Working paper

Digital platforms in Asia: Access and Use

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About this report

This paper was commissioned by the World Bank. It is based on the analysis of survey data collected through nationally representative surveys conducted by LIRNEasia in six Asian countries between 2017 and 2022. The design and implementation as well as the analysis of data collected in these nationally representative surveys was funded through grants from the International Development Research Centre of Canada (IDRC), the Ford Foundation and the Swedish International Development Cooperation Agency (SIDA).

About LIRNEasia

LIRNEasia is a pro-poor, pro-market think tank whose mission is *Catalyzing policy change and solutions through research to improve the lives of people in the Asia and Pacific using knowledge, information and technology.* LIRNEasia has been active in the Asia Pacific since 2005, conducting both demand- and supply-side research as well as advocating for policy changes in the ICT sector on issues ranging from universal service policy to open data, gender, big data and more. For more information, visit lirneasia.net or follow @LIRNEasia.

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Table of Contents

List of figures

List of tables

1. Executive Summary

Digital platforms are growing in popularity and use and are enabling the purchase of various goods and services. The report analyses the drivers of platform use, the extent of awareness and use, and barriers to use of digital platforms that enable the purchase of goods and services. It relies primarily on quantitative data from two rounds of nationally representative surveys conducted in 2017-18 in six South and Southeast Asian countries – India, Sri Lanka, Bangladesh, Pakistan, Nepal, and Cambodia – and again in 2021 in India and Sri Lanka. Descriptive statistics as well as modelling is done to arrive at the findings, which are as follows:

Use of platforms: The use of digital platforms to buy and sell goods among internet users differed considerably amongst six countries studied. 12% of the population aged 15-65 in Sri Lanka had used platforms to buy/sell goods and services at least once in their lives while only 1% of the population in Nepal had done so. Noteworthy is that in populous countries such as India, Bangladesh, and Pakistan (all with populations above 100 million; India having over a billion), the absolute market size (as measured by number of people buying or selling on platforms) is greater than that of its peers. This is important since the scale translates to more growth potential. For example, between 2017 and 2021, the number of platform users in India had grown from 63 million to 113 million. Goods/products and transport platforms were the most popular in the majority of the countries studied.

Facilitators of, and barriers to, platform use: Platform use by individuals is driven by multiple factors such as income, age, gender, education. To understand the relative importance among these various factors, we develop a binary logistic model which shows that digital skills have a very strong impact on platform use, with those with digital skills being five times more likely to use platforms, even when other factors pertaining to digital access and use, access to finance and demography are controlled for. Using cashless payment methods such as mobile money, debit or credit cards too drives platform use strongly. Further, belonging to a wealthier family (SEC A), having a tertiary education, and belonging to a younger demographic group, and living in an urban area, increases the odds of using platforms. Unsurprisingly, digital preconditions such as owning a device (desktop/laptop computer and/or a smartphone) too more than doubled the odds of using platforms.

Perceptions around the use of platforms also play a key role in determining uptake. When we asked non-users why they were not using platforms, an overwhelming majority (ranging from 73% of non-users in Nepal to 37% in Bangladesh in 2017/2017) indicated that they did not see the need to use platforms. The perceived lack of skills only came in a distant second in many countries, though the proportion of people stating this had increased over time. Elements of trust too were areas of concern to some.

COVID-19 impacts on platform use: Education was a sector that relied heavily on digital technology and digital platforms during the COIVID-19 lockdowns. Our data shows there was a sharp contrast in schoolchildren's use of online mediated education (including platforms-based education) in India and Sri Lanka" while 60% of enrolled children in Sri Lanka used online means to receive education during the lockdown period, only 16% of schoolchildren in India did the same. Outside of education, platform use was impacted by the restrictions too. Anecdotally, we know that the COVID-19 imposed movement restrictions made some sections of the population rely on food and other delivery platforms to access their needs. Some asserted that such disruptions in the market would lead to a permanent shift in the use of platforms. But in the case of food delivery, only 62% and 45%

of those who used platforms during the lockdowns in India and Sri Lanka did so afterwards, indicating that a permanent shift to online purchasing had not happened due to COVID-19.

Policy implications: The basic need for internet connectivity and use is a primary requirement for platform use. People who are online and comfortable being online are more likely to become aware of platforms and then to use them. As such, all policy actions to increase the affordability of handsets and connectivity while providing acceptable broadband quality still remain policy targets. However, as the data makes clear, there are plenty of people who are online but are not using platforms. For these people, the barriers are meaningful skills (to enable them to use platforms confidently, and safely) and access to financial payment mechanisms to facilitate transactions (trusted payments). Like the internet, platform use too follows the pattern of richer, more educated, urban, younger persons adopting first, leaving others behind. Im order to break the pattern, its important to understand points of intervention.

2. Context and literature

2.1. Background

Digital platforms have been growing in their importance in mediating various transactions between buyers and sellers of goods and services. While early platforms such as Amazon Mechanical Turk started in developed economies, they soon transitioned to finding labor in emerging economies due to cheaper labor cost in those countries and increasing internet connectivity. Global and local platforms that enable everything from ride hailing to finding odd jobs now operate in a majority of emerging Asian economies.

This report explores what the literature says about the use and benefits of platforms in general, and in Asia in particular. It then uses data from two rounds of data collection via nationally representative surveys in six Asian countries to quantify the extent to which digital platforms are used and explores factors that contribute towards adoption.

2.2. Literature

Digital labor platforms have been gradually reshaping the world of work for the past decade. From ride sharing to ordering groceries online to freelancing online, they enable buyers and sellers to interact in a "shared marketplace" and create value as part of a larger digital or the gig economy (Huang et al, 2020). They have evolved to the extent of transitioning from merely being marketplaces to "being the market makers" of the present (Gurumurthy et al, 2018). Gig-economy platforms are by definition 'digital, service based, on-demand platforms that enable flexible work arrangements' (Greenwood et al, 2017), that facilitate tasks to be undertaken online or offline (Bogenhold, 2017). This is reflected in the ILO (2021) classification of web platforms into the two broad categories of online web-based platforms (where work is done in a web-based setting) and location-based platforms (where work is done offline). Online web-based platforms let businesses remotely outsource their processes and source talent globally, thereby increasing their gains from trade by enhanced matching of employers to employees (Agrawal et al, 2013). They enable a seamless inbuilt recruitment process, reducing costs and improving efficiency (World Bank,2015). Location-based platforms enable the likes of restaurants and retail stores to achieve higher profitability and greater productivity that comes through increased convenience and accessibility. They're able to adapt to customer preferences rapidly, hence grow and expand their markets by positioning themselves in diverse geographies (ILO, 2021). Digital platforms effectively cater "solely to individuals, facilitate and exchange between buyers and sellers or act as a labor platform that mediates" work (ILO, 2021). Though the actual number is uncertain, in 2020, it was estimated that there were between 30- 40 million workers engaged in platform mediated work in the Global South, with a 30% annual rate of growth (Heeks, 2020). Literature identifies a number of benefits of digital labor platforms for workers as well as clients. One source identifies platforms themselves as a conduit to address information failures and inefficiencies in traditional labor markets (Drouillard, 2017).

Multiple gains are recognized for workers including higher incomes than previously earned, greater flexibility of working hours or location, and more objective management processes (Surie and Koduganti, 2016; Heeks, 2017). For example, Upwork workers in India were able to "operate from home and avoid difficult commutes as well as escaping from the micro- politics, supervisory controls and interpersonal issues that accompanied organizational life [and] enjoyed the flexibility of setting their own daily schedule and pace" (D'Cruz and Noronha, 2016). However, other research point to absurdly long work hours, lack of social protection payments, and an isolation of individuals in the workforce that "hinders collective voice" as being the costs of using platforms to generate an income (Kashyap & Bhatia, 2018; Wood et al., 2018). Uber/Ola drivers in India were found to endure "fatigue, stress, hunger and sleep deprivation" to generate sufficient income from platform

labor to repay loans that were taken out under the premise of a specific level of income (Kashyap & Bhatia, 2018). Surveys of digital gig workers report no platforms paying for sick leave, health/life insurance or pension contributions (Berg, 2016; Berg et al., 2018). Research by Howson et al (2022) found that 30% of platform workers are cheated out of their wages even after successfully completing a task. Although globalization of online tasks through platforms has brought new jobs to the Global South (Codagnone et al., 2016), including the promise of better economic prospects for women and young people (Malik, 2018), platform work is essentially seen as a 'trade-off' due to the existence of such drawbacks. That is, they provide work opportunity and flexibility for developing country workers but at the cost of "chronic precarity and inequality" (Heeks, 2017). Heeks (2017) further points out that in developing countries "the positives rarely outweigh the negatives" (ibid), as online gig economy workers mostly work under "digital sweatshop like conditions" (Zittrain in Malik et al, 2018).

Berg et al, (2018) finds that most Indian workers who use Amazon MTurk and CrowdFlower use their income from these platforms as their primary income. Although developing country crowdworkers generally earn more than their national average wages through crowdwork (Heeks, 2017), they are dissatisfied since workers abroad who engage in the same tasks are better paid (Berg, 2018). Berg (2018) also states that dependence on crowd work is underestimated in literature and 48% of crowd workers do not have other types of employment that generate income. Despite this, research by Galpaya and Senanayake (2018) observe that Indian and Sri Lankan platform workers mostly use their income from platform work as supplementary income.

The literature presents a similarly mixed view in the debate on quality of platform work for clients of platforms. Noticeably, most buyers reside in high income countries while sellers are more geographically dispersed. According to the OLI (2020), 41.7% of the online labor demand originates from the United States, followed by 8.1% from the United Kingdom. Work is mostly carried out by relatively low-income countries at a lower price (Kanat et al, 2018) as pointed out in the previous paragraphs. Data from the OLI (2020) which state that majority (54%) of the online labor supply is provided collectively by India, Bangladesh and Pakistan, confirms this. It is also worth noting that 70 per cent of the global revenues generated through platforms are concentrated in just the United States and China (ILO,2021). This dynamic inevitably creates a significant imbalance of power between these countries (Graham, et al, 2017). As a result, clients benefit from lower costs and higher service standards (Dreyer et al., 2017). Conversely, other sources point to clients that use platforms in a negative light or having negative repercussions– such as avoiding tax payments (Olbert and Spengel, 2017) and clients being cheated by workers (Kaganer et al., 2013). While there is a growing body of evidence of both pros and cons of platform work for both workers and clients, as of yet there has been very little research that has produced a systematic framework or index to compare the implications of platform work and platform use or draw comparisons in different geographies within or between countries, especially the ones in the Global South.

The impact platforms have on workers and clients on a micro level as discussed above translates to the macro-economy by altering the pre-platform dynamics of the labor composition of the economy overtime. When platform work became widely adopted, it seemed to contract the formal employment sector and channel more labor into employment that was more decentralized and informal. However, it may be inaccurate to say platforms purely drove this transformation. For example, in Latin America the trend first emerged in the late 20th Century when governments in the region revised their labor laws in a way that incentivized businesses to cut down on formal employment and enable outsourcing and subcontracting to cheaper and more informal operations (Americas Quarterly, 2015). This phenomenon was exacerbated by the emergence of globalization when companies initially started using the internet to derive the competitive advantage of accessing better quality labor for a significantly lesser cost - as hiring was no longer limited to geographical

boundaries (Graham et al, 2017). Large-scale platform companies like Uber, Airbnb, Amazon, Task Rabbit then emerged, and informalized their respective sectors further – while remaining unregulated for the most part (Americas quarterly, 2015). Employment in these platforms created the grey area between the formal and informal sectors (KCET, 2019). With the emergence of crowd work, companies like Amazon M Turk were able to access an informal labor force that they could 'expand and contract on demand, without any significant transaction costs or logistical hurdles'. As global operations they were largely able to 'hide' from view of regulators (Bergvall-Kåreborn and Howcroft, 2014).

In the developed world, the trend of workers moving from formal occupations to the informal sector as 'independent' workers is especially noticeable. According to the findings by McKinsey (2022), 36% of employed Americans identify as independent workers, a rise from the same figure being 27% in 2016. This, along with companies increasingly assigning tasks such as software development and graphic designing (OLI ,2020) to the informal gig economy seem to be effectively 'informalizing the formal sector', or blurring the line between the two (KCET, 2019).

Meanwhile, the developing world is shifting away from being largely made up of informal work towards work in more formal settings. The digital transformation spreading to the parts of the world where such technology was previously inaccessible, disrupts the previous dynamics of their economies. Ng'weno and Porteus (2018) argue that this transformation occurs in a stepwise process, minimizing costs of operation such as advertising and contracts incrementally as opposed to directly switching from informal to formal processes. Traceable and documented services by platforms including 'offer(ing) advice on how to set prices, training on how to handle customers, ratings to provide incentives for good behavior…, accounting and analytics, offer(ing) credit, collect(ing) sales taxes'(ibid) bring in a degree of formality into economic activity that could have previously taken place largely in the undocumented and unregulated informal economy.

Nevertheless, it remains to be examined if the benefits of formalizing platform work and reaping the benefits of it in the form of higher wages, and other measures of reducing employment insecurity and enhancing worker wellbeing extends to all platform workers. Literature suggests that in reality this may not always be the case. The power imbalance caused by the vast majority of buyers belonging to regions in the Global North and the resulting competition from workers in both the Global North and South cashing the same jobs, causes a loss of bargaining power for workers to demand higher wages for themselves (Graham, 2017). The global nature of platforms also enables clients to practice 'labor arbitrage', or buying labor from where it is cheapest, and offer payment that falls below what is considered to be an established fair wage. The result is '(worker) disempowerment, an inability of workers to exert any significant bargaining power, and a race to the bottom in wage rates' (ibid). Additionally, according to Graham et al (2018), intermediation on platforms enable clients, who are themselves contractors that are able to attract higher paid tasks (driven by their higher ratings), to outsource their tasks to other contractors that have lower ratings at a cost below their minimum wage, and by extension denying them the opportunity to earn higher wages through the use of platforms. Economic exclusion and discrimination is also prevalent in some platform work, making it easier for a certain demographic of workers to acquire jobs that are denied to workers that are non-Caucasian (Ming Curran, 2021), work outside buyers home countries, disabled etc. (Heeks, 2017). Additionally, platform architecture is largely extractive. As Srniek (2017) points out, platforms pass on much of their costs to workers while adopting what is called the 'lean platform' model (Uber, AirBnb), while charging a percentage commission on each transaction mediated by them.

