GSMA

Methodology: The Mobile Gender Gap Report 2023

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For this study, Ipsos worked with the GSMA as a fieldwork partner and, as such, is not responsible for the analysis or conclusions in this report or The Mobile Gender Gap Report 2023.

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Introduction

This document details the methodology behind The Mobile Gender Gap Report 2023. This GSMA report is part of an annual series analysing the gender gap in mobile ownership and mobile internet use in low- and middle-income countries (LMICs).[1] This accompanying methodology report describes the analysis and modelling techniques we used and highlights important methodological changes from previous years.

This document is designed as a supplement to the main report and includes:

1. The parameters of the GSMA Consumer Survey 2022, on which the findings of this study are based.
2. Extrapolation models, which provide estimates of the gender gaps in mobile ownership, mobile internet use, smartphone ownership and spending on mobile services in LMICs not included in the GSMA Consumer Survey.
3. Analytical approaches used to investigate the results of survey questions on mobile use, and the barriers preventing mobile ownership and mobile internet use.

Comparisons with GSMA Connected Women's earlier work

Every year the wording and structure of the GSMA Consumer Survey are revised and the underlying methodology is refined. Care should therefore be taken in drawing conclusions about country-level, year-on-year changes from previous *Mobile Gender Gap* reports. Any trends identified in this year's report are based on longitudinal assessments of gender-disaggregated data by GSMA and third parties, and have been determined to have sufficient evidence on a case-by-case basis.

1. See Table 1 for definitions of the gender gap and other key terms.

Table 1
Definitions of key terms

KEY TERM	DEFINITION
ARPU	Average revenue per user. Calculated as recurring revenues divided by total number of unique subscribers.
Low- and middle-income countries (LMICs)	Countries classified as low income (GNI per capita of $1,085 or less in 2021), lower-middle income (GNI per capita between $1,086 and $4,255) or upper-middle income (GNI per capita between $4,256 and $13,205) by the World Bank.[2]
Mobile internet user	A person who has used the internet on a mobile phone at least once in the last three months.[3] Mobile internet users do not have to personally own a mobile phone and, therefore, can be non-mobile phone owners who use mobile internet by accessing it on someone else's mobile phone.
Socio-economic class (SEC)	A classification system to indicate the economic and social status of an individual based on factors such as employment, education level and living standards. Exact definitions and classification criteria vary by country.
Unique smartphone subscriber	Unique smartphone subscribers are calculated by taking the number of smartphone connections from GSMA Intelligence data and dividing this by the average number of SIMs per smartphone user using a combination of GSMA Intelligence and survey data to obtain an estimate of "unique" smartphone connections.
Unique subscriber	A unique user who is subscribed to mobile services at the end of a period. Subscribers differ from connections in that a unique user can have multiple connections. Note that this methodology report also refers to unique subscribers as mobile owners and mobile phone owners. These terms are used interchangeably to mean a person who has sole or main use of a SIM card or a mobile phone that does not require a SIM and uses it at least once a month. The vast majority of SIM owners also have sole or main use of a handset (ranging from 87% to 98% across the sample countries).
Unique subscriber penetration	Total subscribers at the end of a period expressed as a percentage share of the total market population.
Gender gap	The gender gap in mobile ownership (also referred to as SIM ownership), mobile internet use and smartphone ownership is calculated using the following formula:

$$\text{Gender gap in ownership / use (\%)} = \frac{\text{Male owners / users (\% of male population)} - \text{Female owners / users (\% of female population)}}{\text{Male owners / users (\% of male population)}}$$

2. The World Bank Country and Lending Groups includes 138 countries. See: World Bank Country and Lending Groups, FY 2023.

3. Respondents were asked the question: "Have you ever used the internet on a mobile phone? Please think about all the different ways of using the internet on a mobile phone. Just to confirm, people are using the internet on their mobile phones when they do any of the following: visit internet websites (e.g. Google or Amazon), visit social networking websites (e.g. Facebook, Twitter, YouTube, Weibo), send emails or instant messages (e.g. WhatsApp, Snapchat, WeChat, LINE) or download apps." Mobile internet users are those who answered, "Yes, I have used the internet on a mobile phone in the last three months."

