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Profiling users and non-users of meal delivery services in Belgium using latent class analysis

Laura Oostenbach, Matthew Keeble, Thomas Vanoutrive, Maartje Poelman, Carlijn Kamphuis & Lukar Thornton

Laura Oostenbach

Postdoctoral researcher
Faculty of Business and Economics
Department of Marketing

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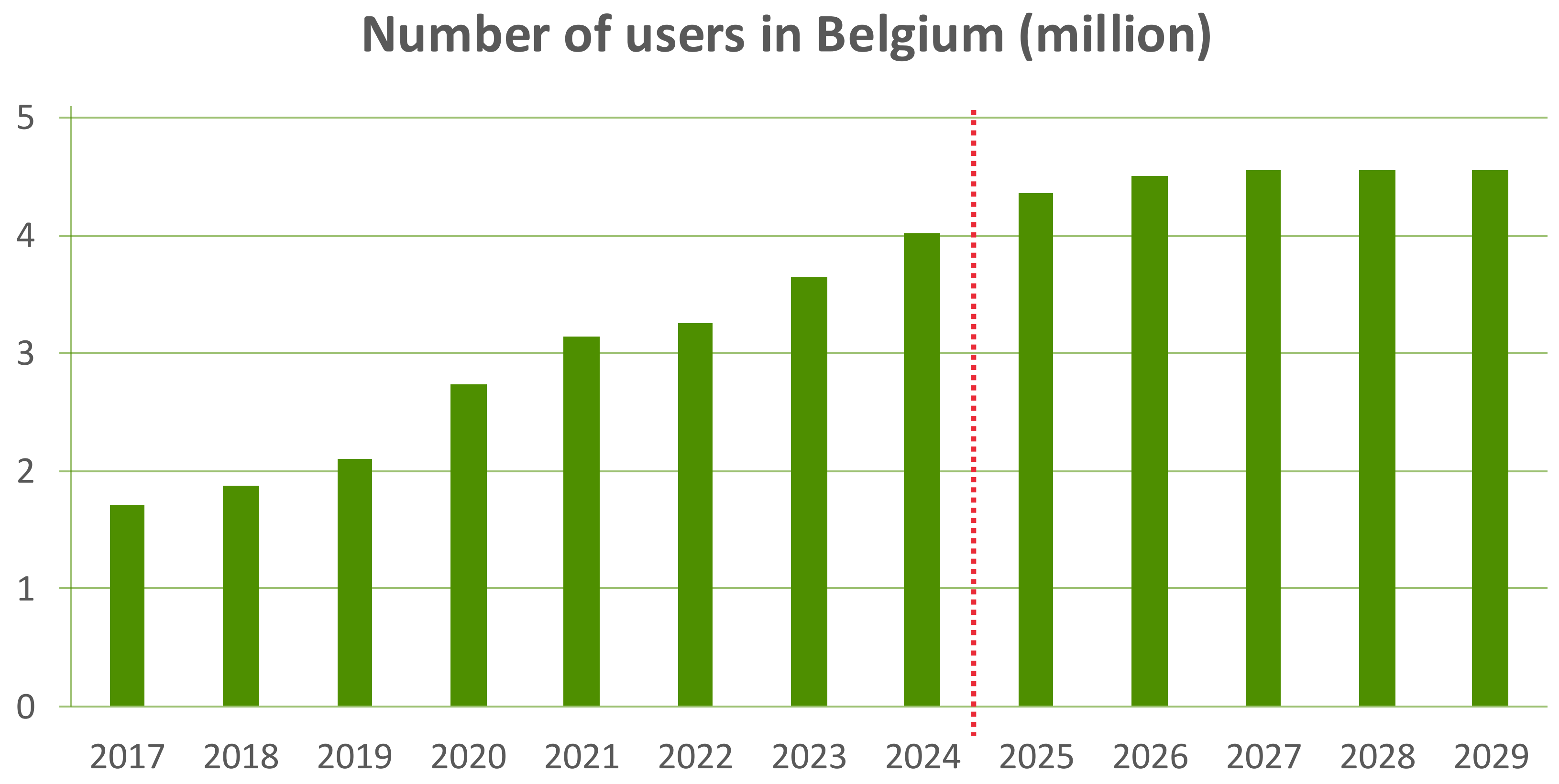
laura.oostenbach@uantwerpen.be
www.linkedin.com/in/laura-oostenbach

