0.039
Socio-economic characteristics								
Low income	-0.528*	0.308	-3.594	0.021	0.501	0.735	2.446	0.031
Medium income	-0.303**	0.154	-3.879**	0.021	-0.110	0.607	-0.133	0.016
Age	-0.102*	0.005	-1.636*	0.011	-0.086*	0.048	-5.297***	0.023
Gender	-0.221*	0.121	-2.385*	0.017	1.212	0.890	6.906***	0.036
Level of studies	-0.308**	0.136	-2.884*	0.024	0.701	1.391	7.058***	0.083
Occupation: student	-0.269	0.299	-2.212	0.022	-5.732*	3.172	-11.31*	0.028
Occupation: retired	0.217	0.204	3.154	0.025	0.218	0.897	1.404	0.023
Vacation-related characteristics								
Party: family	-0.268	0.169	-3.217*	0.028	-0.166	0.729	0.618	0.026
Party: partner	-0.109	0.162	-0.149	0.026	0.068	0.787	0.807	0.025
Party: Friends	-0.174	0.223	-1.539	0.028	-2.552**	1.268	-11.70***	0.049
Distance	-0.0002**	0.001	-1.252***	0.006	0.00006	0.0001	0.904	0.008
Nights	-0.001	0.005	-0.839	0.005	-0.025	0.031	-0.804	0.008
Intercept	-9.866***	2.369	29.0***	0.141	7.126	5.139	18.71***	0.127
δ	12.127***	2.439	-20.560***	0.096	-0.746	0.677	-20.960***	0.091
% Correct fit with cut-off=0.5	70.36		100		82.04		100	
% Correct fit with cut-off=0.911 (B) or 0.958 (E)	65.27		100		75.69		99.72	
DIC	612.399		171.576		296.834		83.67	
AIC	646.399		115.9		330.834		74.16	
BIC	719.668		180.6		396.992		136.4	

Notes: *** indicates 1% significance level. ** indicates 5% significance level. * indicates 10% significance level.

All the information criteria (DIC, AIC and BIC) are lower for asymmetric Bayesian estimations, indicating better results in terms of fit. Moreover, for the cut-offs of 0.5 and the sample means, these estimations also give better results for both Barbados and Ethiopia, in terms of classification, indicating the best leverage of all models considered.

3.2.2. Willingness to recommend

According to the Barbados frequentist estimation in Table 4, there is only one determinant that explains the probability to recommend the destination, i.e., the number of nights tourists spend at destination. Specifically, each night that the tourist is at the destination, the probability of recommending it increases with a level of significance of 5%. Bayesian estimations increase this relationship and detect three new determinants, although with a weak significance (α = 10%). Women and traveling with family or a partner (in contrast to doing it alone) increase the probability of recommending the destination under Bayesian estimations.

For Ethiopia, frequentist maximization procedure failed to converge to a solution, so only Bayesian estimations are shown. These reveal several important and significant determinants to explain intention to recommend. Again, the number of nights is a positive factor that increases the probability of recommending. In this case, men (α = 1%) are most likely to recommend this destination. Moreover, tourists visiting the destination with a degree or a master's and/or tourists who are retired increase their probability of recommending Ethiopia (α = 5%). Finally, under a Bayesian estimation, visiting the destination with a partner increases the probability to recommend (α = 5%).

Table 4: **Asymmetric Frequentist/Bayesian estimations for willingness to recommend**

