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Research paper

A latent class approach to estimate air travelers' propensity toward connecting itineraries

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ABSTRACT

Travelers' choices have been widely studied, and insights have been established on the values associated with different itinerary attributes. This paper extends the current literature by including a novel determinant of air travelers' behavior—that is, the extent to which a connecting itinerary is marketed and handled by an operating carrier. By relying on a stated preference survey, we collect passengers' preferences and analyze them by means of a latent class choice model accounting for both service-related and individual characteristics. Individual characteristics comprise attitudes derived from a factor analysis performed on attitudinal responses toward travel, namely *anxiety* and *timeliness and quality*. The results reveal that individuals who care more about timeliness and quality are less sensitive to price, more sensitive to time, and more likely to opt for a nonstop alternative. Additionally, the value assigned to handled connections is considerable (higher for anxious travelers).

1. Introduction

The planning and development of air transport networks is a challenging and multi-stage task that heavily relies on advanced predictive and prescriptive analytics to make optimal decisions. A key input to the planning process is the estimation of air travel demand. In this domain, increasing attention has been devoted to the capturing of passenger behavior so as to anticipate and possibly address competitive dynamics. Literature and practice mostly rely on discrete choice modeling to mirror itinerary choice by passengers as a function of key supply-related variables—such as price, flight time, routing, and departure time preferences (Garrow, 2016). These variables are partly under control of airlines in structuring their networks and pricing control algorithms. Hence, anticipating how passengers will react to changes in the level of supply, and conditional upon the offering by competing airlines, is paramount. This is even more important in complex networks where self-competition dynamics and shared supply among overlapping itineraries operated by the same company exist (Birolini, Besana, Cattaneo, Redondi, & Sallan, 2022). Moreover, having a demand model that captures the trade-offs and substitution patterns between demand and air travel services is key for policy-making and authorities aiming to assess the impact of network changes from a societal perspective and drive their sustainable/welfare-oriented development.

Despite established models bring strong evidence on macro-factors affecting passenger allocation (e.g., on the magnitude of price elasticities and average value of times), the ongoing changes of the industry—including changes in the passenger mix, their attitudes and perceptions toward air traveling, and business models—require a continuous (re-)assessment of model coefficients to effectively drive decision-making.

Our paper contributes to the literature on itinerary choice in three major ways. First, it develops a tailored stated preference survey to investigate key trade-off(s) between level-of-service and connection quality attributes, while considering a novel feature, that is, whether connecting itineraries are actively marketed and handled by an airline or not—as in the case of self-hubbing, where passengers arrange their trip, bearing the risk of misconnection and the burden of undergoing repeated security screening—and explore its impact on different lengths of haul. The focus on handled vs. self-connect itineraries is motivated by the recent hybridization of airline business models, under which low-cost carriers (LCCs) have started to exploit their extensive network of flights to provide attractive connections and possibly increase their profits. Despite the topic having spurred numerous studies in the last 15 years (see, e.g., Fageda, Suau-Sanchez, & Mason, 2015; Klophaus, Conrady, & Fichert, 2012; Maertens, Pabst, & Grimme, 2016; Malighetti, Paleari, & Redondi, 2008; Morlotti, Birolini, Cattaneo, & Redondi, 2020), to our knowledge, there is no study to date that empirically investigates the demand potential of self-hubbing itineraries and

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the premium of integrated transfer services. Nonetheless, this is key to support decision-making on connection planning by LCCs (Birolini et al., 2022) and makes one of the key intended contributions of this paper.

Second, this work implements an exploratory factor analysis (EFA), followed by a latent class choice model (LCCM). The factors identified in the EFA, i.e., *timeliness and quality* and *travel anxiety* are included in the LCCM model as features determining class membership (along with demographic determinants, such as age and gender) and are found to significantly affect passenger preferences toward connecting itineraries.

Third, we focus specifically on millennials, that is, individuals born between the early 1980s and early 2000s. Millennials are recognized as one of the largest traveling population segment and, at the same time, they exhibit a different travel behavior and to make different transport choices compared to past generations (Delbosc et al., 2019; Delbosc & Ralph, 2017; Garikapati, Pendyala, Morris, Mokhtarian, & McDonald, 2016), making them worthy of investigation.

Ultimately, this study contributes to advancing knowledge around air itinerary choice behavior and bringing novel insights regarding new business models underpinning the current evolution of the sector.

The remainder of this paper is structured as follows. Section 2 reviews the current literature on travel choices. Sections 3 and 4 detail the research design and the methodology of our work. Section 5 illustrates the outcomes of our analysis, providing interesting insights. Finally, Section 6 includes concluding remarks, comprehending limitations, avenues for future research, and policy implications.

2. Literature review

In this section, we review the related literature on which we build our study. We first provide background on the notion of discrete choice modeling (DCM) that is relevant to our paper. We then review the use of discrete choice models in an aviation context, and specifically related to the modeling of itinerary choice.

Introduced first by McFadden in 1974 (McFadden, 1974), the theory and methodology of DCM has quickly developed in the last fifty years, providing researchers and practitioners with a powerful toolkit to model consumer behavior and systematically interiorize this information into the (effective) design of products and services (see, e.g., Ben-Akiva, Lerman, Lerman, et al., 1985; Train, 2009, for a review). DCM is rooted in the random utility theory, according to which people choose a given alternative based on its utility and the utilities of the other alternatives in the choice set. The utility of an alternative is modeled as a two-part function: a deterministic (or observable) component, that is, the part of the utility that can be measured by the modeler, and a random (or unobservable) component, capturing those factors that impact the choice but are not directly accounted for by the modeler. Based on the assumption about the distribution of the random component, different DCM formulations are derived. The simplest and most widely used formulation is the *multinomial logit* (MNL). Assuming that the random terms are independently and identically distributed (IID) following an extreme-value Gumbel distribution, an exponential closed-form function for the choice probabilities can be obtained. This, in turn, makes the MNL highly readable and interpretable, which is one of the reasons for its wide use and application. However, the MNL formulation suffers from two main limitations that limit its applicability and thus motivate the development of advanced and more flexible discrete choice models. In particular, the MNL model cannot properly deal with passenger heterogeneity and may provide unrealistic substitution patterns due to its intrinsic independence of irrelevant alternatives (IIA) property. Among the advance methods that are capable of addressing these issues, there are *Nested Logit* models, which overcome the IIA shortcoming by grouping similar alternatives into nests to capture relevant correlation patterns; *Mixed Logit (ML) models*, which solve both the heterogeneity issues and IIA shortcoming by means of random parameters; and *Latent class* methods, which instead explicitly capture heterogeneous preferences by simultaneously grouping individuals into subgroups and estimating a separate set of coefficients for each group. In this paper, we implement a latent class approach to explicitly investigate the preference toward connecting itineraries of different users, which will be detailed better in Section 4.

Discrete choice models have been widely used in aviation studies (Garrow, 2016). In particular, a number of studies have leveraged DCM to investigate the drivers of passenger allocation among different travel alternatives, either between airlines and airports or at the level of single itineraries (e.g., Hsiao & Hansen, 2011; Marcucci & Gatta, 2011; Munoz & Laniado, 2021). In conjunction with models that estimate the total market size—that is, the total amount of passengers that are expected in a given city-pair—demand allocation models are key input for airline and airport planning processes that are aimed at matching air transport supply and passenger demand in the most profitable way (Birolini, Antunes, Cattaneo, Malighetti, & Paleari, 2021). Table 1 reports some of the most relevant studies of itinerary choice. These models investigate the role of a variety of factors that concur to explain and capture passengers' behavior and explore the use of up-to-date discrete choice methodologies to enhance modeling accuracy.