As Mark Graham (2020) articulates 'the gig economy is built by design to convenience customers, to return profit to platforms and ultimately, to disempower workers'. It is necessary to address this

crucial design flaw and provide a just space for workers to market their labor – in an environment that improves the overall work experience and quality of life of workers. This might be especially relevant for workers from developing countries. Gig work offers the opportunity to boost economic growth (Banik, 2019) and hence create positive externalities in their economies. Literature points to processes and policies that can be set in place to achieve this objective, by both platform companies and regulators, to create 'decent digital work' standards for all. Heeks (2017) presents a code to necessitate the same by providing measures for workers to have access to benefits under different employment contexts such as 'stability and security of work', 'decent working time' and 'dignity and respect at work'. Graham et al (2017) explores the imposing of labor laws that cover gig work in countries, the possibility of platforms undergoing fairwork certification programs, effective dispute settlement mechanisms for workers, formal employment contracts for all gig work (as opposed to operating as independent contractors), among others to address some of the key issues associated with gig work. Collective dialogue and subsequent action by all the stakeholders involved could potentially shape the future of gig work in such a way that the benefits of it can be reaped by all that contribute towards it.

The COVID 19 pandemic brought about further changes to the platform economy. In India, the pandemic brought about an increase of the demand and supply to the access of food, groceries, and even medical services, hence expanding the market of platforms that catered to those needs remotely and decreasing the activity of platforms that enabled microwork and freelance due to uncertainties of business continuity (Rani et al, 2020). For example, in Sri Lanka the effects of COVID-19 expanded the ecommerce sector. However, the ride sharing economy was affected in an inverse manner since in the first quarter of 2020, the number of riders dropped by 50-70 percent, landing gig workers working with Uber and PickMe in the territory of severe income uncertainty.

3. Methodology

This section provides details about the various methods involved in data collection and analysis.

3.1. Survey methodology

This report draws on data from 2 rounds of nationally representative, face to face surveys of households and individuals in across 6 countries in South & Southeast Asia. Round 1 of surveys was conducted in 2017 and 2018 in 6 countries (India, Sri Lanka, Bangladesh, Pakistan, Nepal, and Cambodia) under the AfterAccess[1] initiative that conducted similar surveys across countries in Asia, Africa and Latin America. In this round, only in Sri Lanka, we also surveyed small and medium enterprises. Round 2 of nationally representative surveys was done in 2 of these countries, India[2] and Sri Lanka[3], in 2021. The aim of the 2021 survey was particularly to understand the impact of the pandemic in the two countries.

The key objective of the methodology is to ensure national representation at the desired levels of precision. This was achieved by using a comprehensive national sample frame at the most granular level possible (census enumerator areas (EAs) or blocks in the best case[4] or most granular administrative division level data) and ensuring random selection at every level of sample selection (i.e.: at EA, household, individual level)

Table 1. Sample sizes and margin of errors at country level

Round	Country	Sample size (actual achieved)	Margin of Error at 95% Confidence Level (National Estimates)
Round 1 (2017 -2018 AfterAccess surveys)	Sri Lanka	2,017	±3.3%
	India	5,069	±2.0%
	Pakistan	2,002	±3.3%
	Bangladesh	2,020	±3.3%
	Cambodia	2,123	±3.3%
	Nepal	2,008	±3.3%
Round 2 (2021 COVID Impacts surveys)	Sri Lanka	2,500	±2.8%
	India[5]	7,000	±1.7%

Note: The state of Kerala was excluded from the sample in the 2021 India survey since fieldwork could not be carried out in Kerala throughout the duration of the survey period due to particularly strict travel restrictions imposed by the state to control the prevailing COVID-19 pandemic situation. Hence, the final achieved sample size was limited to 7,000 households and individuals instead of the planned 7,500. As such all the estimates from the 2021 India survey are excluding the state of Kerala.

[1] See https://lirneasia.net/after-access. Note there were a larger number of African and Asian countries included in this round of surveys. The full data is available at www.afteraccess.net

[2] https://lirneasia.net/2021/11/impact-of-COVID-19-on-households-and-the-workforce-in-india-survey-methodology-notes/

[3] https://lirneasia.net/2021/12/impact-of-COVID-19-on-households-and-the-workforce-in-sri-lanka-survey-methodology-note/

[4] A census divides a country in to blocks or EAs which have a rough density of 200 households. This is generally considered a manageable number of households that can be listed within a day.

[5] All India excluding the state of Kerala

The target populations for the two rounds of surveys were as follows,

- Round 1 (2017-2018 AfterAccess surveys) – All households and population aged 15-65
- Round 2 (2021 COVID Impacts surveys) – All households and population aged 15 and above

Round 1 and Round 2 base sampling methodology in steps is as follows

- Separation of national sample frame into urban and rural primary sample locations (PSUs)
- Sampling the required number of PSUs from each stratum (urban and rural) using probability proportionate to size (PPS)
- Segmentation of the PSUs where the number of households exceeds a certain threshold (about 200 to 250 households)
- Mapping, listing, and marking all households in the selected PSU or a randomly selected segment of the PSU
- The lists serve as the sample frame for simple random selection of households. This was done with the assistance of key informants (e.g.: ward/ village leader, etc.)
- Systematic random selection of the required number of households (20-25) from each selected PSU or the PSU segment
- Listing all household members or visitors aged 15-65 staying the night at the selected household
- Simple random selection (using the CAPI programme) of one household member for individual survey from household list compiled in the previous step

In each country, the methodology outlined above was adjusted depending on the availability and granularity of sample frames, and ground realities. The lowest administrative level sampling frames available to the public were Grama Niladhari Divisions (GND) in Sri Lanka, villages and wards in India and Bangladesh, villages in Cambodia and wards in Nepal. No sampling frame was publicly available for Pakistan. Hence, the Pakistan Bureau of Statistics conducted the sampling of EAs from the national census sampling frame for us, as per our specifications.

Where the EA sampling frame was not available, the lowest-level administrative units publicly available for each country (ward, village, or GNDs as appropriate) were divided into smaller areas listing and enumeration. These administrative units typically have a larger number of households than an EA. For instance, some wards (specifically in Mumbai, India) can have as many as 100,000 households, making the listing all households impossible if selected into the sample. Therefore, such large administrative units were segmented while in the field, according to pre-defined methodology, and one or more smaller segments then randomly selected for listing and enumeration. It is important to note that the core principle of random selection was incorporated at every stage of sample selection to ensure national representation. There was no purposive, convenience or quota selection of any kind.

The questionnaire design, questionnaire localization, data analysis and quality checks were carried out by LIRNEasia. The fieldwork was conducted by market research firms that were selected through a competitive, open tendering process in each country. These companies were involved in the fieldwork set-up (including scripting, translating, and pilot testing of the questionnaire and training of enumerators) and execution as well as dataset delivery. The market research firms conducted on-field and off-field quality checks such as accompaniments, back checks, spot checks, voice checks, map checks and real time fieldwork monitoring.

LIRNEasia also independently monitored fieldwork, by participating in field training and monitoring fieldwork, both on the ground as well as remotely. The remote fieldwork monitoring was done every

day. The LIRNEasia research team conducted household count checks, questionnaire content checks and whether the field teams are adhering to the survey methodology.

As already explained, Kerala, India fieldwork could not be done on time due to prevailing COVID-19 pandemic situation of the country at the time.

Table 2. Coverage and sample frame related information on 2017-2018 AfterAccess survey and 2021 COVID impact surveys

Round	Country	Coverage	Sample frame used	Level of representation	Fieldwork time
Round 1 (2017-18 AfterAccess Surveys)	Sri Lanka	100 GNDs covering all nine provinces	GND-level data from the National Census of Population and Housing 2012	National, and urban-rural level	November 2018 – January 2019
	India	250 wards and villages covering 19 states and 108 districts	Ward (urban) and village (rural) level data from the 2011 National Primary Census Abstract Data	National, and urban-rural level	October – November 2017
	Pakistan	100 Enumerator areas. The AJK, FATA and Gilgit-Baltistan provinces – amounting to approximately 2% of the were excluded from the sample frame due to practical and security considerations	2017 Census of Pakistan sampling frame.	National, and urban-rural level	October-December 2017
	Bangladesh	100 wards and villages covering 40 Zillas	Ward (urban) and village (rural) level data from the 2011 National Census Data	National, and urban-rural level	October – November 2017
	Cambodia	100 villages covering 25 provinces	village-level data from the 2014 inter-censual survey	National, and urban-rural level	September – October 2017
	Nepal	100 wards covering 7 provinces	ward-level data from the National Population and Housing Census 2011 based on the	National, and urban-rural level	April – May 2017

			new structure of 753 local units		
Round 2 (2021 COVID impacts surveys)	Sri Lanka	125 GNDs covering all 25 districts and provinces	GND-level data from the National Census of Population and Housing 2012	National, urban-rural level, Western provinces vs other provinces	March – October 2021
	India*	350 wards and villages covering 22 states and 150 districts. The state of Kerala is18xcluded from the sample.	Ward (urban) and village (rural) level data from the 2011 National Primary Census Abstract Data	National, urban-rural level and five states (National Capital Territory of Delhi, Maharashtra, Tamil Nadu, Azzam and Kerala[6])	March – August 2021

Figure 1. 2017-18 AfterAccess survey sample locations based on GPS coordinates recorded during fieldwork

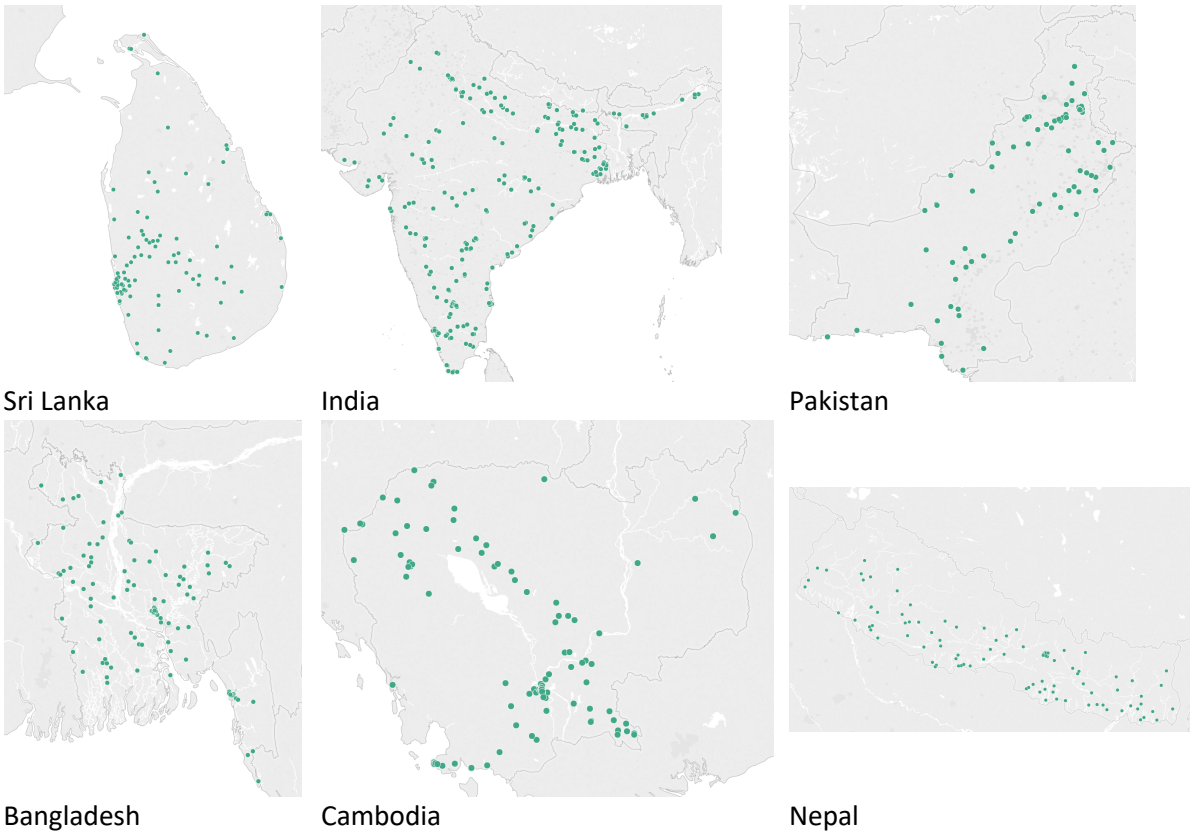
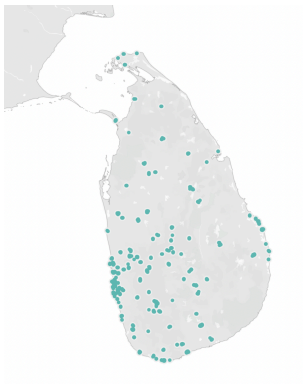
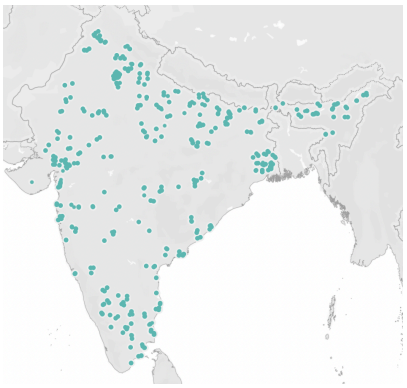


Figure 2. 2021 COVID impact survey sample locations based on GPS coordinates recorded during fieldwork

[6] Kerala fieldwork could not be done on time due to prevailing COVID-19 pandemic situation of the country and especially in the state at the time



Sri Lanka



India

Sample size determination
The desired level of accuracy was set to a confidence level of 95% and an absolute precision (relative margin of error) of 5%. The population proportion (p) was set conservatively to 0.5, which yields the largest sample size. The minimum sample size (n) was determined by the following equation:

$$n = \left(\frac{Z_a \sqrt{p(1-p)}}{C_p} \right)^2 = \left(\frac{1.96\sqrt{0.5(1-0.5)}}{0.05} \right)^2 = 384$$

Where,
n = Minimum sample size
Za= Z-value for 0.05 level of significance
Cp = Margin of error
p = Population proportion

Inserting the parameters for the survey yields the minimum sample size for simple random sampling; therefore, for our sample design (stratified with multiple levels in some cases) the minimum sample size was multiplied by the design effect variable.

In the absence of empirical data from previous surveys that would have suggested a different value, a value of 2 was used as the design effect for each country. The actual sample size increased beyond the minimum requirement to compensate for clustering effects, and allow for urban/rural disaggregation of data, as well as gender-based disaggregation and more importantly to have representative data at more granular levels in the 2021 sample.

Sri Lanka 2018, Small and medium sized enterprises (SME) survey
LIRNEasia 2018, SME survey was done alongside the nationally representative household and individual survey in Sri Lanka. The fieldwork was conducted in the same sample locations.