	Sun and beach (Barbados, *n*=550)				**Cultural heritage (Ethiopia, *n*=362)**	
	Frequentist		**Bayesian**		**Bayesian**	
Variables	$\hat{\beta}$	**SE**	$\hat{\beta}$	**MCE**	$\hat{\beta}$	**MCE**
Previous experience						
First-visit	-0.108	0.193	2.108	0.049	-1.123	0.055
Pre-visits: 2-4	-0.180	0.241	1.182	0.046	2.087	0.052
Pre-visits: ≥5	-0.132	0.232	2.42	0.046	-3.384	0.035
Socio-economic characteristics						
Low income	-0.148	0.251	-0.249	0.028	5.35	0.027
Medium income	-0.207	0.151	-2.792	0.023	1.955	0.022
Age	-0.007	0.005	-1.857	0.012	-0.659	0.009
Gender	-0.196	0.122	-2.738*	0.023	7.625***	0.034
Level of studies	-0.032	0.127	1.788	0.035	9.987**	0.078
Occupation: student	-0.235	0.271	-2.592	0.026	3.77	0.019
Occupation: retired	0.089	0.201	2.209	0.027	12.23**	0.017
Vacation-related characteristics						
Party: family	0.184	0.165	5.284*	0.036	5.234	0.022
Party: partner	0.136	0.154	4.201*	0.019	11.09**	0.015
Party: Friends	0.156	0.209	3.906	0.033	-4.14	0.025
Distance	0.00005	0.00005	1.231	1.505	-0.147	1.86
Nights	0.023**	0.009	4.208***	0.019	6.943***	0.026
Intercept	-12.616***	0.952	30.45***	0.123	19.13***	0.097
δ	13.605***	0.805	-20.21***	0.085	-15.61***	0.057
% Correct fit with cut-off=0.5	91.09		100		100	
% Correct fit with cut-off=0.911 (B) or 0.958 (E)	59.27		100		96.13	
DIC	318.91		78.85		30.25	
AIC	350.91		69.49		43.18	
BIC	419.87		142.8		97.66	

Notes: *** indicates 1% significance level. ** indicates 5% significance level. * indicates 10% significance level.

Again, in the case of Barbados, all the information criteria (DIC, AIC and BIC) are lower for asymmetric Bayesian estimations indicating better results in terms of fit. Moreover, for the cut-offs of 0.5 and the sample mean, these estimations also give better results in terms of classification, indicating the best leverage of all models considered. Regarding Ethiopia, a high percentage of correct fits (100% for a cut-off of 0.5 and 96.13% for the sample mean as the cut-off) can be observed.

3.2.3. Post-Estimation

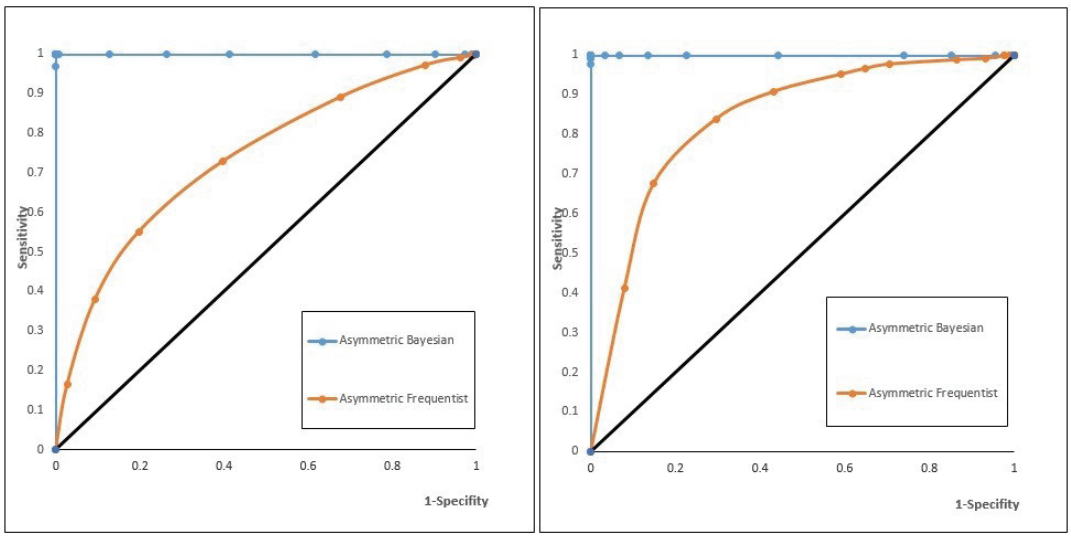
This section analyzes the post-estimation results from the frequentist and Bayesian estimations. In this sense, it shows some descriptive statistics for the estimated probabilities and illustrates the fittings of the models by using the ROC curves.