The determinants considered are many and encompass a variety of attributes related to level-of-service, connection quality, carrier-related factors, and passenger attributes. Most of the studies listed in Table 1 consider some proxies of the out-of-pocket cost of travel incurred by passengers (e.g., ticket price or the average airfare), travel times, itinerary detours (e.g., proxied by the number of stops or the itinerary routing factor), and service frequency. Additional relevant features involve airport and airline characteristics—mostly captured by fixed effects for each individual operator (e.g., Adler, Falzarano, & Spitz, 2005; Birolini, Cattaneo, Malighetti, & Morlotti, 2020; Proussaloglou & Koppelman, 1999) or considering, for example, the distinction between airline types (Hsiao & Hansen, 2011; Jung & Yoo, 2014)—the aircraft type and configuration (e.g., Coldren, Koppelman, Kasturirangan, & Mukherjee, 2003; Warburg, Bhat, & Adler, 2006), the punctuality and reliability of air travel itineraries (Warburg et al., 2006; Yimga, 2017), the schedule convenience—captured by schedule delay and time-of-day preference functions (e.g., Coldren & Koppelman, 2005; Koppelman, Coldren, & Parker, 2008; Lurkin, Garrow, Higgins, Newman, & Schyns, 2017; Proussaloglou & Koppelman, 1999)—the risk of misconnection, and the trade-off between a too-short/too-long connection time (e.g., Herring, Lurkin, Garrow, Clarke, & Bierlaire, 2019; Theis, Adler, Clarke, & Ben-Akiva, 2006), the timing of the booking (Freund-Feinstein & Bekhor, 2017), as well as more qualitative factors such as carrier image and passenger loyalty (Proussaloglou & Koppelman, 1999; Seelhorst & Liu, 2015).

Several demographic and trip-related characteristics were also investigated, including passenger's gender, trip purpose, age, employment status, income level, and travel frequency (Seelhorst & Liu, 2015; Warburg et al., 2006). Along with these passenger-related attributes, more recently, attitudinal factors have been introduced into discrete choice models, although the proof of their key role dates back to the late eighties (Ajzen, 1991; Kuppam, Pendyala, & Rahman, 1999; Train, McFadden, & Goett, 1987). An attitude can be defined as an intrinsic feature of an individual, referring to their way of behaving with regards to life and society (Bahamonde-Birke, Kunert, Link, & de Dios Ortúzar, 2017). Literature on travel behavior underlines the importance in accounting for emotional factors and travel-related attitudes when investigating individuals' choices (*e.g.* He & Thøgersen, 2017; Kroesen, Handy, & Chorus, 2017), often proving to be more significant than other factors (Kuppam et al., 1999). Evidence on the impact of attitudes in influencing travel behavior is particularly demonstrated in mode choice studies. Among the most investigated attitudes, concern about the natural environment is deeply explored as a determinant of choices toward more sustainable transport modes (Popuri, Proussaloglou, Ayvalik, Koppelman, & Lee, 2011; Scorrano & Danielis, 2021; Shiftan, Outwater, & Zhou, 2008). Safety, privacy, comfort, and stress

Table 1
Studies on air travel itinerary choice modeling.

#	Paper	Scope	Data			Method
			RP	SP	Source	
1	Proussaloglou and Koppelman (1999)	US markets	x	x	Mail & phone	MNL
2	Coldren et al. (2003)	US markets	x		CRS/OAG	Aggr. MNL
3	Coldren and Koppelman (2005)	US & Canadian markets	x		CRS/OAG	Aggr. MNL, NL, WNL
4	Adler et al. (2005)	US markets	x	x	Online survey	MMNL
5	Warburg et al. (2006)	US markets	x	x	Online survey	MMNL
6	Theis et al. (2006)	US markets		x	RSG extended	MNL
7	Koppelman et al. (2008)	US markets	x		CRS/OAG	Aggr. MNL
8	Hsiao and Hansen (2011)	US markets	x		DB1B	Aggr. NL
9	Jung and Yoo (2014)	Short-haul markets in South Korea		x	CAI	MNL & NL
10	Seelhorst and Liu (2015)	Prototypical routes	x	x	RSG extended	MNL & LCCM
11	Lurkin et al. (2017)	US markets	x		ARC	MNL
12	Freund-Feinstein and Bekhor (2017)	Markets from Tel Aviv		x	Online Survey	MCNL
13	Yimga (2017)	US markets	x		DB1B/OTP	Aggr. NL
14	Lhéritier, Bocamazo, Delahaye, and Acuna-Agost (2019)	European markets	x		GDS logs	MNL, LCCM, RF
15	Herring et al. (2019)	US markets	x		ARC	MNL
16	Birolini et al. (2020)	Markets from Italy	x		OAG	Aggr. NL
17	Acuna-Agost, Thomas, and Lhéritier (2021)	European markets	x		GDS	DL

Methods: MNL—Multinomial Logit; NL—Nested Logit; WNL—weighted nested logit models; MMNL—Mixed Multinomial Logit; LCCM—Latent Class Choice Model; MCNL—Mixed Logit Cross Nested Logit; RF—Random Forest; DP—Deep Learning.
Data sources: CRS—Computer Reservation System; OAG—Official Airline Guide; RSG—Resource Systems Group (RSG) Airline Survey; DB1B—Origin and Destination Survey Data from the Bureau of Transportation Statistics (BTS) in the US; CAI—Computer-aided interview; ARC—Airlines Reporting Corporation; OTP—On time performance data from the BTS in the US; GDS—Airline global distribution systems.

are the attitudes most recognized as affecting individuals' travel preferences (Bahamonde-Birke et al., 2017; Bahamonde-Birke & Ortúzar, 2014; Beck, Rose, & Merkert, 2018; Glerum, Atasoy, & Bierlaire, 2014; Popuri et al., 2011; Shiftan et al., 2008; Spears, Houston, & Boarnet, 2013). Other studied attitudes include sensitivity to time (Bahamonde-Birke et al., 2017; Shiftan et al., 2008; Spears et al., 2013), tolerance for waiting (Popuri et al., 2011), and willingness to use transit (Shiftan et al., 2008). From a methodological standpoint, there are two main distinct ways in which attitudes may be incorporated into choice models (e.g., Ben-Akiva et al., 2002). The first approach involves a two-step analysis that begins with a factor analysis on the attitudinal indicators, followed by the inclusion of the derived fitted latent factors into the utility (e.g., De Vos, Derudder, Van Acker, & Witlox, 2012; He & Thøgersen, 2017; Hunecke, Haustein, Böhler, & Grischkat, 2010; Popuri et al., 2011; Spears et al., 2013). The second approach, referred to as hybrid choice models (HCMs), involves the integration of latent variable models into discrete choice models (e.g., Ashok, Dillon, & Yuan, 2002; Glerum et al., 2014; Hess & Stathopoulos, 2013; Prato, Bekhor, & Pronello, 2012; Train et al., 1987).

In terms of empirical setting, it is clear from Table 1 that most previous studies have focused on domestic routes (mostly in the United States). Less research has been devoted to long-haul travel and a more explicit comparison between different travel lengths. Additionally, most of the studies have been conducted considering revealed preference data, that is, observed choices by passengers in their real life. While this ensures the reliability of the analysis, it limits the investigation of alternatives and attributes that do not yet exist in the market (Wardman, 1988).

The majority of the studies mentioned thus far used a simple MNL model of choice to examine air travelers' behavior (Coldren et al., 2003; Freund-Feinstein & Bekhor, 2017; Koppelman et al., 2008; Proussaloglou & Koppelman, 1999; Theis et al., 2006). A few studies have used a nested logit model to capture specific correlation patterns between alternatives (e.g. Coldren & Koppelman, 2005; Jung & Yoo, 2014), or to simultaneously capture multiple decisions, such as whether to travel and how to travel (Birolini et al., 2020; Hsiao & Hansen, 2011). Other studies have instead deployed ML (Adler et al., 2005; Warburg et al., 2006) and latent class models (e.g. Lhéritier et al., 2019; Seelhorst & Liu, 2015) to explicitly account for heterogeneous passenger preferences. Eventually, two recent papers (Lhéritier et al., 2019) and Acuna-Agost et al. (2021) deployed machine learning methods and deep learning to estimate itinerary choice, showing how the use of data-driven methods has the potential to improve model predictability (though in general at the expense of lower interpretability).

This paper contributes to the current literature on DCM by considering as a determinant of itinerary choice the extent to which a one-stop alternative is marketed and fully handled by the operating airline. This is pursued by means of a LCCM, in which passengers related attributes are acknowledged as playing a key role. Specifically, we first reduce the dimensionality of our attitudinal variables using an EFA model to derive key factors. To better distinguish different groups of travelers, these factors are then included into a LCCM model that simultaneously estimates the membership and class-specific utility functions. Further details are available in Section 4.