A separate listing exercise was carried out to list down all SMEs in the selected primary sample locations (Same 100 GN divisions mentioned in the table 2 under round 1 Sri Lanka). Four SMEs were randomly selected from each Primary Sample Location. This yielded a sample of 400 SMEs for Sri Lanka.

The same design effect factor (2) was considered to calculate the margin of error of the estimates. The LIRNEasia SME survey estimates had a margin of error or +/-6.9% with 95% confidence level at Sri Lanka national level.

Gap calculation

The gap calculations were done as per the following equation.

$$Gap\ \% = \frac{(\%\ of\ the\ population\ having\ the\ charesteristic\ of\ interest\ in\ group\ 1) - (\%\ of\ the\ population\ having\ the\ charesteristic\ of\ interest\ in\ group\ 2)}{(\%\ of\ the\ population\ having\ the\ charesteristic\ of\ interest\ in\ group\ 1)}$$

Socio-economic classification (SEC)[7]

Socio economic classification is based on the education and occupation of the household head and is a proxy for household income. The five high-level SEC categories are being used in this report. The SEC A denotes the richest households and SEC E denotes the poorest households.

Digitally skilled population

Those who could do the at least one of the six activities mentioned below, by themselves, are considered as digitally skilled.

1. Search for information or other content online
2. Install an application on mobile phone
3. Create login details (user) and a password to use a particular service or a website online
4. Locate and adjust settings on an application or service on mobile phone
5. Post any information on the online
6. Make a payment or complete a transaction online or by phone

[7] https://lirneasia.net/wp-content/uploads/2013/03/Method-Note_Final_report_uploaded-on-website.pdf

3.2. Digital Platforms Categorization

The platforms were categorized using following questions in both Round 1 (2017-18 surveys) as well as in the Round 2 (2021 surveys). The questions mentioned in the example below is the one that was used to identify the awareness of various platforms in Sri Lanka. Similar follow-up questions were asked to identify use as well as non-use.

Table 3. Survey questions[8] used to categorize the platforms and the comparative world bank definition.

LIRNEasia survey questions			Comparative World Bank categorization		
"Some people use the Internet or mobile apps to **buy and sell goods or services that they need**. This is through websites and mobile apps such as Uber, Pickme, Daraz, upwork.com, e-bay, ikman.lk as well as on Facebook, Instagram, etc. Goods you can buy online include household products, food, mobile phones, raw materials, etc. Services can include those like buying movie/train tickets, providing/hiring taxi services or other types of hired help. This also include services done online like data entry, designing etc. Some of these sites often require buyers / sellers/workers to create a user profile in order to find and accept assignments, whilst some sites also coordinate payments **Have you heard of Internet platforms or applications being available to buy and sell goods in the following areas?**					
Q.	Platform	Awareness	ISIC rev.4 Division	Category code	Name
Pf.1a	Transport/ taxi services (Uber, PickMe)	[1] yes [0] no	49-53	Code 1.10	Transportation & Logistics
Pf.1b	Goods/products (Daraz, Amazon, AliExpress, eBay, ikman.lk, Takas)	[1] yes [0] no	45-47	Code 1.3	**E-commerce**
Pf.1c	Microwork/freelance (Upwork, Fiverr etc.)	[1] yes [0] no	69-75, 77-82	Code 1.5	**Labor**
Pf.1d	Tickets and appointments (movie/railway/ doctor appointments, ticketslk, Doc990)	[1] yes [0] no	45-47	Code 1.3	**E-commerce**
Pf.1e	Hired help (Finding domestic helpers, plumbers)	[1] yes [0] no	69-75, 77-82	Code 1.5	**Labor**

[8] The examples are from the Sri Lanka questionnaire. Relevant local platform names/brands from each country were included in each of country-specific questionnaires.

Pf.1h	Delivery services[9] (Delivery Malli, Quickee)	[1] yes [0] no	49-53	Code 1.10	**Transportation & Logistics**
Pf.1f	Accommodation (Airbnb, Booking.com, TripAdvisor)	[1] yes [0] no	55-56	Code 1.9	**Tourism and local services**

3.3. Chi-square test

The chi-square test of independence was used to determine whether there is a relationship between three categorical dependent variables,

- Overall platform awareness
- Platform use for buying goods or services
- Platform use for selling goods or services

and the other facilitating factors such as socio demographic characteristics and other enabling factors of platform awareness and use (for both buy and sell goods and services). These factors are also categorical variables. The Chi-square statistic's statistical significance was measured at .05, .03 and .01 level.

3.4. Logistic regression model

Logistic regression modeling is used to understand the factors which predict for,

- Overall platform awareness
- Platform use for buying goods or services
- Platform use for selling goods or services.

Table 4. Outcome variables for logistic regression models

Model	Value	Meaning
Awareness	1	Aware of at least one type of platform
	0	Not aware of any type of platform
Buying	1	Have used at least one type of platform to buy goods or services
	0	Have not used any type of platform to buy goods or services
Selling	1	Have used at least one type of platform to sell goods or services
	0	Have not used any type of platform to sell goods or services

Logit regressions are a form of binary regression modeling, which is suited to the case where the variable of interest (in this case sharing and verification) is dichotomous (Table 4). Similar applications to technology adoption and use have been made by Rice and Katz (2003), Chabossou et al. (2009), de Silva, Zainudeen and Ratnadiwakara (2009), Amarasinghe (2018), inter alia, to understand what factors contribute to the odds (directly related to the probability) of the outcome of interest happening or not.

Logit models tie the determining and mediating factors to the outcome (Y) variable (see Table 4) through contributions to the probability of the outcome variable taking a value above or below a threshold that would lead to the observable outcome. Therefore, the logit model assigns a probability of awareness, use for buying or selling based on the various determining and mediating factors:

$$Probability\ (Yi) = \frac{1}{1 + \exp\left(-\alpha - \sum_{t=1}^{n} \beta_i X_i\right)}$$

[9] Delivery services platform type was not available in the 2017-18 surveys for any country

Where Y_i is the outcome of interest, a dichotomous variable as per Table 4, and X_i are the factors that impact such activity (also referred to as determining and mediating factors or influential factors). β_i values are factor sensitivities of each influential factor, X_i. Influential factors, X_i, can be scale or categorical variables; dummy variables are used to represent the 'states' in case of qualitative variables.

The use of an exponential function to model the dependent variable ensures the predicted value of the dependent variable is bound between 0 and 1.

4. Findings

We utilize the findings from the two rounds of nationally representative surveys of individuals and households to analyze the use of platforms in six countries.

At an individual level, we first do a deep dive into the use of transactional platforms[10], where we examine levels of use for seven types of platforms. In our analysis of transactional platforms, we look at both online web-based platforms (e.g.: microwork platforms) and location-based platforms (e.g.: goods/products (e-commerce) and transport/taxi platforms). Table 5 shows localized examples for each of these seven categories active in Sri Lanka and India at the time of writing the report[11]. We first analyze high level trends associated with the use of these platforms, then analyze facilitators of use (including socio-economic and demographic factors and other digital enablers), and we finally explore the impact of COVID-19 on the use of platforms for education and food delivery.

Table 5. Examples of transactional platforms in India and Sri Lanka

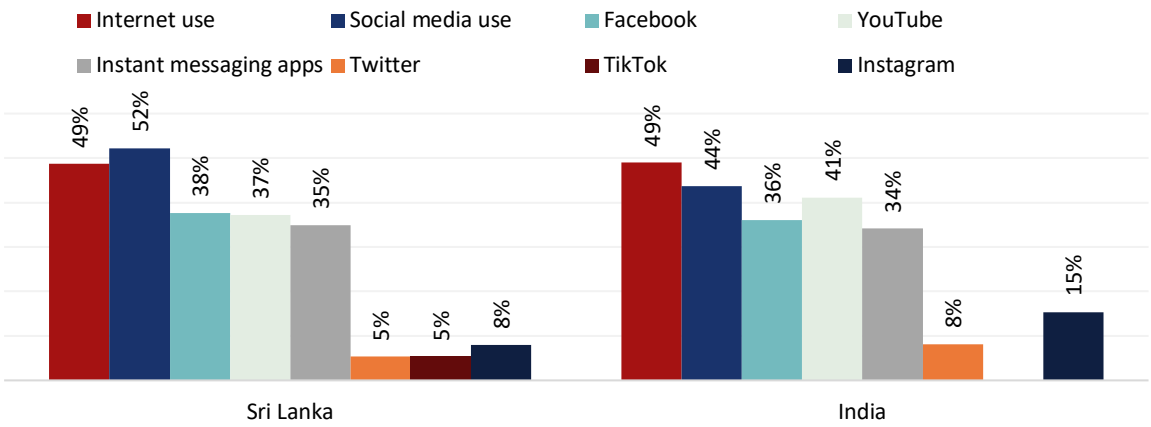
Country	Platform/type						
	Goods/ product (e-commerce)	**Transport**	**Tickets and appointments**	**Accommodation**	**Hired help**	**Microwork and freelance**	**Delivery Services**
India	Amazon India, Myntra, Flipkart Ajio	Uber, Ola, Lyft India, Meru cabs,	Bookmyshow, IRCTC, PayTM ticketnew	Airbnb, Goibibo, Booking.com, Tripadvisor	UrbanCompany, Quikr	Upwork, Fiver, Amazon Mechanical Turk	DTDC, Fastrack, Blue Dart, FedEx
Sri Lanka	Daraz, AliExpress, eBay, ikman.lk, Takas.lk	Uber, PickMe	Doc990, Tickets.lk, Bookmyshow lk, Taktik Book.lk	Airbnb, Booking.com, Tripadvisor, agoda.com,	Onawadak.lk, work.lk, hodabass.lk	Upwork, Fiverr	Delivery malli, Quickee

Content, or social media, platforms could also be used to market and sell products and services. In 2021, 52% of the population aged 15-65 in Sri Lanka used social media platforms in contrast to 44% in India. Facebook and YouTube were the most popular social media platforms in both India and Sri Lanka, followed closely by instant messaging platforms (Figure 3). We don't have further information to understand how these are used for buying or selling, however, so will focus solely on transactional platforms from sections 4.1 to 4.5. We will revisit social media use from the lens of SMEs in section 4.6, however.

[10] We use the term 'transactional platform' to refer to the platforms whose primary purpose is to facilitate the exchange of goods and services. We distinguish these from Social media platforms (Instagram, Facebook/Meta, etc.) which can of course facilitate the exchange of goods and services but whose primary aim is to increase visibility of goods and services (advertising) through attractive content and the attraction of attention.

[11] Examples of platforms active in each of 6 countries at the time of survey fieldwork were given to respondents for both rounds of the survey. This includes locally owned and global/regional platforms active in the country.

Figure 3. Internet and Social media use (percentage of age 15-65 population, 2021)



4.1. Use of platforms by individuals - high level trends

In 2017/2018, the use of transactional platforms varied amongst the six countries studied. Sri Lanka had the highest proportion of the population using transactional platforms (12% of the population; 1.7 million individuals) (Figure 4; Figure 5). India followed, with 7% of the population having used platforms by this time. Although this is a smaller proportion of the population compared to Sri Lanka, the number translates to 63 million users given India's large population size of 1.3 billion. Platform use was lowest in Nepal, with a mere 1% of the population having used platforms at the time of survey administration. The proportion of population using platforms were mostly in line with relative levels of GDP per capita (PPP, constant international dollars)12 in 2017/2018, where countries with higher the GDP per capita had higher level of platform use. There was one exception, however. Although Cambodia's GDP per capita ($ 4,159) was below that of Bangladesh ($ 5,198) at the time of survey, a larger proportion of its population in Cambodia had used platforms.

In Sri Lanka, where platform use was most common, 6% of the population had used transport platforms by this time. This is unsurprising given that ride hailing platforms such as PickMe and Uber had been active in the country since 2015. Use levels for goods/product platforms were similar to that of transport platforms. These two platform types continued to be the most popular in 2021, with 10% of the population using both types of platforms. Goods/products platforms were the most popular in India in both 2017 and 2021. Its popularity relative to other platforms is unsurprising given the seeming ubiquity of platforms such as Flipkart and Myntra. However, it is worth noting that even in 2021, only 7% of the population had used such platforms. But overall, the growth of platform in general had close-to-doubled between 2017/18 and 2021 in India.

Notably, in 2017, goods/products platforms had only been used by 0.2% of the population in Pakistan (vs 4% using transport platforms). However, this number is likely to have increased subsequently with the growth of platforms such as Daraz [13], OLX[14], Shophive, Pakwheels and Zameen[15] and the strategic focus provided by the government through its e-Commerce Policy[16]. Also

[12] https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD?end=2018&locations=LK-IN-BD-PK-NP-KH&start=2017
[13] https://www.reuters.com/business/retail-consumer/pakistan-e-commerce-platform-daraz-aims-beef-up-amazon-eyes-market-2021-11-25/
[14] https://aimgroup.com/2021/03/25/olx-pakistan-expands-into-e-commerce/
[15] https://www.trade.gov/country-commercial-guides/pakistan-ecommerce
[16] https://www.commerce.gov.pk/wp-content/uploads/2019/11/e-Commerce_Policy_of_Pakistan_Web.pdf

worth highlighting is that hired help platforms were as popular in Cambodia as transport platforms in 2017.