The GSMA Consumer Survey 2022

Scope of the survey

The Mobile Gender Gap Report 2023 is based primarily on nationally representative[4] surveys of 12 LMICs conducted as part of the GSMA Consumer Survey 2022 (see Figure 1 and Table 2). This year the survey had more than 13,800 respondents and, for the first time, included Ethiopia. *The Mobile Gender Gap Report* series covers 29 countries representing up to 75% of the adult population in LMICs. (See Table 2 for a comprehensive list of countries covered by the annual GSMA Consumer Survey). The survey is representative of the entire adult population of these countries, including both mobile users and non-mobile users.

Figure 1
Surveyed countries in this report

4. Except Ethiopia, where no interviews were conducted in the Tigray region and six other zones due to local conflict and security concerns.

Table 2
Surveyed countries, by region

COUNTRY	2017	2018	2019	2020	2021	2022
Algeria	✓	✓	✓	✓	–	–
Argentina	✓	✓	–	–	–	–
Bangladesh	✓	✓	✓	✓	✓	✓
Brazil	✓	✓	✓	–	–	–
Chile	✓	–	✓	–	–	–
China	✓	✓	–	–	–	–
Colombia	✓	✓	–	–	–	–
Côte d'Ivoire	✓	✓	–	–	–	–
Dominican Republic	✓	✓	–	–	–	–
Egypt	✓	–	–	–	✓	✓
Ethiopia	–	–	–	–	–	✓
Ghana	✓	–	–	–	–	✓
Guatemala	✓	✓	✓	✓	✓	✓
India	✓	✓	✓	✓	✓	✓
Indonesia	✓	✓	✓	–	✓	✓
Kenya	✓	✓	✓	✓	✓	✓
Mexico	✓	✓	✓	–	✓	✓
Mozambique	–	✓	✓	✓	–	–
Myanmar	✓	✓	✓	✓	–	–
Nicaragua	✓	–	–	–	–	–
Nigeria	✓	✓	✓	✓	✓	✓
Pakistan	✓	✓	✓	✓	✓	✓
Philippines	✓	–	–	–	–	–
Senegal	–	–	✓	–	✓	✓
South Africa	✓	✓	✓	–	–	–
Tanzania	✓	✓	–	–	–	–
Thailand	✓	–	–	–	–	–
Uganda	–	–	✓	–	–	–
Vietnam	✓	–	–	–	–	–

Sampling and fieldwork

In each country, a minimum of 1,000 interviews were conducted with adults aged 18 and over. In India (and China, when covered), 2,000 interviews were conducted. The samples are nationally representative, except in Ethiopia where no interviews were conducted in the Tigray region and six other zones[5] due to local conflict and security concerns. These areas represent 12% of Ethiopia's population, therefore, the sample was representative of the remaining 88% of the population living outside these areas.

To achieve a nationally representative sample, quotas were applied in line with census data (or other appropriate sources) on the following metrics:

- Age category, by gender
- Urban and rural distribution, by gender
- Region/state
- Socio-economic class (SEC) to ensure a representative segment of lower income respondents were included (no such quota was applied in Mozambique, when covered, in the absence of reliable SEC profiling data)

While a quota was not applied to education (other than where it contributed to SEC classification), it was tracked regionally and nationally during and after fieldwork as an important indicator of a representative sample.

Sampling points where interviews were conducted, were distributed proportionately between urban and rural areas in accordance with census data and national statistics offices. To achieve wide geographical coverage and to reduce the effects of clustering, a minimum of 100 sampling points were used in each country (200 in India).

The research used a mix of purposive and random sampling approaches. Depending on the country, sampling points were either randomly distributed – with an administrative area's probability of selection proportionate to the size of its population (random sampling) – or selected to reflect the linguistic, cultural and economic variations of each country (purposive sampling). Local experts and national statistics offices checked the sampling frames to ensure they were valid and representative.

