Which factors influence mode choice with bike and e-scooter sharing systems?

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Short summary

New forms of transportation, such as shared micro-mobility services, have recently emerged in cities. Researchers have explored various factors influencing people's choice of transportation for these new micro-mobility services. Even though some micro-mobility services are unsuitable for medium-distance trips, few studies have considered multimodal alternatives. This study analyzes mode choice with bike-sharing system (BSS) and e-scooter-sharing system combined with public transportation (ESSPT). We collected the data in a stated preference experiment at ENTPE in Lyon (France) and analyzed the data using a mixed logit model. The findings indicate that individuals are less likely to choose bike and BSS when it rains. Individuals are less likely to choose car, bike, and BSS when the time related to the return trip increases. Finally, the out-of-vehicle time has a larger impact than the travel time on the choice of ESSPT.
Keywords: Mode Choice, New Mobility, Stated Preferences, Mixed Logit Model, Forecasting

1 Introduction

In recent years, new micro-mobility services such as e-scooter sharing systems (ESS) and bike-sharing systems (BSS) have emerged in urban environments. These new mobility services result from technical innovations (e.g., electrification of micro-mobility services), the redesign of traditional transport modes (e.g., from personal to shared services), or the emergence of new technologies in other fields (e.g., smartphone apps for multimodal trips). Understanding the main factors influencing individuals' travel behavior with these new mobility services is essential. Early studies examined the impact of a few factors on ESS and BSS using aggregated models(Bai & Jiao, 2020; Caspi et al., 2020; Younes et al., 2020). They found that ESS is primarily used near universities and may be used for multimodal trips. Additionally, weather conditions such as precipitation or temperature affect ESS users less than BSS occasional users.

Further studies investigated the influence of personal information using disaggregate models. Revealed preferences (RP) or stated preferences (SP) data can be used to estimate such models. RP data contains information on trips done by respondents in real life, while SP data contains information on the respondent's choice within a hypothetical situation (Varotto et al., 2024). A previous study showed that travel distance greatly influences the choice of shared mobility services (Reck et al., 2021). To address this issue, researchers have adopted three different modelling approaches. The first is to consider micro-mobility services as a first/last mile alternative, the second is to include these modes and make them available only for certain distances, and the third is to consider them available regardless of the distance and study the impact of distance (or time) on the mode choice.

Azimi et al. (2021), Baek et al. (2021), and Nikiforiadis et al. (2023) used the first approach. Azimi et al. (2021) developed a logit model based on RP data for public transportation's (PT) access and egress modes. They found that BSS was mainly used for attending universities. Baek et al. (2021) and Nikiforiadis et al. (2023) studied egress mode for PT with ESS and SP data, Nikiforiadis et al. (2023) also included egress mode for car. The mixed logit model developed by Baek et al. (2021) shows that e-scooter is a competitive mode to town buses for the last mile due to the time reduction. The hybrid choice model by Nikiforiadis et al. (2023) indicates that city center residents integrate ESS into their trips more often.

Krauss et al. (2022) and Liao et al. (2020) investigated the second approach. To estimate mixed logit models, they conducted an SP experiment with ESS and BSS for short-distance trips (Krauss et al., 2022) and EBSS for short and medium-distance trips (Liao et al., 2020).Krauss et al. (2022) found that cost and travel time had the same impact on BSS and ESS, and that increasing the cost of PT or car might increase the shares of BSS and ESS. Liao et al. (2020) found that EBSS has many potential users for short-distance trips, that EBSS is preferred to walking to access the metro, and that individuals could be interested in multimodal trips.

The third approach is to study the influence of distance by investigating shared micro-mobility services as full modes. Reck & Axhausen (2021), Reck et al. (2021), and Jaber et al. (2023) developed probit and mixed logit models to analyze mode choice for micro-mobility services only. They found that shared micro-mobility users are young, educated men with full-time jobs, no kids, and no car. Also, trip and access distance or time were crucial for developing shared services. Reck et al. (2022), Esztergár-Kiss et al. (2022), and Curtale & Liao (2023) investigated mode choice with conventional modes and shared services in logit and mixed logit models. Esztergár-Kiss et al. (2022) found that preferences for ESS vary from country to country. Reck et al. (2022) showed that precipitation is a main factor affecting mode choice with shared services. Curtale & Liao (2023) found that existing and potential users of ESS were younger generations, highly educated, high-income earners, and living in large cities.