Figure 4. Use of the platforms for buying or selling goods or services (percentage of age 15-65 population)

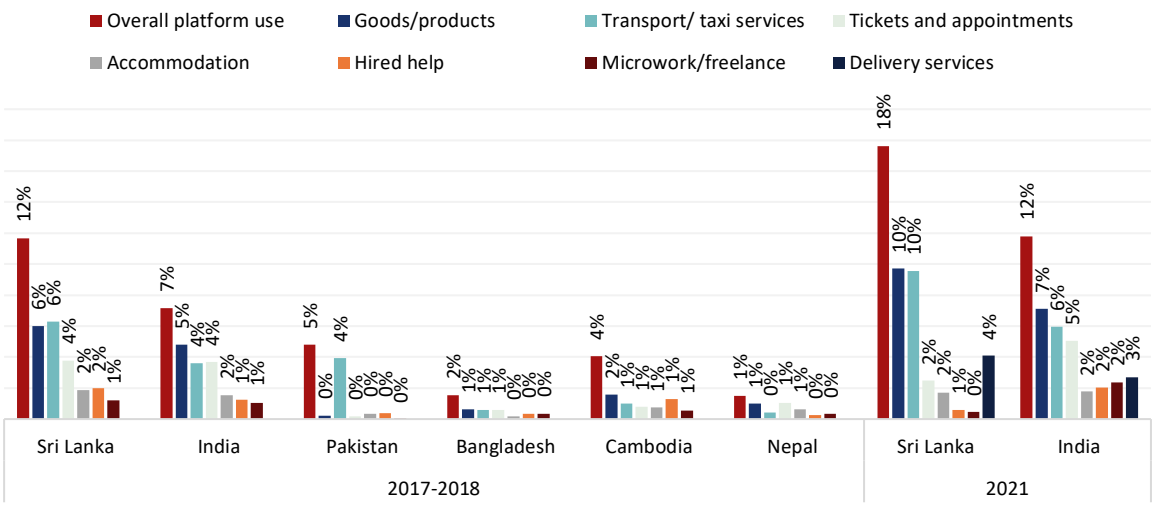
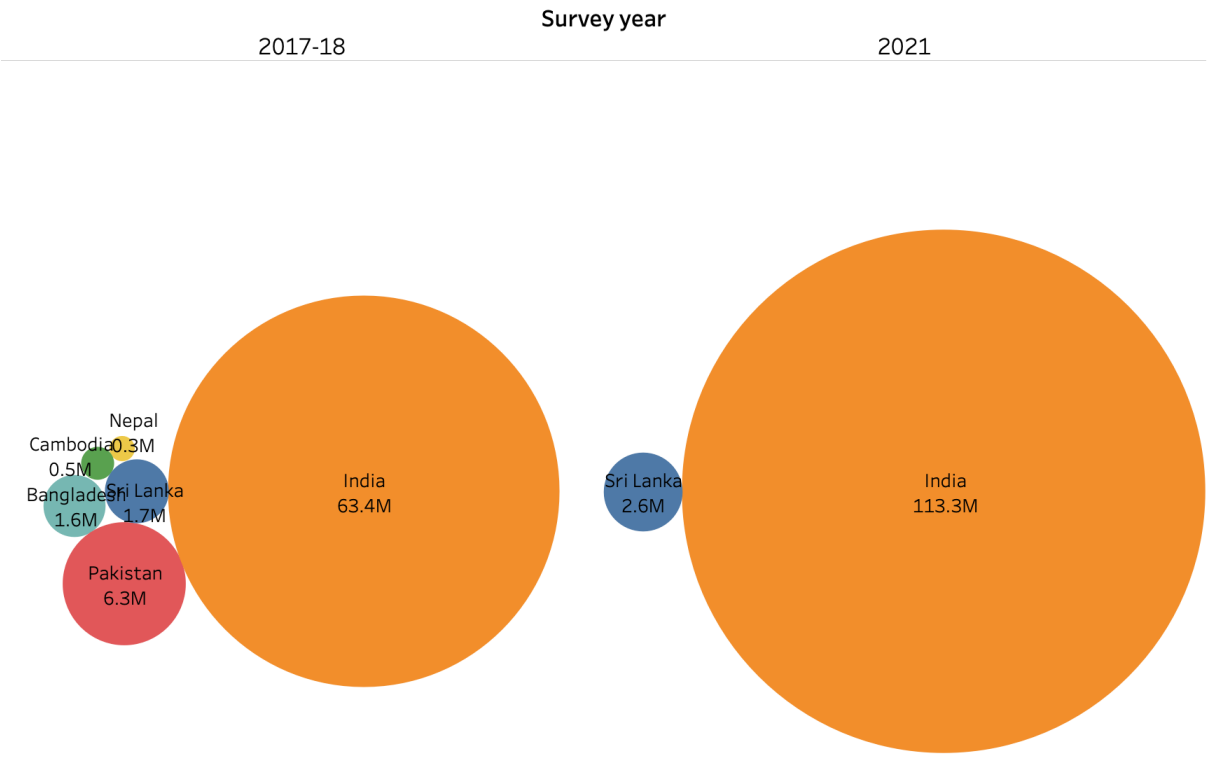


Figure 5. Overall market size for platform use for buying or selling, measured by number of buyers and sellers (age 15-65 population)



Above analysis considers both those who have used a platform buying a good or service as well as those who have used platform to sell a good or service as 'users'. However, we know that buying and selling have different impacts on people. Buying via platforms is about reduced transaction costs and is likely to have a larger use base who experience the efficiency of buying online. Selling on the other hand is about entrepreneurial people, who can grow from micro entrepreneurs/enterprises into small, medium, or large businesses. It is also about possibly participating in global value chains and capturing a large portion of the value chain. As such encouraging both is important to reach slightly different outcomes. We look at these two groups separately in Annex 2 and Annex 3 of this report. We also understand that people's awareness of the availability of, and/or possibility of using, platforms may differ between countries and time periods. This is examined in Annex 1.

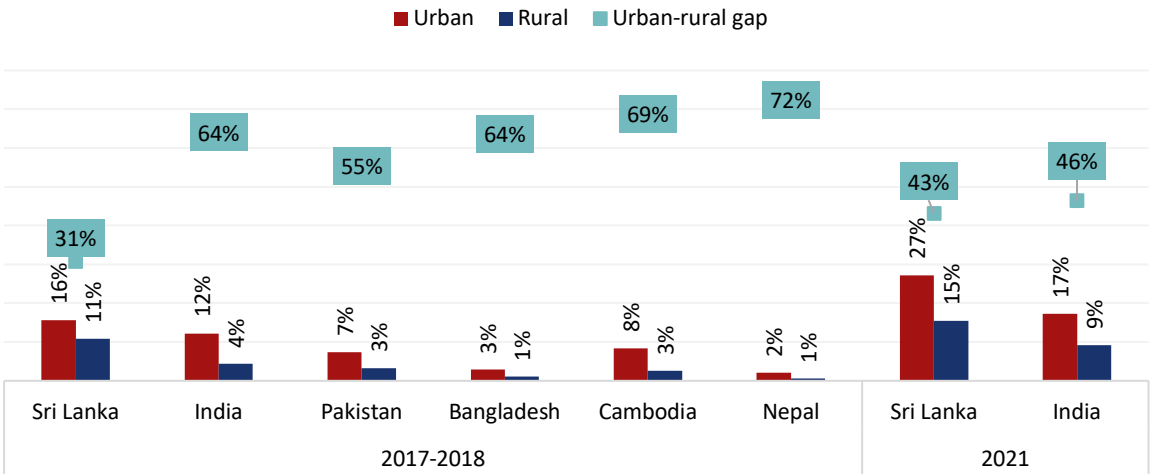
4.2. Facilitators of platform use

Many factors will drive individuals' choice to use (or not use) digital platforms. We consider demographic (e.g.: age, gender, socio-economic category, urban/rural dwelling) factors, as well as other digital enablers (e.g.: device ownership, skills) and access to finance (e.g.: bank account ownership, use of cashless payment methods).

4.2.1. Demography

Both Sri Lanka and India are rural dominated countries per the 2011 population census which showed 18% and 31% of the population living in urban areas in each country. Figure 6 shows that there is an urban rural gap in platform use in Sri Lanka and India stands at 43% and 46% respectively. The gaps haven't changed since 2017-18 as seen in the same figure.

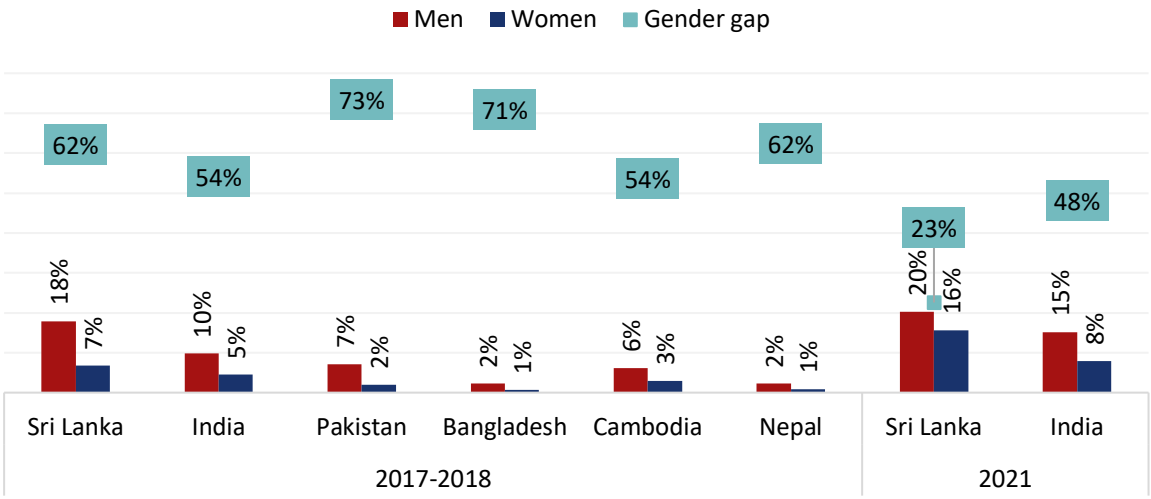
Figure 6. Use of platforms by urbanity (percentage of age 15-65 population)



A higher gender gap is observable when the data analyzed by gender. As per Figure 7, a high gender gap was observable with platform use in 2017-18 for all the countries. In all the countries studied, the gender gap in platform use was greater than above 50%. In 2021, the gender gap in platform

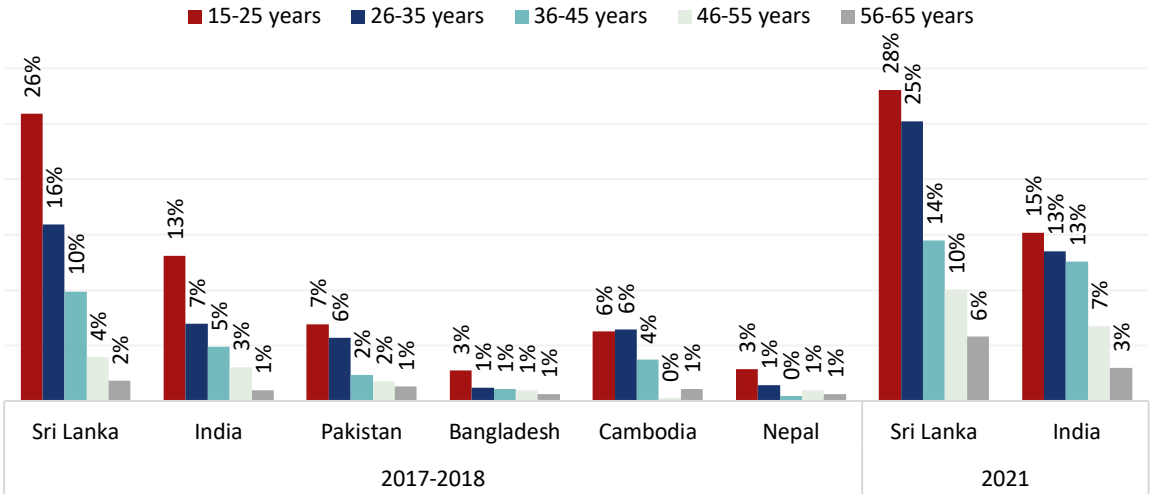
awareness in India remained at a level as high as 48%. Contrastingly, Sri Lanka has drastically reduced the gender gap in platform use.

Figure 7. Use of platforms by gender (percentage of age 15-65 population)



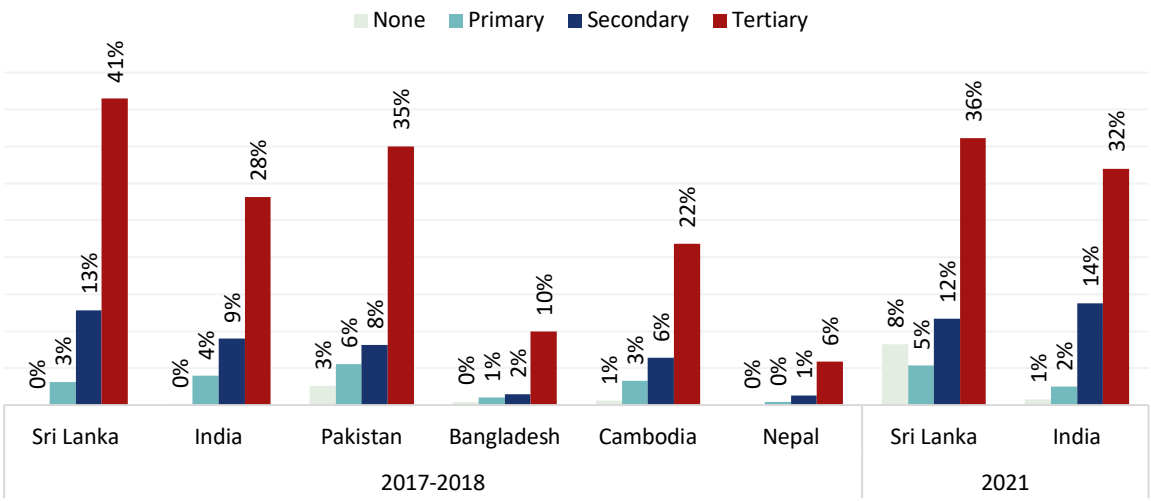
As per Figure 8, the younger population showed a higher platform use across the six countries studied in 2017-18. The same pattern is evident in 2021 for both Sri Lanka and India. The older population lagged to grasp the opportunities platforms brought about to the Asian region countries.

Figure 8. Use of platforms by age (percentage of age 15-65 population)



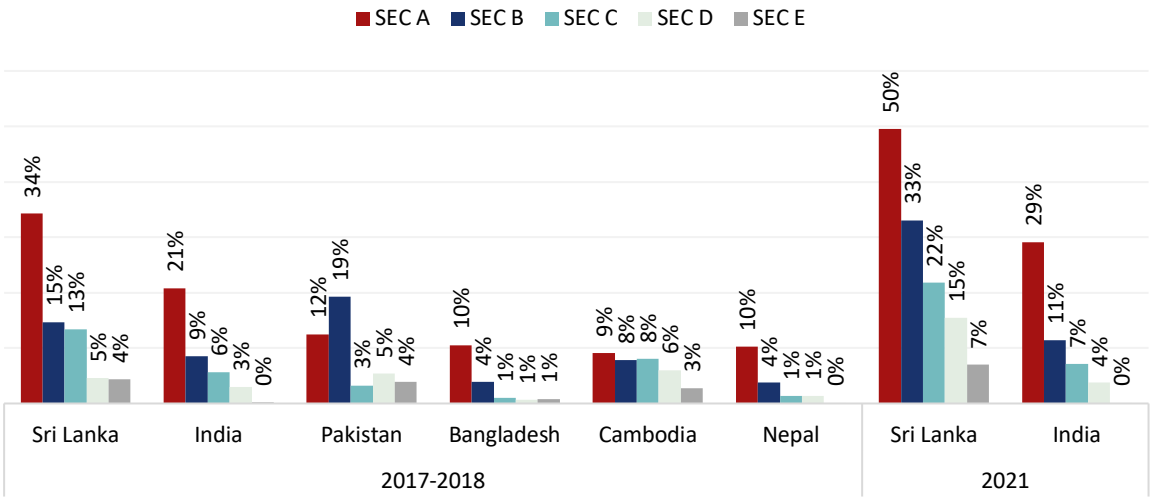
Those who had a higher education level indicate a higher platform use in both 2017-18 and 2021 (Figure 9). Interestingly, the platform use has remained at a similar level for the population with less than tertiary education in Sri Lanka. In other words, some less educated people have also become platform users in 2021.