The survey was delivered via interviewer-administered computer-assisted personal interviewing (CAPI). Survey interviews were conducted in the local language(s) by both female and male interviewers. Interviews were conducted at respondents' homes. Within sampling points, systematic random routes were used for residence selection.

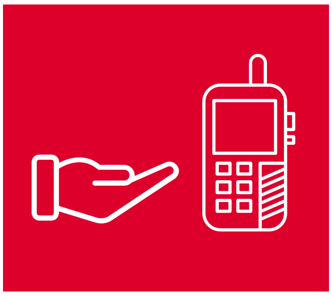
Weights were applied to the data using a random iterative method (RIM) whereby several non-interlocking quotas were applied in an iterative sequence and repeated as many times as needed for the quotas to converge. This corrected any imbalances in the profiles, although weightings (and the resulting impact on effective sample sizes) were minimised as much as possible by controlling key quota variables over the course of the fieldwork.

The sampling approach was designed to achieve full national representation where practical; however, some more remote rural areas or regions with on-going unrest or security concerns were excluded from sampling. This may have had an impact on the results, especially since mobile phone coverage, access and use will be different – and likely most limited – in these areas, particularly for women.

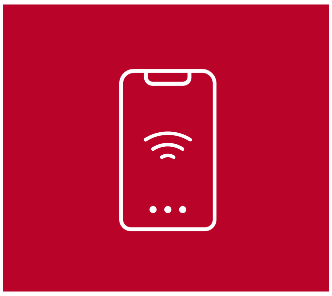
5. Metekel-Zone (Benishangul Gumz), Zone 2 (Afar), West Wellega-Zone (Oromia), Guji-Zone (Oromia), Kelem Wellega Zone (Oromia) and Horo Gudru Wellega-Zone (Oromia).

Gender gap extrapolation models

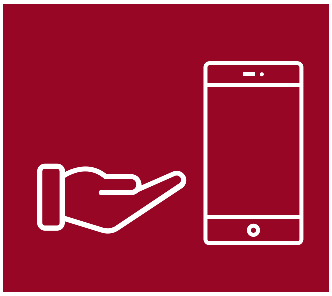
The Mobile Gender Gap Report 2023 provides estimates the gender gaps in LMICs for four key metrics:



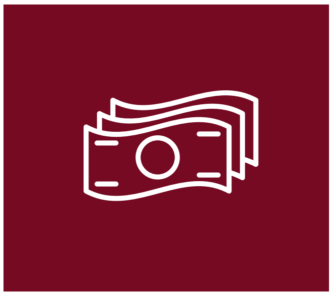
MOBILE OWNERSHIP



MOBILE INTERNET ADOPTION



SMARTPHONE OWNERSHIP



SPENDING ON MOBILE SERVICES

In addition, we relied on third-party and publicly available survey data when we considered it robust. This provided gender gap proxy measures for selected years for: mobile ownership for another 10 countries; mobile internet use (11 countries) and smartphone ownership (two countries).[6] See Box 1 for a list of countries where third-party survey data was sourced for the extrapolation model.

6. Data was sourced from After Access (Cambodia, Paraguay, Peru and Rwanda for mobile and mobile internet for 2017), Pew Global Attitudes and Trends (mobile and mobile internet for Jordan and Lebanon for 2017, and Philippines for 2018 and 2019), ITU (Iran for mobile and mobile internet for 2017 to 2019), RLMS-HES (Russia for mobile, mobile internet and smartphone for 2018 and 2019); CNNIC (China mobile internet for 2017 to 2022) and ZimStat (Zimbabwe for mobile, mobile internet and smartphone for 2020).