Growing use of ready-to-eat meal delivery services in Belgium



Source: [Statista Market Insights, 2024]

Ready-to-eat meal delivery services = delivery of meals from restaurants or fast-food outlets ordered via apps or direct phone or website orders

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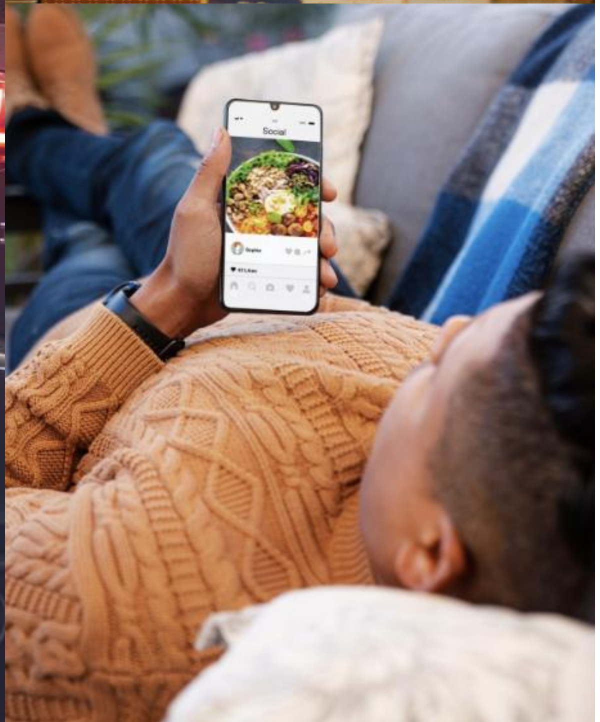


Meal delivery services have changed how consumers interact with food outlets

- Meal delivery reduces effort and expands access to out-of-home food by removing the need for in-person visits.
- Little is known about who uses meal delivery services and why.
- Reasons for non-use are largely unknown.
- Understanding determinants of use is important to support effective public health strategies.

A cross-sectional online survey of users and non-users of meal delivery services

An example of our digital flyers

- **Recruitment via paid and non-paid posts** on various social media platforms between April and July 2024.
    - Online design allowed us to explore reasons for non-use beyond simply no internet access or digital illiteracy.
- Survey was available in Dutch, French and English.
- **Participant eligibility**
    - ≥18 years old
    - live in Flanders or Brussels, Belgium
- **Final sample n=1304**
    - Users: 821 (63%) = used in the last 6 months
    - Non-users: 483 (37%) = no prior use or not in the last 6 months

Survey set-up

USER SECTION

Indicators related to use (yes/no)

- Important factors (e.g., fast delivery)
- Reasons for use (e.g., time for leisure activities)
- Behaviours (e.g., choose based on promotions)

NON-USER SECTION

Reasons for non-use (yes/no)

- Costs too much
- Prefer eating in restaurants
- Lack trust in hygiene of meals
- …

COMMON SECTION

Health and socio-demographic characteristics

- Self-rated health
- Body mass index (BMI)
- Age
- Sex
- Education
- Employment status
- Children in household
- Residential location
- …

Study aims

→ identify **profiles of users** of ready-to-eat meal delivery services based on indicators related to meal delivery ordering [latent class analysis]

→ explore **reasons for non-use** amongst individuals who do not use these services [descriptive exploration]

- **Users and non-users were examined separately.**
- **All analysis were conducted in Stata 18.**

USERS ONLY

Statistical analysis – Latent class analysis to identify user profiles

- **Steps we took:**
  1. Considered 23 binary indicators and excluded those with low frequencies (≤15%)
  2. Checked collinearity → combined into a joint-item
  3. Fitted logit latent class models (1-4 classes), using *gsem* command with *lclass()* option
     - 17 indicators
     - robust SEs, 100 random sets of starting values x 100 iterations
  4. Assessed model fit (e.g., convergence, local independence, BIC, class size, and average maximum posterior probabilities) and selected final model accordingly
  5. Assigned participants to best-fitting class based on highest posterior probability
  6. Descriptively compared classes by socio-demographic and health attributes, and frequency of meal delivery use
- Complete-case analysis n=720

(Collins 2009; Masyn, 2013; Sinha, 2021)

NON-USERS ONLY

Statistical analysis – to explore reasons for non-use

- We descriptively explored reasons for not ordering food for delivery.