These studies considered only the outward trip. With micro-mobility services, however, respondents can choose PT on the outward trip and BSS or ESS on the return trip. This possibility might have an impact on the choice of the outward trip.

2 Research gaps and research objective

Previous studies have investigated the factors influencing mode choice with micro-mobility services for the first/last mile, as available only for specific distances and for all trips regardless of the distance. However, no studies considered mode choice for medium-distance trips in urban environments while accounting for ESS combined with other modes. Previous studies suggest that individuals use ESS for medium-trip distances by combining it with PT (Bai & Jiao, 2020; Caspi et al., 2020; Baek et al., 2021; Nikiforiadis et al., 2023), creating a competition with conventional mode and BSS that hasn't been studied yet. Also, no studies considered the potential influence of the return trip on the choice of the outward trip. This study aims to analyze the factors influencing medium-distance trips with conventional modes, BSS, and ESS in combination with PT, considering information on the return trip in the mode choice for the outward trip.

3 Methodology

Experimental design and data collection

The designed SP experiment considered realistic travel behavior during home-university trips in Lyon. Respondents were asked the following: "Consider this situation: you need to go to the ENTPE from your home. The weather for the day is ... and you have access to the following alternatives ... Which one would you choose for the outward trip?". The alternatives were chosen based on hypothetical trips from Villeurbanne (3.97 km, close suburb), Lyon Croix-Rousse (7.37 km, city center), and Venissieux (9.37 km, further suburb) to the ENTPE. The alternatives available were car, PT, bike, BSS, and e-scooter-sharing system combined with PT (ESSPT). Walking and ESS were considered unavailable due to the distances (Reck et al. (2021)). Respondents were provided with travel time, out-of-vehicle time, cost, and number of transfers for each alternative, available docks at arrival for BSS, parking search time on the return trip for car, bike, and BSS, and time spent in congestion on the return trip for car. The travel time for each alternative was calculated based on Google Maps. The costs were calculated using the fares of the service provider for PT, BSS, and ESS, and the average fuel price was combined with the average consumption for the car alternative. The out-of-vehicle time and parking search time levels were based on Krauss et al. (2022). Respondents were informed regarding the presence of rain on the outward trip and the probability of rain on the return trip. The information on the return trip was presented as knowledge based on past experience. In addition, respondents reported their socio-economic characteristics based on the ones collected in the RP survey for mode choice "Enquête ménage déplacement" (CEREMA (2015)) conducted in 2015 in Lyon. They also reported their mobility ownership and habits as done in previous studies (Krauss et al., 2022; Jaber et al., 2023; Curtale & Liao, 2023). For mobility habits, respondents reported the first and the second most used combinations of commuting modes. The choice situations were created using the software for S-efficient design Ngene (Rose & Bliemer, 2013; ChoiceMetrics, 2018). The survey was implemented in Qualtrics (Qualtrics (2014)) with 5 blocks of 6 questions and sent via email to every staff member and student of the ENTPE in July 2023. Each individual was requested to answer 2 blocks chosen randomly. We collected answers from 398 respondents (staff members and students), achieving a response rate of 36%. We considered responses in which the respondents answered the socio-economic questions and at least one choice situation. In the end, we had 333 respondents and 3631 observations. Table 1 presents some respondent statistics.

Table 1: Characteristics of the respondents

Characteristics	Level	Proportion
Gender	Men	45.65%
	Women	52.55%
	Other	1.80%
Age	25<	74.47%
	26-35	8.11%
	36-45	6.91%
	46-55	5.71%
	<56	4.50%
	Missing	0.30%
Home location	City-center	13.51%
	Suburb	78.68%
	Rural	3.00%
Number of car	0	51.35%
	1+	48.65 %
Number of bike	0	40.24%
	1+	59.76
Subscription to PT	No	41.14%
	Yes	58.86%

Data analysis methods

Some statistical tests were conducted on the socio-economic variables and mobility habits. We conducted the χ^2 test for the categorical variables and a Kruskal-Wallis test for continuous variables to understand significant differences between alternatives. When there was a significant difference, the variable was tested in the model specification.