Box 1
Countries covered by third-party surveys, by region

Third-party survey country coverage

Region	Country	2017–2018 (9 countries)	2018–2019 (4 countries)	2019–2020 (3 countries)	2020–2021 (2 countries)	2021–2022 (1 country)	2022–2023 (1 country)	Sources
AFRICA	Rwanda	✓	–	–	–	–	–	After Access
	Zimbabwe	–	–	–	✓	–	–	ZimStat
ASIA	Cambodia	✓	–	–	–	–	–	After Access
	China	✓	✓	✓	✓	✓	✓	CNNIC
	Philippines	–	✓	✓	–	–	–	Pew Global Attitudes and Trends
EUROPE & CENTRAL ASIA	Russia	✓	✓	–	–	–	–	RLMS-HES
LATIN AMERICA	Paraguay	✓	–	–	–	–	–	After Access
	Peru	✓	–	–	–	–	–	After Access
MIDDLE EAST & NORTH AFRICA	Iran	✓	✓	✓	–	–	–	ITU
	Jordan	✓	–	–	–	–	–	Pew Global Attitudes and Trends
	Lebanon	✓	–	–	–	–	–	Pew Global Attitudes and Trends

To estimate the size of the mobile gender gaps in the remaining LMICs, we relied on machine learning (ML) classifiers, which are trained using data from countries where observations of gender gaps in mobile technology are available. We combined these observations into a dataset that included other variables that are potential predictors of mobile gender gaps, such as indicators of technology adoption and socio-economic conditions.

We used this dataset as training data to teach the classifiers what patterns of technology adoption and socio-economic conditions are associated with higher or lower mobile gender gaps. The trained classifiers then used these recognised patterns to make predictions about gender gaps in countries where it is not observed. We used separate classifiers to estimate each type of mobile gender gap (mobile ownership, mobile internet use, smartphone ownership and spending on mobile services).

Datasets

We gathered data on potential predictors of mobile gender gaps. This data, which was not uniformly available for every country and year, included indicators sourced from the United Nations Human Development Index, the World Bank, Gallup World Poll and others (Table 3).

Given that some data was missing for certain country-year combinations, we relied on a multiple imputation technique. This created several estimates for each missing value based on the patterns observed in other variables of the dataset.

We relied on MICE (Multiple Imputation by Chained Equations) forests,[7] which is a specific implementation of multiple imputation that uses decision trees to impute missing values.[8] The MICE forests algorithm works by creating a decision tree for each variable with missing data and using these trees to predict the missing values based on the patterns observed in the other variables. The predictions from each tree are then combined to create a single imputed dataset.

In general, we found there were only minimal changes to our gender gap estimates when we used different imputed datasets. Therefore, to minimise computation time, we relied on two imputed datasets. To reflect the minimal variation in estimates, the predicted gender gap values were calculated as the average across the two imputed datasets.

7. The "forests" part of the name comes from the fact that MICE forests can generate multiple imputed datasets, each of which contains a different set of plausible values for the missing data. These imputed datasets are then used to perform the analysis. The results are combined to produce a final estimate, which also can be used to understand the uncertainty associated with that estimate.
8. van Buuren, S. (2018). *Flexible Imputation of Missing Data*. Second Edition.

Table 3
Variables used as predictors of mobile gender gaps

Variable(s)	Source
Mean schooling years – females and males and gender ratio[9]	UN Human Development Reports
Expected schooling years for a child entering education – females and males and gender ratio	UN Human Development Reports
Human Development Index – overall and females only	UN Human Development Reports
Gender Inequality Index	UN Human Development Reports
Gender Development Index	UN Human Development Reports
Gross national income (GNI) per capita – female and male absolute income and gender ratio	UN Human Development Reports
Gross domestic product (GDP) per capita, purchasing power parity (PPP)	IMF World Economic Outlook
Percentage of persons with access to internet – overall and females only	Gallup World Poll
Gender gap in internet	Gallup World Poll
Percentage of persons owning a mobile phone for personal calls – overall and females only	Gallup World Poll
Gender gap in mobile ownership for personal calls	Gallup World Poll
Facebook Gender Gap	GSMA Intelligence analysis of Facebook Audience Insights
World region dummy variables	World Bank regional groupings
Income group dummy variables	World Bank analytical classifications
Measure of gender equality under law – overall index score and individual area scores	World Bank Women, Business and the Law indicators
Average revenue per subscriber	GSMA Intelligence database

Source: GSMA Intelligence analysis

9. The gender ratio for a variable is calculated by taking the female value and dividing it by the male value. For example, the gender ratio for mean schooling years is equal to mean female schooling years divided by mean male schooling years.

