TP1 - Exploration et transformation des données

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In [1]:
```
#%pip install pandas numpy matplotlib ydata_profiling, sklearn
#%pip install ipywidgets

%matplotlib inline
import pandas as pd
import numpy as np
import seaborn as sns
from scipy.stats import chi2_contingency
import matplotlib.pyplot as plt
import time
```

Étape 1 : On considère le fichier train_users_2.csv

- Indiquer les points marquants l'exploration.
- Pour chaque observation, indiquer l'opération à effectuer qui serait la plus appropriée.

In [2]:
```
df = pd.read_csv('train_users_2.csv', index_col=0)
```

In [3]:
```
print('\nAffichage du dataset\n')
display(df.head(10))
```

```
Affichage du dataset
```

id	date_account_created	timestamp_first_active	date_first_booking	gender	age	signup_method	signup_f
gxn3p5htnn	2010-06-28	20090319043255	NaN	-unknown-	NaN	facebook	
820tgsjxq7	2011-05-25	20090523174809	NaN	MALE	38.0	facebook	
4ft3gnwmtx	2010-09-28	20090609231247	2010-08-02	FEMALE	56.0	basic	
bjjt8pjhuk	2011-12-05	20091031060129	2012-09-08	FEMALE	42.0	facebook	
87mebub9p4	2010-09-14	20091208061105	2010-02-18	-unknown-	41.0	basic	
osr2jwljor	2010-01-01	20100101215619	2010-01-02	-unknown-	NaN	basic	
lsw9q7uk0j	2010-01-02	20100102012558	2010-01-05	FEMALE	46.0	basic	
0d01nltbrs	2010-01-03	20100103191905	2010-01-13	FEMALE	47.0	basic	
a1vcnhxeij	2010-01-04	20100104004211	2010-07-29	FEMALE	50.0	basic	
6uh8zyj2gn	2010-01-04	20100104023758	2010-01-04	-unknown-	46.0	basic	

In [4]:
```
#!pip install pandas_profiling
# from ydata_profiling import ProfileReport
# profile = ProfileReport(df)
# profile.to_file(output_file="dortie.html")
```

In [5]:
```
#%pip install sweetviz
# import numpy as np
# if not hasattr(np, 'VisibleDeprecationWarning'):
#       np.VisibleDeprecationWarning = DeprecationWarning
# import sweetviz as sv
# report = sv.analyze(df)
# report.show_html("sortie.html")
```

1.1. Quels sont les descripteurs (colonnes) du dataset?

In [6]:
```
print("Les descripteurs du dataset:")
print(df.columns.tolist())
```

```
Les descripteurs du dataset:
['date_account_created', 'timestamp_first_active', 'date_first_booking', 'gender', 'age', 'signup_method', 'signup_flow', 'language', 'affiliate_channel', 'affiliate_provider', 'first_affiliate_tracked', 'signup_app', 'first_device_type', 'first_browser', 'country_destination']
```

1.2. Combien d'enregistrements (lignes) ont été fournis ?

In [7]:
```
nombre_enregistrements = df.shape[0]
print("Le nombre d'enregistrements:",nombre_enregistrements)
```

```
Le nombre d'enregistrements: 213451
```

1.3. Quel est le format des données. Par exemple, dans quel format les dates sont fournies, existe-t-il des valeurs numériques, à quoi ressemblent les différentes valeurs catégorielles ?

In [8]:
```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 213451 entries, gxn3p5htnn to nw9fwlyb5f
Data columns (total 15 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   date_account_created     213451 non-null  object 
 1   timestamp_first_active   213451 non-null  int64  
 2   date_first_booking       88908 non-null   object 
 3   gender                   213451 non-null  object 
 4   age                      125461 non-null  float64
 5   signup_method            213451 non-null  object 
 6   signup_flow              213451 non-null  int64  
 7   language                 213451 non-null  object 
 8   affiliate_channel        213451 non-null  object 
 9   affiliate_provider       213451 non-null  object 
 10  first_affiliate_tracked  207386 non-null  object 
 11  signup_app               213451 non-null  object 
 12  first_device_type        213451 non-null  object 
 13  first_browser            213451 non-null  object 
 14  country_destination      213451 non-null  object 
dtypes: float64(1), int64(2), object(12)
memory usage: 26.1+ MB
None
```

Les données de types date: 'date_account_created', 'timestamp_first_active', 'date_first_booking' Les données numériques: 'age', 'signup_flow' Les données categorielles: 'gender', 'signup_method', 'language', 'affiliate_channel', 'affiliate_provider', 'first_affiliate_tracked', 'signup_app', 'first_device_type', 'first_browser', 'country_destination'

Les dates sont de types objet et int. elles seront converties en type datetime (format ci-dessous) pour en extraire proprement les champs 'date_account_created' utilise le format 'YYYY-MM-DD' 'timestamp_first_active' utilise le format 'YYYYMMDDhhmmss' 'date_first_booking' utilise le format 'YYYY-MM-DD'

In [9]:
```
cols = ['gender', 'signup_method', 'signup_flow', 'language', 'affiliate_channel', 'affiliate_provider', '

print('Ci-dessous les valeurs catégorielles:\n')
for col in cols:
    print(col,':', df[col].unique(), '\n')
```

```
Ci-dessous les valeurs catégorielles:

gender : ['-unknown-' 'MALE' 'FEMALE' 'OTHER']

signup_method : ['facebook' 'basic' 'google']

signup_flow : [ 0  3  2  1 24  8  6  5 10 25 12  4 16 15 20 21 23]

language : ['en' 'fr' 'de' 'es' 'it' 'pt' 'zh' 'ko' 'ja' 'ru' 'pl' 'el' 'sv' 'nl'
 'hu' 'da' 'id' 'fi' 'no' 'tr' 'th' 'cs' 'hr' 'ca' 'is']

affiliate_channel : ['direct' 'seo' 'other' 'sem-non-brand' 'content' 'sem-brand'
 'remarketing' 'api']

affiliate_provider : ['direct' 'google' 'other' 'craigslist' 'facebook' 'vast' 'bing' 'meetup'
 'facebook-open-graph' 'email-marketing' 'yahoo' 'padmapper' 'gsp' 'wayn'
 'naver' 'baidu' 'yandex' 'daum']

first_affiliate_tracked : ['untracked' 'omg' nan 'linked' 'tracked-other' 'product' 'marketing'
 'local ops']

signup_app : ['Web' 'Moweb' 'iOS' 'Android']

first_device_type : ['Mac Desktop' 'Windows Desktop' 'iPhone' 'Other/Unknown'
 'Desktop (Other)' 'Android Tablet' 'iPad' 'Android Phone'
 'SmartPhone (Other)']

first_browser : ['Chrome' 'IE' 'Firefox' 'Safari' '-unknown-' 'Mobile Safari'
 'Chrome Mobile' 'RockMelt' 'Chromium' 'Android Browser' 'AOL Explorer'
 'Palm Pre web browser' 'Mobile Firefox' 'Opera' 'TenFourFox' 'IE Mobile'
 'Apple Mail' 'Silk' 'Camino' 'Arora' 'BlackBerry Browser' 'SeaMonkey'
 'Iron' 'Sogou Explorer' 'IceWeasel' 'Opera Mini' 'SiteKiosk' 'Maxthon'
 'Kindle Browser' 'CoolNovo' 'Conkeror' 'wOSBrowser' 'Google Earth'
 'Crazy Browser' 'Mozilla' 'OmniWeb' 'PS Vita browser' 'NetNewsWire'
 'CometBird' 'Comodo Dragon' 'Flock' 'Pale Moon' 'Avant Browser'
 'Opera Mobile' 'Yandex.Browser' 'TheWorld Browser' 'SlimBrowser' 'Epic'
 'Stainless' 'Googlebot' 'Outlook 2007' 'IceDragon']

country_destination : ['NDF' 'US' 'other' 'FR' 'CA' 'GB' 'ES' 'IT' 'PT' 'NL' 'DE' 'AU']
```

1.4. Y a-t-il des valeurs manquantes?

In [10]:
```
print("Valeurs manquantes par colonne:\n")
print(df.isnull().sum())
```

```
Valeurs manquantes par colonne:

date_account_created            0
timestamp_first_active          0
date_first_booking         124543
gender                          0
age                         87990
signup_method                   0
signup_flow                     0
language                        0
affiliate_channel               0
affiliate_provider              0
first_affiliate_tracked      6065
signup_app                      0
first_device_type               0
first_browser                   0
country_destination             0
dtype: int64
```

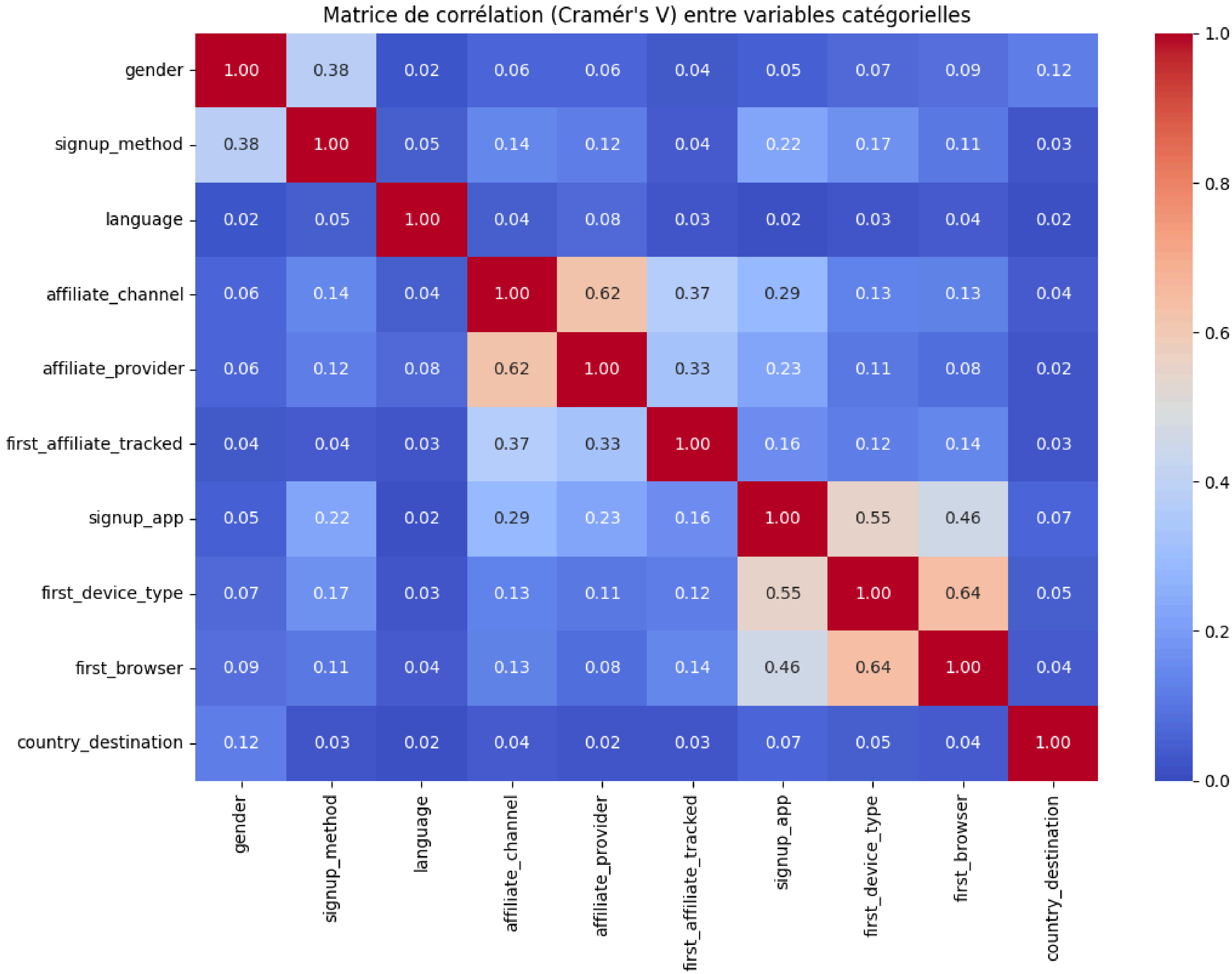
1.5. Est-ce qu’il y’a des dépendances évidentes au niveau des descripteurs?