Table 5 shows the mean, standard deviation, skewness, kurtosis, minimum and maximum and some percentiles for the estimated probabilities obtained from the Barbados and Ethiopia databases for loyalty and recommend models. This table also shows the *c*-statistics, the area under the ROC curve that is represented in Figure 1. This curve links, in the [0-1] interval, sensitivity with (1-specificity) for all the models. The larger *c*-statistic corresponds with a better fitting of the model, which translates into a larger area under the curve. When sensitivity and specificity are equal to 1, the maximum *c*-statistic is obtained (see Guillén, 2004, for further details). As can be seen, the asymmetric Bayesian model produces the best fittings.

Table 5: **Descriptive statistics for estimated probabilities in the intention to revisit and recommend**

	Sun and beach (Barbados, *n*=550)		Cultural heritage (Ethiopia, *n*=362)	
	Frequentist	**Bayesian**	**Frequentist**	**Bayesian**
Panel A: *Willingness to repeat*				
Mean	0.669	0.668	0.755	0.755
Standard deviation	0.178	0.417	0.232	0.395
Skewness	-0.183	-0.711	-1.246	-1.184
Kurtosis	2.484	1.523	3.694	2.425
Minimum	0.066	0.028	0.067	0.020
Maximum	0.999	0.999	0.991	1
Percentiles				
p_{25}	0.538	0.092	0.654	0.827
p_{50}	0.667	0.945	0.832	0.980
p_{75}	0.826	0.976	0.939	0.994
p_{90}	0.918	0.987	0.975	0.998
c-statistic	0.731	1	0.834	1
Panel B: *Willingness to recommend*				
Mean	0.911	0.911	---	0.958
Standard deviation	0.042	0.247	---	0.160
Skewness	-0.617	-2.833	---	-4.567
Kurtosis	3.062	9.342	---	22.079
Minimum	0.771	0.069	---	0.136
Maximum	1	1	---	1
Percentiles				
p_{25}	0.883	0.981	---	0.985
p_{50}	0.919	0.989	---	0.996
p_{75}	0.941	0.994	---	0.999
p_{90}	0.961	0.998	---	1
c-statistic	0.819	0.823	---	1

Figure 1: **ROCs curves for willingness to repeat: Barbados (left) and Ethiopia (right)**



3.3. Discussion of results

The main empirical findings are discussed in this section and are supported by the employment of post-estimation probabilities and its relationship with different underpinnings. Specifically, the use of semi-parametric methods based on rolling windows are employed, as they provide a better picture of the non-linear relationship between the probabilities and the variables.

3.3.1. Willingness to repeat

First visit

The parameter associated with first visit is negative and significant for Barbados. This suggests that tourists are willing to visit the island only once, and it is different to Meleddu et al. (2015). That makes sense when alternative sun and beach destinations are available, and it reinforces the idea of sun and beach destination competition. For Ethiopia, the parameter is also negative but not significant. Thus, it suggests that many tourists face 'discovery satiation' after visiting cultural heritage destinations, but for some cultural heritage remains more appealing to repeat after the first visit than sun and beach destinations.