The factors influencing mode choice were analyzed in a mixed-logit model (ML) Train (2009). The factors included trip attributes, environmental characteristics, socio-economic variables, and mobility habits. We introduced individual-specific error terms to capture unobserved correlations between repeated observations over time and across alternatives for the same individual. The utility of alternative i for individual n in choice situation k $U^i_{n,k}$ is given by equation 1:

$$U^i_{n,k} = ASC^i + \beta^i \times X^i_{n,k} + \gamma^i \times \sigma_n + \varepsilon^i_{n,k} \tag{1}$$

where ASC^i is the alternative specific constant, β^i is the vector of parameters to be estimated, $X^i_{n,k}$ is the vector of explanatory variables, γ^i is the vector of parameters associated with the vector of individual specific normal-distributed error term σ_n, and $\varepsilon^i_{n,k}$ is the i.i.d Extreme Value-distributed error term. The probability that individual n chooses mode i in choice situation k is given by equation 2:

$$P_j(i,k) = \frac{\exp^{ASC^i + \beta^i \times X^i_{n,k} + \gamma^i \times \sigma_n}}{\sum_{m \in I} \exp^{ASC^m + \beta^m \times X^m_{n,k} + \gamma^m \times \sigma_n}} \tag{2}$$

where I is the set of alternatives. To find the final specification, we included the variables in the following order: attributes of the alternatives, socio-economic characteristics of the individual, weather characteristics, and individual-specific errors. Each individual-specific error was included in each utility function. The errors capture unobserved preferences influencing an individual's choice of a specific alternative. To capture unobserved correlations across alternatives for an individual, we also tested multiple errors in each utility function. The variables and errors that were not significant were dropped. Significant impacts and differences across alternatives were tested, and a likelihood ratio test was performed. Finally, we kept the model with the best goodness of fit.

4 Estimation results

In this section, we present the results of the model. The model was estimated using Biogeme (Bierlaire, 2023). The statistics of the intermediate models are summarized in table 2. The final log-likelihood of the model significantly improved when adding variables. When the individual-specific error term was included in the mixed-logit model, several socio-economic characteristics were not significant anymore.

Table 2: Number of parameter and final log-likelihood of intermediate models

	Number of parameter	Final log-likelihood
Logit with trip attributes	12	-4039
Logit with socio-economics	40	-3176
Logit with weather	43	-2973
Mixed logit	28	-2513

The utility functions of car (U^{car}), PT (U^{pt}), bike (U^{bike}), BSS (U^{bss}), ESSPT (U^{esspt}), for individual n in choice situation k, for the mixed logit model are as given by equations 3 to 7:

$$\begin{aligned} U^{car}_{n,k} &= \beta^{car}_{TT} \times TT^{car}_k + \beta_{COST} \times COST^{car}_k + \beta^{car,bike,bss}_{AdT} \times AdT^{car}_k + \beta^{car}_{mCar} \times mCar_n \\ &+ \beta^{car,bike}_{subPT} \times (1 - subPT_n) + \beta^{car}_{subBSS} \times subBSS_n + \beta^{car}_{nbMV} \times nbMV_n + \gamma^{car} \times \sigma^1_n \end{aligned} \tag{3}$$

$$U^{pt}_{n,k} = ASC^{pt} + \beta^{pt}_{TT} \times ToT^{pt}_k + \beta_{COST} * COST^{pt}_k + \beta^{pt}_{NT} \times NT^{pt}_k + \gamma^{pt} \times \sigma^2_n \tag{4}$$

$$\begin{aligned} U^{bike}_{n,k} &= ASC^{bike} + \beta^{bike}_{TT} \times TT^{bike}_k + \beta^{car,bike,bss}_{AdT} \times AdT^{bike}_k + \beta^{bike}_{mmPMM} \times mmPMM_n \\ &+ \beta^{bike}_{smPT} \times smPT_n + \beta^{car,bike}_{subPT} \times (1 - subPT_n) + \beta^{bike}_{nbMinor} \times nbMinor_n \\ &+ \beta^{bike}_{nbBike} \times nbBike_n + \beta^{bike,bss}_{RAIN} \times (RO_k + RR_k) + \gamma^{bike} \times \sigma^3_n \end{aligned} \tag{5}$$