Figure 9. Use of platforms by the level of education (percentage of age 15-65 population)



As Figure 10 shows, the platform use levels can be seen decreasing as we move to lower SEC classifications. The pattern has remained constant for 2017-18 and in 2021 for both Sri Lanka and India.

Figure 10. Use of platforms by socio economic classification (percentage of age 15-65 population)



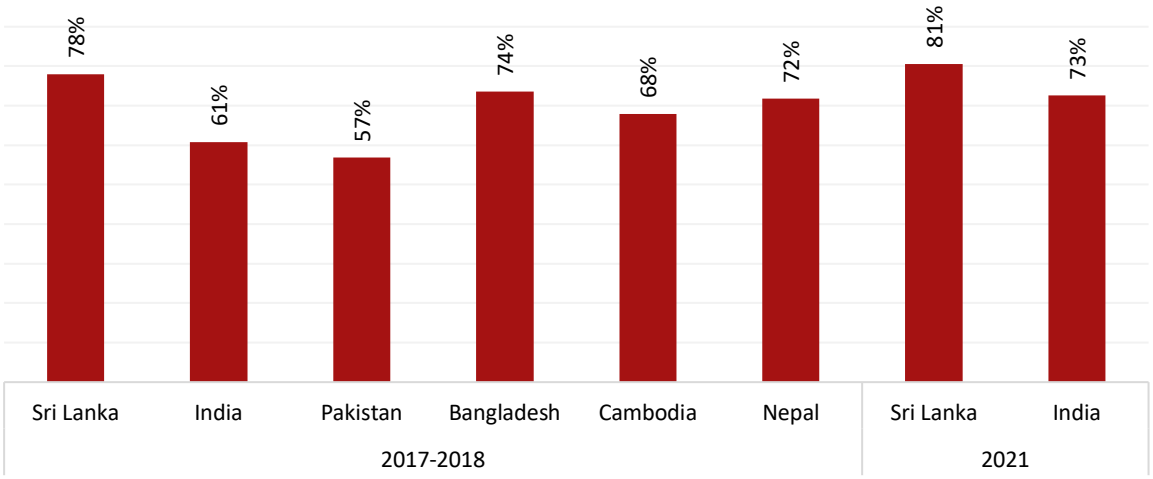
4.2.2. Digital access and use

Access to devices (such as internet capable smartphones or computers) allow people to use the internet and therefore platforms. It is thus a necessary to understand platform use in the context of these digital facilitators.

Mobile phones are the most common methods used to access the internet in the region. Figure 11 shows that the mobile ownership among the population aged 15-65 was ranging from 57% (Pakistan) to 78% (Sri Lanka) in the six countries in 2017/2018. Further, by 2021, mobile ownership had increased in both Sri Lanka and India. The rate of increase in the two countries differed, however; the increase in Sri Lanka was significantly lower than India (3 percentage points in Sri Lanka vs 12 percentage points in India). The difference in growth could be attributed to mobile

ownership being 17 percentage points greater in Sri Lanka 4 years prior– so India has been playing catch up over the years in this regard.

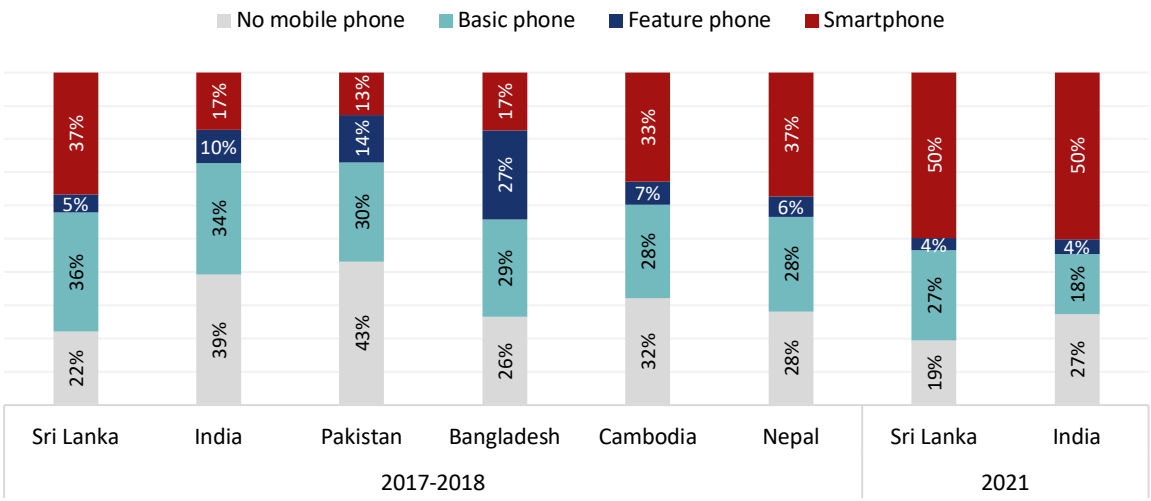
Figure 11. Mobile phone ownership (percentage of age 15-65 population)



Platform related work requires these devices to be internet capable. In 2017/18, the mobile phone market was dominated by basic handsets with no or limited internet. Smartphone ownership was greater than basic phone ownership in Cambodia, Nepal, and Sri Lanka. Noteworthy is that Cambodia and Nepal, the two poorest counties in the countries studied (GDP per capita of 1512.13 USD and 1178.53 USD respectively), had similar level of smartphone ownership to Sri Lanka, the richest country studied in the region (GDP per capita of 4059.21 USD). Smartphone ownership in Sri Lanka was over 2x that of India in 2017/2018. While smartphone ownership increased in both India and Sri Lanka, but this growth was most notable in India, where smartphone ownership increased nearly 3x. In 2021, 50% of the population aged 15-65 owned smartphones in both countries[17] (Figure 12).

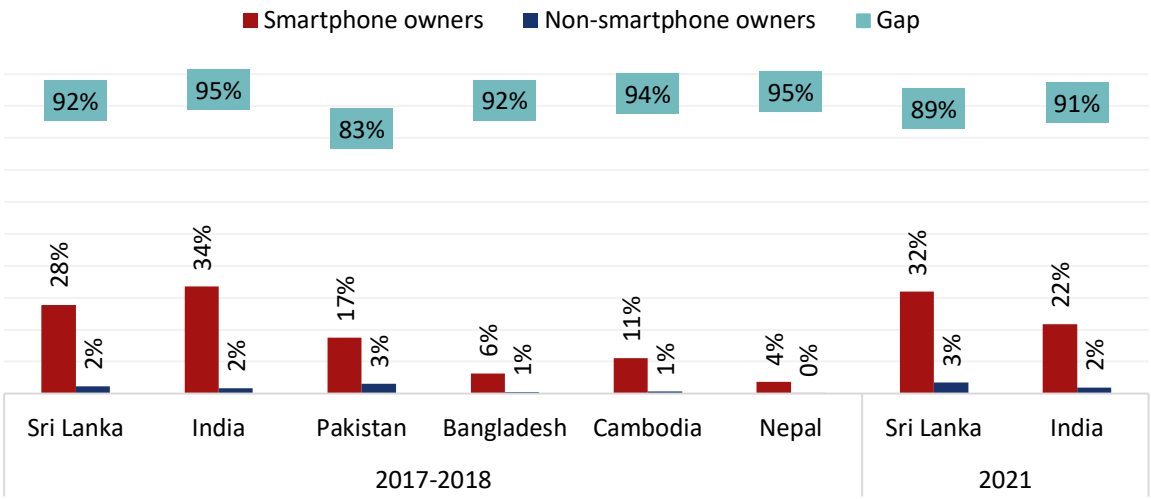
[17] There were considerable amount of people owning more than one mobile device even multiple device types. We considered the most advanced device as the type of device owned whenever the respondents had multiple devices. E.g., If a respondent had a feature phone and a smartphone, that respondent considered as a smartphone owner.

Figure 12. Type of mobile phone owned (percentage of age 15-65 population)



As per Figure 13, the platform use was high among the smartphone owners across the countries. The level of platform use remained similar among the basic and feature phone owners across the countries.

Figure 13. Use of platforms by smartphone ownership (percentage of age 15-65 population)



Access to computers too can facilitate the use of platforms. It would be particularly useful for microworkers/online freelancers using platforms such as Upwork – i.e. sellers on platforms. However, computer ownership (desktop or laptop) in households was low in all 6 countries, with only 2% of households owning computers in Pakistan in 2017. In 2021, only 10% of households in Sri Lanka, and 5% of households in India owned computers (Figure 13). Figure 15 indicates that computer owners were 74% or more likely to use platforms than non-owners across countries and time periods.

Figure 14. Computer ownership (Desktop or laptop ownership) (percentage of age 15-65 population)

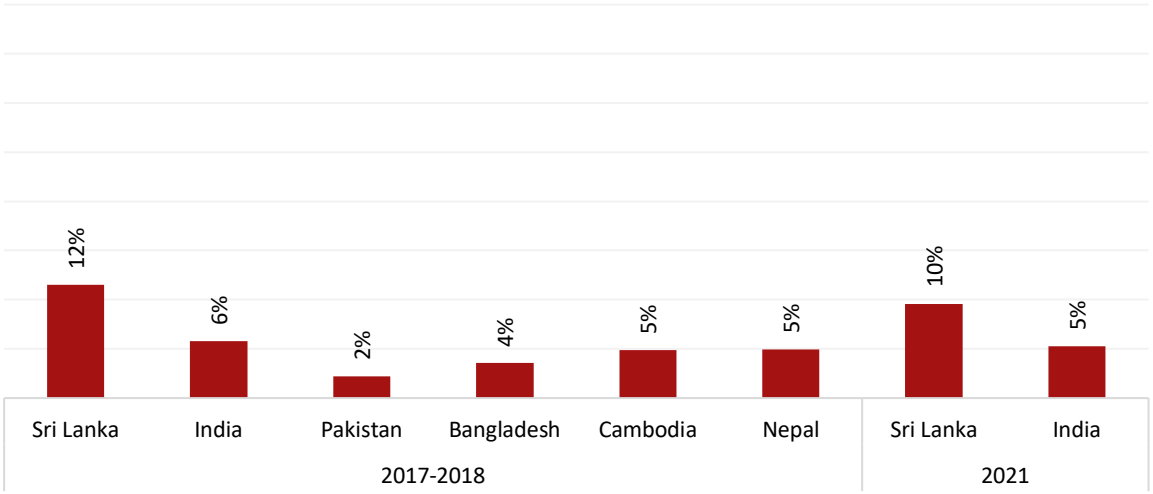
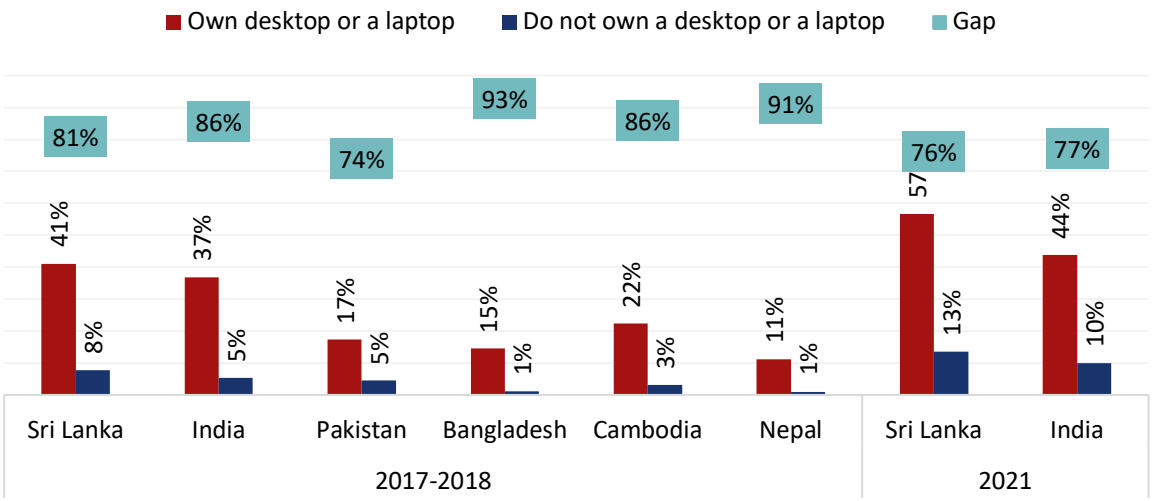


Figure 15. Use of platforms by computer ownership (percentage of age 15-65 population)



Digital skills too are a necessary precondition to facilitate internet and platform use. Digital skills had been low in both Sri Lanka and Nepal in 2018. It has improved only marginally in Sri Lanka over 3 years. In 2021, only a third of the population was able to search for content online, and post information online. Just 11% were able to make a payment or complete a transaction online; meanwhile this was ~3x greater in India (Figure 16). A large gap in platform use was seen amongst those with and without basic digital skills. In India in 2021, only 1% of the population without basic digital skills had ever used platforms unlike the 22% of those with such skills (Figure 17).