Oui, il peut exister des dépendances entre certains descripteurs. Par exemple, entre:

- ('language', 'country_destination'): Un utilisateur qui s'inscrit avec la langue française a plus de chances de reserver en France
- ('date_account_created', 'timestamp_first_active', 'date_first_booking'): 'date_account_created' est toujours antérieure à 'timestamp_first_active' et 'date_first_booking' est toujours postérieure aux deux premières dates.
- ('first_device_type', 'first_browser'): certains types d'appareils influencent fortement le navigateur utilisé
- ('affiliate_provider', 'affiliate_channel'): certains providers peuvent privilégier certains canaux.
  Nous allons validé ces dépendances à l'aide ds matrices de corrélations ci-dessous

Corrélations entre variables qualitatives

In [11]:
```
categorical_columns = [
    'gender', 'signup_method', 'language', 'affiliate_channel','affiliate_provider', 'first_affiliate_track
]

# Fonction pour calculer le coefficient de Cramér
def cramers_v(x, y):
    confusion_matrix = pd.crosstab(x, y)
    chi2 = chi2_contingency(confusion_matrix)[0]
    n = confusion_matrix.sum().sum()
    phi2 = chi2 / n
    r, k = confusion_matrix.shape
    phi2corr = max(0, phi2 - ((k-1)*(r-1))/(n-1))
    rcorr = r - ((r-1)**2)/(n-1)
    kcorr = k - ((k-1)**2)/(n-1)
    return np.sqrt(phi2corr / min((kcorr-1), (rcorr-1)))

# Créer une matrice de corrélation
correlation_matrix = pd.DataFrame(index=categorical_columns, columns=categorical_columns)

# Remplir la matrice avec les coefficients de Cramér
for col1 in categorical_columns:
    for col2 in categorical_columns:
        correlation_matrix.loc[col1, col2] = cramers_v(df[col1], df[col2])

# Convertir la matrice en valeurs numériques
correlation_matrix = correlation_matrix.astype(float)

# Afficher la matrice de corrélation avec une heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", vmin=0, vmax=1)
plt.title("Matrice de corrélation (Cramér's V) entre variables catégorielles")
plt.show()
```

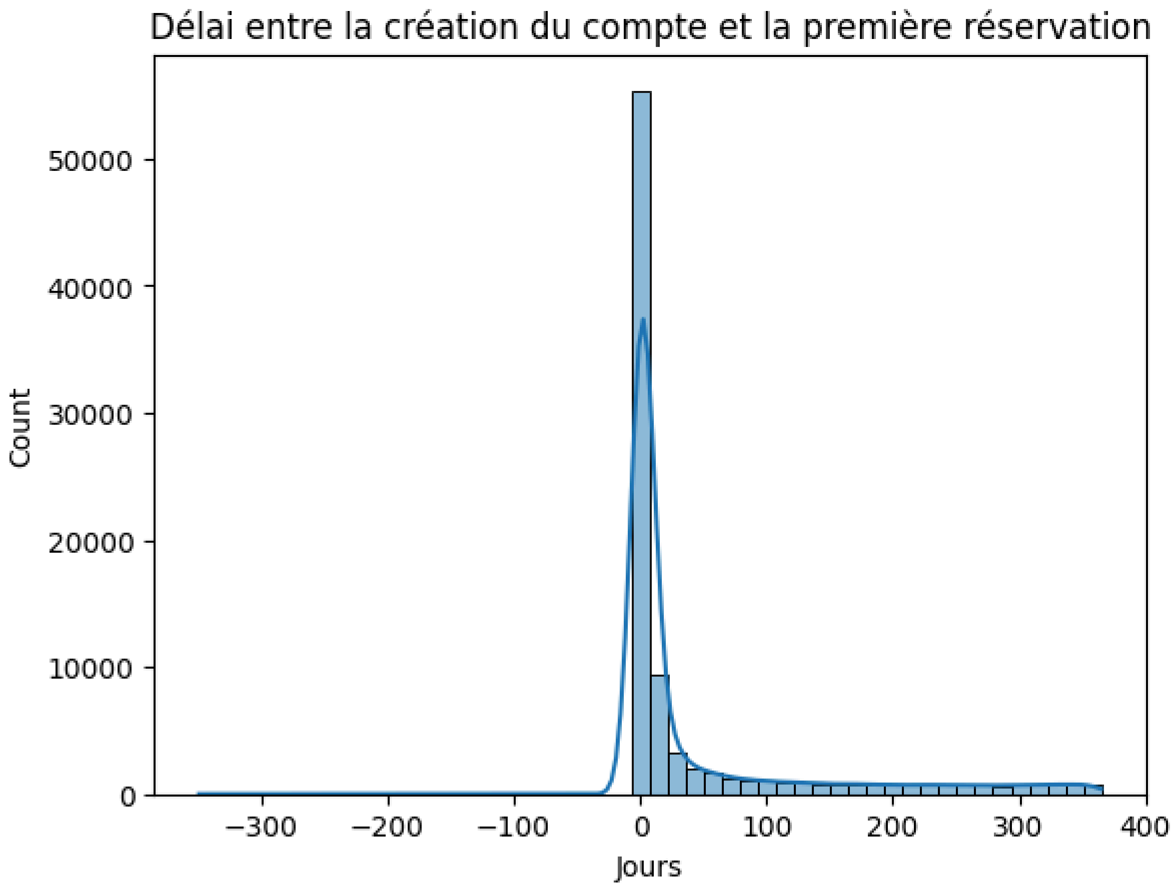

Matrice de corrélation (Cramér's V) entre variables catégorielles
gender
signup_method
language
affiliate_channel
affiliate_provider
first_affiliate_tracked
signup_app
first_device_type
first_browser
country_destination
1.00 0.38 0.02 0.06 0.06 0.04 0.05 0.07 0.09 0.12
0.38 1.00 0.05 0.14 0.12 0.04 0.22 0.17 0.11 0.03
0.02 0.05 1.00 0.04 0.08 0.03 0.02 0.03 0.04 0.02
0.06 0.14 0.04 1.00 0.62 0.37 0.29 0.13 0.13 0.04
0.06 0.12 0.08 0.62 1.00 0.33 0.23 0.11 0.08 0.02
0.04 0.04 0.03 0.37 0.33 1.00 0.16 0.12 0.14 0.03
0.05 0.22 0.02 0.29 0.23 0.16 1.00 0.55 0.46 0.07
0.07 0.17 0.03 0.13 0.11 0.12 0.55 1.00 0.64 0.05
0.09 0.11 0.04 0.13 0.08 0.14 0.46 0.64 1.00 0.04
0.12 0.03 0.02 0.04 0.02 0.03 0.07 0.05 0.04 1.00
1.0
0.8
0.6
0.4
0.2
0.0

La matrice de corrélation met en lumière les dépendances mentionnées précédemment

Corrélations entre variables numériques

In [12]:
```
df_original = df.copy()
# Vérifier les dépendances temporelles
# Vérifier que les timestamps sont bien ordonnés
df["date_account_created"] = pd.to_datetime(df["date_account_created"]) #Convesion de la colonne "date_acc

# Conversion de la colonne 'date_account_created' en datetime si ce n'est pas déjà fait
df["timestamp_first_active"] = pd.to_datetime(df["timestamp_first_active"], format='%Y%m%d%H%M%S')
df["date_first_booking"] = pd.to_datetime(df["date_first_booking"])

# Vérifier si `timestamp_first_active` est toujours avant ou égal à `date_account_created`
df["timestamp_issue"] = df["timestamp_first_active"] > df["date_account_created"]
print("Nombre de cas où `timestamp_first_active` est postérieur à `date_account_created` :", df["timestamp_

# Visualiser l'écart entre `date_account_created` et `date_first_booking`
df["booking_delay"] = (df["date_first_booking"] - df["date_account_created"]).dt.days
sns.histplot(df["booking_delay"].dropna(), bins=50, kde=True)
plt.title("Délai entre la création du compte et la première réservation")
plt.xlabel("Jours")
plt.show()

print('Dataset avec dates converties:\n')
display(df)
```

```
Nombre de cas où `timestamp_first_active` est postérieur à `date_account_created` : 213273
```




```
Dataset avec dates converties:
```

	date_account_created	timestamp_first_active	date_first_booking	gender	age	signup_method	signup_f
id							
gxn3p5htnn	2010-06-28	2009-03-19 04:32:55	NaT	-unknown-	NaN	facebook	
820tgsjxq7	2011-05-25	2009-05-23 17:48:09	NaT	MALE	38.0	facebook	
4ft3gnwmtx	2010-09-28	2009-06-09 23:12:47	2010-08-02	FEMALE	56.0	basic	
bjjt8pjhuk	2011-12-05	2009-10-31 06:01:29	2012-09-08	FEMALE	42.0	facebook	
87mebub9p4	2010-09-14	2009-12-08 06:11:05	2010-02-18	-unknown-	41.0	basic	
...	...	...	...	...	...	...	
zxodksqpep	2014-06-30	2014-06-30 23:56:36	NaT	MALE	32.0	basic	
mhewnxesx9	2014-06-30	2014-06-30 23:57:19	NaT	-unknown-	NaN	basic	
6o3arsjbb4	2014-06-30	2014-06-30 23:57:54	NaT	-unknown-	32.0	basic	
jh95kwisub	2014-06-30	2014-06-30 23:58:22	NaT	-unknown-	NaN	basic	
nw9fwlyb5f	2014-06-30	2014-06-30 23:58:24	NaT	-unknown-	NaN	basic	

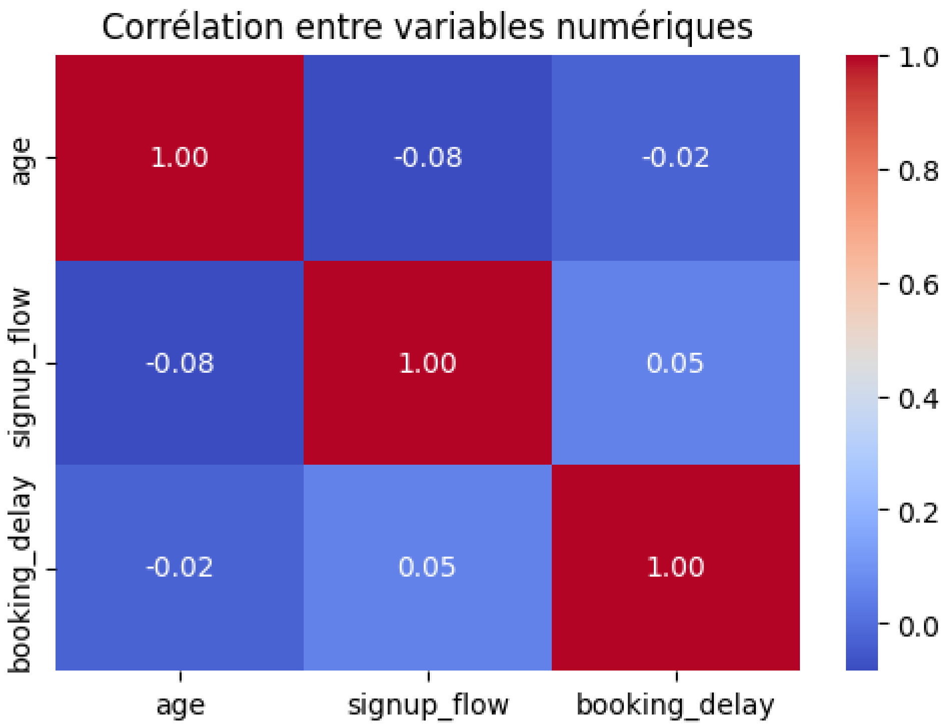
213451 rows × 17 columns

Si timestamp_first_active est après date_account_created, il y a un problème dans les données. La distribution des délais de réservation permet de voir combien de temps les utilisateurs attendent avant leur première réservation.

In [13]:
```
# Convertir l'âge en numérique et traiter les valeurs aberrantes
df["age"] = pd.to_numeric(df["age"], errors="coerce")
df_FilteredAge = df[(df["age"] > 17) & (df["age"] <= 120)]  # Filtrer des âges aberrants
display(df_FilteredAge['age'])

# Matrice de corrélation
```

```python
num_vars = ["age", "signup_flow", "booking_delay"]
corr_matrix = df_FilteredAge[num_vars].corr()

# Affichage
plt.figure(figsize=(6, 4))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Corrélation entre variables numériques")
plt.show()
```

```
id
820tgsjxq7    38.0
4ft3gnwmtx    56.0
bjjt8pjhuk    42.0
87mebub9p4    41.0
lsw9q7uk0j    46.0
              ...
omlc9iku7t    34.0
0k26r3mir0    36.0
qbxza0xojf    23.0
zxodksqpep    32.0
6o3arsjbb4    32.0
Name: age, Length: 124522, dtype: float64
```

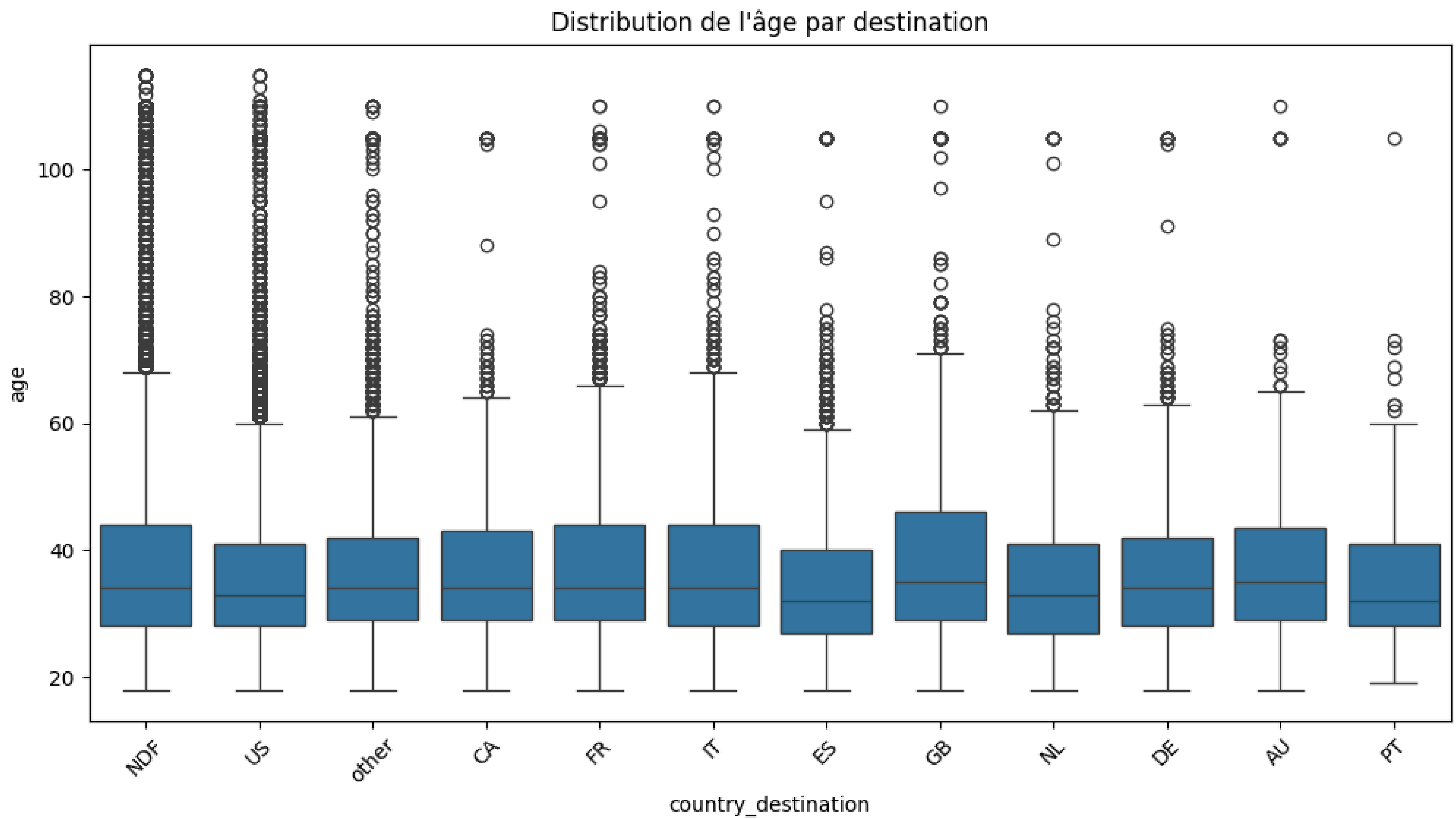


La matrice de corrélation montre qu'il n'y a pas de dépendances entre les variables quantitatives