3. Survey design

Our work investigates millennials' travel preferences by means of a stated preference survey. Survey responses were collected in Lombardy (in northern Italy) from January to March 2019. The survey structure comprised two main sections. The first section collected respondents' demographic characteristics and details on travel attitudes, while the second part was dedicated to collecting respondents' stated preferences.

3.1. Profile of respondents

To map respondents' characteristics, the survey includes questions related to demographic attributes (i.e., gender and age) as well as travel attitude statements that respondents are asked to rank according to a *Likert scale*. Attitudes are recognized to be a great help in explaining individuals' travel choices (Ajzen, 1991; Bahamonde-Birke et al., 2017; Kroesen et al., 2017; Kuppam et al., 1999). Grounding on the literature exploring the impact of attitudes on travel behavior, we ask respondents to evaluate their agreement with respect to different travel attitudes, as detailed in Table 2. First, *A1* explores individuals' air travel frequency. Sensitivity to time (Bahamonde-Birke et al., 2017; Shiftan et al., 2008; Spears et al., 2013) is tested with *A2*, *A4*, *A7*, and *A3*, which also comprehends the propensity toward travelers' tolerance for waiting (Popuri et al., 2011). Specifically, the posed questions explore different aspects of sensitivity to time, in terms of willingness to pay (*A2*), waiting between two flight legs (*A3*), the value of a timely service (*A4*), and the perception of flight delays (*A7*). Finally, the level of stress (Bahamonde-Birke et al., 2017; Popuri et al., 2011; Shiftan et al., 2008) is included in questions related to *A3*, *A5*, *A6*, and *A8*,

Table 2
Descriptive statistics of the respondents' demographic characteristics and travel attitudes (*245 respondents*).

Variable	Description	Average value	St. Dev	Min	Max
Male	1 if respondent's gender is male, 0 otherwise	0.8082	0.3946	0	1
Age		28.9878	4.7637	19	40
[A1] How often do you travel by airplane in a year?	Rank from 1(Never) to 5(Every day)	2.4000	0.6363	1	4
[A2] I am always willing to pay more for the quickest travel alternative	Rank from 1(Disagree) to 5(Fully Agree)	2.5837	0.7828	1	5
[A3] I feel uncomfortable waiting for a long time in a crowded place	Rank from 1(Disagree) to 5(Fully Agree)	2.3878	0.6900	1	5
[A4] Arriving at destination on time is of primary importance to me	Rank from 1(Disagree) to 5(Fully Agree)	2.8204	0.8733	1	5
[A5] I always carefully check trip details before and throughout a trip (e.g. gate, terminal, transfer at destination, etc.)	Rank from 1(Disagree) to 5(Fully Agree)	3.4449	0.6969	2	5
[A6] I always arrive at the airport far before the scheduled departure time	Rank from 1(Disagree) to 5(Fully Agree)	3.1265	0.7440	1	5
[A7] Flight delays are a common issue in the aviation industry and do not concern me too much	Rank from 1(Disagree) to 5(Fully Agree)	2.4082	0.5978	1	4
[A8] A recurrent thought I have when flying is about collecting my luggage at the destination	Rank from 1(Disagree) to 5(Fully Agree)	2.3592	0.7955	1	5

addressing respondents' ratings in relation to their travel experiences. Along with sensitivity to time, *A3* examines respondents' willingness to spend connecting time in a crowded place. In *A5*, individuals self-evaluate the concern with respect to trip details, while *A6* focuses on scheduling-related stress. Lastly, *A8* appraises respondents' anxiety with regards to loosing luggage.

Descriptive statistics of the first section responses are available in Table 2. Interviewed respondents were mainly men whose age ranged from 19 to 40 years old. Only 10 out of 245 respondents did not travel by air and 10 of them flew once per week (*A1*). A few individuals (11%) indicated that they were always willing to pay more for the quickest alternative, assigning a value over 4 to the Likert scale for *A2*. At the same time, almost 40% of the respondents did not consider arriving at their destination on time to be of primary importance (value below 2 assigned to *A4*). Flight delays were not considered to be a common issue for more than 60% of the respondents (who assigned a value above 4 to *A7*). Only seven of the interviewed millennials noted feeling uncomfortable waiting for a long time in a crowded place (these respondents assigned a value above 4 to *A3*) and only 15 were recurrently worried about collecting their luggage at the destination (those who assigned a value above 4 to *A8*). The percentage of respondents who assigned a value below 2 to *A6 (I always arrive at the airport far before the scheduled departure time)* was equal to 17%. No one disagreed with the statement "I always carefully check trip delays before and throughout a trip" (*A5*).

3.2. Respondents' stated preferences

A stated preference approach makes it possible to test how individuals respond when faced with a hypothetical alternative choice set, where each alternative is characterized by specific pre-defined attributes. We designed the second survey section into three different experiments ('games'), one per length of haul (short—SH, medium—MH, and long—LH). Each game offered three alternatives, differentiating for five attributes, selected according to their acknowledged influence on individuals' choices (Birolini et al., 2020; Coldren et al., 2003; Lurkin et al., 2017; Seelhorst & Liu, 2015). Alternative attributes included whether it is a direct or one-stop connection (*Direct*), *Airfare*, flying time (*FT*), connecting time (*CT*), and *Integrated* transfer. *Airfare* was computed as the total price paid by the traveler for the round trip. *FT* and *CT* represented the total flying and connecting time, respectively. When the offered alternative was direct, the connecting time was set to 0. When the alternative was not direct (one-stop), no information on how the price and the flying time were split between the two flight steps was provided. Finally, *Integrated* denotes whether the flight implies the reservation of a unique ticket, guaranteed connecting flights, single check-in, and luggage claim at the final destination (i.e., connection handled by the airline).

Attribute values are reported in Table 3. For each experiment, the survey always proposed a nonstop option and two one-stop alternatives, of which one offering an integrated flight service. Respondents were asked to rank them according to their preferences.[1] Nonstop flying time was fixed for all length of hauls (90, 180, and 480 min for SH, MH, and LH, respectively), while fares for both one-stop and direct alternatives were randomly drawn from the pricing options portrayed in the table. In case of one-stop connections, flying and connecting time were randomly assigned to alternatives. All games aim to consider realistic situations and they are designed to avoid dominant or dominated alternatives, and orthogonality among attributes. Since the flying time for nonstop alternatives was lower than that of one-stop flights, the fare of the direct alternative was always set at a higher price compared to the connecting options. This approach prevented the nonstop itinerary from being, by definition, the most preferred one, should it have been more convenient in terms of both time (lower flying time and no connecting time) and cost. Similarly, the integrated alternative was generally offered at a higher price with respect to the non-integrated one—ceteris paribus. Otherwise, the one-stop integrated vs. not integrated alternatives were designed to present a time trade-off. Ultimately, we tested the preference of an integrated option with a lower fare that however implied longer CT, FT, or both (total travel time—TT) to accurately estimate the premium value of the integrated service. Fig. 1 illustrates the differences in Airfare, CT, FT, and TT of the integrated versus the non-integrated one-stop alternative tested in the games. Note first that there is never a case in which the integrated alternative is less costly ($\Delta Airfare < 0$), with a lower connecting ($\Delta CT < 0$), flying ($\Delta FT < 0$) and total travel ($\Delta TT < 0$) time (i.e., the bottom left corner in Fig. 1 is empty). On the contrary, any other quadrant is not empty, which allows exploring and disentangling different trade-offs (e.g., the monetary value of integration compared to connecting times or flight times).

[1] Ranking alternatives allows us to observe more than one choice per game. In detail, given a set of alternatives $I = \{a, b, c\}$, $Pr(a, b, c)$ being the probability of ranking alternatives from a (most preferred) to c (least preferred), the Luce and Suppes Ranking Choice Theorem (Chapaaan & Staelin, 1982) allows us to write $Pr(a, b, c)$ such that $Pr(a, b, c) = Pr(a|I) \cdot Pr(b, c) = Pr(a|I) \cdot Pr(b|I - \{a\}) \cdot Pr(c|I - \{a, b\})$. Applying this theorem to the stochastic utility model, given a ordered choice set of individual q, varying from $w = 1$ (most preferred) to W (least preferred), $U_{q1} \geq U_{q2} \geq \cdots \geq U_{qW}$ can be decomposed into $W - 1$ statistically independent choice observations, such that $U_{qw^*} \geq U_{qw}$, with $w^* = 1, \ldots, W - 1$ and $w = w^*, \ldots, W$ (Chapaaan & Staelin, 1982).