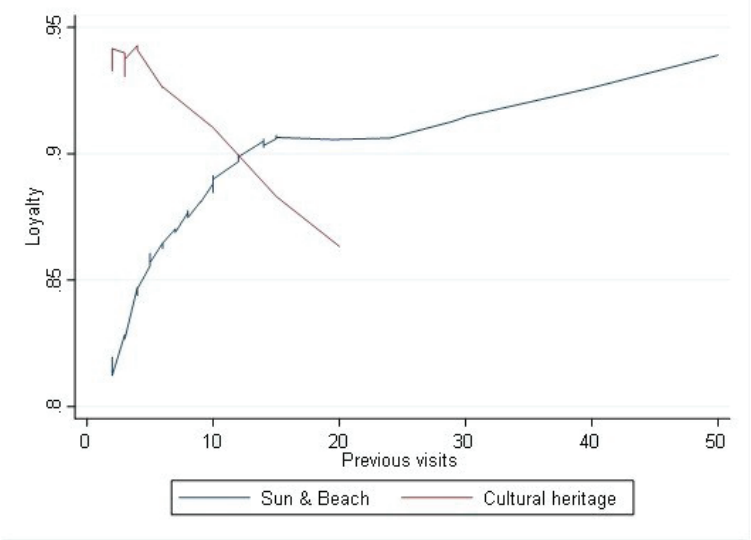
Previous visits

The significance of the number of previous visits is valuable information for understanding loyalty patterns. In papers examining the factors that affect the intention to return using logit regressions, authors have found that the "number of visits" had a positive effect on the probability to return (e.g., Gabe et al., 2006; Meleddu et al., 2015; Jin et al., 2022).

The differences between Barbados and Ethiopia are very interesting. Loyalty is more likely to happen in Ethiopia when the number of previous visits is not very high. This suggests the presence of a cap on the number of revisits in cultural heritage destinations. However, the Barbados case is different. The loyalty pattern shows that more visits reinforce the repeat visit intention. It encourages loyalty. It suggests that, for sun and beach destinations, tourists may establish a life-long relationship. Similar results were found by Meleddu et al. (2015) analyzing the tourist destination of Sardinia (Italy).

To compare CHD and SBD, we have employed the following strategy. Given that the sampling techniques differ for each destination (see Section 4.1), we have chosen to graphically compare the estimated probabilities between SBD and CHD for the variables of interest. These comparisons are presented in Figure 2, where we plot the estimated probabilities using the asymmetric logit model against the number of previous visits. In this figure, it is clearly observable that the probability of revisiting increases in SBD as the number of previous visits rises, while it decreases in CHD. Therefore, the probability patterns with respect to previous visits differ, which could provide supportive evidence for H1.

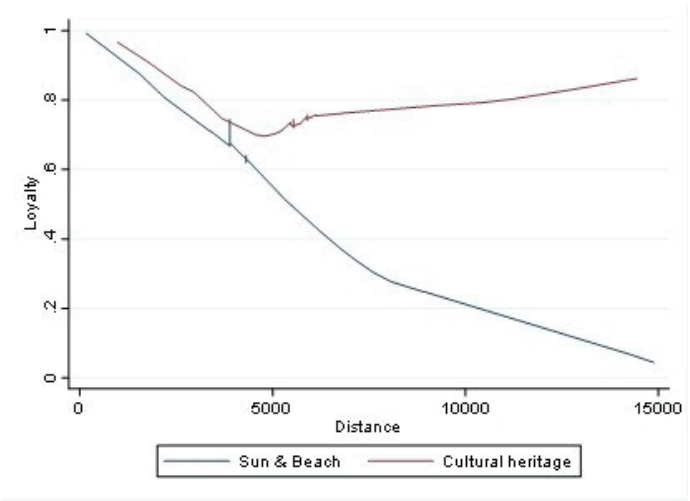
Figure 2: **The relationship between the number of previous visits and loyalty by kind of tourism destination**



Distance

The parameter associated with distance is significant and negative for Barbados, which shows that farther sun and beach destinations are less likely to be revisited (Jin et al., 2022, obtained a positive result for short distances - 167-km versus 312-km). Figure 3 shows a similar decreasing relationship between distance and the probability to revisit, but after a certain distance threshold, the loyalty for cultural heritage remains, whereas the loyalty for sun and beach keeps decreasing.

Figure 3: **The relationship between distance and loyalty by kind of tourism destination**



Our intuition about this result is as follows. Sun and beach destinations are available around the world. The Caribbean, for example, has got hundreds of alternative destinations to choose from. Obviously, each destination is different, but they satisfy similar needs of relaxation and enjoyment. The distance between place of residence and the destination represents a fixed cost for tourists in terms of travel cost and travel time. Unless the destination quality makes a difference, tourists prefer repeating sun and beach destinations that are closer. The estimation shows that distance is not relevant for visiting Ethiopia. Cultural heritage destinations are unique destinations. For instance, if tourists wish to visit 'Lucy', the only place she can be seen is there. Tourists must travel the required distance to enjoy this kind of cultural heritage. These results suggest that sun and beach destinations work under competition while cultural heritage destinations function as natural monopolies.