1.6. D’autres observations sur le dataset qui pourraient être pertinentes ?

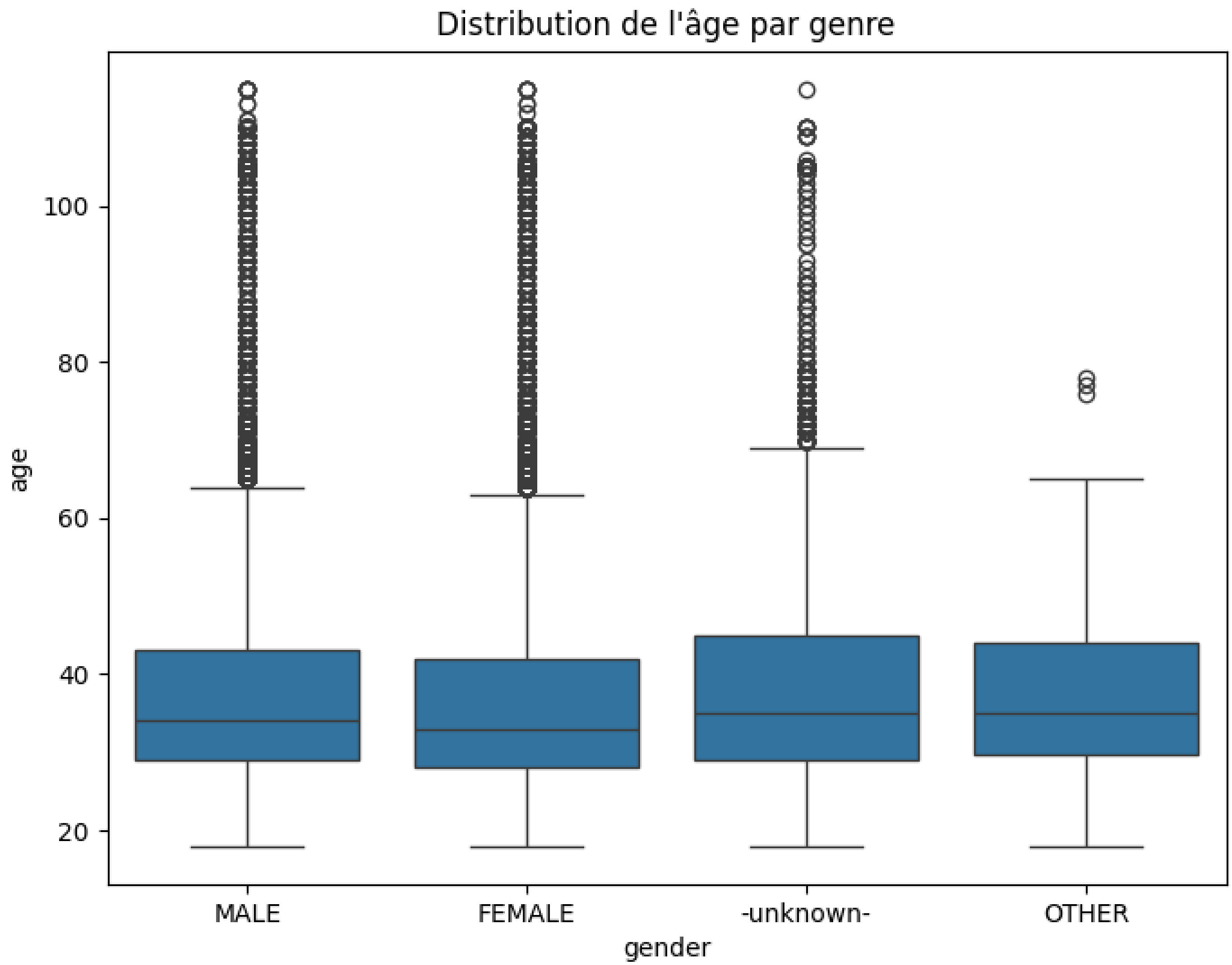
Boxplot de l'âge en fonction du pays de destination

In [14]:
```
#L'âge semble être la seule variable continue intéressante pour un boxplot.
plt.figure(figsize=(12, 6))
sns.boxplot(x="country_destination", y="age", data=df_FilteredAge)
plt.xticks(rotation=45)
plt.title("Distribution de l'âge par destination")
plt.show()
```



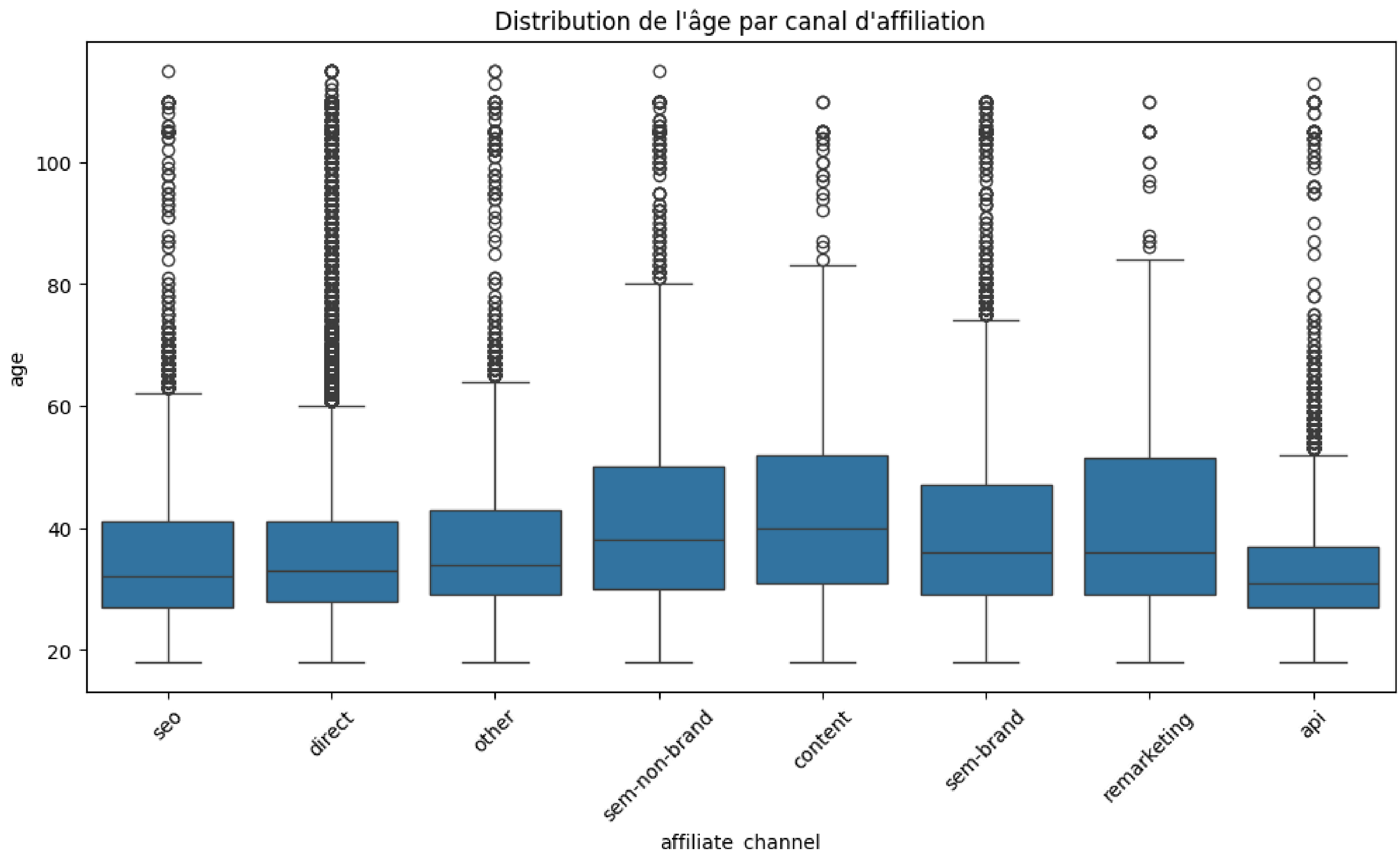
Boxplot de l'âge selon le sexe :

In [15]:
```
plt.figure(figsize=(8, 6))
sns.boxplot(x="gender", y="age", data=df_FilteredAge)
plt.title("Distribution de l'âge par genre")
plt.show()
```



Boxplot de l'âge selon le canal d'affiliation :

In [16]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(x="affiliate_channel", y="age", data=df_FilteredAge)
plt.xticks(rotation=45)
plt.title("Distribution de l'âge par canal d'affiliation")
plt.show()
```



Détection des valeurs aberrantes de l'âge (outliers)

In [17]:
```
Q1 = df['age'].quantile(0.25)
Q3 = df['age'].quantile(0.75)
IQR = Q3 - Q1

outliers = df[(df['age'] < (Q1 - 1.5 * IQR)) | (df['age'] > (Q3 + 1.5 * IQR))]
display(outliers[['age']])  # Liste des outliers
```

	age
id	
dgatsm5ocq	69.0
3qsa4lo7eg	5.0
47wdhtdini	72.0
uhbkw5exeg	70.0
kw7qyvlhsq	70.0
...	...
pw9nfo1ulb	95.0
y37l7vzjpa	66.0
jl5f10hu4t	69.0
gfend4omwv	105.0
l8tltghomx	69.0

5594 rows × 1 columns

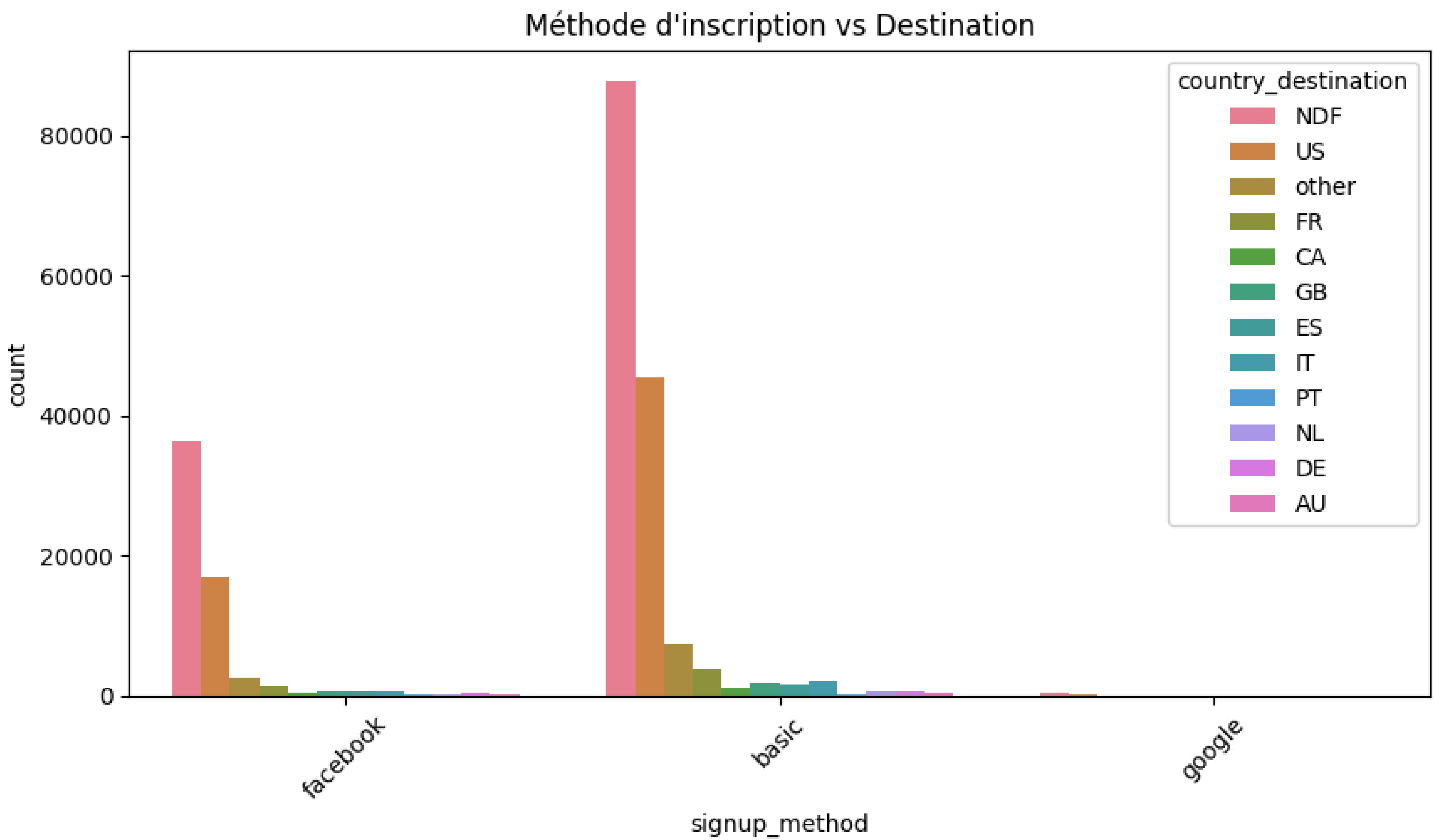
In [18]:
```
print(df['age'].describe())
```