Table 3
Attributes and their values in the stated preference experiments ('games').

Game	Alternative	Roundtrip Airfare (€)	*FT* (min)	*CT* (min)	Integrated transfer
1. Short Haul	One-stop	50	120	30	Yes
		100	180	60	No
		150	240	120	
		200	300	180	
	Direct		90	0	No
2. Medium Haul	One-stop	100	210	60	Yes
		200	240	120	No
		300	300	240	
		400	330	300	
	Direct		180	0	No
3. Long Haul	One-stop	400	510	60	Yes
		500	540	180	No
		600	600	300	
		700	660	360	
	Direct		480	0	No

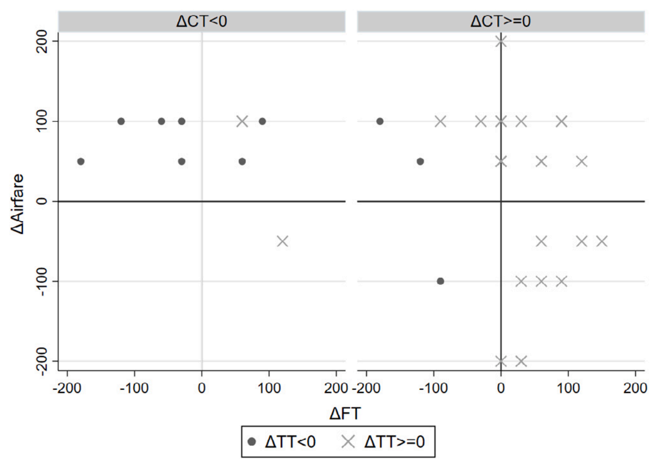


Fig. 1. Difference in one-stop integrated and not-integrated alternative-specific features.
$\Delta Y = Y_{integrated} - Y_{not-integrated}$, where $Y = Airfare, CT, FT, TT$.

4. Methodology

This section describes the methodological approach of our work, which grounds on two main frameworks, namely a latent class choice model to estimate the impact of itinerary attributes and personal traits on travelers' preferences, and a factor analysis, which identifies the attitudes affecting travelers' behavior.

Respondents' choices are analyzed by means of an LCCM accounting for respondents' heterogeneity. The LCCM captures heterogeneous preferences by grouping respondents in a predefined number of classes. In detail, for each respondent q belonging to class c, the utility function associated with any alternative $i \in I$ is:

$$U_{qi|c} = \alpha_c + \beta_c X_{qi} + \epsilon_{qi|c}, \tag{1}$$

where α_c is a vector of unknown parameters for class $c \in C$, and X_{qi} is a vector of alternative specific variables, *that is*, whether the alternative consists in a direct or one-stop flight (*Direct*, equal to 1 if the alternative is nonstop), *Airfare*, *FT*, and *CT*, and whether it is an integrated transfer (*Integrated*). β_c is the estimated vector of class-specific coefficients and $\epsilon_{qi|c}$ is the error term.

In such a model, the probability of an alternative i being chosen by respondent q ($P_q(i)$) consists of two terms, namely, the probability of choosing alternative i given that individual q belongs to class c ($P_q(i|c)$), and the probability that individual q belongs to class c ($H_q(c)$). Specifically:

$$P_q(i) = \sum_{c=1}^{C} P_q(i|c) \cdot H_q(c) \tag{2}$$

where

$$P_q(i|c) = \frac{\exp(\alpha_c + \beta_c X_{qi})}{\sum_{i=1}^{I} \exp(\alpha_c + \beta_c X_{qi})} \tag{3}$$

and

$$H_q(c) = \frac{\exp(\theta_c Z_q)}{\sum_{c=1}^{C} \exp(\theta_c Z_q)}. \tag{4}$$

$H_q(c)$, also called class membership function, is assumed to have a multinomial logit distribution (Greene & Hensher, 2003; Seelhorst & Liu, 2015; Wen & Lai, 2010), with Z_q being a vector of class-related variables. In our study, Z_q comprehends travel attitudes, and respondents' demographic characteristics, *that is*, gender (*Male*) and age (*Age*).

To include travel related attitudes in our model, we conducted an EFA. This approach has the main aim of reducing a large set of variables into a smaller number of underlying factors, which capture the relationships among a set of interrelated variables, providing interesting insights and reducing complexity. The identified factors are considered to be latent variables, unable to be directly measured. EFA outcomes detail the number of factors needed to significantly explain common, but unobserved, influences among the considered variables and the extent to which each variable is associated with the factors (i.e., factor loadings) (Cudeck, 2000).

To estimate the impact of attitudes, norms, and perceptions on travel behavior or mode choice, several studies in the transportation literature (e.g., De Vos et al., 2012; He & Thøgersen, 2017; Hunecke et al., 2010; Popuri et al., 2011; Spears et al., 2013) ground on factor analysis to reduce the dimensionality of the explored attitudinal indicators and derive the underlying latent variables. In this paper, we rely on factor analysis to investigate hidden relationships among travel attitudes and responses as well as to reduce the number of variables included in the choice model.[2]

In our sample, Bartlett's test of sphericity on attitudinal factors results to be significant (237.86; $p < .001$), suggesting variables are intercorrelated, thus corroborating the importance of applying a factor

[2] To reduce the computational costs of simultaneous estimation of both latent classes and latent variables, we rely on a sequential approach, which, in our context is considered to lead to valid outcomes (e.g. Bahamonde-Birke & de Dios Ortúzar, 2014). Please refer to Ashok et al. 2002, Bahamonde-Birke and de Dios Ortúzar 2014, Chorus and Kroesen 2014 for further discussion on the topic.

Table 4
Factors loadings—variables with a factor loading between −0.3 and 0.3 are not displayed (*245 respondents*).

Attitude	Factor 1	Factor 2	Uniqueness
[A1]	−0.4338	0.3912	0.6770
[A2]	–	0.4572	0.7665
[A3]	–	−0.3829	0.8110
[A4]	–	0.7135	0.4910
[A5]	0.5116	–	0.7317
[A6]	0.6547	–	0.5721
[A7]	–	−0.4573	0.7267
[A8]	0.5739	–	0.6636

analysis. Additionally, the Kaiser–Meyer–Olkin Measure of Sampling Adequacy is 0.59, above the threshold of unacceptability for a factor analysis with 8 variables, which is below the .40s (Kaiser, 1974). Due to the measurement of attitudinal factors with Likert scales, we perform a factor analysis based on polychoric correlations matrices instead of Pearsons correlations (Holgado-Tello, Chacón-Moscoso, Barbero-García, & Vila-Abad, 2010). Additionally, we apply promax rotation in order to ease loadings interpretation. As factors, we select only those with eigenvalues greater than one, indicating that a single factor explains more variance than an observed variable by itself (Cattell, 2012).

5. Results and discussion

5.1. Exploratory factor analysis

The model indicates that two main factors are identifiable in our sample (Fig. 2). Table 4 presents the details on the contribution of each attitude to the factors (minimum factor loading displayed equal to |0.30|). The two identified factors are affected by attitudinal responses as follows.