$$\begin{aligned} U^{bss}_{n,k} &= ASC^{bss} + \beta^{bss}_{TT} \times TT^{bss}_k + \beta_{COST} \times COST^{bss}_k + \beta^{car,bike,bss}_{AdT} \times AdT^{bss}_k \\ &+ \beta^{bss}_{RURAL} \times RURAL_n + \beta^{bike,bss}_{RAIN} \times RO_k + \gamma^{bss} \times \sigma^4_n \end{aligned} \tag{6}$$

$$\begin{aligned} U^{esspt}_{n,k} &= ASC^{esspt} + \beta^{esspt}_{TT} \times TT^{esspt}_k + \beta_{COST} \times COST^{esspt}_k + \beta^{esspt}_{OT} \times OT^{esspt}_k \\ &+ \beta^{esspt}_{subESS} \times subESS_n \end{aligned} \tag{7}$$

The estimation result can be found in Table 3 and the mixed logit model statistics are reported in Table 4. All continuous variables are centered on the mean value.

The alternative specific constants (ASC) were significant for some alternatives. The ASC of car was normalized to 0. Individuals were more likely to choose PT or bike than car and less likely to choose ESSPT than car, everything else being equal. The ASC of BSS was not significant.

The attributes of the alternatives significantly influenced mode choice. Travel time had a significant and negative impact on all alternatives, meaning that an increase in travel time for one alternative would decrease the probability of choosing that alternative. Similarly, an increase in travel cost, out-of-vehicle time in PT, bike, BSS, and ESSPT, parking search time on the return trip in car, bike, and BSS, and congestion time on the return trip in car would significantly decrease the probability of choosing that alternative. The impacts of travel time and out-of-vehicle time (except for bike and BSS) significantly differed across alternatives. The impacts of out-of-vehicle time (resp. congestion time on the return trip) and parking search time on the return trip did not significantly differ for bike and BSS (resp. car). The impact of travel time significantly differs from the impact of out-of-vehicle time (resp. congestion time on the return trip) and parking search time on the return trip for bike and BSS (resp. car). The impacts of travel time and out-of-vehicle time did not significantly differ for PT. The impacts of travel time didn't significantly differ for the ESS and PT legs but significantly differed from the impact of out-of-vehicle time. The number of available docks for BSS and the number of transfers for ESSPT did not significantly impact mode choice.

Table 3: Estimated parameters of the mixed logit model.

Variable	Description of the Variable	Parameter	Value	Rob. p-value
-	Alternative specific constant of PT	ASC^{pt}	3.17	<0.0005
-	Alternative specific constant of bike	ASC^{bike}	2.75	<0.0005
-	Alternative specific constant of BSS	ASC^{bss}	-0.07	0.0873
-	Alternative specific constant of ESSPT	ASC^{esspt}	-1.5	<0.0005
TT_k^{car}	Travel time of car (min)	β_{TT}^{car}	-0.0634	<0.0005
ToT_k^{pt}	Sum of travel time and out-of-vehicle time of PT (min)	β_{TT}^{pt}	-0.0761	<0.0005
TT_k^{bike}	Travel time of bike (min)	β_{TT}^{bike}	-0.0917	<0.0005
TT_k^{bss}	Travel time of BSS (min)	β_{TT}^{bss}	-0.0725	<0.0005
TT_k^{esspt}	Sum of travel time of the ESS leg and PT leg (min)	β_{TT}^{esspt}	-0.0443	0.0006
$COST_k^{i}$	Cost of alternative i (€)	β_{COST}	-0.138	0.0438
AdT_k^{bike}	Out-of-vehicle time and parking search time on the return trip of bike (min)	$\beta_{AdT}^{car,bike,bss}$	-0.00653	<0.0005
AdT_k^{bss}	Out-of-vehicle time and parking search time on the return trip of BSS (min)			
AdT_k^{car}	Parking search time on the return trip and congestion time on the return trip of car (min)			
OT_k^{esspt}	Out of vehicle time for ESSPT (min)	β_{OT}^{esspt}	-0.11	<0.0005
NT_k^{pt}	Number of transfer of PT 0, 1, 2	β_{NT}^{pt}	-0.315	<0.0005
$RURAL_n$	Binary variable equal to 1 if n lives outside of a metropolis	β_{RURAL}^{bss}	-6.34	<0.0005
$mCar_n$	Binary variable equal to 1 if main or secondary modes include car	β_{mCar}^{car}	2.19	<0.0005
$mmPMM_n$	Binary variable equal to 1 if main modes include private micro-mobility	β_{mmPMM}^{bike}	2.37	<0.0005
$smPT_n$	Binary variable equal to 1 if secondary modes include PT	β_{smPT}^{bike}	-1.13	0.0006
$subBSS_n$	Binary variable equal to 1 n has a subscription to BSS	β_{subBSS}^{car}	-0.927	0.0183
$subPT_n$	Binary variable equal to 1 if n has a subscription to PT	$\beta_{subPT}^{car,bike}$	1.33	<0.0005
$subESS_n$	Binary variable equal to 1 if n has a subscription to ESS	β_{subESS}^{esspt}	4.49	<0.0005
$nbMV_n$	Number of car and motorcycle in the household	β_{nbMV}^{car}	0.732	<0.0005
$nbBike_n$	Number of bike in the household	β_{nbBike}^{bike}	0.474	<0.0005
$nbMinor_n$	Number of minor in the household	$\beta_{nbMinor}^{bike}$	-0.837	0.0059
RO_k	Binary variable equal to 1 if it rains on the outward trip	$\beta_{RAIN}^{bike,bss}$	-2.45	<0.0005
RR_k	Probability of rain on the return trip [0, 1]			
σ_n^1	Individual specific error term 1	γ_1^{car}	-1.96	<0.0005
σ_n^2	Individual specific error term 2	γ_2^{pt}	-1.71	<0.0005
σ_n^3	Individual specific error term 3	γ_3^{bike}	-1.55	<0.0005
σ_n^4	Individual specific error term 4	γ_4^{bss}	1.8	<0.0005