  → **Frequencies of users reporting each reason were examined.**

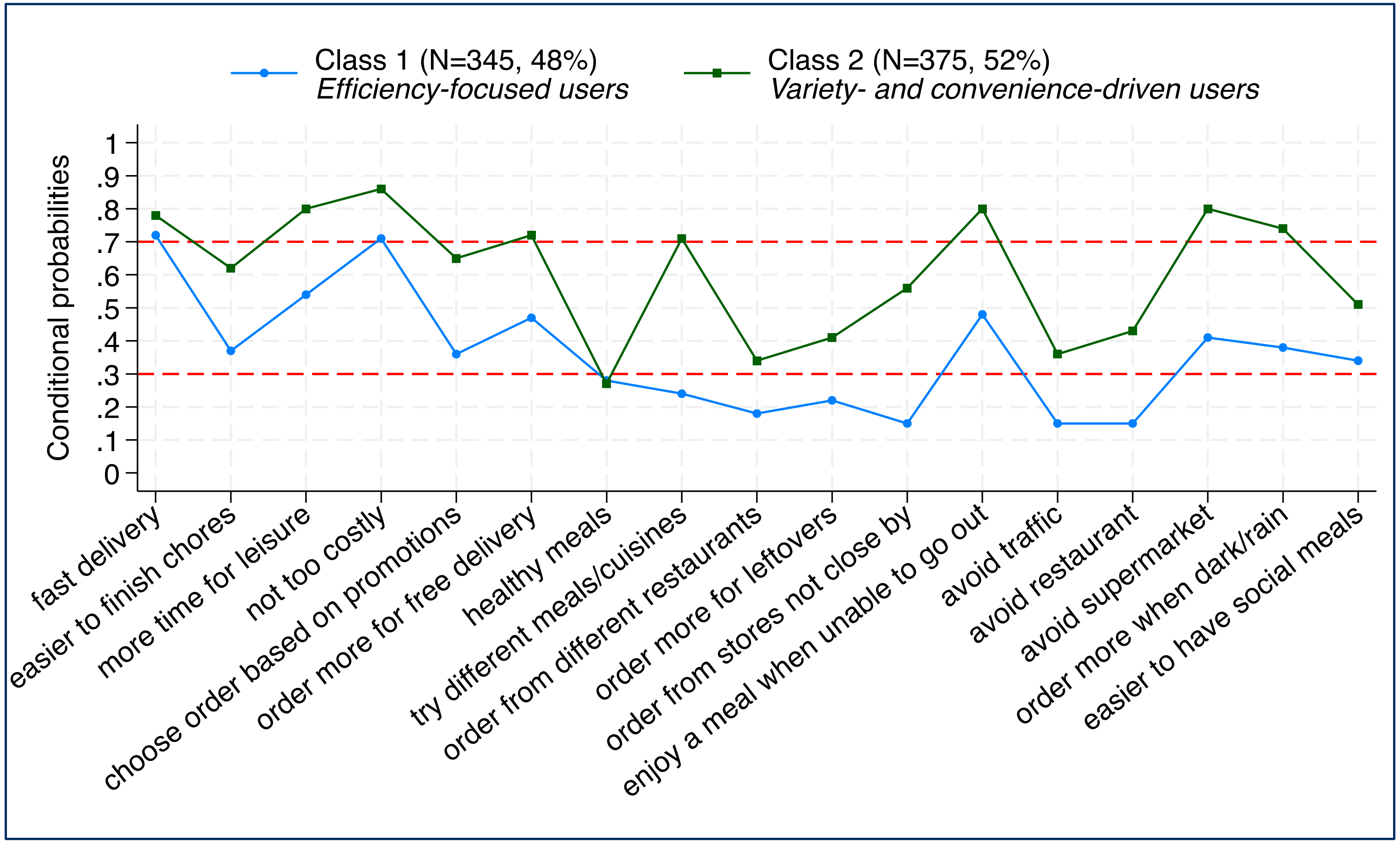
- Non-users without meal delivery services in their area were excluded (n=92).