```
count    125461.000000
mean         49.668335
std         155.666612
min           1.000000
25%          28.000000
50%          34.000000
75%          43.000000
max        2014.000000
Name: age, dtype: float64
```

On constate que la colonne 'age' contient des données abbérantes. Nous ferons un filtrage á l'étape 2.

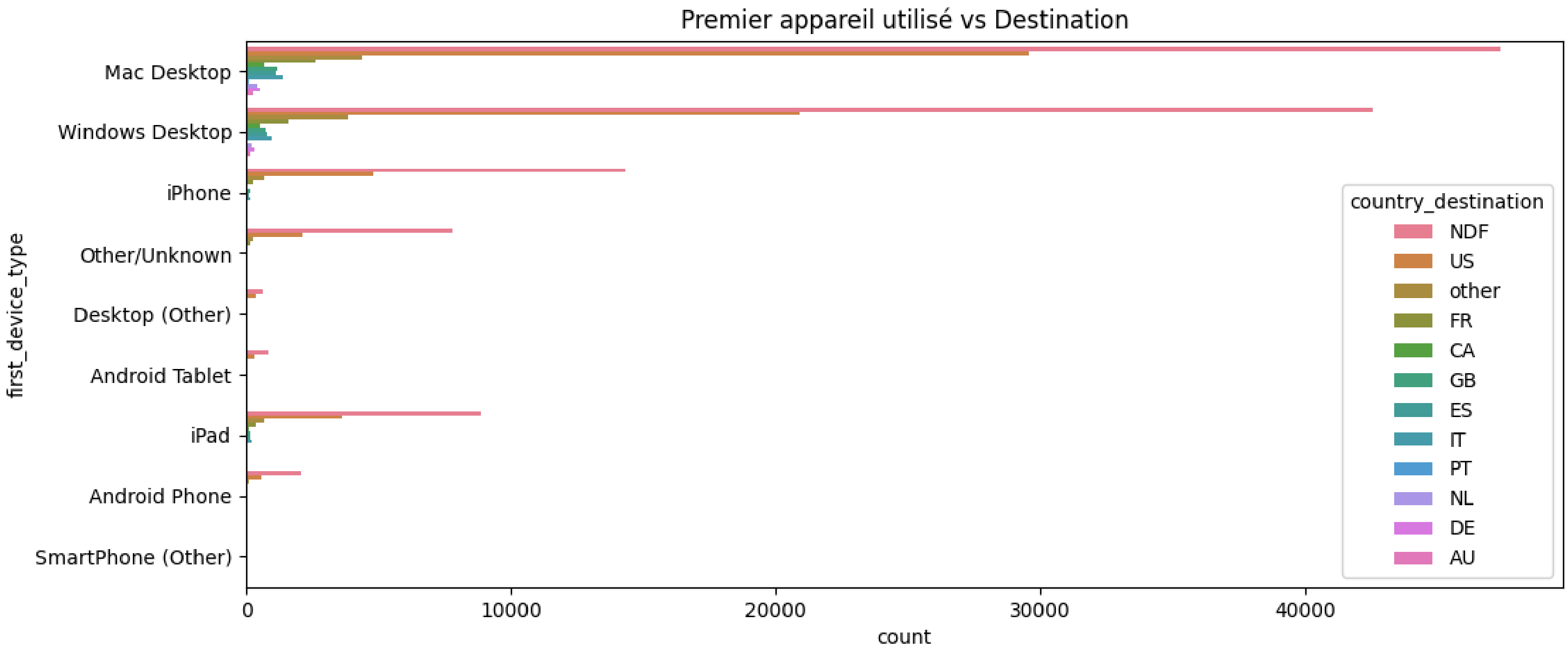
Relations entre variables catégorielles

In [19]:
```
#Impact de signup_method sur country_destination
plt.figure(figsize=(10, 5))
sns.countplot(data=df, x="signup_method", hue="country_destination")
plt.title("Méthode d'inscription vs Destination")
plt.xticks(rotation=45)
plt.show()
```



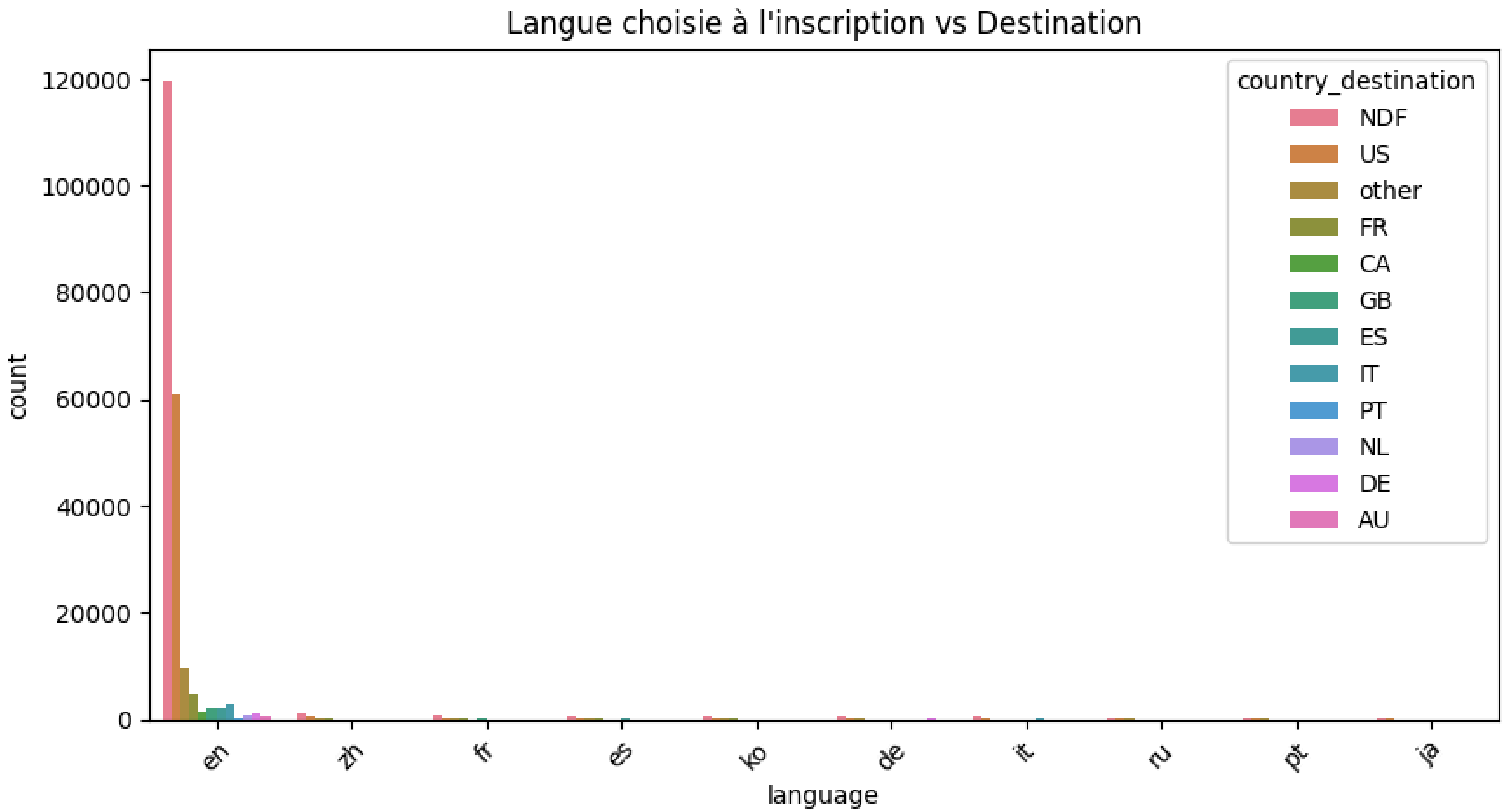
Certains modes d'inscription sont peut-être plus populaires pour certaines destinations. Par exemple, les utilisateurs inscrits via Google ou Facebook peuvent être différents de ceux inscrits par email.

In [20]:
```
#Influence de first_device_type sur country_destination
plt.figure(figsize=(12, 5))
sns.countplot(data=df, y="first_device_type", hue="country_destination")
plt.title("Premier appareil utilisé vs Destination")
plt.show()
```



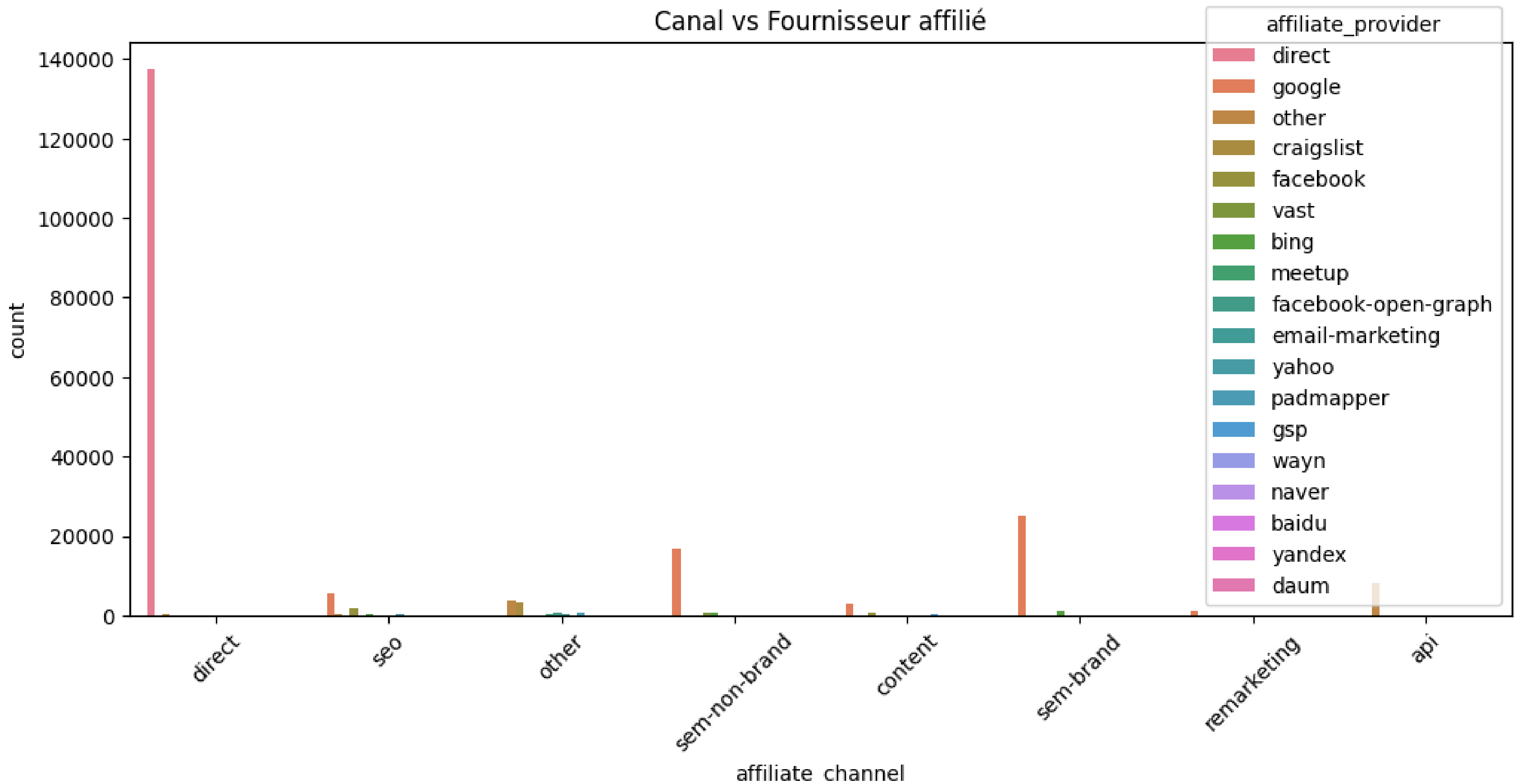
On constate que les utilisateurs mobiles (iPhone, Android) réservent plus rapidement que ceux sur ordinateur

In [21]:
```
#Langue (language) et destination
plt.figure(figsize=(10, 5))
sns.countplot(data=df, x="language", hue="country_destination", order=df["language"].value_counts().index[
plt.title("Langue choisie à l'inscription vs Destination")
plt.xticks(rotation=45)
plt.show()
```



On confirme que La langue d'inscription influence la destination finale

In [22]:
```
# Vérifier les relations entre affiliés
plt.figure(figsize=(12, 5))
sns.countplot(data=df, x="affiliate_channel", hue="affiliate_provider")
plt.title("Canal vs Fournisseur affilié")
plt.xticks(rotation=45)
plt.show()
```



Le diagramme ci-dessus confirme que certains fournisseurs affiliés sont spécialisés dans certains canaux de conversion

Étape 2 : On considère le fichier train_users_2.csv et test_users.csv

- Implémenter les correctifs soulignés dans l'étape 1.

In [23]:
```
#!pip install scikit-learn
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestRegressor
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
```