- Factor 1—*Travel Anxiety*:
  Attitude 1 (*A1*) is negatively correlated with it, while attitudes 5 (*A5*), 6 (*A6*), and 8 (*A8*) positively load on Factor 1. This factor summarizes an overall anxious attitude toward traveling (*travel anxiety*), negatively correlated with the frequency of air travel and, at the same time, positively correlated with all statements representing the level of stress, thus expressing uneasiness about travel's features.
- Factor 2—*Timeliness and Quality*:
  It is heavily loaded by (A4), and negatively correlated with attitudes 3 (*A3*) and 7 (*A7*). Along with attitude 1 (*A1*), attitude 2 (*A2*) has a positively loading on Factor 2. This factor represents travelers' attitudes toward a *timeliness and quality* of service, being positively correlated with air travel frequency and sensitivity to time factors, that is, the importance of arriving at a destination on time, willingness to pay more for the quickest travel alternative, and concern about flight delays.[3]

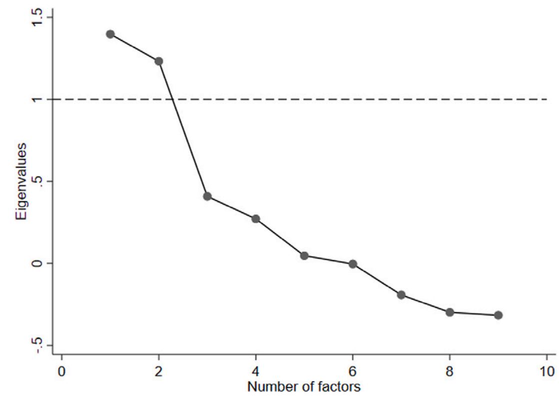


Fig. 2. Factor analysis eigenvalues.

5.2. Itineary choice model

The results of our analysis are shown in Table 5. The first three columns portray the outcomes of two benchmark models—i.e, conditional logit (CL) (Column 1) and ML (columns 2 and 3). Columns 4 to 6 then represent the class-specific model results obtained from our LCCM, considering three classes.[4] Eventually, Columns 7 and 8 show the results of the class membership model, where, for identification, class membership characteristics of one segment (Class 3) are normalized to zero (Greene & Hensher, 2003).

Based on our class membership model, Class 1 (15% of the respondents) places great importance on timely and quality service and it is characterized by lower travel anxiety; Class 2 (49% among the respondents) individuals are younger and tend to be less anxious when travelling; Class 3 (36% of the respondents) tends to be significantly more anxious than other segments. For these three classes, the LCCM returns different sets of coefficients, which highlight different preferences and sensitivities to choice determinants.

Overall, consistent with the previous literature, we find that travelers prefer cheaper and direct options (e.g., Evangelinos, Staub, Marcucci, & Gatta, 2021; Seelhorst & Liu, 2015; Wen & Lai, 2010), and the choice probability decreases with travel time (e.g., Seelhorst & Liu, 2015; Shen, 2009; Wen & Lai, 2010). Along with these traditional factors, the impact of *Integrated* on choice, the variable testing the effect of offering a connecting itinerary fully handled by an airline, is positive and significant.

The impact of the selected itinerary specific determinants is statistically significant, reasonably consistent, and bears the expected sign for all class-specific models. However, their magnitudes vary among classes to a significant extent, providing insights into substitution trade-offs and the choice behavior of different types of passengers. *Airfare* estimated coefficients suggest that Class 3 respondents are more sensitive to price with respect to other classes, while flying and connecting time have larger negative impacts for Class 3 and Class 1 respondents relative to Class 2. The effects of *Integrated* and *Direct* are greater for Class 3, indicating that respondents belonging to this segment are more sensitive to these two attributes relative to the other groups. This can be interpreted in light of the higher importance assigned by anxious travelers to factors limiting uncertainties, such as direct and integrated

[3] Reasonably, travelers with a positive attitude towards timeliness and quality should not positively rate waiting for a long time (A3). However, we believe that the specification of waiting in crowded places may have influenced respondents' rates. This is corroborated by the low variation in responses' values: in 89% of cases, to A3 is assigned a value between 2 and 3. Moreover, note that factor A3 is the one that contribute less to the value of Factor 2 (Table 4). Hence, it does not significantly undermine the definition of the factors and the validity of the analysis.

[4] The latent class model requires a definite number of classes to be tested. Accordingly, we rely on *BIC* (Bayesian Information Criterion), *AIC* (Akaike Information Criterion) and Consistent *AIC* (*CAIC*) indices to select the most appropriate number of classes (Louviere, Hensher, & Swait, 2000; Seelhorst & Liu, 2015; Shen, 2009; Wen & Lai, 2010). The model with three latent classes registers the lowest *BIC* and *AIC* values. BIC and AIC estimates of the model with $C = 2$ are equal to 1,645 and 1,298, respectively.

Table 5
Choice Model results.

Variables	*Conditional Logit (CL)*	*Mixed Logit (ML)*		*Latent Class Choice Model (LCCM)*			*Membership function*	
	(1)	*(2) Mean*	*(3) SD*	*(4) Class 1*	*(5) Class 2*	*(6) Class 3*	*(7) Share 1*	*(8) Share 2*
Airfare	−0.0100***	−0.0155***	0.0083***	−0.0099**	−0.0150***	−0.0192***		
	(0.0008)	(0.0014)	(0.0012)	(0.0044)	(0.0015)	(0.0036)		
FT	−0.0145***	−0.0191***	−0.0047***	−0.0228***	−0.0159***	−0.0264***		
	(0.0011)	(0.0018)	(0.0025)	(0.0064)	(0.0018)	(0.0046)		
CT	−0.0047***	−0.0090***	−0.0072***	−0.0261***	−0.0040***	−0.0124***		
	(0.0006)	(0.0011)	(0.0012)	(0.0076)	(0.0010)	(0.0030)		
Integrated	1.6367***	2.4646***	−0.1265	1.8832***	1.3697***	7.4961***		
	(0.1212)	(0.1912)	(0.2821)	(0.6559)	(0.1833)	(1.9635)		
Direct	1.6394***	2.4863***	−0.3223	3.2650***	1.3751***	7.3910***		
	(0.1742)	(0.2470)	(0.3440)	(1.2634)	(0.2599)	(2.0043)		
Travel Anxiety							−1.7326***	−0.9789***
							(0.6176)	(0.3702)
Timeliness and Quality							3.1987***	0.0224
							(0.7244)	(0.3757)
Male							12.9077	−0.5572
							(279.1945)	(0.5218)
Age							0.1163	−0.2256***
							(0.0789)	(0.0547)
Constant							−19.8859	8.8082***
							(279.2084)	(2.0071)
% Class				15%	49%	36%		
Observations	3,660	3,660		Observations	3,660	AIC	1,528	
LL	−858.5	−800.1		LL	−738.9	BIC	1,615	
Respondents	245	245		Respondents	245	No. of groups	1,464	

connections. In line with the importance assigned to timely and quality service, Class 1 members are more sensitive to the *Direct* attribute with respect to the *Integrated* one.

Ultimately, we highlight the benefits of using a latent class approach—as opposed to CL models that do not account for heterogeneity and ML models that capture heterogeneity through random coefficients using a pooled dataset. We first observe that the main insights (in terms of average impacts) are overall consistent across the three models (as evident from the coefficients reported in Table 5 and the value of attributes in Table 6). However, LCCM better captures choice heterogeneity in our sample: when applying the heterog model, the *Direct* and *Integrated* SD coefficients are not statistically significant (column 3 of Table 5), underscoring the benefits of developing specialized models.

5.3. Value of attributes

To clarify and better highlight differences in the travel behavior, we computed the value of the different attributes. Table 6 reports the value of attributes estimated by class, derived from the CL, ML, and LCCM outcomes shown in Table 5. *FT* and *CT* variables allow us to estimate respondents' value of time (VOT). The estimates of VOT seen in the former literature, be it with regards to access, flying, or connecting time, largely vary, also depending on several factors, such as the trip purpose or travelers' income (e.g., Adler et al., 2005; Garrow, Jones, & Parker, 2007; Landau, Gosling, Small, & Adler, 2016; Lurkin et al., 2017). In our study, by considering the full sample, estimated VOT derived from the CL (ML) is found to be equal to €43.50 (€36.68) and €14.10 (€16.80) per hour for flying and connecting time, respectively. Interestingly, this value greatly varies across classes. Class 1, characterized by a low level of *travel anxiety* and a high level of *timeliness and quality* compared to other classes, has the highest VOT (€69.09 and €79.09 per hour for *FT* and *CT*, respectively). Consistently, lower levels of *timeliness and quality* are associated with a lower VOT (Classes 2 and 3).

The value of a nonstop option (*Direct*) is, on average, equal to €81.97 (€77.65 in the ML model). In their attempt to estimate the value of a direct itinerary relative to connecting options, scholars realize that this may vary in relation to travelers' characteristics (e.g., Adler et al., 2005; Warburg et al., 2006). Accordingly, our outcomes suggest that the value associated with a nonstop connection increases with travelers' anxiety. Indeed, the group of respondents with the highest *travel anxiety* assigns a value of €192.47 to a direct flight (Class 3). Additionally, Class 1 assigns a high value to direct itineraries (€164.90), while younger and less anxious travelers evaluate this attribute as €45.84.