- Final sample of non-users: n=366

USERS

Latent class analysis of user profiles

Probability of indicator endorsement conditional on class membership



Profile characteristics

Efficiency-focused users mainly prioritised fast delivery and low cost.

Variety- and convenience-driven users endorsed most indicators, valuing convenience, free time, and variety.

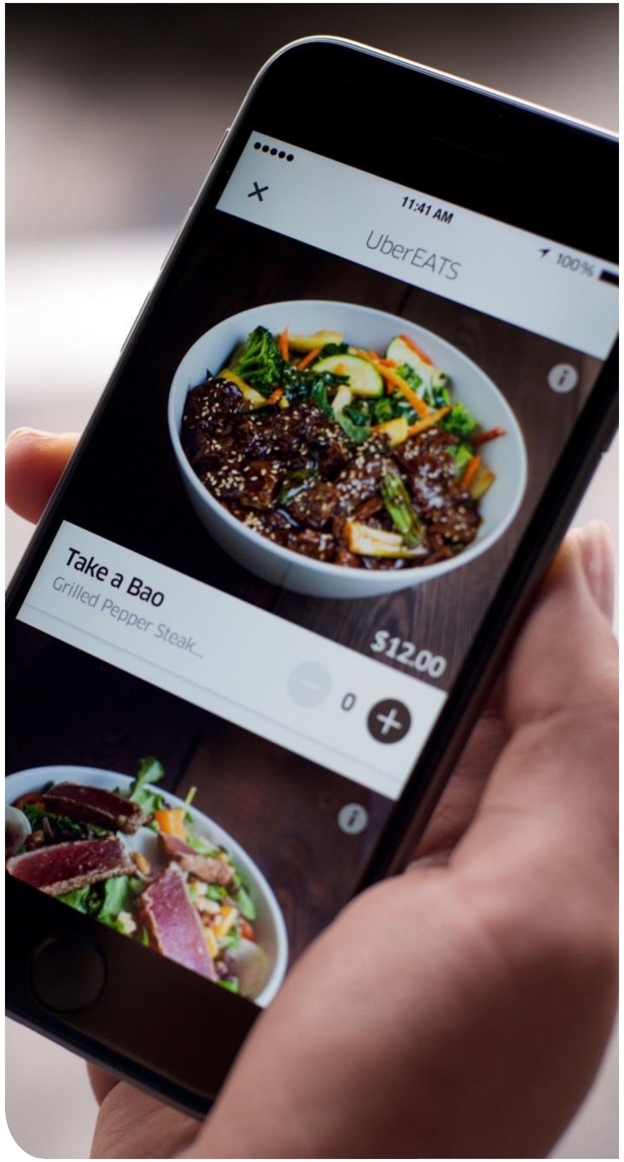
Variety- and convenience driven users were younger, had poorer self-rated health, lived in city centres, employed or studying, and ordered more often.

No major differences in sex, education, presence of children and BMI between profiles.

NON-USERS

Reasons for non-use (from most to least frequently reported)

	Non-users (N=366)
Prefer to cook my own meals	289 (79.0%)
Prefer to shop for food at supermarkets	275 (75.1%)
Don't want to spend money with meal delivery services	248 (67.8%)
Costs too much	204 (55.7%)
Cooking with family is important	192 (52.5%)
Prefer to eat in a restaurant	183 (50.0%)
Bad for the environment	142 (38.8%)
Unhealthy	136 (37.2%)
Long delivery time	129 (35.2%)
Lack trust in the hygiene of meals	82 (22.4%)
Heard negative things	80 (21.9%)
Not tasty	70 (19.1%)
Lack trust in ingredients due to food allergies	50 (13.7%)
Don't like trying new foods	20 (5.5%)



Potential implications

- Cost and delivery speed are important for all users.
- Unhealthy meal choices may be the norm.
- Public health strategies could be adapted to user profiles.