Therefore, probability patterns against distance are clearly different, and it could indicate favorable evidence for H2.

It is worth noting that our distance decay pattern in SBD is like the decay pattern in international tourism found by McKercher (2008). The short-haul market tends to be more homogenous, while the long-haul tends to be more exclusive (McKercher, 2009). McKercher (2009) pointed out that these differences translate into significant differences in the profile, travel patterns and behavior at destination.

Level of studies and income

The parameter associated with the level of studies is positive and highly significant for cultural heritage. It shows that tourists who hold degrees or masters are very interested in repeating visits to cultural heritage destinations (85.04% of these tourists). However, the parameter associated for sun and beach is negative and significant. It suggests that less educated tourists are more interested in sun and beach than cultural heritage destinations (76.11% of these tourists). Figure 4 shows this relationship, again, by combining it with age.

Figure 4: **The relationship between the level of studies and loyalty by kind of tourism destination**

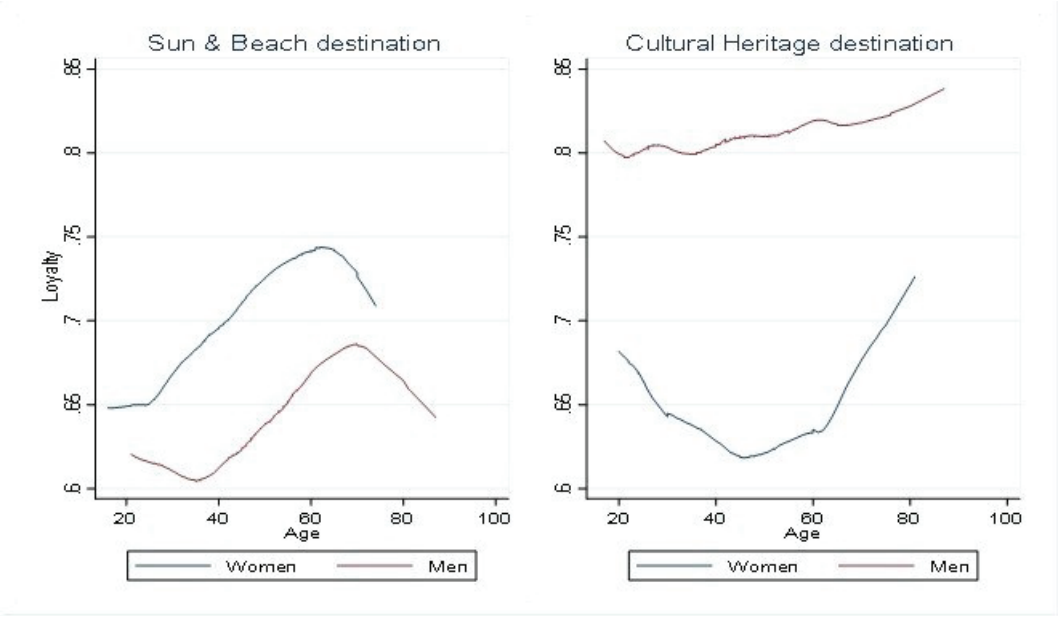
Therefore, probability patterns against age by low and high level of studies are different, and it could indicate favorable evidence for H3.

The variable income seems to be important for willingness to repeat in Barbados. It shows that tourists with high incomes are more likely to repeat (70.99 %) than those with medium (59.89%) or low (51.81%) incomes. It is worth noting that Meleddu et al. (2015) also found high income tourists have greater probability to revisit than low- and medium-income tourists studying the SBD of Sardinia (Italy).

Gender

The results show a marked difference between genders. Men are less interested than women in repeating visits to sun and beach destinations (63.57% for men and 71.61% for women), but on the contrary, they are much more interested in revisiting cultural heritage destinations than women (87.37% for men and 77.88% for women). Figure 5 provides a richer picture of this relationship by combining probability of willingness to return with age. It shows that women are more interested in repeating traveling to sun and beach destinations than men for all ages. On the contrary, men are much keener on repeating cultural heritage destinations for all ages.