Table 6
Value of attributes by class.

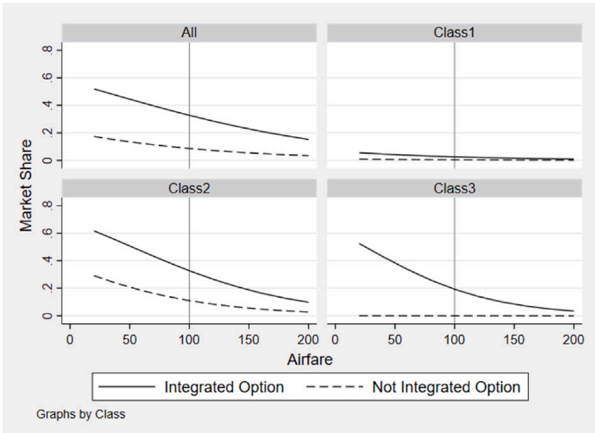
Value of Attributes (€)	CL	ML[a]	Class 1	Class 2	Class 3
FT (per hour)	43.50	36.68	69.09	31.80	41.25
CT (per hour)	14.10	16.80	79.09	8.00	19.38
Integrated	81.84	76.74	95.11	45.66	195.21
Direct	81.97	77.65	164.90	45.84	192.47

[a]Estimated by relying on a Monte Carlo simulation generating 1000 samples, each of 1000 games, as in Birolini, Malighetti, Redondi, and Deforza (2019).

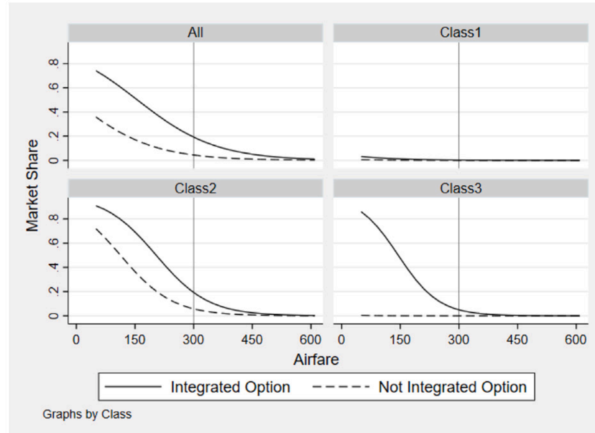
A connection fully handled by the airline has an estimated value of €81.84 (€76.74 in the ML model), very similar to the average value of *Direct*. For both Class 2 and Class 3, the value of *Integrated* and *Direct* attributes are very close. The former is equal to €46 for both classes. The latter is equal to €192 and €195 for Class 2 and 3, respectively. This result suggests that offering a one-stop flight with a unique ticket, guaranteed connecting flights, single check-in, and luggage claim at the final destination is considered equivalent to a nonstop option. This is not true for Class 1. Passengers with a more intense attitude toward timely and quality services assign a value €70 lower than the direct alternative to the one-stop integrated attribute.

5.4. Handled connections impact on travelers' choice

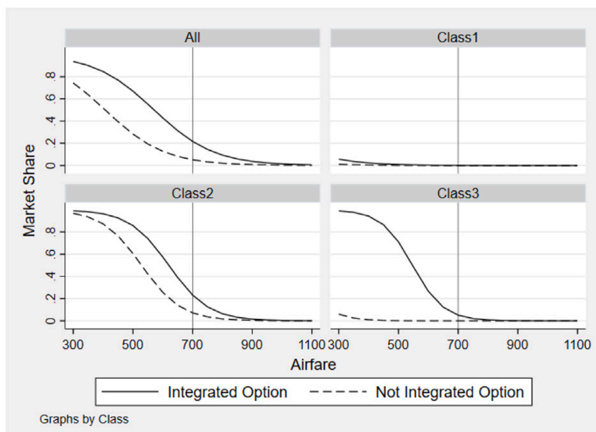
By relying on the results of our LCCM, it is possible to assess the impact of offering a handled connection on travelers' choice. In Fig. 3, we illustrate how the estimated coefficients derived from our model can be utilized to make itinerary share predictions. In detail, for a varying length of haul, we suppose two different alternatives are offered to travelers. The first option is always a nonstop flight, with flying time as in Table 3 and airfare equal to €100, €300, and €700 for short, medium, and long haul, respectively. The second itinerary alternative



(a) Short Haul
Nonstop flight: $FT = 90$ min, $Airfare$=€100
One-stop alternative: $FT = 120$ min, $CT = 60$ min



(b) Medium Haul
Nonstop flight: $FT = 180$ min, $Airfare$=€300
One-stop alternative: $FT = 240$ min, $CT = 90$ min



(c) Long Haul
Nonstop flight: $FT = 480$ min, $Airfare$=€700
One-stop alternative: $FT = 510$ min, $CT = 90$ min

Fig. 3. Itinerary shares of integrated and not integrated one-stop alternatives varying by airfare with respect to the related nonstop option, by length of haul.

is a one-stop connection with a flying and connecting time equal to 120 and 60 min for SH, 240 and 90 min for MH, and 510 and 90 min for LH, respectively. For varying values of airfare for the one-stop alternative, we are able to compute the share of passengers that would prefer this to the direct option, whether the connecting flight is handled by the airline (*Integrated*) or not.

Fig. 3a portrays how the itinerary market share of the one-stop alternative varies in a short haul setting. The solid and dashed lines represent the portion of passengers choosing the one-stop alternative in case *Integrated* option is available or not, respectively. For all classes, the integrated option has a higher share than the not integrated one. Interestingly, the difference in the market share greatly varies by segment and airfare. Passengers who give great importance to timely and quality service (Class 1) tend not to choose the one-stop option, even if the connection is fully handled by the airline or charged at a very low price. The one-stop alternative reaches a maximum value of 5.53% in case of an integrated connection with a price of €20, that is, €80 less than the nonstop flight. For anxious travelers (Class 3), the one-stop not integrated option has a probability close to zero of being chosen, even at low airfare levels. On the contrary, the share of the one-stop integrated alternative records a value which varies from 3.38% (when *Airfare* is twice the direct alternative price) to 52.47% when the price is equal to 20€. This confirms the importance of offering a connection handled by airlines to travelers characterized by a high travel anxiety, as already discussed in Section 5.2. Finally, Class 2 shows an overall higher propensity for connecting itineraries. Indeed, offering a one-stop alternative at the same price of the direct connection results in 32.73% (11.00%) of travelers choosing the integrated (not integrated) option.

Similar patterns can be discussed for medium (Fig. 3b) and long hauls (Fig. 3c), although with different estimates. For all length of hauls, Class 1 travelers do not consider a one-stop alternative to be valuable, even if they are offered a handled connection. This enforces the importance of offering a direct connection for passengers that assign a strong importance to timely and quality service. The difference in itinerary shares of Class 3 for integrated and not integrated alternatives becomes larger as the one-stop price drops and the share of the not integrated connection (dashed line) is close to zero even for LH itineraries. In the case of high discounts, the one-stop alternative is chosen by more than the 90% of young and non-anxious travelers and it is not attributed a great value to the integrated feature (Class 2).

6. Conclusions

This paper explores the factors influencing travelers' choices in the context of air transportation, contributing to the current literature by including a novel determinant—the extent to which a connecting flight is marketed and fully handled by the operating carrier. Although the topic of fully-handled connecting itineraries has already gained much attention from scholars, especially in the context of LCCs (Birolini et al., 2022; Morlotti et al., 2020), to the best of our knowledge, no estimates on the (dis)utility associated with this factor have yet been provided.

We rely on a stated preference survey conducted in 2019, in which we mapped respondents' profile characteristics (i.e., age, gender, and travel attitudes) and their preferences in relation to alternative itinerary options. Specifically, each respondent was asked to rank a set of three alternative trips with different attributes in terms of airfare, travel time, connecting time, number of stops, and the possibility of having a fully handled connection. The structure of the survey allows us to explore how both individual and itinerary features affect travelers' behavior. Accordingly, we analyze survey responses by means of a latent class choice model, where individual characteristics are included in the membership function. Along with traditional demographic factors, we consider two travel-related attitudes, namely *travel anxiety* and *timeliness and quality*, derived by implementing an EFA for specific attitudinal questions.