Table 4: Statistics of the mixed logit model. The initial log-likelihood is computed from the model with constants only.

	Value
Number of parameters	28
Number of observations	3631
Number of draws	10 000
Initial log-likelihood	-4171
Final log-likelihood	-2513
$\bar{\rho}^2$	0.40

Certain characteristics and commuting habits of the respondents significantly impacted the mode choice. Individuals living outside the metropolitan area are less likely to choose BSS. Individuals with minors in the household are less likely to choose bike. Individuals using car or private micro-mobility as the main or secondary mode are more likely to choose car. Individuals using PT as a secondary mode are less likely to choose bike. Individuals with a PT subscription are less likely to choose car and bike, while individuals with a BSS subscription are less likely to choose car. ESS pass owners are more likely to choose ESSPT. Individuals with cars and motorcycles in the household are more likely to choose car, while individuals with bikes are more likely to choose bike. Environmental characteristics had a significant impact on some alternatives. When it rains during the outward trip, individuals are less likely to choose bike and BSS. When the probability of rain on the return trip is high, the probability of choosing bike during the outward trip decreases. The impacts did not differ significantly.

Four individual-specific error terms significantly impacted the utility functions of car, PT, bike, and BSS. This result means that certain individuals had an unobserved preference for one of these alternatives. We could not identify significant unobserved preferences across alternatives.

An out-of-sample validation has been conducted to investigate the model's ability to replicate the choices of individuals outside the estimation sample (Table 5). The characteristics of the individuals were homogeneous across folds (job category, age, and gender). When comparing the log-likelihood with the model with constants only, we notice that the final model is more accurate in predicting the mode choice in each fold and on average. Hence, we conclude that the final mixed logit model helps to predict the mode choice of individuals not included in the estimation sample.

Table 5: Cross-validation results. $\mathcal{L}$ indicates the final log-likelihood of the final model and $\mathcal{L}_c$ the final log-likelihood of the model with constants only.

Fold	Observations	$\mathcal{L}$	$\mathcal{L}_c$	Percentage improvement
1	732	-511.26	-908.06	43.70%
2	742	-517.57	-1085.49	52.32%
3	715	-513.91	-1120.77	54.15%
4	738	-512.36	-1046.41	51.04%
5	704	-494.01	-1050.91	52.99%
Mean		-509.95	-1042.02	51.06%
Number of draws			1000	
Number of parameter			28	
Number of parameter constants model			4	

5 Forecasting

The values of time (VoT) for travel time (TT), out-of-vehicle time (OT), parking search time on the return trip (PST), and congestion time on the return trip (CT) are computed for car, PT, BSS, and ESSPT to investigate how much individuals are willing to pay to save time (Ben-Akiva & Lerman, 1985). An average value of time is computed for each alternative as the weighted mean of values of time for each observation's chosen mode. The weights are determined by the time values in the observation. Results are displayed in table 6.