Predicting mobile gender gaps

We tested multiple classifiers to evaluate their accuracy in predicting mobile gender gaps. We evaluated their performance using two primary metrics:

- Mean absolute error of prediction (in percentage points)
- R-squared (R^2), which measures the proportion of variance in gender gaps explained by the predictive model

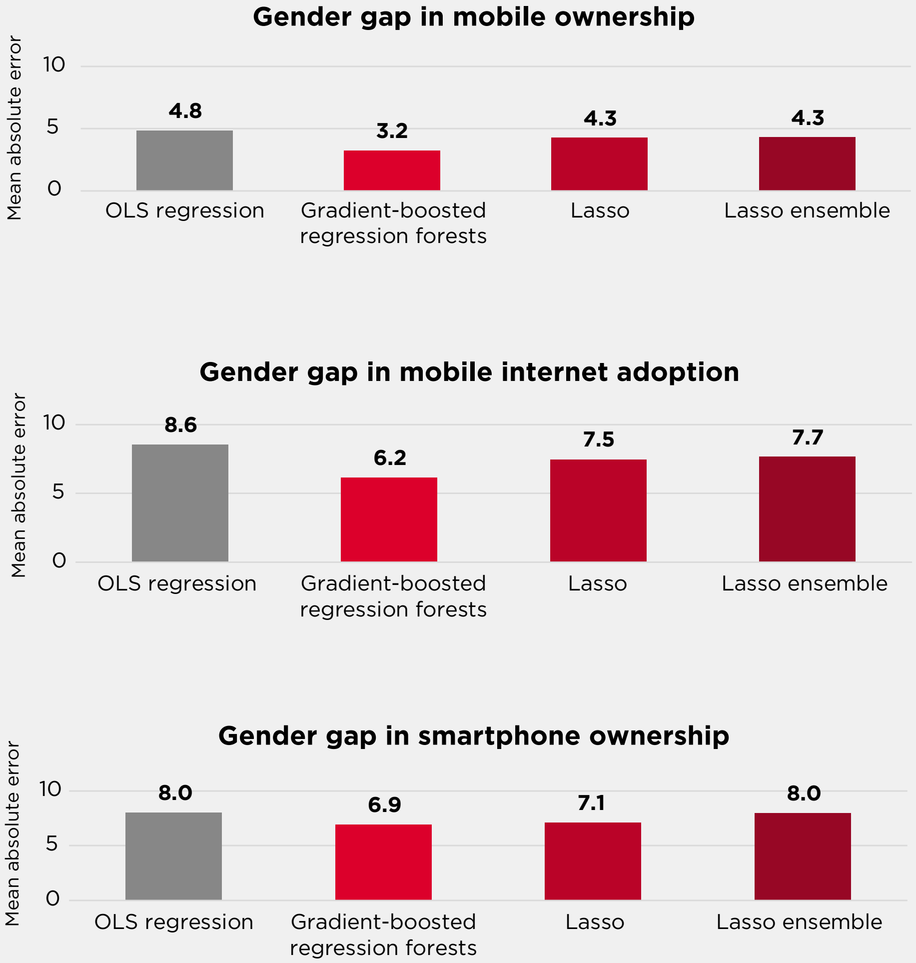
These performance metrics were estimated using cross-validation.[10] Cross-validation is a technique used to evaluate the performance of a predictive model. It involves splitting the available data into multiple subsets, using some of them to train the model and the others to test its performance. By repeatedly training and testing the model on different subsets of the data, cross-validation helps to ensure that the model is not overfitting any subset, and that it can generalise well to new, unseen data. We relied on seven-fold cross validation, which means that performance was calculated as the average performance measured over seven splits of the training dataset. We relied on GroupKFold variation of cross-validation, which ensured that the same country was not represented in both the testing and training sets.