Compelling insights emerge from our results. Our sample is found to be composed of three different classes. Class 1 represents frequent travelers who place a lot of importance on timely and quality service. Class 2 members consist of young individuals characterized by a low level of travel anxiety. Finally, Class 3 respondents are anxious travelers who are not used to flying frequently. Although itinerary attribute coefficients coherently impact travelers' choices, corroborating previous literature outcomes, intriguing differences emerge among the classes. Class 2 and 3 individuals are more sensitive to prices than were those in Class 1. Class 1 individuals are more sensitive to time and to a direct connection than are those from other segments. When testing the effect of a fully handled connection on itinerary choice, our coefficients show that the value of this attribute for anxious travelers (Class 3) is around two and four times that of Class 1 and 2, respectively. This implies that anxious travelers place more value on the integrated option, considering it equivalent to a direct flight (the value of this attribute is €195 and €192, respectively). Additionally, young and non-anxious individuals assign almost the same value to a nonstop and a fully handled connection, although it is lower (€46). Finally, Class 1, that is, passengers with a more intense attitude toward timely and quality service, places much more value on a direct flight than on an integrated option (€165 and 95€, respectively).

Our analysis reports captivating results, interesting for both practitioners and researchers, and provides foundations for future research. First, air transport players can take strategic decisions with the information provided by our study. In detail, airlines that are planning to introduce handled connecting itineraries can leverage our results to target the optimum markets, according to the passenger mix seen within those markets. Second, our estimates provide decision-makers with insights into the monetary value associated with an integrated itinerary, which vary according to different market segments. From a research perspective, further investigation can be conducted to test whether different methodological frameworks bring varied results, thus commenting on the potential emerging differences and possibly corroborating our analysis. Another direction for future research lies in enlarging the sample toward examining how a different geographical context, as well as additional individual features, may impact the value associated with connections handled by the operating carriers. Finally, since COVID-19 has been found to affect individuals' propensity and willingness to travel, as well as to impact travel-related attitudes (e.g., Kim, Park, Kim, Lee, & Sigala, 2021; Kim et al., 2022) and passengers' sensitivity to prices (e.g., Morlotti & Redondi, 2023), further studies could investigate the potential variations of our estimates following the pandemic outbreak.

CRediT authorship contribution statement

Chiara Morlotti: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Sebastian Birolini:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Paolo Malighetti:** Conceptualization, Methodology, Supervision. **Renato Redondi:** Visualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Acuna-Agost, R., Thomas, E., & Lhéritier, A. (2021). Price elasticity estimation for deep learning-based choice models: an application to air itinerary choices. *Journal of Revenue and Pricing Management*, *20*(3), 213–226.

Adler, T., Falzarano, C. S., & Spitz, G. (2005). Modeling service trade-offs in air itinerary choices. *Transportation Research Record*, *1915*(1), 20–26.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Ashok, K., Dillon, W. R., & Yuan, S. (2002). Extending discrete choice models to incorporate attitudinal and other latent variables. *Journal of Marketing Research*, *39*(1), 31–46.

Bahamonde-Birke, F., & de Dios Ortúzar, J. (2014). Is sequential estimation a suitable second best for estimation of hybrid choice models? *Transportation Research Record*, *2429*(1), 51–58.

Bahamonde-Birke, F. J., Kunert, U., Link, H., & de Dios Ortúzar, J. (2017). About attitudes and perceptions: finding the proper way to consider latent variables in discrete choice models. *Transportation*, *44*(3), 475–493.

Bahamonde-Birke, F. J., & Ortúzar, J. d. D. (2014). On the variability of hybrid discrete choice models. *Transportmetrica A: Transport Science*, *10*(1), 74–88.

Beck, M. J., Rose, J. M., & Merkert, R. (2018). Exploring perceived safety, privacy, and distrust on air travel choice in the context of differing passenger screening procedures. *Journal of Travel Research*, *57*(4), 495–512.

Ben-Akiva, M. E., Lerman, S. R., Lerman, S. R., et al. (1985). *vol. 9*, *Discrete choice analysis: theory and application to travel demand*. MIT Press.

Ben-Akiva, M., Walker, J., Bernardino, A. T., Gopinath, D. A., Morikawa, T., & Polydoropoulou, A. (2002). Integration of choice and latent variable models. *Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges*, *2002*, 431–470.

Birolini, S., Antunes, A. P., Cattaneo, M., Malighetti, P., & Paleari, S. (2021). Integrated flight scheduling and fleet assignment with improved supply-demand interactions. *Transportation Research, Part B (Methodological)*, *149*, 162–180.

Birolini, S., Besana, E., Cattaneo, M., Redondi, R., & Sallan, J. M. (2022). An integrated connection planning and passenger allocation model for low-cost carriers. *Journal of Air Transport Management*, *99*, Article 102160.

Birolini, S., Cattaneo, M., Malighetti, P., & Morlotti, C. (2020). Integrated origin-based demand modeling for air transportation. *Transportation Research Part E: Logistics and Transportation Review*, *142*, Article 102050.

Birolini, S., Malighetti, P., Redondi, R., & Deforza, P. (2019). Access mode choice to low-cost airports: Evaluation of new direct rail services at Milan-Bergamo airport. *Transport Policy*, *73*, 113–124.

Cattell, R. (2012). *The scientific use of factor analysis in behavioral and life sciences*. Springer Science & Business Media.

Chapaaan, R. G., & Staelin, R. (1982). Exploiting rank ordered choice set data within the stochastic utility model. *Journal of Marketing Research*, *19*(3), 288–301.

Chorus, C. G., & Kroesen, M. (2014). On the (im-) possibility of deriving transport policy implications from hybrid choice models. *Transport Policy*, *36*, 217–222.

Coldren, G. M., & Koppelman, F. S. (2005). Modeling the competition among air-travel itinerary shares: GEV model development. *Transportation Research Part A: Policy and Practice*, *39*(4), 345–365.

Coldren, G. M., Koppelman, F. S., Kasturirangan, K., & Mukherjee, A. (2003). Modeling aggregate air-travel itinerary shares: logit model development at a major US airline. *Journal of Air Transport Management*, *9*(6), 361–369.

Cudeck, R. (2000). Exploratory factor analysis. In *Handbook of applied multivariate statistics and mathematical modeling* (pp. 265–296). Elsevier.

De Vos, J., Derudder, B., Van Acker, V., & Witlox, F. (2012). Reducing car use: changing attitudes or relocating? The influence of residential dissonance on travel behavior. *Journal of Transport Geography*, *22*, 1–9.

Delbosc, A., McDonald, N., Stokes, G., Lucas, K., Circella, G., & Lee, Y. (2019). Millennials in cities: Comparing travel behaviour trends across six case study regions. *Cities*, *90*, 1–14.

Delbosc, A., & Ralph, K. (2017). A tale of two millennials. *Journal of Transport and Land Use*, *10*(1), 903–910.

Evangelinos, C., Staub, N., Marcucci, E., & Gatta, V. (2021). The impact of airport parking fees on the tourist's airport/airline choice behavior. *Journal of Air Transport Management*, *90*, Article 101961.

Fageda, X., Suau-Sanchez, P., & Mason, K. J. (2015). The evolving low-cost business model: Network implications of fare bundling and connecting flights in Europe. *Journal of Air Transport Management*, *42*, 289–296.

Freund-Feinstein, U., & Bekhor, S. (2017). An airline itinerary choice model that includes the option to delay the decision. *Transportation Research Part A: Policy and Practice*, *96*, 64–78.

Garikapati, V. M., Pendyala, R. M., Morris, E. A., Mokhtarian, P. L., & McDonald, N. (2016). Activity patterns, time use, and travel of millennials: a generation in transition? *Transport Reviews*, *36*(5), 558–584.

Garrow, L. A. (2016). *Discrete choice modelling and air travel demand: theory and applications*. Routledge.