Figure 5: **The relationship between gender and loyalty by kind of tourism destination**



Party composition

The results show that parties composed of friends are not interested in repeating visits to Ethiopia. This makes sense as Ethiopia still has insufficient places to enjoy during the afternoon or night, especially in Lalibela and Axum. This idea is reinforced by the negative sign for students, who are less interested in repeating visits to the country. Moreover, the results also show that the parameter associated with parties composed by families is negative for Barbados. This parameter needs to be understood together with the other categories. It suggests that the island is more oriented towards tourists traveling alone, and at a lower degree, parties with friends or partners rather than families.

Age

The parameters associated with age are negative and significant. Literature in this regard has found mixed results regarding SBD. For example, Jin et al. (2022) found similar results such as Mallorca, but Meleddu et al. (2015) found the opposite for Sardinia.

Thus, older tourists are less likely to repeat visits. That is an expected result since younger tourists are expected to have more time to revisit than older people. However, the parameter for Ethiopia is larger than that for Barbados. This can be explained by the need to be more active in Ethiopia than in Barbados. Ethiopia, especially Lalibela, does not have the resources to address the needs of elderly tourists with reduced mobility. If older tourists cannot enjoy the destination sufficiently, they will be less interested in repeating the visit. That is a particular problem in Ethiopia, but provided mobility is achieved safely it may not be the case in other cultural heritage destinations.

3.3.2. Revisit vs. recommend intention

The results of willingness to recommend are less marked than those obtained from the willingness to repeat visits. This occurs because most tourists state that they are willing to recommend. This is problematic for the frequentist estimation since it cannot obtain results, as in the Ethiopian case, and the number of significant determinants is very limited. The Bayesian approach provides a richer picture of results as well, as it can be estimated for the Ethiopian case. Nevertheless, the results provide a similar but not equal picture to the repeat visits case.

The main difference lies in the irrelevance of certain variables. Distance is not significant to recommend, but it is to revisit. This suggests that despite most tourists understanding that distance is problematic to repeat visits to Barbados, it is worth recommending, even if they live far from it. Moreover, the number of previous visits makes no difference on the emphasis to recommend. The same applies to income and age. The differences are found in gender. Men are more likely to recommend Ethiopia than women, whereas women are more likely to recommend Barbados than men. Tourists who hold a degree or master's degree are more likely to recommend visiting Ethiopia than tourists who do not. Parties composed by partners or families are more likely to recommend visiting Barbados, but Ethiopia is only recommended by parties composed of partners and retired tourists.

Overall, the results show that the intention to revisit or recommend are not the same. They are certainly correlated, but they are underpinned by different factors in terms of behavior.

CONCLUSIONS

This study analyzes the probability to revisit and recommend a destination based on the intention to revisit (behavioral loyalty) and recommend (attitudinal loyalty) the destination by proposing the use of an asymmetric Bayesian logit model, which considers the asymmetric pattern of the destination's loyalty variable. This methodology has not previously been employed in this context. The paper compares this model with the asymmetric frequentist approach. These models introduce new statistically significant factors to explain why a destination's loyalty probability is different to others. That is, the asymmetric Bayesian model identifies several important new factors with respect to the frequentist model, namely the gender, the tourist's level of studies and the number of previous visits; all of them for the Ethiopia destination and the intention to repeat; and the gender and party composition for the Barbados destination and the intention to recommend.

Next, we conclude with the theoretical and practical implications of our study.

Theoretical implications

The results show that the proposed asymmetric Bayesian logit model is better fitted than the frequentist model to assess determinants of destination loyalty. Particularly, the percentage of correct fits, the information criteria and the *c*-statistic support the importance of considering the asymmetry in the discrete choice models for Barbados and Ethiopia's database, respectively. Therefore, asymmetric Bayesian models can be used to assess the effects of several determinants explaining destination loyalty.