The performance metrics for the evaluated models of each type of mobile gender gap are summarised in Figure 1. The evaluated models include Ordinary Least Squares regression models, which have been used in previous *Mobile Gender Gap* reports,[11] gradient-boosted regression forests, lasso and ensembles of lasso models. For gradient-boosted regression forests, lasso and ensembles of lasso, we relied on cross validation to find the values of certain model-tuning parameters (hyperparameters) that maximised the predictive performance.

Based on the evaluation results, we selected gradient-boosted regression forests to predict all the mobile gender gaps. Gradient-boosted regression forests outperformed other models in the reliability of the predicted gender gaps in mobile ownership, mobile internet adoption and smartphone ownership (Figure 2). The exception was the gender gap in mobile spending, which had higher prediction errors than the other models. This might be due to the relatively smaller training dataset for the mobile spending gender gap which, unlike the other gender gaps, was not part of the GSMA Consumer Survey in 2019 and 2020. However, given the relatively small difference in performance, and for the sake of simplicity, we used gradient-boosted regression forests to predict the mobile spending gender gap. Overall, the evaluated models had relatively similar estimates for all types of gender gaps (Figure 3).

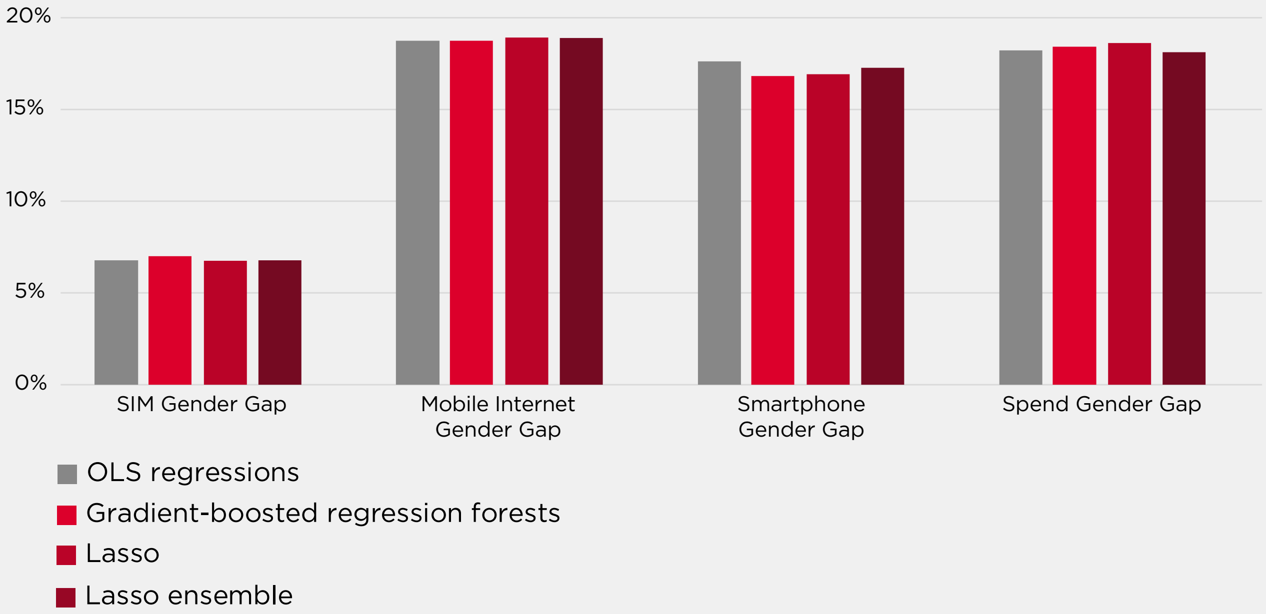
10. Arlot, S. and Celisse, A. (2010). "A survey of cross-validation procedures for model selection". *Statistics Surveys*, Vol. 4, pp. 40–79.
11. GSMA. (2022). *Methodology: The Mobile Gender Gap Report 2022*.