Figure 16. Digital skills (age 15-65 population)

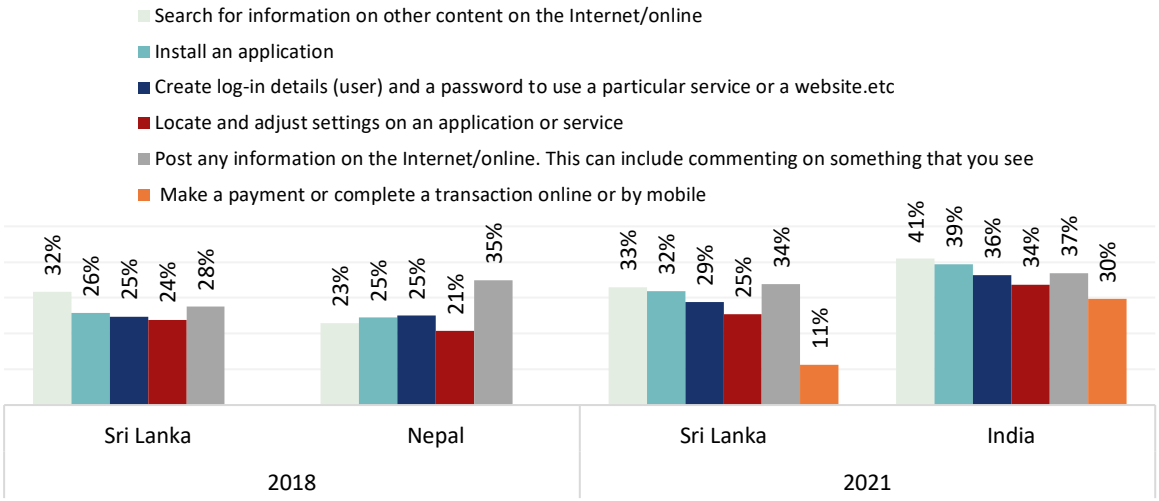
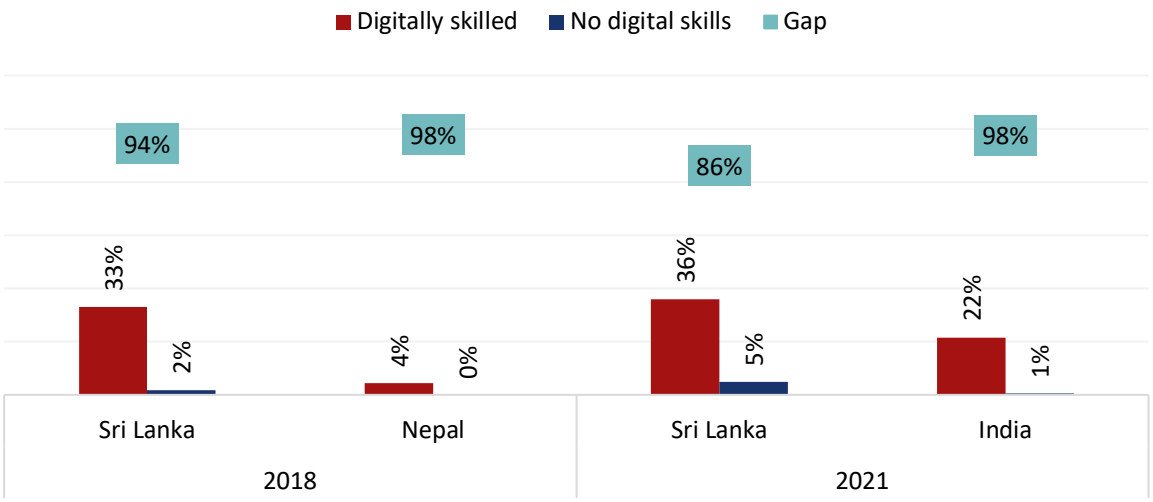


Figure 17. Use of platforms by digital skills (percentage of age 15-65 population)



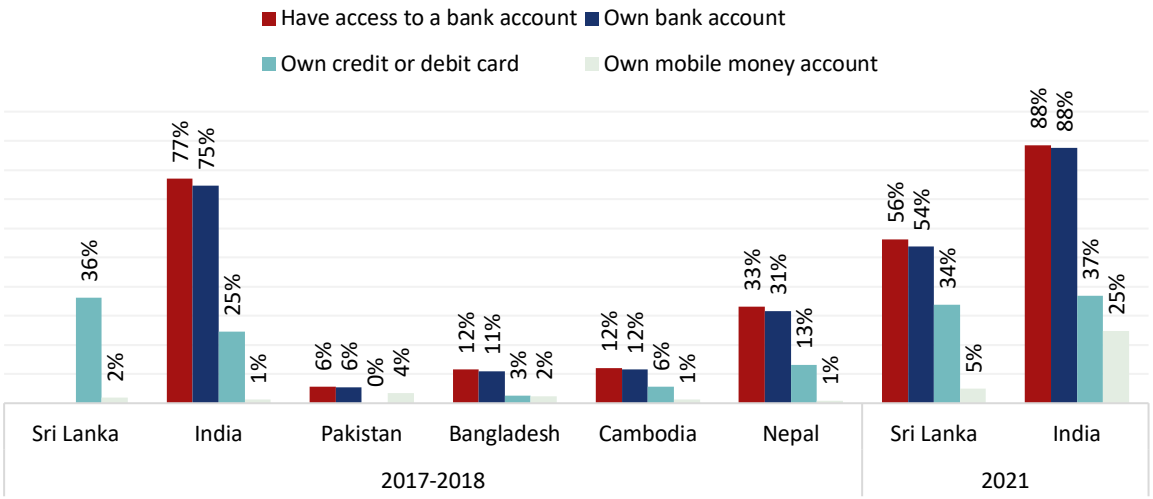
4.2.3.Access to financial tools

Access to financial tools is also a critical factor for platform use. We measure financial inclusion by studying access to different financial products and instruments including bank accounts, credit/debit cards, and mobile money. This is an important complement to the use of digital platforms, as it can enable access to finance and facilitate payments. Among sellers it could indicate ability to receive payments from buyers or ability to obtain lines of credit or loans for investing in the business. Among buyers, it could indicate ability to make payments for goods and services bought via platforms using bank transfers, credit cards and mobile wallets. Financial inclusion is a term that is used loosely but at its best includes the financial products and knowledge that enable people to make decisions (such as investments) that make their lives better. But at the more basic end, access to a bank account or mobile wallet are entry points to financial inclusion.

By this latter measure, both India and Sri Lanka had relatively high levels of basic financial inclusion In 2017/2018, debit and credit card ownership (which is driven by the access to bank accounts) was higher in Sri Lanka and India than the countries studied. By 2021, 88% of the population aged 15-65 in India and 56% in Sri Lanka owned a bank account[18] . Our 2021 survey shows that financial inclusion in India has further improved since 2017 – the increase in mobile money use from 1% to 25% over the 5 years is good indicator of this (Figure 18). Comparative data for Sri Lanka for 2018 was not available through our survey, so it was not possible to track growth via our survey. However, data from the Central Bank of Sri Lanka validates growth, given that mobile banking transaction volumes in Sri Lanka grew from 8 million transactions in 2018 to 28 million transactions in 2021 – a 240% increase (CBSL Payment Bulletins, 2022)[19].

These findings complement the conclusions drawn in World Bank (2022)[20] which shows that India had the most mature digital financial system in South Asia. India was in the third of the four stages in a Pazarbasioglu et al (2020)[21] classification, while Sri Lanka and Bangladesh were closely behind. Pakistan and Nepal were at the first stage, along with others such as Afghanistan and Maldives, indicating that transactions are still predominantly cash based.

Figure 18. Bank account access and ownership[22], credit or debit card and mobile money account ownership (percentage of age 15-65 population)



Our findings indicate that platform use is greater amongst bank account owner (vs those who don't own bank accounts). In 2017/2018, 19% of bank account owners in Pakistan used platforms, while this was only true of 4% of those who didn't own bank accounts. (Figure 19)

Figure 19. Use of platforms by bank account ownership (percentage of age 15-65 population)

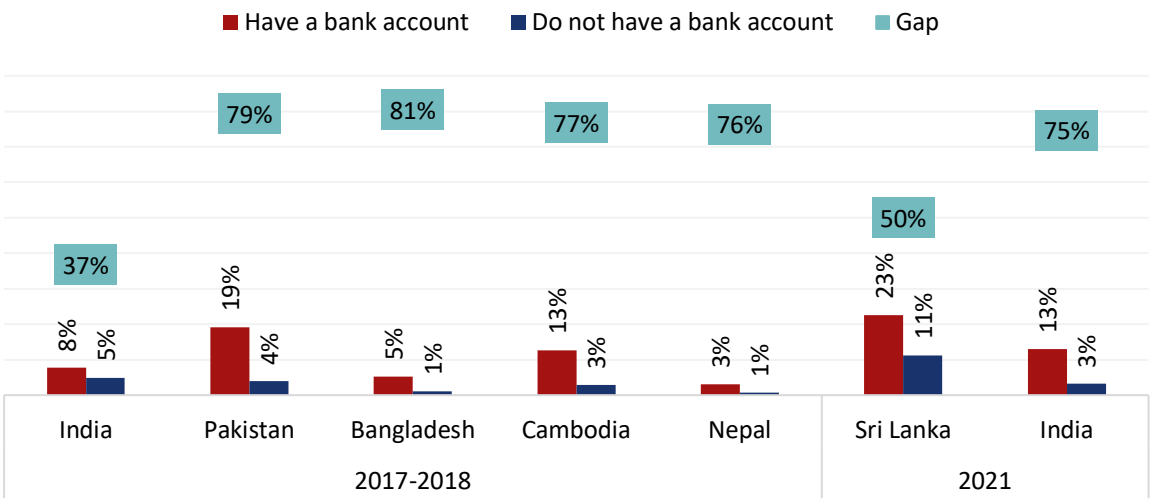
[18] In Sri Lanka, we only examined the use of formal banks. Samurdhi bank account owners were not recognized as bank account owners since this type of bank account is restrictive in how the consumers can operate it and is a mandatory measure to receive social welfare payments.

[19] https://www.cbsl.gov.lk/sites/default/files/Payments_Bulletin_1Q2022_e.pdf , https://www.cbsl.gov.lk/sites/default/files/Payments_Bulletin_1Q2019.pdf

[20] https://openknowledge.worldbank.org/bitstream/handle/10986/37230/P1723000a851780140ae1102cc761255f79.pdf?sequence=4&isAllowed=y

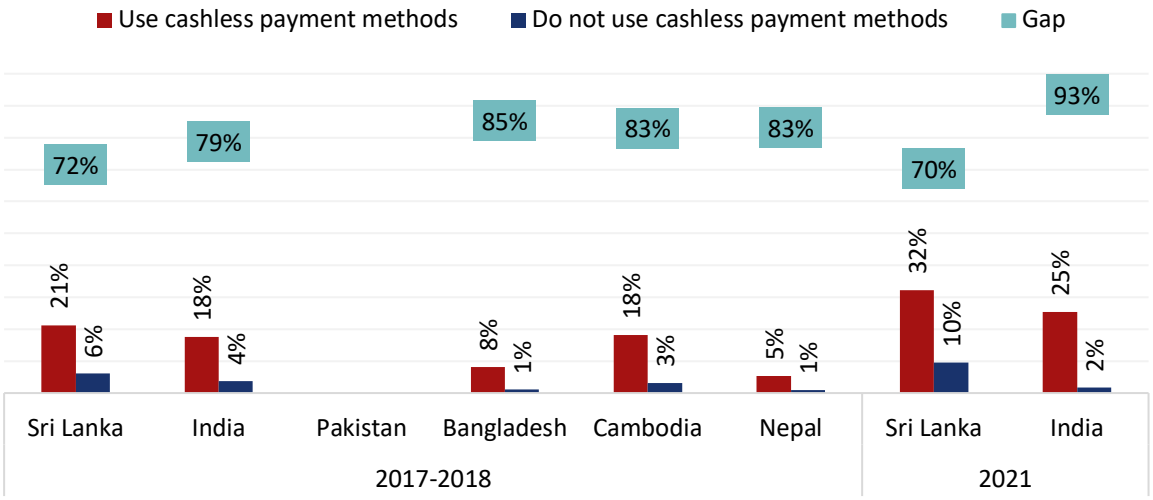
[21] https://pubdocs.worldbank.org/en/230281588169110691/Digital-Financial-Services.pdf

[22] Comparable data is not available for Sri Lanka in 2018



Cashless payment methods (including credit and debit cards, and mobile money) allow for a convenient payment mechanism when using platforms. As Figure 20 demonstrates, those who have access to cashless payment methods were more likely to use platforms in 2017-18. The gap has slightly decreased in 2021 for both Sri Lanka and India but remained at a high level.

Figure 20. Use of platforms by cashless payment methods (credit or debit card[23] and mobile money) ownership (percentage of age 15-65 population)



[23] Credit card or debit card ownership data was not available for Pakistan

Box: Prioritizing among many factors: binary logistic model

In the three preceding sections, we looked at the impact of various indicators (demographic, as well as those associated with digital access and use and access to finance) in isolation. However, these factors are interdependent and can impact each other through multiple pathways. We use a binary logistic regression model to disaggregate these impacts and help us move a step closer to making causal inferences[24]. Data from the two countries have been combined, but country dummies have been included to disaggregate country level effects. The model fit is good, with the model correctly classifying 88% of the cases.

Table 6. Binary logistic regression model for platform use for buying and selling

Model fit estimates			
Nagelkerke R Square			0.390
Percentage of cases correctly classified by the model			88.0
Variable	**Sign of the relationship**	**Odds**	**Significance**
Location: Urban (vs Rural)	(+)	1.445	***
Gender: Female (vs Male)	(-)	0.866	
Age (15-25 years is the reference category)			**
26-35 years	(-)	0.895	
36-45 years	(+)	1.077	
46-55 years	(-)	0.754	
56-65 years	(-)	0.603	**
Level of education (No education is the reference category)			***
Primary	(+)	1.338	
Secondary	(+)	1.910	**
Tertiary	(+)	2.267	***
SEC (SEC E is the reference category)			***
SEC A	(+)	2.856	***
SEC B	(+)	1.608	***
SEC C	(+)	1.535	**
SEC D	(+)	1.376	
Employed	(+)	1.164	
Married	(-)	0.909	
Type of mobile phone device owned (no mobile phone owned is the reference category)			***
Basic or feature phone	(-)	0.712	
Smartphone	(+)	2.135	***

[24] Other factors such as levels of internet use, and awareness of the availability of platforms may also impact whether individuals use platforms. However, these impacts cannot be explored in our model due to the manner in which the questionnaire was designed.

Own personal desktop or laptop	(+)	2.309	***
Own a bank account	(-)	0.909	
Use cashless payment method (mobile money or credit/debit cards)	(+)	3.400	***
Digital skills[25]	(+)	4.908	***
India (compared to Sri Lanka)	(-)	0.299	***
Constant	(-)	0.010	***
(+) Indicates a positive relationship with the dependent variable (platform use). (-) Indicates a negative relationship with the dependent variable (platform use). ... Indicates the overall categorical variable is not significantly contributing to the model. * The variable is significantly contributing to the model at the .05 level. ** The variable is significantly contributing to the model at the .03 level. *** The variable is significantly contributing to the model at the .01 level.			