```
df_train = df_original.copy()

df_test = pd.read_csv('test_users.csv', index_col=0)

print("Données de Train:")
display(df_train)

print("Données de Test:")
display(df_test)
```

```
Données de Train:
```

	date_account_created	timestamp_first_active	date_first_booking	gender	age	signup_method	signup_f
id							
gxn3p5htnn	2010-06-28	20090319043255	NaN	-unknown-	NaN	facebook	
820tgsjxq7	2011-05-25	20090523174809	NaN	MALE	38.0	facebook	
4ft3gnwmtx	2010-09-28	20090609231247	2010-08-02	FEMALE	56.0	basic	
bjjt8pjhuk	2011-12-05	20091031060129	2012-09-08	FEMALE	42.0	facebook	
87mebub9p4	2010-09-14	20091208061105	2010-02-18	-unknown-	41.0	basic	
...	...	...	...	...	...	...	
zxodksqpep	2014-06-30	20140630235636	NaN	MALE	32.0	basic	
mhewnxesx9	2014-06-30	20140630235719	NaN	-unknown-	NaN	basic	
6o3arsjbb4	2014-06-30	20140630235754	NaN	-unknown-	32.0	basic	
jh95kwisub	2014-06-30	20140630235822	NaN	-unknown-	NaN	basic	
nw9fwlyb5f	2014-06-30	20140630235824	NaN	-unknown-	NaN	basic	

213451 rows × 15 columns

```
Données de Test:
```

	date_account_created	timestamp_first_active	date_first_booking	gender	age	signup_method	signup_fl
id							
5uwns89zht	2014-07-01	20140701000006	NaN	FEMALE	35.0	facebook	
jtl0dijy2j	2014-07-01	20140701000051	NaN	-unknown-	NaN	basic	
xx0ulgorjt	2014-07-01	20140701000148	NaN	-unknown-	NaN	basic	
6c6puo6ix0	2014-07-01	20140701000215	NaN	-unknown-	NaN	basic	
czqhjk3yfe	2014-07-01	20140701000305	NaN	-unknown-	NaN	basic	
...	...	...	...	...	...	...	
cv0na2lf5a	2014-09-30	20140930235232	NaN	-unknown-	31.0	basic	
zp8xfonng8	2014-09-30	20140930235306	NaN	-unknown-	NaN	basic	
fa6260ziny	2014-09-30	20140930235408	NaN	-unknown-	NaN	basic	
87k0fy4ugm	2014-09-30	20140930235430	NaN	-unknown-	NaN	basic	
9uqfg8txu3	2014-09-30	20140930235901	NaN	FEMALE	49.0	basic	

62096 rows × 14 columns

In [24]:
```
import numpy as np
if not hasattr(np, 'VisibleDeprecationWarning'):
        np.VisibleDeprecationWarning = DeprecationWarning
import sweetviz as sv
comparison_report = sv.compare([df_train, "Train"], [df_test, "Test"])

# Sauvegarder et afficher le rapport
comparison_report.show_html("comparison_report.html")
```

```
                                                    |      | [  0%]   00:00 -> (? left)
Report comparison_report.html was generated! NOTEBOOK/COLAB USERS: the web browser MAY not pop up, regardle
ss, the report IS saved in your notebook/colab files.
```

* Existance les doublons

In [25]:
```
print("Doublons dans les doneées de train:", df_train.duplicated().unique())
print("Doublons dans les doneées de test:", df_test.duplicated().unique())
```

```
Doublons dans les doneées de train: [False]
Doublons dans les doneées de test: [False]
```

2.1. Conversion de type/format (les dates)

* Dataset de Training

In [26]:
```
df_train['date_account_created'] = pd.to_datetime(df_train['date_account_created'])
df_train.drop(['date_first_booking'], axis=1, inplace=True) # Supprimer la colonne 'date_first_booking' ca
#df_train.drop(['timestamp_first_active'], axis=1, inplace=True)
#df['timestamp_first_active'] = pd.to_datetime(df['timestamp_first_active'], format='%Y%m%d%H%M%S')
#df_train.drop(['signup_flow'], axis=1, inplace=True)


display(df_train)
```

	date_account_created	timestamp_first_active	gender	age	signup_method	signup_flow	language	affili
id								
gxn3p5htnn	2010-06-28	20090319043255	-unknown-	NaN	facebook	0	en	
820tgsjxq7	2011-05-25	20090523174809	MALE	38.0	facebook	0	en	
4ft3gnwmtx	2010-09-28	20090609231247	FEMALE	56.0	basic	3	en	
bjjt8pjhuk	2011-12-05	20091031060129	FEMALE	42.0	facebook	0	en	
87mebub9p4	2010-09-14	20091208061105	-unknown-	41.0	basic	0	en	
...	...	...	...	...	...	...	...	
zxodksqpep	2014-06-30	20140630235636	MALE	32.0	basic	0	en	
mhewnxesx9	2014-06-30	20140630235719	-unknown-	NaN	basic	0	en	
6o3arsjbb4	2014-06-30	20140630235754	-unknown-	32.0	basic	0	en	
jh95kwisub	2014-06-30	20140630235822	-unknown-	NaN	basic	25	en	
nw9fwlyb5f	2014-06-30	20140630235824	-unknown-	NaN	basic	25	en	

213451 rows × 14 columns

* Dataset de Test

In [27]:
```
df_test['date_account_created'] = pd.to_datetime(df_test['date_account_created'])
df_test.drop(['date_first_booking'], axis=1, inplace=True)
#df_test.drop(['timestamp_first_active'], axis=1, inplace=True)
#df_test.drop(['signup_flow'], axis=1, inplace=True)
#df_test['timestamp_first_active'] = pd.to_datetime(df_test['timestamp_first_active'], format='%Y%m%d%H%M%S

display(df_test)
```

id	date_account_created	timestamp_first_active	gender	age	signup_method	signup_flow	language	affili
5uwns89zht	2014-07-01	20140701000006	FEMALE	35.0	facebook	0	en	
jtl0dijy2j	2014-07-01	20140701000051	-unknown-	NaN	basic	0	en	
xx0ulgorjt	2014-07-01	20140701000148	-unknown-	NaN	basic	0	en	
6c6puo6ix0	2014-07-01	20140701000215	-unknown-	NaN	basic	0	en	
czqhjk3yfe	2014-07-01	20140701000305	-unknown-	NaN	basic	0	en	
...	...	...	...	...	...	...	...	
cv0na2lf5a	2014-09-30	20140930235232	-unknown-	31.0	basic	0	en	
zp8xfonng8	2014-09-30	20140930235306	-unknown-	NaN	basic	23	ko	
fa6260ziny	2014-09-30	20140930235408	-unknown-	NaN	basic	0	de	
87k0fy4ugm	2014-09-30	20140930235430	-unknown-	NaN	basic	0	en	
9uqfg8txu3	2014-09-30	20140930235901	FEMALE	49.0	basic	0	en	

62096 rows × 13 columns

2.2. Remplacement de valeurs manquantes

* Dataset de Train

La colonne 'age', présentant un nombre considérable (87990) de valeurs manquantes, nous utiliser une méthode de prédiction (RandomForest) au lieu d'un Immputer pour remplacer les données manquantes et évite d'aplatir la distribution des âges. C'est une méthode plus réaliste, surtout si l'âge a un impact sur la destination

In [28]:
```
age_data = df_train[df_train['age'].notnull()]
age_target = age_data['age']
age_features = age_data.drop(['age'], axis=1).select_dtypes(include=[np.number])


age_model = RandomForestRegressor()
age_model.fit(age_features, age_target)

# Prédire les valeurs manquantes dans 'age'
missing_age_data = df_train[df_train['age'].isnull()]
predicted_ages = age_model.predict(missing_age_data.drop(['age'], axis=1).select_dtypes(include=[np.number]
df_train.loc[df_train['age'].isnull(), 'age'] = predicted_ages

display(df_train)
```

	date_account_created	timestamp_first_active	gender	age	signup_method	signup_flow	language
id							
gxn3p5htnn	2010-06-28	20090319043255	-unknown-	41.044167	facebook	0	en
820tgsjxq7	2011-05-25	20090523174809	MALE	38.000000	facebook	0	en
4ft3gnwmtx	2010-09-28	20090609231247	FEMALE	56.000000	basic	3	en
bjjt8pjhuk	2011-12-05	20091031060129	FEMALE	42.000000	facebook	0	en
87mebub9p4	2010-09-14	20091208061105	-unknown-	41.000000	basic	0	en
...	...	...	...	...	...	...	...
zxodksqpep	2014-06-30	20140630235636	MALE	32.000000	basic	0	en
mhewnxesx9	2014-06-30	20140630235719	-unknown-	35.735665	basic	0	en
6o3arsjbb4	2014-06-30	20140630235754	-unknown-	32.000000	basic	0	en
jh95kwisub	2014-06-30	20140630235822	-unknown-	33.777159	basic	25	en
nw9fwlyb5f	2014-06-30	20140630235824	-unknown-	33.777159	basic	25	en

213451 rows × 14 columns

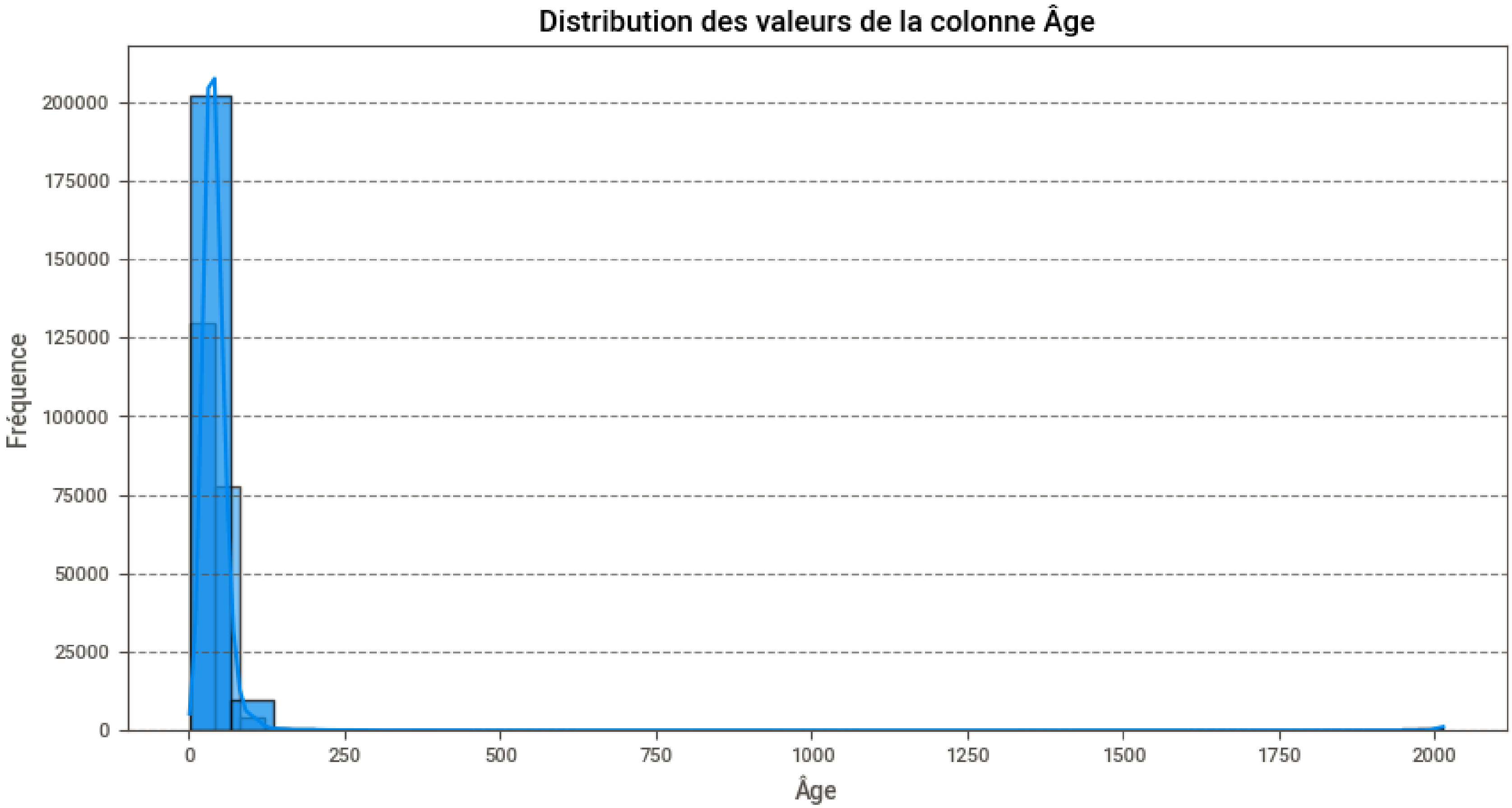
Remplacement des valeurs manquantes de 'first_affiliate_tracked' par sa valeur médiane

In [29]:
```
# c. Remplacement de first_affiliate_tracked avec la médiane
df_train['first_affiliate_tracked'].fillna(df_train['first_affiliate_tracked'].mode()[0], inplace=True)
```

```
/var/folders/dz/dt7pkrls1kxg9y931v65tmz40000gn/T/ipykernel_13597/3441638130.py:2: FutureWarning: A value is
trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object
on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=T
rue)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df_train['first_affiliate_tracked'].fillna(df_train['first_affiliate_tracked'].mode()[0], inplace=True)
```

In [30]:

```
# Afficher la distribution des valeurs de la colonne 'age'
plt.figure(figsize=(10, 5))
sns.histplot(df_train["age"].dropna(), bins=50, kde=True)
plt.hist(df_train['age'].dropna(), bins=30, edgecolor='black', alpha=0.7)
plt.xlabel('Âge')
plt.ylabel('Fréquence')
plt.title('Distribution des valeurs de la colonne Âge')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

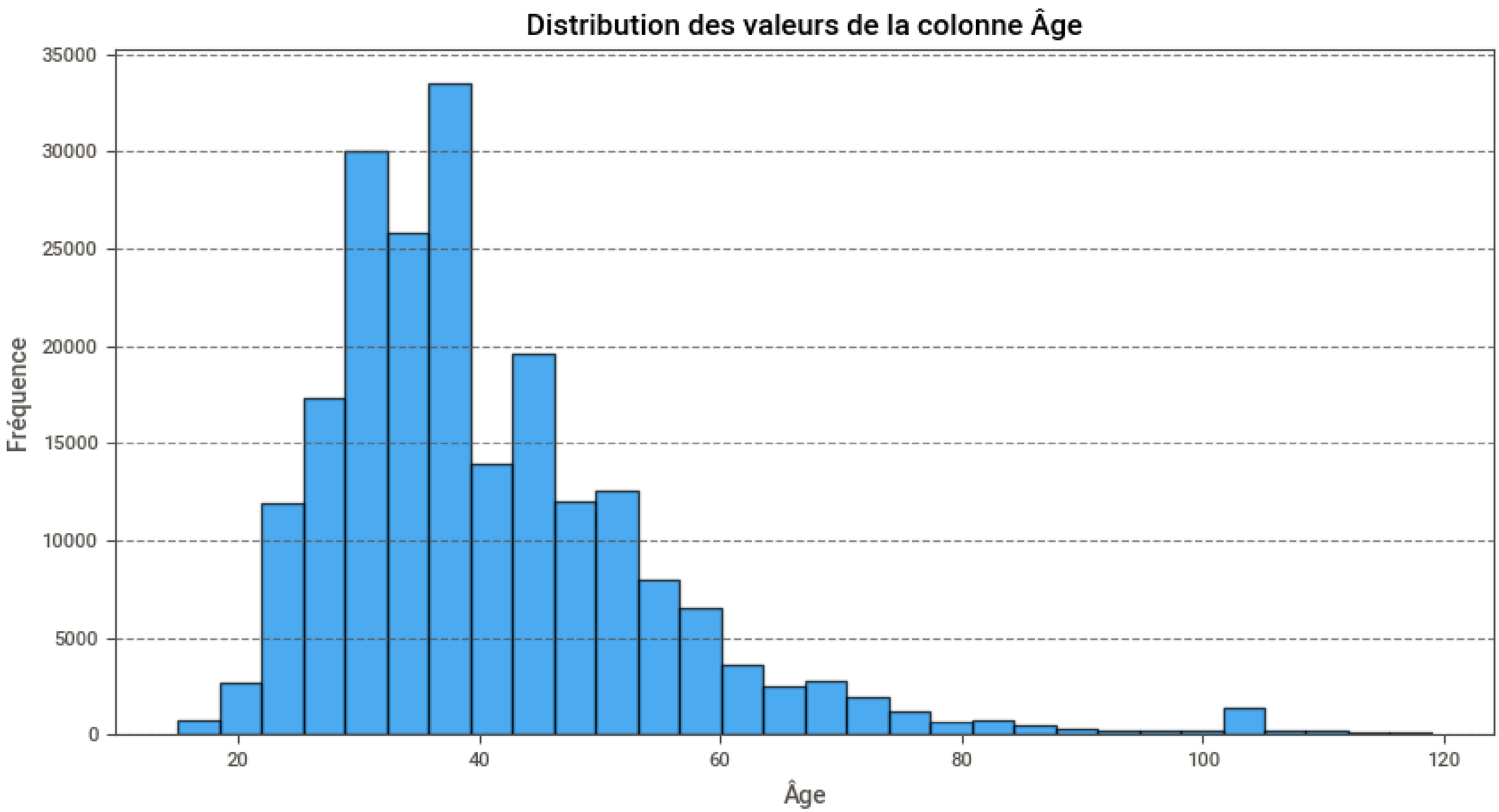


On constate la présence de valeurs aberrantes dans la colonne 'age'. Pour y remédier, nous supprimons les enregistrements où l'âge est inférieur à 15 ou supérieur à 120.

In [31]:
```
# 3. Correction/Suppression de valeurs aberrantes/erronées
df_train = df_train[(df_train['age'] >= 15) & (df_train['age'] <= 120)]  # Suppression des âges aberrants
df_train['age'] = df_train['age'].astype(int)
```

In [32]:
```
# Afficher la distribution des valeurs de la colonne 'age'
plt.figure(figsize=(10, 5))
plt.hist(df_train['age'].dropna(), bins=30, edgecolor='black', alpha=0.7)
plt.xlabel('Âge')
plt.ylabel('Fréquence')
plt.title('Distribution des valeurs de la colonne Âge')
```

```
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



In [33]:

```
from scipy import stats

# Effectuer le test de D'Agostino and Pearson
stat, p_value = stats.normaltest(df_train['age'].dropna())

# Afficher le résultat du test
print(f"Statistique de D'Agostino : {stat}")
print(f"Valeur p : {p_value}")

# Interprétation du test
if p_value > 0.05:
```

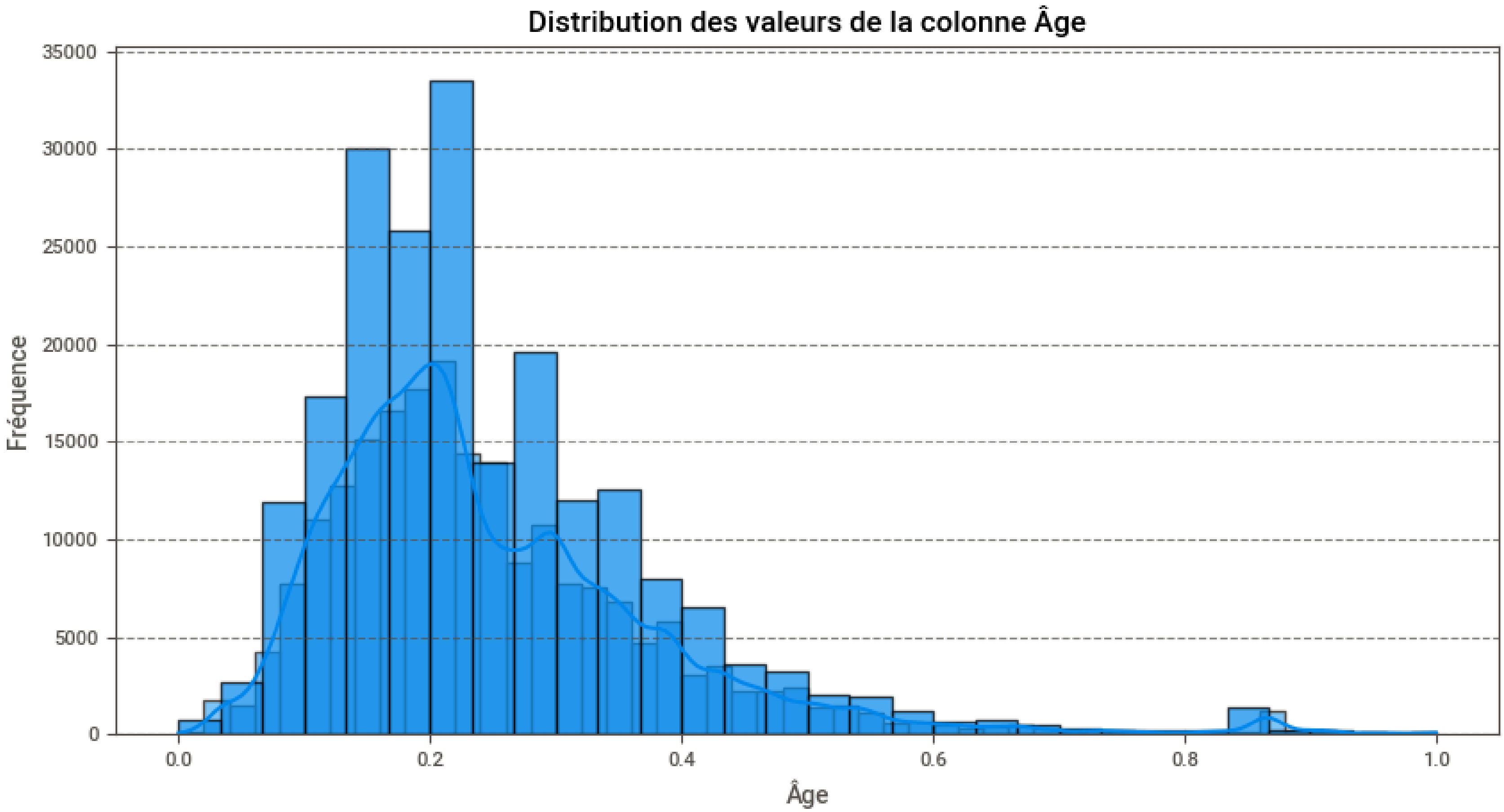
```
    print("La distribution de l'âge suit une loi normale (pas de rejet de l'hypothèse nulle).")
else:
    print("La distribution de l'âge ne suit pas une loi normale (hypothèse nulle rejetée).")
```

```
Statistique de D'Agostino : 72223.06987101675
Valeur p : 0.0
La distribution de l'âge ne suit pas une loi normale (hypothèse nulle rejetée).
```

Ayant eliminé les outliers, la plage des âges se situe entre 15 et 120. Nous allons appliquer le MinMaxScaler pour la standardisation de la colonne Age.

In [34]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

# Appliquer le scaler sur les données numériques
df_train['age'] = scaler.fit_transform(df_train[['age']])
```

In [35]:
```
# Afficher la distribution des valeurs de la colonne 'age'
plt.figure(figsize=(10, 5))
sns.histplot(df_train["age"].dropna(), bins=50, kde=True)
plt.hist(df_train['age'].dropna(), bins=30, edgecolor='black', alpha=0.7)
plt.xlabel('Âge')
plt.ylabel('Fréquence')
plt.title('Distribution des valeurs de la colonne Âge')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



In [36]:
```
display(df_train)
```

	date_account_created	timestamp_first_active	gender	age	signup_method	signup_flow	language
id							
gxn3p5htnn	2010-06-28	20090319043255	-unknown-	0.250000	facebook	0	en
820tgsjxq7	2011-05-25	20090523174809	MALE	0.221154	facebook	0	en
4ft3gnwmtx	2010-09-28	20090609231247	FEMALE	0.394231	basic	3	en
bjjt8pjhuk	2011-12-05	20091031060129	FEMALE	0.259615	facebook	0	en
87mebub9p4	2010-09-14	20091208061105	-unknown-	0.250000	basic	0	en
...	...	...	...	...	...	...	...
zxodksqpep	2014-06-30	20140630235636	MALE	0.163462	basic	0	en
mhewnxesx9	2014-06-30	20140630235719	-unknown-	0.192308	basic	0	en
6o3arsjbb4	2014-06-30	20140630235754	-unknown-	0.163462	basic	0	en
jh95kwisub	2014-06-30	20140630235822	-unknown-	0.173077	basic	25	en
nw9fwlyb5f	2014-06-30	20140630235824	-unknown-	0.173077	basic	25	en

211400 rows × 14 columns

* Dataset de Test

Les commentaires du dataset de train s'appliquent aussi pour le test. Nous allons réutilisé le même age_model que le train.

In [37]:
```
print(df_test.describe())
print("Valeurs manquantes par colonne:\n")
print(df_test.isnull().sum())  # Compte les valeurs manquantes par colonne
```