Figure 2
Mean absolute error of prediction of evaluated models (percentage points)



Source: GSMA Intelligence analysis

Figure 3
Comparison of estimated 2022 global gender gaps across evaluated models



Source: GSMA Intelligence analysis

Estimating the number of mobile subscribers and the size of the commercial opportunity

To estimate the number of mobile subscribers, mobile penetration rates and the size of the commercial opportunity if mobile gender gaps were closed, we combined our estimated gender gaps with GSMA Intelligence data.

Adult male and female mobile subscribers

This was calculated by using the estimated gender gap in mobile ownership, GSMA Intelligence estimates and forecasts of the adult mobile penetration rate, and UN estimates of the adult population by gender.

Adult male and female mobile internet users

This was calculated by using the estimated gender gap in mobile internet use, GSMA Intelligence estimates and forecasts of the adult mobile internet penetration rate, and UN estimates of the adult population by gender.

Adult male and female smartphone users

This was calculated in three steps:

- First, to estimate the number of unique smartphone subscribers, we scaled down GSMA Intelligence data on smartphone subscriptions to adjust for the average number of devices per subscriber in the GSMA Intelligence database. This number was further adjusted by the GSMA Consumer Survey estimate of the average number of devices per smartphone user to reflect that smartphone users generally tend to own more devices than an average non-smartphone mobile user.

- Next, we adjusted the estimated number of unique smartphone subscribers based on the proportion of adults among the total smartphone subscribers. This yielded an estimate of unique adult smartphone subscribers. Given a lack of data on the share of smartphone users, we relied on GSMA Intelligence data on the share of adults among total mobile internet subscribers (all ages).

- Finally, we used the estimated gender gap in smartphone ownership to calculate the number of unique adult female and adult male mobile subscribers and the mobile penetration rates.

Adult male and female mobile spending

This was calculated by applying the estimated gender gap in mobile spending to GSMA Intelligence data and forecasts on average revenue per subscriber.

Size of the commercial opportunity if certain mobile gender gaps were closed

We estimated the size of the commercial opportunity for mobile network operators (MNOs) under the following scenario:

- **Simultaneous closure of the mobile ownership and mobile spending gender gaps,** which could generate increased revenue due to an increase in the number of female subscribers and average revenue per female subscriber. It should be noted that this opportunity would normally be greater than the mobile ownership or mobile spending gender gap closing on their own. This is because, based on our assumptions, a higher number of female subscribers would also have higher levels of mobile spending.

We assumed that the mobile gender gaps would close gradually from 2023 to 2030 (at which point there would be no gaps), with the size of the commercial opportunity corresponding to the cumulative additional revenue from 2023 to 2030. Over this period, we assumed there would be a linear reduction in the gender gaps. Our estimates rely on GSMA Intelligence forecasts for the main input variables, such as the projected number of mobile subscribers and the projected average revenue per subscriber. Additional revenues are expressed in current (2022) US dollars (USD).

It should be noted that these estimates exclude a few countries where the estimated gender gap is less than zero (i.e. adoption and/or mobile spending are higher among females than males).

Analysing mobile use and barriers

Barriers to mobile ownership and mobile internet adoption

In the survey for *The Mobile Gender Gap Report 2023*, respondents who did not own a mobile phone were asked about the potential barriers that were preventing them from owning one, and mobile users who were aware of mobile internet but had not used it in the last three months were asked about barriers preventing them from adopting it.[12]

The GSMA Consumer Survey 2022 allowed respondents to identify barriers by level of importance, ranging from "This is a barrier" to "This is one of the most important barriers" to "This is the single most important barrier". By staggering the questions, we could analyse in detail the key barriers women (and men) face to mobile ownership and mobile internet adoption. Survey respondents were asked to identify barriers to mobile ownership from a list of 14 barriers, and barriers to mobile internet adoption from a list of 19 barriers (see Table 4 for a comprehensive list). To analyse the top barrier to mobile ownership and mobile internet adoption, similar barriers were grouped into five broad themes identified by the GSMA in earlier research.