Future research

- Assess what is available on meal delivery platforms in Belgium.
- Assess dietary and health impacts of meal delivery use, including overall diet quality and compensatory behaviours.
- Explore reallocation of time freed by meal delivery.

Some limitations

- Data captured with binary responses for LCA needs and interpretability.

  → **Relative importance of each indicator is unknown.**

- Users assigned to latent classes based on their highest posterior probability.

  → **Classes reflect patterns, not exact attitudes/behaviours.**

- 6-month cut-off to distinguish users/non-users and capture recent, habitual behaviours.

  → **Very occasional users may have been classified as non-users.**

Take-home message

- **Two latent classes of users were identified.**
  - *Efficiency-focused users*, mainly focused on fast and affordable service.
  - *Variety- and convenience-driven users*, valued a wider range of factors, including convenience, free time and variety. This class included more frequent users.
- **Preference for home cooking and in-store food shopping were the most frequently reported reasons for non-use.**
- **Profiles differed in socio-demographic and health characteristics.**
  - E.g., *variety- and convenience-driven users* were younger, lived in city centres, employed or studying, had poorer self-rated health, and ordered more often.

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Thank you!

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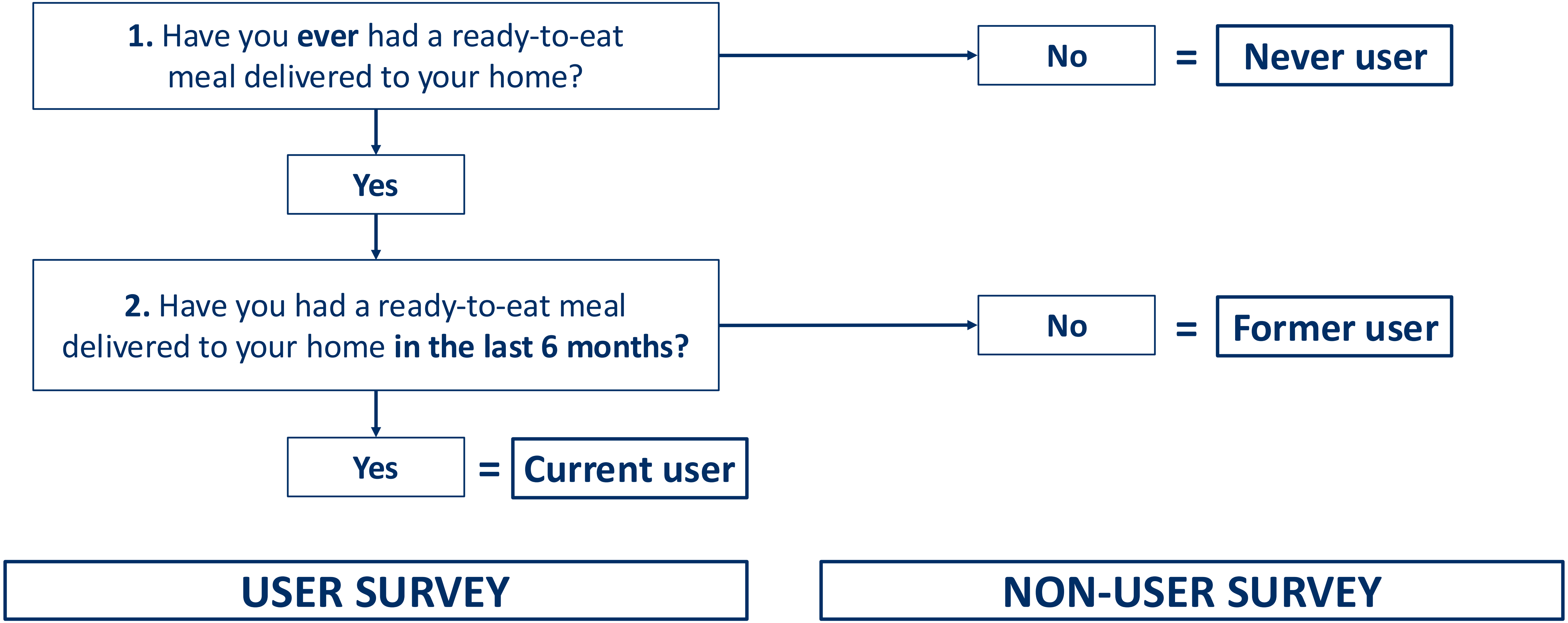
Latent class analysis: model selection