```
                 date_account_created  timestamp_first_active           age  \
count                           62096            6.209600e+04  33220.000000
mean   2014-08-14 19:24:31.631022848            2.014081e+13     37.616677
min              2014-07-01 00:00:00            2.014070e+13      1.000000
25%              2014-07-24 00:00:00            2.014072e+13     26.000000
50%              2014-08-14 00:00:00            2.014081e+13     31.000000
75%              2014-09-05 00:00:00            2.014091e+13     40.000000
max              2014-09-30 00:00:00            2.014093e+13   2002.000000
std                               NaN            8.024585e+07     74.440647

        signup_flow
count  62096.000000
mean       7.813885
min        0.000000
25%        0.000000
50%        0.000000
75%       23.000000
max       25.000000
std       11.254291
Valeurs manquantes par colonne:

date_account_created           0
timestamp_first_active         0
gender                         0
age                        28876
signup_method                  0
signup_flow                    0
language                       0
affiliate_channel              0
affiliate_provider             0
first_affiliate_tracked       20
signup_app                     0
first_device_type              0
first_browser                  0
dtype: int64
```

In [38]:

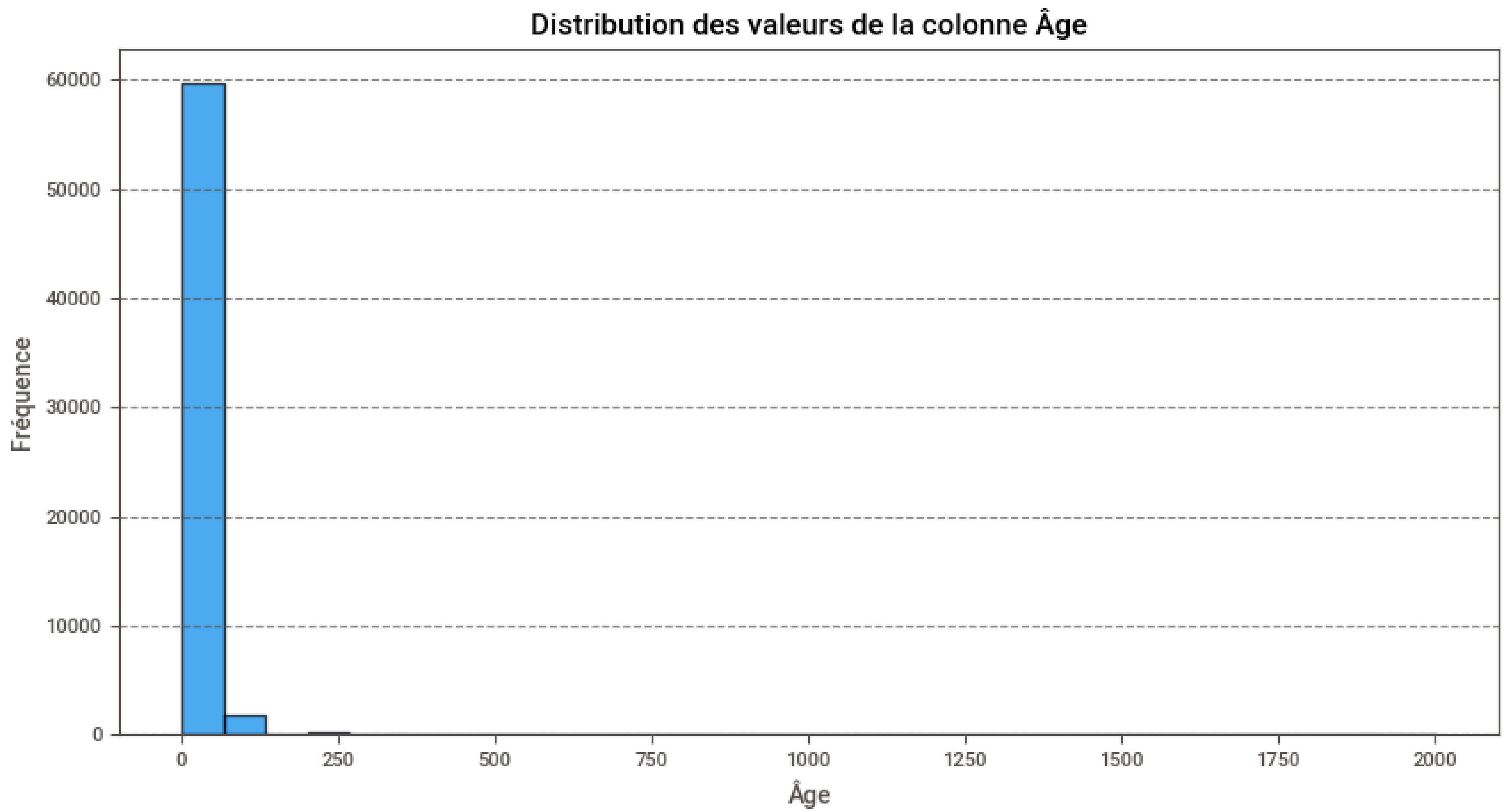
```
age_data = df_test[df_test['age'].notnull()]
age_target = age_data['age']
age_features = age_data.drop(['age'], axis=1).select_dtypes(include=[np.number])

#age_model = RandomForestRegressor()
age_model.fit(age_features, age_target)
```

```
# Prédire les valeurs manquantes dans 'age'
missing_age_data = df_test[df_test['age'].isnull()]
predicted_ages = age_model.predict(missing_age_data.drop(['age'], axis=1).select_dtypes(include=[np.number]
df_test.loc[df_test['age'].isnull(), 'age'] = predicted_ages
```

In [39]:
```
# c. Remplacement de first_affiliate_tracked avec la médiane

df_test['first_affiliate_tracked'].fillna(df_test['first_affiliate_tracked'].mode()[0], inplace=True)
```

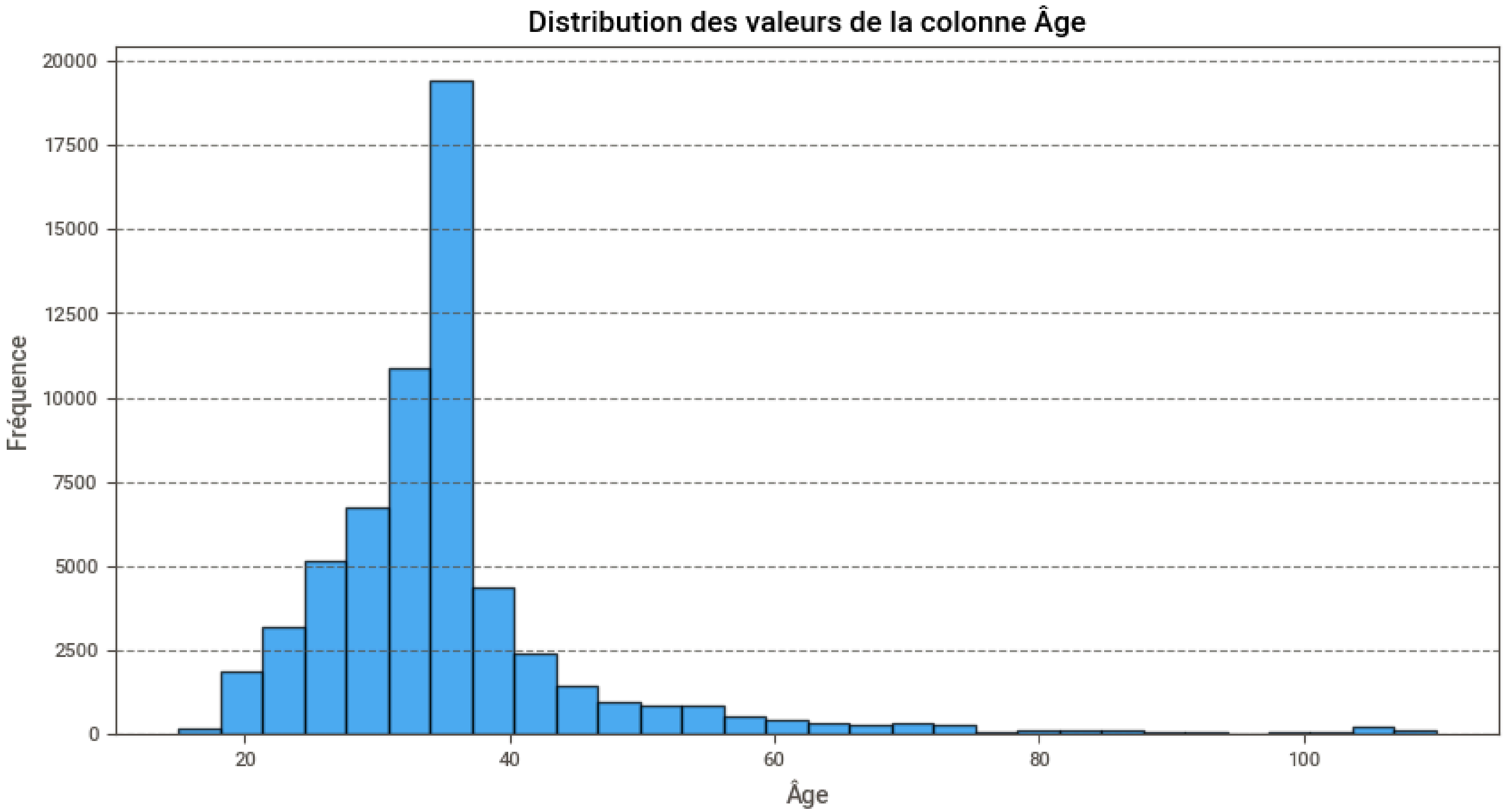
```
/var/folders/dz/dt7pkrls1kxg9y931v65tmz40000gn/T/ipykernel_13597/961816202.py:3: FutureWarning: A value is
trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object
on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=T
rue)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df_test['first_affiliate_tracked'].fillna(df_test['first_affiliate_tracked'].mode()[0], inplace=True)
```

In [40]:
```
# Afficher la distribution des valeurs de la colonne 'age'
plt.figure(figsize=(10, 5))
plt.hist(df_test['age'].dropna(), bins=30, edgecolor='black', alpha=0.7)
plt.xlabel('Âge')
plt.ylabel('Fréquence')
plt.title('Distribution des valeurs de la colonne Âge')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



In [41]:
```
# 3. Correction/Suppression de valeurs aberrantes/erronées
df_test = df_test[(df_test['age'] >= 15) & (df_test['age'] <= 120)]  # Suppression des âges aberrants
df_test['age'] = df_test['age'].astype(int)
```

In [42]:
```
# Afficher la distribution des valeurs de la colonne 'age'
plt.figure(figsize=(10, 5))
plt.hist(df_test['age'].dropna(), bins=30, edgecolor='black', alpha=0.7)
plt.xlabel('Âge')
plt.ylabel('Fréquence')
plt.title('Distribution des valeurs de la colonne Âge')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



In [43]:
```
# from sklearn.preprocessing import MinMaxScaler

# scaler = MinMaxScaler()

# Appliquer le scaler sur les données numériques
df_test['age'] = scaler.fit_transform(df_test[['age']])
```

In [44]:
```
display(df_test)
```

	date_account_created	timestamp_first_active	gender	age	signup_method	signup_flow	language
id							
5uwns89zht	2014-07-01	20140701000006	FEMALE	0.210526	facebook	0	en
jtl0dijy2j	2014-07-01	20140701000051	-unknown-	0.210526	basic	0	en
xx0ulgorjt	2014-07-01	20140701000148	-unknown-	0.210526	basic	0	en
6c6puo6ix0	2014-07-01	20140701000215	-unknown-	0.210526	basic	0	en
czqhjk3yfe	2014-07-01	20140701000305	-unknown-	0.210526	basic	0	en
...	...	...	...	...	...	...	...
cv0na2lf5a	2014-09-30	20140930235232	-unknown-	0.168421	basic	0	en
zp8xfonng8	2014-09-30	20140930235306	-unknown-	0.221053	basic	23	ko
fa6260ziny	2014-09-30	20140930235408	-unknown-	0.210526	basic	0	de
87k0fy4ugm	2014-09-30	20140930235430	-unknown-	0.210526	basic	0	en
9uqfg8txu3	2014-09-30	20140930235901	FEMALE	0.357895	basic	0	en

61517 rows × 13 columns

2.3. Standardisation de la dataset train

In [45]:
```
import pandas as pd

df_qualitatives = df_train.select_dtypes(include=['object'])
df_quantitatives = df_train.select_dtypes(include=[np.number])
df_dates = df_train.select_dtypes(include=['datetime64'])
```

```
target = df_train['country_destination']

display(df_qualitatives)
display(df_quantitatives)
display(df_dates)
display(target)
```

	gender	signup_method	language	affiliate_channel	affiliate_provider	first_affiliate_tracked	signup_app
id							
gxn3p5htnn	-unknown-	facebook	en	direct	direct	untracked	Web
820tgsjxq7	MALE	facebook	en	seo	google	untracked	Web
4ft3gnwmtx	FEMALE	basic	en	direct	direct	untracked	Web
bjjt8pjhuk	FEMALE	facebook	en	direct	direct	untracked	Web
87mebub9p4	-unknown-	basic	en	direct	direct	untracked	Web
...	...	...	...	...	...	...	...
zxodksqpep	MALE	basic	en	sem-brand	google	omg	Web
mhewnxesx9	-unknown-	basic	en	direct	direct	linked	Web
6o3arsjbb4	-unknown-	basic	en	direct	direct	untracked	Web
jh95kwisub	-unknown-	basic	en	other	other	tracked-other	iOS
nw9fwlyb5f	-unknown-	basic	en	direct	direct	untracked	iOS

211400 rows × 10 columns

	timestamp_first_active	age	signup_flow
id			
gxn3p5htnn	20090319043255	0.250000	0
820tgsjxq7	20090523174809	0.221154	0
4ft3gnwmtx	20090609231247	0.394231	3
bjjt8pjhuk	20091031060129	0.259615	0
87mebub9p4	20091208061105	0.250000	0
...	...	...	...
zxodksqpep	20140630235636	0.163462	0
mhewnxesx9	20140630235719	0.192308	0
6o3arsjbb4	20140630235754	0.163462	0
jh95kwisub	20140630235822	0.173077	25
nw9fwlyb5f	20140630235824	0.173077	25

211400 rows × 3 columns

	date_account_created
id	
gxn3p5htnn	2010-06-28
820tgsjxq7	2011-05-25
4ft3gnwmtx	2010-09-28
bjjt8pjhuk	2011-12-05
87mebub9p4	2010-09-14
...	...
zxodksqpep	2014-06-30
mhewnxesx9	2014-06-30
6o3arsjbb4	2014-06-30
jh95kwisub	2014-06-30
nw9fwlyb5f	2014-06-30

211400 rows × 1 columns