Garrow, L. A., Jones, S. P., & Parker, R. A. (2007). How much airline customers are willing to pay: An analysis of price sensitivity in online distribution channels. *Journal of Revenue and Pricing Management*, *5*(4), 271–290.

Glerum, A., Atasoy, B., & Bierlaire, M. (2014). Using semi-open questions to integrate perceptions in choice models. *Journal of Choice Modelling*, *10*, 11–33.

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research, Part B (Methodological)*, *37*(8), 681–698. http://dx.doi.org/10.1016/S0191-2615(02)00046-2.

He, S. Y., & Thøgersen, J. (2017). The impact of attitudes and perceptions on travel mode choice and car ownership in a Chinese megacity: The case of Guangzhou. *Research in Transportation Economics*, *62*, 57–67.

Herring, J., Lurkin, V., Garrow, L. A., Clarke, J.-P., & Bierlaire, M. (2019). Airline customers' connection time preferences in domestic US markets. *Journal of Air Transport Management*, *79*, Article 101688.

Hess, S., & Stathopoulos, A. (2013). A mixed random utility—random regret model linking the choice of decision rule to latent character traits. *Journal of Choice Modelling*, *9*, 27–38.

Holgado-Tello, F. P., Chacón-Moscoso, S., Barbero-García, I., & Vila-Abad, E. (2010). Polychoric versus Pearson correlations in exploratory and confirmatory factor analysis of ordinal variables. *Quality and Quantity*, *44*(1), 153–166. http://dx.doi.org/10.1007/s11135-008-9190-y, URL: https://link.springer.com/article/10.1007/s11135-008-9190-y.

Hsiao, C.-Y., & Hansen, M. (2011). A passenger demand model for air transportation in a hub-and-spoke network. *Transportation Research Part E: Logistics and Transportation Review*, *47*(6), 1112–1125.

Hunecke, M., Haustein, S., Böhler, S., & Grischkat, S. (2010). Attitude-based target groups to reduce the ecological impact of daily mobility behavior. *Environment and Behavior*, *42*(1), 3–43.

Jung, S.-Y., & Yoo, K.-E. (2014). Passenger airline choice behavior for domestic short-haul travel in South Korea. *Journal of Air Transport Management*, *38*, 43–47.

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, *39*(1), 31–36.

Kim, J., Park, J., Kim, S., Lee, D. C., & Sigala, M. (2021). COVID-19 restrictions and variety seeking in travel choices and actions: The moderating effects of previous experience and crowding. *Journal of Travel Research*, Article 00472875211037744.

Kim, J., Park, J., Lee, J., Kim, S., Gonzalez-Jimenez, H., Lee, J., et al. (2022). COVID-19 and extremeness aversion: the role of safety seeking in travel decision making. *Journal of Travel Research*, *61*(4), 837–854.

Klophaus, R., Conrady, R., & Fichert, F. (2012). Low cost carriers going hybrid: Evidence from Europe. *Journal of Air Transport Management*, *23*, 54–58.

Koppelman, F. S., Coldren, G. M., & Parker, R. A. (2008). Schedule delay impacts on air-travel itinerary demand. *Transportation Research, Part B (Methodological)*, *42*(3), 263–273.

Kroesen, M., Handy, S., & Chorus, C. (2017). Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. *Transportation Research Part A: Policy and Practice*, *101*, 190–202.

Kuppam, A. R., Pendyala, R. M., & Rahman, S. (1999). Analysis of the role of traveler attitudes and perceptions in explaining mode-choice behavior. *Transportation Research Record*, *1676*(1), 68–76.

Landau, S., Gosling, G. D., Small, K., & Adler, T. (2016). Measuring air carrier passengers' values of time by trip component. *Transportation Research Record*, *2569*(1), 24–31.

Lhéritier, A., Bocamazo, M., Delahaye, T., & Acuna-Agost, R. (2019). Airline itinerary choice modeling using machine learning. *Journal of Choice Modelling*, *31*, 198–209.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: Analysis and applications*. Cambridge University Press.

Lurkin, V., Garrow, L. A., Higgins, M. J., Newman, J. P., & Schyns, M. (2017). Accounting for price endogeneity in airline itinerary choice models: An application to Continental US markets. *Transportation Research Part A: Policy and Practice*, *100*, 228–246.

Maertens, S., Pabst, H., & Grimme, W. (2016). The scope for low-cost connecting services in Europe—Is self-hubbing only the beginning? *Research in Transportation Business & Management*, *21*, 84–93.

Malighetti, P., Paleari, S., & Redondi, R. (2008). Connectivity of the European airport network:"Self-help hubbing" and business implications. *Journal of Air Transport Management*, *14*(2), 53–65.

Marcucci, E., & Gatta, V. (2011). Regional airport choice: Consumer behaviour and policy implications. *Journal of Transport Geography*, *19*(1), 70–84.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, *3*(4), 303–328.

Morlotti, C., Birolini, S., Cattaneo, M., & Redondi, R. (2020). Introducing connecting flights in LCCs' business model: Ryanair's network strategy. *Journal of Air Transport Management*, *87*, Article 101849.

Morlotti, C., & Redondi, R. (2023). The impact of COVID-19 on airlines' price curves. *Journal of Air Transport Management*, *107*, Article 102328.

Munoz, C., & Laniado, H. (2021). Airline choice model for international round-trip flights: The role of travelers' satisfaction and personality traits. *Research in Transportation Economics*, *90*, Article 101121.

Popuri, Y., Proussaloglou, K., Ayvalik, C., Koppelman, F., & Lee, A. (2011). Importance of traveler attitudes in the choice of public transportation to work: findings from the Regional Transportation Authority Attitudinal Survey. *Transportation*, *38*(4), 643–661.

Prato, C. G., Bekhor, S., & Pronello, C. (2012). Latent variables and route choice behavior. *Transportation*, *39*, 299–319.

Proussaloglou, K., & Koppelman, F. S. (1999). The choice of air carrier, flight, and fare class. *Journal of Air Transport Management*, *5*(4), 193–201.

Scorrano, M., & Danielis, R. (2021). Active mobility in an Italian city: Mode choice determinants and attitudes before and during the Covid-19 emergency. *Research in Transportation Economics*, *86*, Article 101031.

Seelhorst, M., & Liu, Y. (2015). Latent air travel preferences: Understanding the role of frequent flyer programs on itinerary choice. *Transportation Research Part A: Policy and Practice*, *80*, 49–61.

Shen, J. (2009). Latent class model or mixed logit model? A comparison by transport mode choice data. *Applied Economics*, *41*(22), 2915–2924. http://dx.doi.org/10.1080/00036840801964633, URL: http://www.tandfonline.com/doi/abs/10.1080/00036840801964633.

Shiftan, Y., Outwater, M. L., & Zhou, Y. (2008). Transit market research using structural equation modeling and attitudinal market segmentation. *Transport Policy*, *15*(3), 186–195.

Spears, S., Houston, D., & Boarnet, M. G. (2013). Illuminating the unseen in transit use: A framework for examining the effect of attitudes and perceptions on travel behavior. *Transportation Research Part A: Policy and Practice*, *58*, 40–53.

Theis, G., Adler, T., Clarke, J.-P., & Ben-Akiva, M. (2006). Risk aversion to short connections in airline itinerary choice. *Transportation Research Record*, *1951*(1), 28–36.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge University Press.

Train, K. E., McFadden, D. L., & Goett, A. A. (1987). Consumer attitudes and voluntary rate schedules for public utilities. *The Review of Economics and Statistics*, 383–391.

Warburg, V., Bhat, C., & Adler, T. (2006). Modeling demographic and unobserved heterogeneity in air passengers' sensitivity to service attributes in itinerary choice. *Transportation Research Record*, *1951*(1), 7–16.

Wardman, M. (1988). A comparison of revealed preference and stated preference models of travel behaviour. *Journal of Transport Economics and Policy*, 71–91.

Wen, C. H., & Lai, S. C. (2010). Latent class models of international air carrier choice. *Transportation Research Part E: Logistics and Transportation Review*, *46*(2), 211–221. http://dx.doi.org/10.1016/j.tre.2009.08.004.

Yimga, J. (2017). Airline on-time performance and its effects on consumer choice behavior. *Research in Transportation Economics*, *66*, 12–25.