The findings of this study provide substantial support for existing theories of consumer behavior and loyalty, particularly by illustrating the nuanced dynamics that underpin these concepts. By integrating asymmetric Bayesian approaches into current loyalty frameworks, this research not only enhances the theoretical discourse but also offers a more sophisticated understanding of consumer preferences. Furthermore, the study contributes to methodological advancements in tourism research by demonstrating the superior efficacy of asymmetric Bayesian models compared to traditional methodologies. This methodological innovation allows for a more accurate representation of the complexities inherent in consumer decision-making processes, thereby enriching the overall analytical landscape of the field.

Practical implications

Our results allow us to propose two general practical implications.

On the one hand, the asymmetric structure of the loyalty variable should be included in tourism modeling so that destination loyalty policies can become more defined, based on Bayesian results rather than frequentist models. This updated information should be helpful to several tourism stakeholders, including business entrepreneurs, government bodies and tourism workers.

On the other hand, the study has also allowed us to compare the factors that underpin loyalty between sun and beach and cultural heritage destinations. Based on the Barbados and Ethiopian cases, some interesting differences can be drawn with practical implications for other similar destinations. First, distance matters as a negative determinant for repeating a visit to Barbados, whereas it does not matter for Ethiopia. The higher travel cost sensitivity of Barbados may be related with current higher competition in terms of alternative sun and beach destinations to visit in the Caribbean Sea. However, Ethiopia offers a differentiated tourism product, and travel cost is therefore not perceived as a barrier. Second, current loyalty, measured by the number of previous visits, is a significant determinant of repeat visits in Barbados when the number of previous visits is high,

but not in Ethiopia. However, when the number of previous visits is low, the probability of repeat visits increases in Ethiopia. This shows that long-term loyalty patterns are more likely to be found at sun and beach destinations than at cultural heritage destinations. Third, moreover, there are gender differences. Women are more likely to be loyal to sun and beach destinations, whereas men are more likely to be loyal to cultural heritage destinations. Finally, tourists who hold graduate or post-graduate degrees are more likely to be loyal to cultural heritage destinations (the behavioral probability increases), rather than to sun and beach destinations (the behavioral probability decreases).

Finally, it is essential to issue a compelling call to action for stakeholders, highlighting the necessity of incorporating Bayesian models into their decision-making processes. Stakeholders should be encouraged to adjust their loyalty strategies in accordance with the distinctive characteristics delineated between various types of destinations. By leveraging Bayesian approaches, stakeholders can enhance their understanding of consumer behavior and preferences, ultimately fostering more effective and targeted loyalty initiatives. This strategic adjustment is crucial for maximizing engagement and satisfaction among diverse traveler demographics.

Certain limitations of the study should be acknowledged. Primarily, the main limitation of the paper is the use of data from only two destinations, which restricts the generalizability of the results. Additionally, the sampling techniques differ, and the samples are somewhat dated. Although the tourism industry has undergone significant changes in terms of digital advancements and shifting consumer behaviors, we contend that many fundamental aspects influencing repeat visitation, such as destination appeal, cultural significance, and personal experiences, remain consistent over time. Besides, the database used should incorporate additional variables relevant to the theoretical models employed in the study of destination loyalty. For instance, variables such as satisfaction, perceived quality, and value, as well as other recently incorporated variables like familiarity, could be included in a new database to investigate SBD and CHD. However, the data collected in this study did not allow for the assessment of these variables. Moreover, while other sun and beach or cultural heritage destinations could have been included to achieve more accurate results, they exhibited insufficient variability for our study. Nonetheless, the methodological approach employed can be applied to other similar destinations with high current visitation, such as many European islands and continental CHD destinations (e.g., Italy, Spain, France).

Future research could develop new methodologies, such as the panel data approach, to estimate global or regional destination loyalty. This context allows us to compare different regions in the world such as Asia, Pacific, Oceania, Europe, and America. Also, they could enable analysis of loyalty using the asymmetry logit Bayesian panel data model.

DATA AVAILABILITY STATEMENT

Data associated with this study is not deposited into a publicly available repository. Data will be made available on request.

DECLARATIONS

Review and/or approval by an ethics committee was not needed for this study because it does not include identifiable human material or identifiable data.

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