```
id
gxn3p5htnn      NDF
820tgsjxq7      NDF
4ft3gnwmtx       US
bjjt8pjhuk    other
87mebub9p4       US
              ...
zxodksqpep      NDF
mhewnxesx9      NDF
6o3arsjbb4      NDF
jh95kwisub      NDF
nw9fwlyb5f      NDF
Name: country_destination, Length: 211400, dtype: object
```

Encodage des variables catégorielles de la dataset train

Dans cette étape, nous appliquons le Frequency Encoding afin de convertir les données catégorielles en format numérique et normalisées. Cette transformation crée des indicateurs binaires pour chaque modalité. Notre choix s'est porté sur le Frequency Encoding pour sa simplicité, son efficacité et les modalités de notre dataset ne sont pas des variables ordinales et leur frequence est unique.

In [46]:
```
df_qualitatives = df_qualitatives.drop(['country_destination'], axis=1)
colonnes_qualitatives = df_qualitatives.select_dtypes(include=['object']).columns
```

In [47]:
```
df_encoded = pd.DataFrame()

for col in colonnes_qualitatives:
    frequency_map = df_train[col].value_counts(normalize=True).to_dict()
    df_encoded[col] = df_train[col].map(frequency_map)


display(df_encoded)
```

id	gender	signup_method	language	affiliate_channel	affiliate_provider	first_affiliate_tracked	signup_app
gxn3p5htnn	0.447427	0.282668	0.966485	0.645043	0.643718	0.539096	0.857493
820tgsjxq7	0.255870	0.282668	0.966485	0.040643	0.242687	0.539096	0.857493
4ft3gnwmtx	0.295393	0.714749	0.966485	0.645043	0.643718	0.539096	0.857493
bjjt8pjhuk	0.295393	0.282668	0.966485	0.645043	0.643718	0.539096	0.857493
87mebub9p4	0.447427	0.714749	0.966485	0.645043	0.643718	0.539096	0.857493
...	...	...	...	...	...	...	...
zxodksqpep	0.255870	0.714749	0.966485	0.122502	0.242687	0.206902	0.857493
mhewnxesx9	0.447427	0.714749	0.966485	0.645043	0.643718	0.217081	0.857493
6o3arsjbb4	0.447427	0.714749	0.966485	0.645043	0.643718	0.539096	0.857493
jh95kwisub	0.447427	0.714749	0.966485	0.041693	0.058590	0.028808	0.088713
nw9fwlyb5f	0.447427	0.714749	0.966485	0.645043	0.643718	0.539096	0.088713

211400 rows × 9 columns

In [48]:
```
train = pd.concat([df_dates, df_quantitatives, df_encoded], axis=1)

display(df_dates)
display(df_quantitatives)
display(df_encoded)
```

	date_account_created
id	
gxn3p5htnn	2010-06-28
820tgsjxq7	2011-05-25
4ft3gnwmtx	2010-09-28
bjjt8pjhuk	2011-12-05
87mebub9p4	2010-09-14
...	...
zxodksqpep	2014-06-30
mhewnxesx9	2014-06-30
6o3arsjbb4	2014-06-30
jh95kwisub	2014-06-30
nw9fwlyb5f	2014-06-30

211400 rows × 1 columns

	timestamp_first_active	age	signup_flow
id			
gxn3p5htnn	20090319043255	0.250000	0
820tgsjxq7	20090523174809	0.221154	0
4ft3gnwmtx	20090609231247	0.394231	3
bjjt8pjhuk	20091031060129	0.259615	0
87mebub9p4	20091208061105	0.250000	0
...	...	...	...
zxodksqpep	20140630235636	0.163462	0
mhewnxesx9	20140630235719	0.192308	0
6o3arsjbb4	20140630235754	0.163462	0
jh95kwisub	20140630235822	0.173077	25
nw9fwlyb5f	20140630235824	0.173077	25

211400 rows × 3 columns

	gender	signup_method	language	affiliate_channel	affiliate_provider	first_affiliate_tracked	signup_app
id							
gxn3p5htnn	0.447427	0.282668	0.966485	0.645043	0.643718	0.539096	0.857493
820tgsjxq7	0.255870	0.282668	0.966485	0.040643	0.242687	0.539096	0.857493
4ft3gnwmtx	0.295393	0.714749	0.966485	0.645043	0.643718	0.539096	0.857493
bjjt8pjhuk	0.295393	0.282668	0.966485	0.645043	0.643718	0.539096	0.857493
87mebub9p4	0.447427	0.714749	0.966485	0.645043	0.643718	0.539096	0.857493
...	...	...	...	...	...	...	...
zxodksqpep	0.255870	0.714749	0.966485	0.122502	0.242687	0.206902	0.857493
mhewnxesx9	0.447427	0.714749	0.966485	0.645043	0.643718	0.217081	0.857493
6o3arsjbb4	0.447427	0.714749	0.966485	0.645043	0.643718	0.539096	0.857493
jh95kwisub	0.447427	0.714749	0.966485	0.041693	0.058590	0.028808	0.088713
nw9fwlyb5f	0.447427	0.714749	0.966485	0.645043	0.643718	0.539096	0.088713

211400 rows × 9 columns

In [49]:
```
train.drop(['timestamp_first_active'], axis=1, inplace=True)
train.drop(['signup_flow'], axis=1, inplace=True)

display(train)
```

	date_account_created	age	gender	signup_method	language	affiliate_channel	affiliate_provider	f
id								
gxn3p5htnn	2010-06-28	0.250000	0.447427	0.282668	0.966485	0.645043	0.643718	
820tgsjxq7	2011-05-25	0.221154	0.255870	0.282668	0.966485	0.040643	0.242687	
4ft3gnwmtx	2010-09-28	0.394231	0.295393	0.714749	0.966485	0.645043	0.643718	
bjjt8pjhuk	2011-12-05	0.259615	0.295393	0.282668	0.966485	0.645043	0.643718	
87mebub9p4	2010-09-14	0.250000	0.447427	0.714749	0.966485	0.645043	0.643718	
...	...	...	...	...	...	...	...	
zxodksqpep	2014-06-30	0.163462	0.255870	0.714749	0.966485	0.122502	0.242687	
mhewnxesx9	2014-06-30	0.192308	0.447427	0.714749	0.966485	0.645043	0.643718	
6o3arsjbb4	2014-06-30	0.163462	0.447427	0.714749	0.966485	0.645043	0.643718	
jh95kwisub	2014-06-30	0.173077	0.447427	0.714749	0.966485	0.041693	0.058590	
nw9fwlyb5f	2014-06-30	0.173077	0.447427	0.714749	0.966485	0.645043	0.643718	

211400 rows × 11 columns

Standardisation de la dataset Test

In [50]:
```
df_qualitatives = df_test.select_dtypes(include=['object'])
df_quantitatives = df_test.select_dtypes(include=[np.number])
df_dates = df_test.select_dtypes(include=['datetime64'])

display(df_qualitatives)
display(df_quantitatives)
display(df_dates)
```

id	gender	signup_method	language	affiliate_channel	affiliate_provider	first_affiliate_tracked	signup_app
5uwns89zht	FEMALE	facebook	en	direct	direct	untracked	Moweb
jtl0dijy2j	-unknown-	basic	en	direct	direct	untracked	Moweb
xx0ulgorjt	-unknown-	basic	en	direct	direct	linked	Web
6c6puo6ix0	-unknown-	basic	en	direct	direct	linked	Web
czqhjk3yfe	-unknown-	basic	en	direct	direct	untracked	Web
...	...	...	...	...	...	...	...
cv0na2lf5a	-unknown-	basic	en	direct	direct	untracked	Web
zp8xfonng8	-unknown-	basic	ko	direct	direct	untracked	Android
fa6260ziny	-unknown-	basic	de	direct	direct	linked	Web
87k0fy4ugm	-unknown-	basic	en	sem-brand	google	omg	Web
9uqfg8txu3	FEMALE	basic	en	other	other	tracked-other	Web

61517 rows × 9 columns

	timestamp_first_active	age	signup_flow
id			
5uwns89zht	20140701000006	0.210526	0
jtl0dijy2j	20140701000051	0.210526	0
xx0ulgorjt	20140701000148	0.210526	0
6c6puo6ix0	20140701000215	0.210526	0
czqhjk3yfe	20140701000305	0.210526	0
...	...	...	...
cv0na2lf5a	20140930235232	0.168421	0
zp8xfonng8	20140930235306	0.221053	23
fa6260ziny	20140930235408	0.210526	0
87k0fy4ugm	20140930235430	0.210526	0
9uqfg8txu3	20140930235901	0.357895	0

61517 rows × 3 columns

	date_account_created
id	
5uwns89zht	2014-07-01
jtl0dijy2j	2014-07-01
xx0ulgorjt	2014-07-01
6c6puo6ix0	2014-07-01
czqhjk3yfe	2014-07-01
...	...
cv0na2lf5a	2014-09-30
zp8xfonng8	2014-09-30
fa6260ziny	2014-09-30
87k0fy4ugm	2014-09-30
9uqfg8txu3	2014-09-30

61517 rows × 1 columns

Encodage des variables catégorielles de la dataset test

Dans cette étape, nous appliquons le même Frequency Encoding qui a été utilisé pour le train

In [51]:
```
df_encoded = pd.DataFrame()

for col in colonnes_qualitatives:
    frequency_map = df_train[col].value_counts(normalize=True).to_dict()
    df_encoded[col] = df_test[col].map(frequency_map)


display(df_encoded)
```

	gender	signup_method	language	affiliate_channel	affiliate_provider	first_affiliate_tracked	signup_app
id							
5uwns89zht	0.295393	0.282668	0.966485	0.645043	0.643718	0.539096	0.028581
jtl0dijy2j	0.447427	0.714749	0.966485	0.645043	0.643718	0.539096	0.028581
xx0ulgorjt	0.447427	0.714749	0.966485	0.645043	0.643718	0.217081	0.857493
6c6puo6ix0	0.447427	0.714749	0.966485	0.645043	0.643718	0.217081	0.857493
czqhjk3yfe	0.447427	0.714749	0.966485	0.645043	0.643718	0.539096	0.857493
...	...	...	...	...	...	...	...
cv0na2lf5a	0.447427	0.714749	0.966485	0.645043	0.643718	0.539096	0.857493
zp8xfonng8	0.447427	0.714749	0.003505	0.645043	0.643718	0.539096	0.025213
fa6260ziny	0.447427	0.714749	0.003448	0.645043	0.643718	0.217081	0.857493
87k0fy4ugm	0.447427	0.714749	0.966485	0.122502	0.242687	0.206902	0.857493
9uqfg8txu3	0.295393	0.714749	0.966485	0.041693	0.058590	0.028808	0.857493

61517 rows × 9 columns

In [52]:
```
test = pd.concat([df_dates, df_quantitatives, df_encoded], axis=1)
```

In [53]:
```
test.drop(['timestamp_first_active'], axis=1, inplace=True)
test.drop(['signup_flow'], axis=1, inplace=True)
```

In [54]:
```
print("Data de training:")
display(train)
```

```
Data de training:
```

	date_account_created	age	gender	signup_method	language	affiliate_channel	affiliate_provider	f
id								
gxn3p5htnn	2010-06-28	0.250000	0.447427	0.282668	0.966485	0.645043	0.643718	
820tgsjxq7	2011-05-25	0.221154	0.255870	0.282668	0.966485	0.040643	0.242687	
4ft3gnwmtx	2010-09-28	0.394231	0.295393	0.714749	0.966485	0.645043	0.643718	
bjjt8pjhuk	2011-12-05	0.259615	0.295393	0.282668	0.966485	0.645043	0.643718	
87mebub9p4	2010-09-14	0.250000	0.447427	0.714749	0.966485	0.645043	0.643718	
...	...	...	...	...	...	...	...	
zxodksqpep	2014-06-30	0.163462	0.255870	0.714749	0.966485	0.122502	0.242687	
mhewnxesx9	2014-06-30	0.192308	0.447427	0.714749	0.966485	0.645043	0.643718	
6o3arsjbb4	2014-06-30	0.163462	0.447427	0.714749	0.966485	0.645043	0.643718	
jh95kwisub	2014-06-30	0.173077	0.447427	0.714749	0.966485	0.041693	0.058590	
nw9fwlyb5f	2014-06-30	0.173077	0.447427	0.714749	0.966485	0.645043	0.643718	

211400 rows × 11 columns

In [55]:
```
print("Dataset Target:")
display(target)

target.unique()
```

```
Dataset Target:
```

```
id
gxn3p5htnn      NDF
820tgsjxq7      NDF
4ft3gnwmtx       US
bjjt8pjhuk    other
87mebub9p4       US
              ...
zxodksqpep      NDF
mhewnxesx9      NDF
6o3arsjbb4      NDF
jh95kwisub      NDF
nw9fwlyb5f      NDF
Name: country_destination, Length: 211400, dtype: object
```

Out[55]:
```
array(['NDF', 'US', 'other', 'FR', 'CA', 'GB', 'ES', 'IT', 'PT', 'NL',
       'DE', 'AU'], dtype=object)
```

In [56]:
```
print("Dataset de test:")
display(test)
```

```
Dataset de test:
```

	date_account_created	age	gender	signup_method	language	affiliate_channel	affiliate_provider	fi
id								
5uwns89zht	2014-07-01	0.210526	0.295393	0.282668	0.966485	0.645043	0.643718	
jtl0dijy2j	2014-07-01	0.210526	0.447427	0.714749	0.966485	0.645043	0.643718	
xx0ulgorjt	2014-07-01	0.210526	0.447427	0.714749	0.966485	0.645043	0.643718	
6c6puo6ix0	2014-07-01	0.210526	0.447427	0.714749	0.966485	0.645043	0.643718	
czqhjk3yfe	2014-07-01	0.210526	0.447427	0.714749	0.966485	0.645043	0.643718	
...	...	...	...	...	...	...	...	
cv0na2lf5a	2014-09-30	0.168421	0.447427	0.714749	0.966485	0.645043	0.643718	
zp8xfonng8	2014-09-30	0.221053	0.447427	0.714749	0.003505	0.645043	0.643718	
fa6260ziny	2014-09-30	0.210526	0.447427	0.714749	0.003448	0.645043	0.643718	
87k0fy4ugm	2014-09-30	0.210526	0.447427	0.714749	0.966485	0.122502	0.242687	
9uqfg8txu3	2014-09-30	0.357895	0.295393	0.714749	0.966485	0.041693	0.058590	

61517 rows × 11 columns

```
In [ ]:
```

```
In [ ]:
```