The model shows that, digital skills was the factor which has the highest impact on platform use. People with digital skills were five times more likely to use platforms when all the other factors remain constant. Using cashless payment methods such as debit or credit cards or mobile money was the second strongest positively related factor drive the platform use. Being belong to a richer family (SEC A) was the third strongest driver. Having tertiary education, owning a computer, and owning a smartphone increased the odds of using platforms by more than 2 times. Having secondary education and belong to a family from a higher socio-economic group are also positive factors which has some considerable positive impact of platform use. The oldest population group (age 55-65) group was the most negatively correlated group with platform use. People aged 55-65 were 40% less likely to use platforms compared to people from age 15-25 age group. Basic or feature phone users were 30% less likely to use platforms even compared to the non-mobile phone owner.

As seen in the descriptive statistics, the model confirms that living in a rural setting and being a woman, both reduce the odds of using a platform. However, there are some instances where the model, which controls for the impact of other confounding factors such as socio-economic status gives additional insights to those shown in the descriptive statistic. For example, it only shows a negative weak negative relationship between bank account ownership and platform use, indicating that bank account ownership alone may not be an enabler of platform use. We recognize that having a bank account maybe more important for sellers (to receive payments), but given the small percentage of sellers in the data set and in the population (see Annex 1 and 2), the effects of bank account ownership is minimized. Unlike in the case of bank account ownership, the use of cashless payment methods (such as debit and credit cards) does facilitate platform use, even when other factors are controlled for. The model indicates that having access to these cashless payment methods increase the odds of using platforms by 3.4 times.

We also use select interaction terms to compare the experiences of select subgroups (e.g.:

[25] Those who could do the at least one of the six activities mentioned below by themselves are considered as digitally skilled.
1. Search for information or other content online
2. Install an application on mobile phone
3. Create log-in details (user) and a password to use a particular service or a website online
4. Locate and adjust settings on an application or service on mobile phone
5. Post any information on the online
6. Make a payment or complete a transaction online or by phone

platform use amongst rural men vs rural women)[26]. Annex 4 shows the output of this model. This model shows that women are unambiguously less likely to use platforms compared to men (at the reference level) even when they have access to facilitating factors.

4.3. Facilitators of platform use for e-commerce services and transport and taxi services

It is important to note that the profile or the factors which drive the platform use changes based on which platforms is considered. We have taken the Sri Lanka and India data from 2021 survey to explain those differences. We have chosen Goods/product (e-commerce) and transport/ taxi platforms based on the sample sizes available for different types of platforms. A binary logistic regression is formed to understand the aforementioned differences. The output of this model is available in Table 7.

As per Table 7, it can be observed that education has stronger relationship with using e-commerce platforms compared to transport platforms. Tertiary educated people are more than three times more likely to use e-commerce platforms. The same population group is only 1.5 times more likely to use Transport or taxi platforms.

Digital skills are the factor which has the strongest positive relationship with use of both platforms. However, being digitally skilled increase the odds of using e-commerce platforms by 5.5 times while it increases the odds of using transport platforms by 3.6 times. This indicates the greater importance of digital skills for using e-commerce platforms.

The model further shows that owning a smartphone is more important for use of Transport or taxi services platforms compared e-commerce platforms.

When it comes to SEC, people coming from SEC A households are more likely to use both types of platforms compared to other SECs. However, the odds of using transport platforms by people coming from SEC A households are higher compared to odds of using e-commerce platforms.

There are some factors such as marital status and bank account ownership which show directional changes in the relationships. However, these are not strong relationships when all other variables are taken into consideration.

Other factors are showing similar relationship for the use of both e-commerce and transport or taxi services.

[26] We used 2021 survey data from India and Sri Lanka as inputs for this model. The decision to use only data from the 2021 was taken for two reasons. First, all the national surveys administered in 2017/2018 did not have data on important variables such as skills, while the surveys administered in 2021 did. Second, using only 2021 data gave a more up-to-date view of the impact of these factors. This tradeoff meant data from Bangladesh, Cambodia, Pakistan, and Nepal have been excluded. However, while data from these four countries were excluded in the model, we share descriptive statistics pertaining to these factors (e.g.: urban-rural gaps) for these countries based on the 2017-18 surveys. Furthermore, we recognize that COVID-19 impacted the use of platforms (as seen in Section 4.3) and may have shifted the impact and significance of the facilitators/influencing factors we identify based on our model that uses 2021 data.

Table 7. Binary logistic regression model for platform use for buying and selling via e-commerce and transport platforms

	Platform type	
	Goods/ product (e-commerce)	Transport or taxi
Nagelkerke R Square	0.323	0.288
Percentage of cases correctly classified by the model	92.3	93.2
Location: Urban (vs Rural)	(+) 1.549***	(+) 1.467***
Gender: Female (vs Male)	(-) 0.818*	(-) 0.788**
Age (15-25 years is the reference category)	***	*
26-35 years	(-) 0.851	(-) 0.695**
36-45 years	(-) 0.942	(-) 0.801
46-55 years	(-) 0.659*	(-) 0.595***
56-65 years	(-) 0.345***	(-) 0.67
Level of education (No education is the reference category)	**	...
Primary	(+) 2.486*	(-) 0.826
Secondary	(+) 2.536**	(+) 1.216
Tertiary	(+) 3.147***	(+) 1.467
SEC (SEC E is the reference category)	***	***
SEC A	(+) 2.367***	(+) 3.162***
SEC B	(+) 1.241	(+) 1.526
SEC C	(+) 1.23	(+) 1.274
SEC D	(+) 1.095	(+) 1.518
Employed	(+) 1.247**	(+) 1.182
Married	(-) 0.917	(+) 1.033
Type of mobile phone device owned (no mobile phone owned is the reference category)	***	***
Basic or feature phone	(-) 0.676	(-) 0.654
Smartphone	(+) 1.674**	(+) 2.208***
Own personal desktop or laptop	(+) 2.119***	(+) 1.78***
Own a bank account	(+) 1.119	(-) 0.899
Use cashless payment method (mobile money or credit/debit cards)	(+) 3.152***	(+) 2.808***
Digital skills	(+) 5.544***	(+) 3.629***
India	(-) 0.372***	(-) 0.311***

Constant	(-) 0.004***	(-) 0.01***
(+) Indicates a positive relationship with the dependent variable (platform awareness). (-) Indicates a negative relationship with the dependent variable (platform awareness). ... Indicates the overall categorical variable is not significantly contributing to the model. * The variable is significantly contributing to the model at the .05 level. ** The variable is significantly contributing to the model at the .03 level. *** The variable is significantly contributing to the model at the .01 level.		

The next few paragraphs will explain the use of goods/products (e-commerce) and transport or taxi platforms using descriptive statistics. Data from 2017-18 is also taken into consideration. However, data for Pakistan, Bangladesh, Cambodia, and Nepal are excluded from this analysis due to there being low bases.

Figure 21 and Figure 22 shows a similar level of urban rural divide in use of e-commerce and taxi platforms.

Figure 21. Use of goods/product (e-commerce) platforms by urbanity (percentage of age 15-65 population)

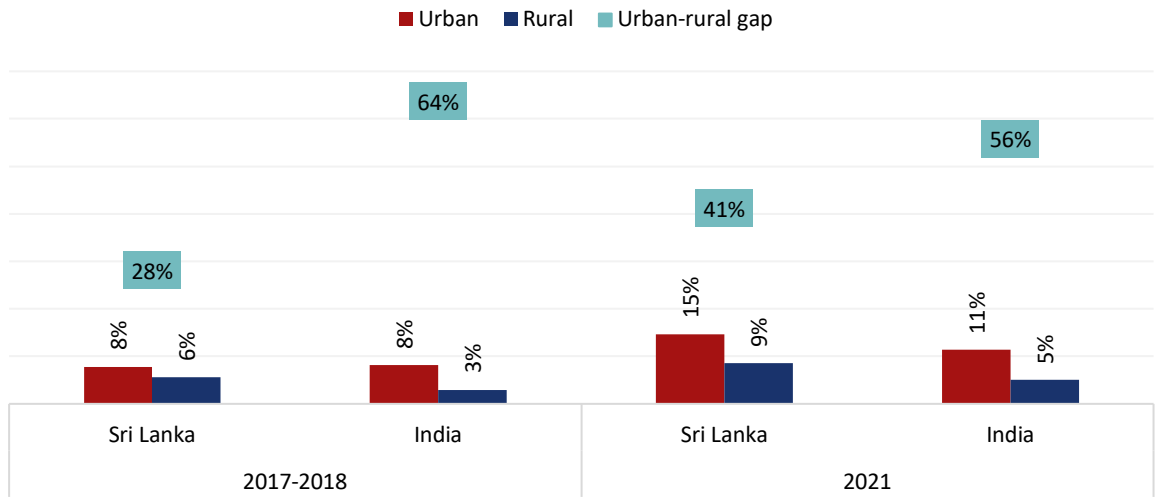
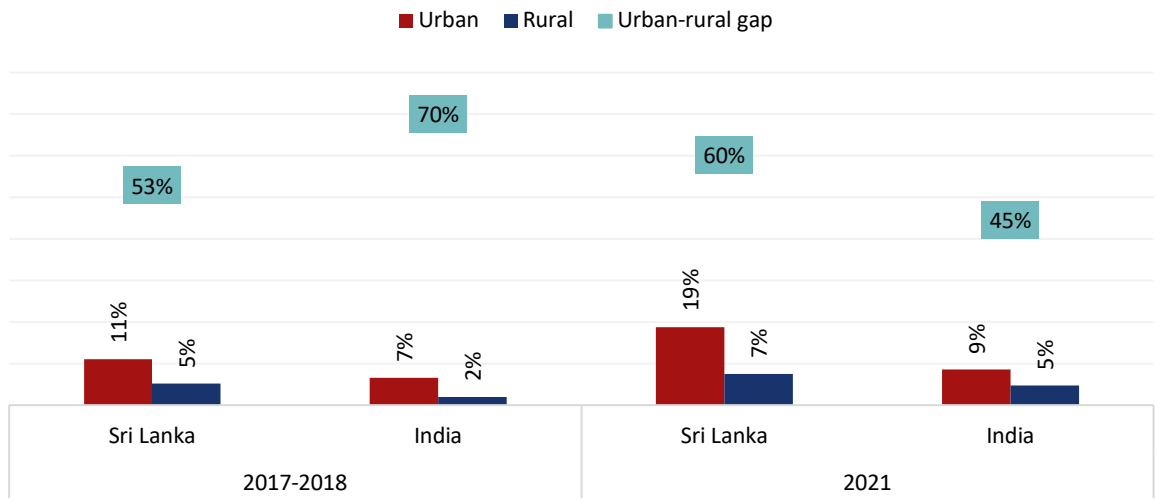


Figure 22. Use of transport or taxi platforms by urbanity (percentage of age 15-65 population)



Men were more likely to use both e-commerce and taxi platforms in 2017-18. The gender gap in platform use for both platforms has reduced for Sri Lanka in 2021, while the gender gap for India remained at a similar level (Figures 23 and 24).

Figure 23. Use of goods/product (e-commerce) platforms by gender (percentage of age 15-65 population)

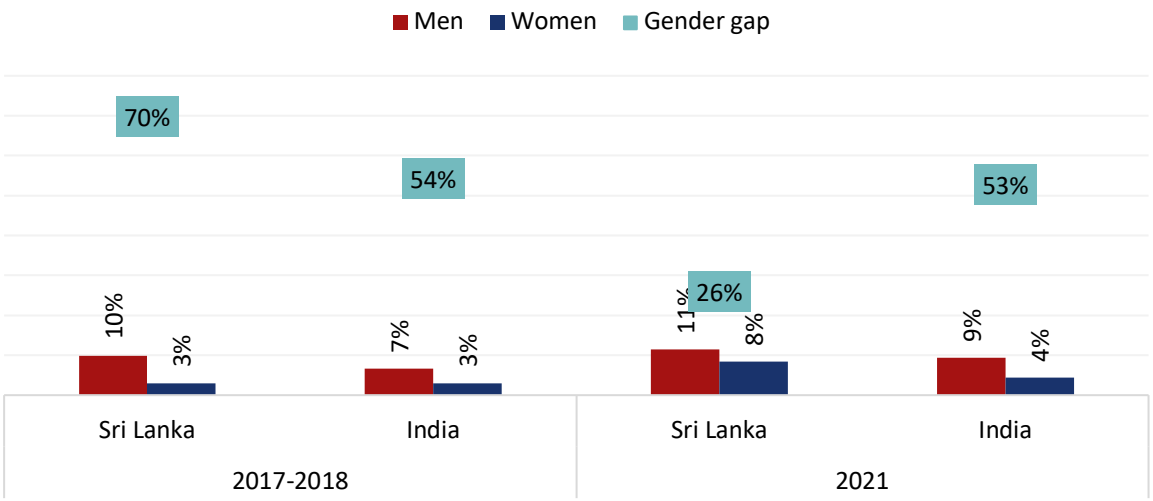


Figure 24. Use of transport or taxi platforms by gender (percentage of age 15-65 population)

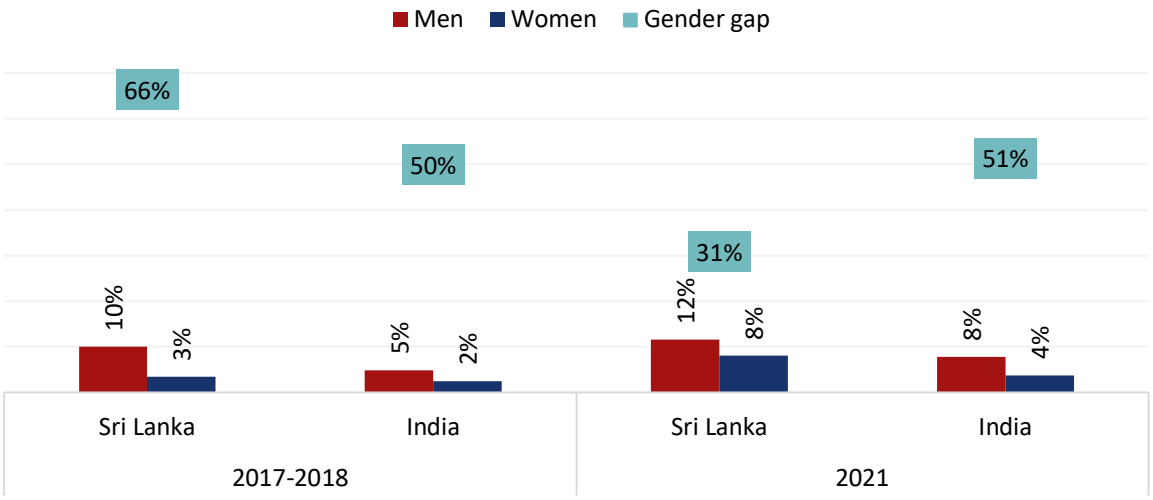


Figure 25 and 26 illustrates that age has a clear negative relationship with platform use for e-commerce and taxi services. Patterns remain similar for both types of platforms in both countries.