Statistic	1 class	2 classes	3 classes	4 classes
LL (Log-Likelihood)	-7747.008	-7536.626	-7486.122	Model non-identification
BIC	15605.86	15303.53	15320.94	
Class 1 size (n, %)	n=720, 100%	n=345, 47.92%	n=261, 36.25%	
Class 2 size (n, %)		n=375, 52.08%	n=128, 17.78%	
Class 3 size (n, %)			n=331, 45.97%	
Avg. posterior prob. Class 1 (mean, SD)		0.88 (0.13)	0.78 (0.15)	
Avg. posterior prob. Class 2 (mean, SD)		0.88 (0.15)	0.80 (0.16)	
Avg. posterior prob. Class 3 (mean, SD)			0.88 (0.15)	
Local Independence		Assumption met	Assumption violated	

Distinguishing users from non-users



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NON-USERS ONLY

Reasons for non-use (from most to least frequently reported)

	Full sample non-users (N=366)	Former users (N=190)	Never users (N=176)	p-value*
Prefer to cook my own meals	289 (79.0%)	144 (75.8%)	145 (82.4%)	0.12
Prefer to shop for food at supermarkets	275 (75.1%)	132 (69.5%)	143 (81.2%)	0.009
Don't want to spend money with meal delivery services	248 (67.8%)	125 (65.8%)	123 (69.9%)	0.40
Costs too much	204 (55.7%)	127 (66.8%)	77 (43.8%)	<0.001
Cooking with family is important	192 (52.5%)	89 (46.8%)	103 (58.5%)	0.025
Prefer to eat in a restaurant	183 (50.0%)	98 (51.6%)	85 (48.3%)	0.53
Bad for the environment	142 (38.8%)	73 (38.4%)	69 (39.2%)	0.88
Unhealthy	136 (37.2%)	75 (39.5%)	61 (34.7%)	0.34
Long delivery time	129 (35.2%)	77 (40.5%)	52 (29.5%)	0.028
Lack trust in the hygiene of meals	82 (22.4%)	25 (13.2%)	57 (32.4%)	<0.001
Heard negative things	80 (21.9%)	44 (23.2%)	36 (20.5%)	0.53
Not tasty	70 (19.1%)	28 (14.7%)	42 (23.9%)	0.027
Lack trust in ingredients due to food allergies	50 (13.7%)	11 (5.8%)	39 (22.2%)	<0.001
Don't like trying new foods	20 (5.5%)	7 (3.7%)	13 (7.4%)	0.12

**p-values of Chi-Square tests comparing former users and never users*

NON-USERS ONLY

Former users vs never users

- Differences in reasons for non use between former and never users.

	Former users (N=190, 52%)	Never users (N=176, 48%)
Prefer to shop for food at supermarkets	132 (69.5%)	143 (81.2%)
Costs too much	127 (66.8%)	77 (43.8%)
Cooking with family is important	89 (46.8%)	103 (58.5%)
Long delivery time	77 (40.5%)	52 (29.5%)
Lack trust in the hygiene of meals	25 (13.2%)	57 (32.4%)
Not tasty	28 (14.7%)	42 (23.9%)
Lack trust in ingredients due to food allergies	11 (5.8%)	39 (22.2%)

- Former users were younger and more often employed. Never users lived more often alone. No differences were observed for other socio-demographic and health characteristics.

Users vs non-users

- **Users were younger than non-users**
  - median age (p25; p75): 33 (28;42) vs 46 (30; 65) years old
- **More users were employed compared to non-users** (73% vs 52%).
- **More users had a university degree compared to non-users** (57% vs 49%).
- **No differences in gender, ability to manage on income, residential location, self-rated health.**