Table 6: Estimated average value of time.

	Car	PT	BSS	ESSPT
TT	27.57 €/h	33.09 €/h	31.52 €/h	19.26 €/h
OT		33.09 €/h	11.43 €/h	45.83 €/h
PST	11.43 €/h		11.43 €/h	
CT	11.43 €/h			
Average	21.06 €/h	33.09 €/h	23.61 €/h	23.83 €/h

For car, the VoT of travel time is higher than that of PST and CT, which is explained by the fact that the purpose of the trip is work and times during the return trip might be less important. In

PT, VoTs are the same for TT and OT. Regarding BSS, we observe the same result as for car. The VoT is higher for TT than other times, meaning that individuals are willing to walk if they will save travel time afterward. In contrast, individuals want to reduce the OT more than the TT in ESSPT. This means that increasing the accessibility of ESS might impact mode choice more than having a faster e-scooter or PT mode. On average, the VoT of PT is higher than the VoT of car, bike, BSS, and ESSPT.

6 Discussion and conclusions

This study investigated the factors influencing mode choice with micro-mobility services. We conducted a stated-preferences experiment at the ENTPE in Lyon and estimated a mixed logit model. The findings confirm that travel time, out-of-vehicle time, cost, and the number of transfers have a significantly negative impact on the probability of choosing an alternative (Baek et al., 2021; Nikiforiadis et al., 2023; Krauss et al., 2022; Jaber et al., 2023; Esztergár-Kiss et al., 2022; Curtale & Liao, 2023). The results showed that the probability of choosing car, bike or BSS decreases as parking search time on the return trip increases. The same effect is observed for congestion time on the return trip and car. Previous studies did not analyze these factors. The findings show that individuals are less likely to choose bike or BSS when it rains, confirming previous results for bike and BSS Reck et al. (2022) and BSS Younes et al. (2020). Finally, the cross-validation demonstrates that the developed model is better for out-of-sample prediction than the model with constants only.

Socio-economic characteristics and mobility habits had a significant effect. Specifically, individuals living outside a metropolitan area are less inclined to use BSS, and individuals with minors in their household are less likely to use bikes. Individuals who already use cars and motorcycles are more likely to use the car, those who already use private micro-mobility are more likely to use bike, and those who sometimes use PT are less likely to use the car. Individuals who have a subscription to PT are less likely to use car and bike, those who have one for BSS are less likely to choose the car, and those who have one for ESS are more likely to use ESSPT. Finally, the individual-specific error terms revealed the existence of heterogeneity related to unobserved factors.

The values of time showed that (in-vehicle) travel time for car, bike, and BSS was the most important time compared to out-of-vehicle time or time related to the return trip. Krauss et al. (2022) found similar results for car and BSS. Travel time and out-of-vehicle time have the same impact on the probability of choosing PT. Nevertheless, out-of-vehicle time is more important than travel time for the ESSPT alternative. Baek et al. (2021) reached to the same conclusion, while Krauss et al. (2022) found the opposite. In terms of magnitude, the values in this study range from 21.06€/h to 33.09€/h which is close to 17.64€/h to 32.34€/h from Curtale & Liao (2023). However, studies that did not include the weather conditions (Jaber et al., 2023; Baek et al., 2021; Krauss et al., 2022) found lower values (between 5€/h and 23.73€/h).

There are several directions for future research. Future analysis could be conducted on the weather, which strongly impacts the choice of bike and BSS. For example, the experiment could have attributes related to storms or heat waves. Future studies could consider other transportation modes available in Lyon (i.e., walking and ESS for short distances and car-sharing system for longer distances). Further research is needed to assess the transferability of the model to non-commuting trips and the general population of Lyon. Finally, revealed-preferences data (e.g., CEREMA (2015)) could be combined to enhance the model's realism.

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- Study conception and design: Nicolas Schoenn-Anchling and Silvia Varotto;
- Analysis and interpretation of results: Nicolas Schoenn-Anchling;
- Data processing: Nicolas Schoenn-Anchling;
- Draft manuscript preparation: Nicolas Schoenn-Anchling and Silvia Varotto.

All authors reviewed the results and approved the final version of the manuscript.

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