The five overarching themes were:

— Affordability
— Literacy and digital skills
— Relevance
— Safety and security
— Access

Within each theme, responses to individual barriers were grouped into a single composite figure, except those under the Access theme, which were too diverse to be combined into one. Table 4 shows how the barriers to mobile ownership and mobile internet adoption were grouped by composite. The composites were calculated by summing the responses across sub-barriers within that composite and are not an average of the values of all barriers within that composite. This helps to illustrate the importance of broad themes, which consumers can experience in a variety of ways. For example, low digital skills or literacy can create a range of barriers to owning or using a mobile phone, and multiple questions must be asked to capture the extent of its influence. By contrast, the importance of cost as a barrier can be captured in just two questions.

12. The proportion of adults considered aware of mobile internet is calculated by summing those who report ever having used mobile internet, and those who report not having used it, but being aware of the internet and that it can be used on a mobile phone (i.e. it is assumed that those who have used mobile internet are aware of it).

Composite barriers therefore allow the various components of more complex barriers to be combined, and the importance of the barrier to be represented more accurately. For both mobile ownership and mobile internet adoption, these composites are shown in the report averaged across survey countries to provide an "All countries" ranking and are also shown at the country level.

Table 4
Individual barriers within each composite theme

Affordability composite		Literacy and digital skills composite		Relevance composite		Safety and security composite		Access (not composite)	
Mobile ownership	**Mobile internet**	**Mobile ownership**	**Mobile internet**	**Mobile ownership**	**Mobile internet**	**Mobile ownership**	**Mobile internet**	**Mobile ownership**	**Mobile internet**
Handset/ SIM cost	Handset cost	Do not know how to use a mobile phone	Do not know how to access internet on a mobile phone	Have access to someone else's mobile phone	Internet is not relevant for me	Personal safety	Harmful content (self/ family)	Battery charging	Internet drains my battery
Credit cost	Data cost	Reading/ writing difficulties	Reading/ writing difficulties	Mobile is not relevant for me	Insufficient content in local language	Strangers contacting me	Strangers contacting me	Network coverage	Network coverage
–	–	–	Do not know how to use a mobile phone	–	–	Information security	Information security	Family does not approve	Family does not approve
–	–	–	Do not have time to learn how to access internet on a mobile phone	–	–	–	–	Access to agent support	Access to agent support
–	–	–	Not sufficient support in learning to use internet	–	–	–	–	ID	Slow connection/ cannot do what I want
–	–	–	–	–	–	–	–	–	No access to internet-enabled phone
–	–	–	–	–	–	–	–	–	Hard to find where to buy an internet-enabled phone

Analysing use of mobile services

The GSMA Consumer Survey 2022 asked mobile owners to identify the types of services they used on a mobile phone. Respondents were asked to select from a list of 23 common use cases ranging from basic services, such as calling and SMS, to more advanced internet-based services (see Table 5). Respondents were also asked to report how frequently they used each type of service. Analysis in *The Mobile Gender Gap Report 2023* focused on weekly usage to exclude services that were used only sporadically.

Questions about mobile use were not exclusive to a respondent's personal handset. Therefore, the survey data is indicative of a respondent's overall usage regardless of who owned the handset.

Table 5
Types of mobile use cases

— Network calls	— Finding information about goods and services
— IP calls	— Managing or paying utility bills
— SMS and MMS	— Using online banking
— Video calling	— Accessing services that improve or monitor health
— Instant messaging apps	— Accessing government services
— Visiting social networking sites	— Looking or applying for jobs
— Playing free games	— Accessing information to support education
— Watching free-to-access online video	— Accessing information on farming or fishery services
— Listening to free online music	— Using maps, timetables and traffic information apps
— Using paid-for entertainment services	— Reading the news
— Sending or receiving money using mobile money	— Using a ride hailing, taxi, e-bike or scooter app
— Ordering and purchasing goods	

For more information about the methodology of *The Mobile Gender Gap Report 2023*, contact **GSMA Connected Women.**

www.gsma.com/r/gender-gap

For more information, visit
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