Figure 25. Use of goods/product (e-commerce) platforms by age (percentage of age 15-65 population)

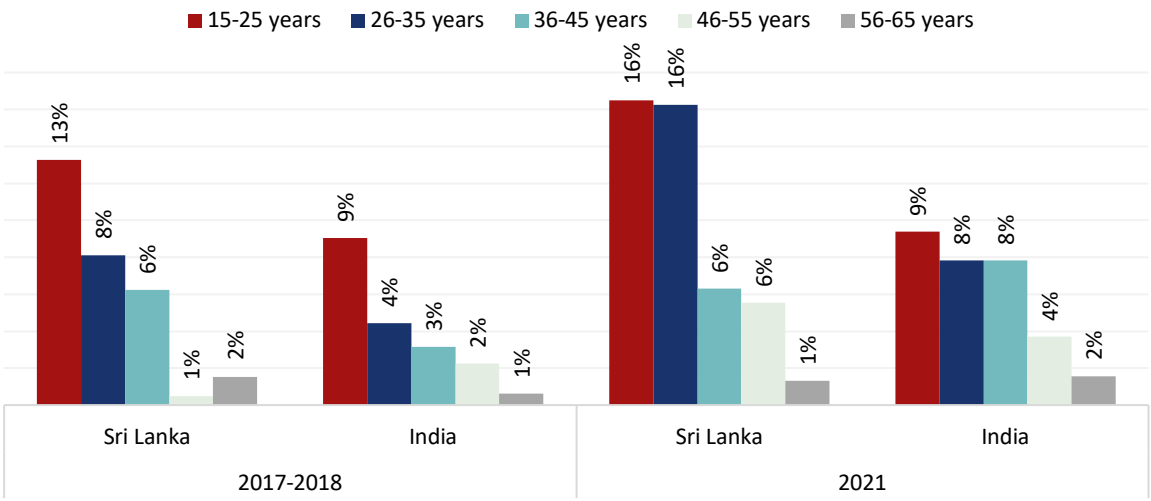
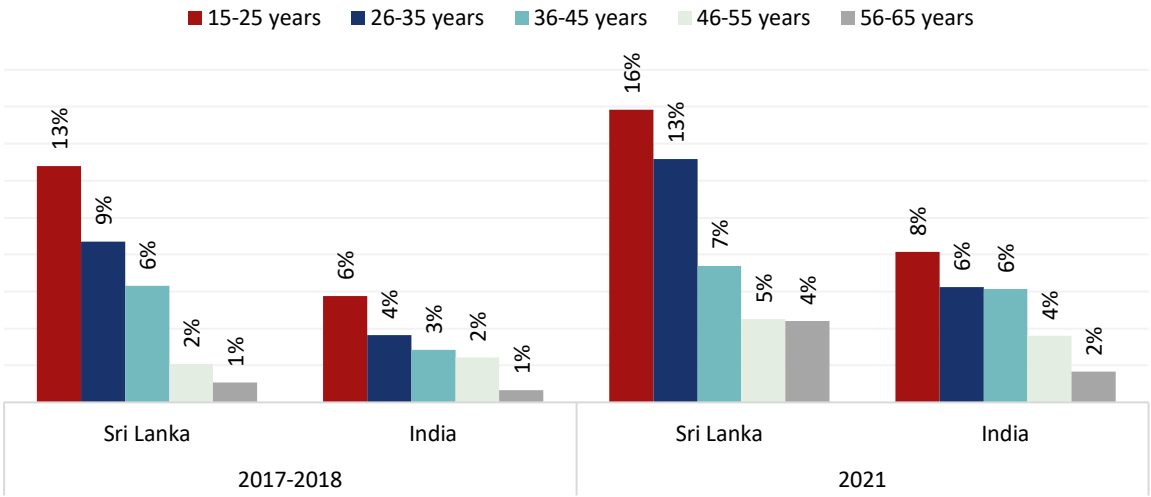


Figure 26. Use of transport or taxi platforms by age (percentage of age 15-65 population)



Figures 27 and 28 show that people with higher education are more likely to use both e-commerce and taxi platforms. A similar pattern exists for both types of platforms in both time periods taken into consideration.

Figure 27. Use of goods/product (e-commerce) platforms by level of education (percentage of age 15-65 population)

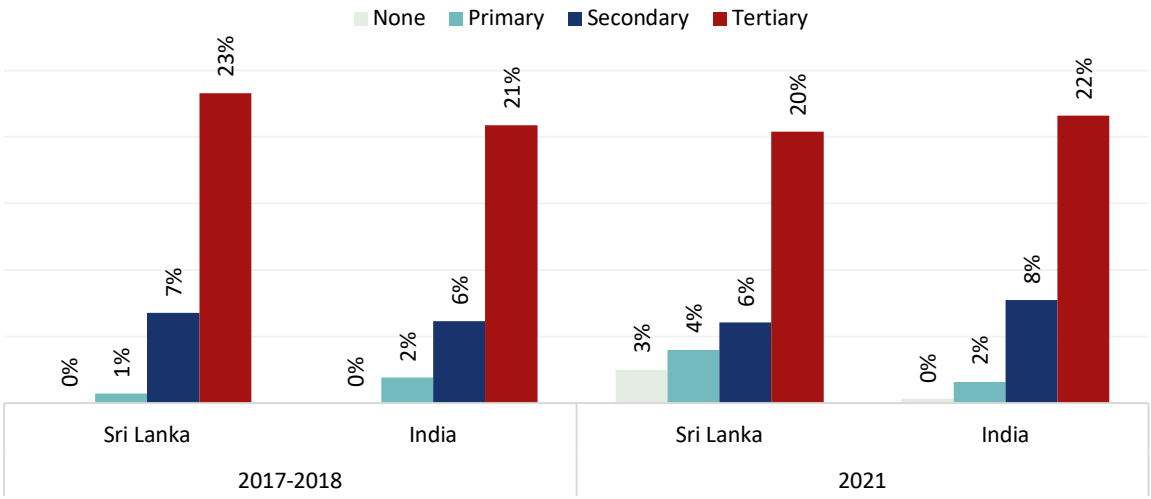
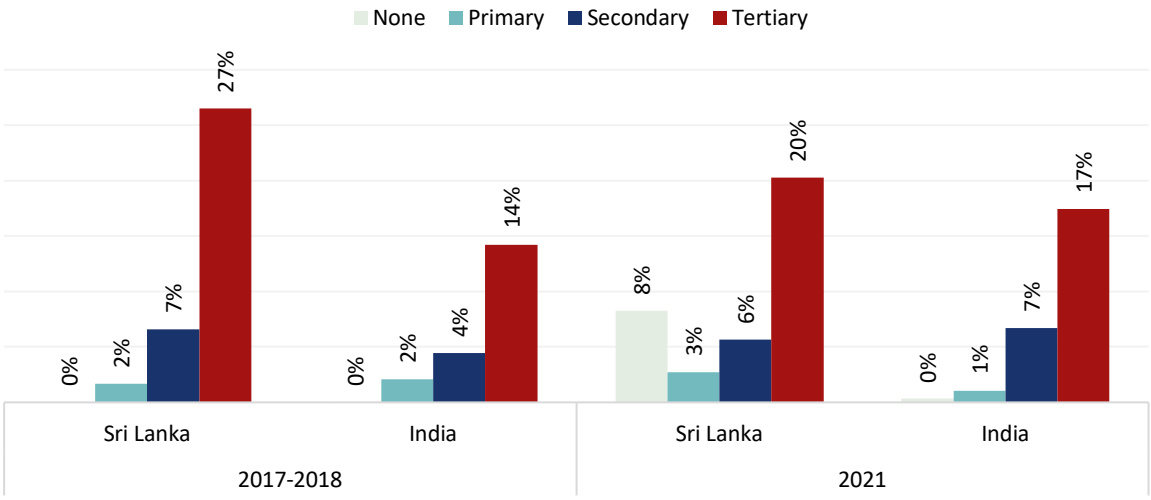


Figure 28. Use of transport or taxi platforms by level of education (percentage of age 15-65 population)



Those belonging to higher socio-economic classification groups were more likely to use both types of platforms (Figure 29 and 30).

Figure 29. Use of goods/product (e-commerce) platforms by socio economic classification (percentage of age 15-65 population)

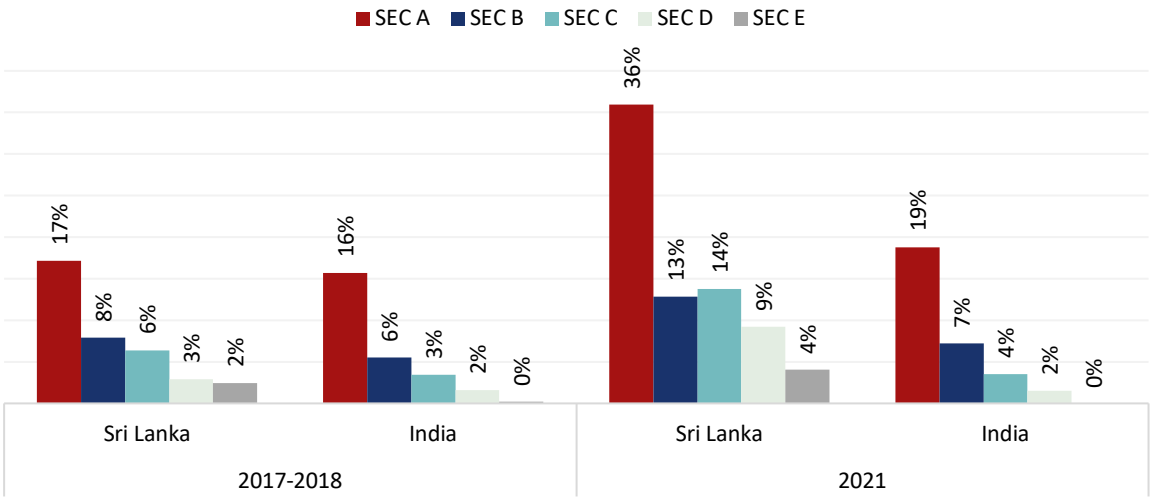
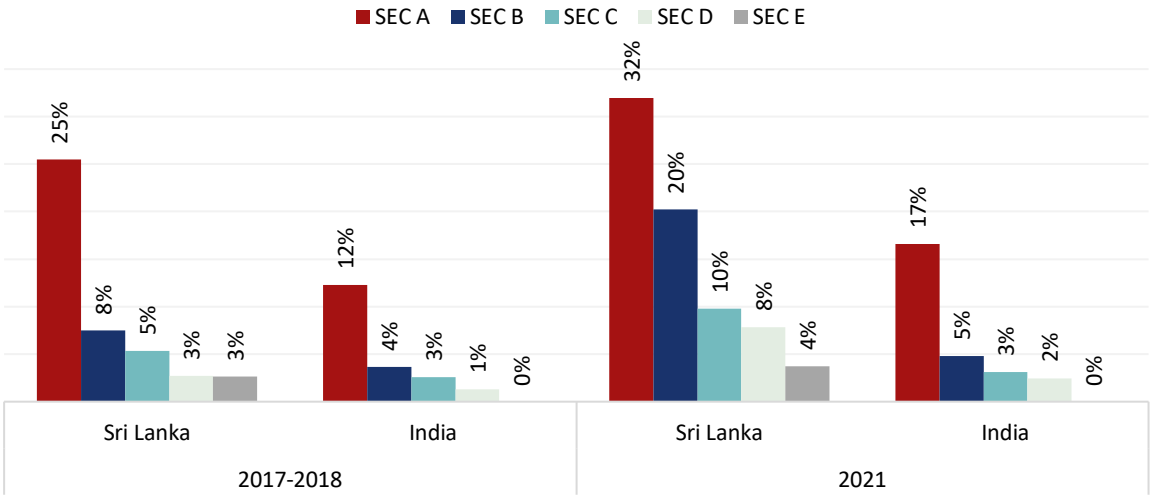


Figure 30. Use of transport or taxi platforms by socio economic classification (percentage of age 15-65 population)



Ownership of a smartphone had a strong positive relationship with both e-commerce and taxi platform usage (Figure 31 and 32).

Figure 31. Use of Goods Goods/product (e-commerce) platforms by smartphone ownership (percentage of age 15-65 population)

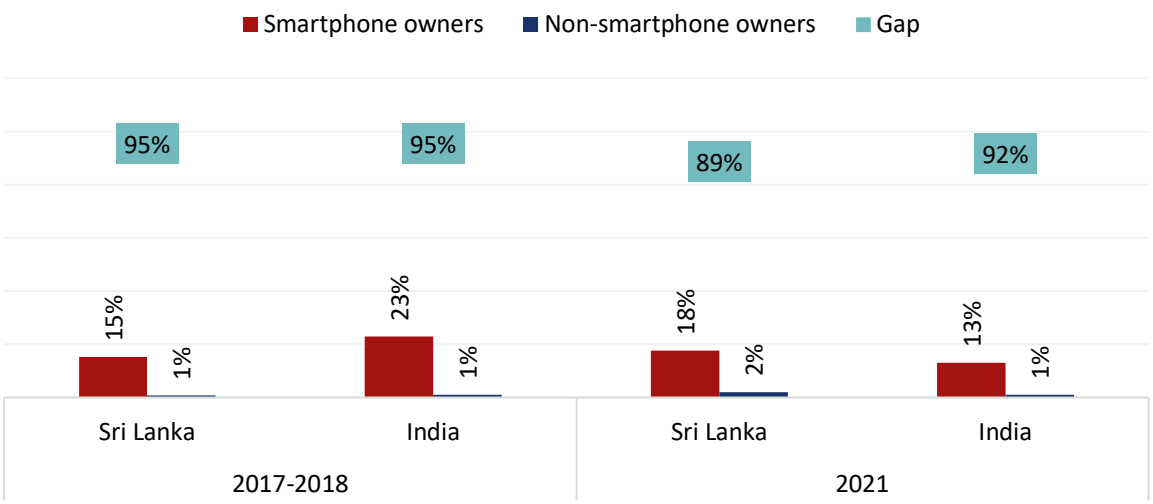
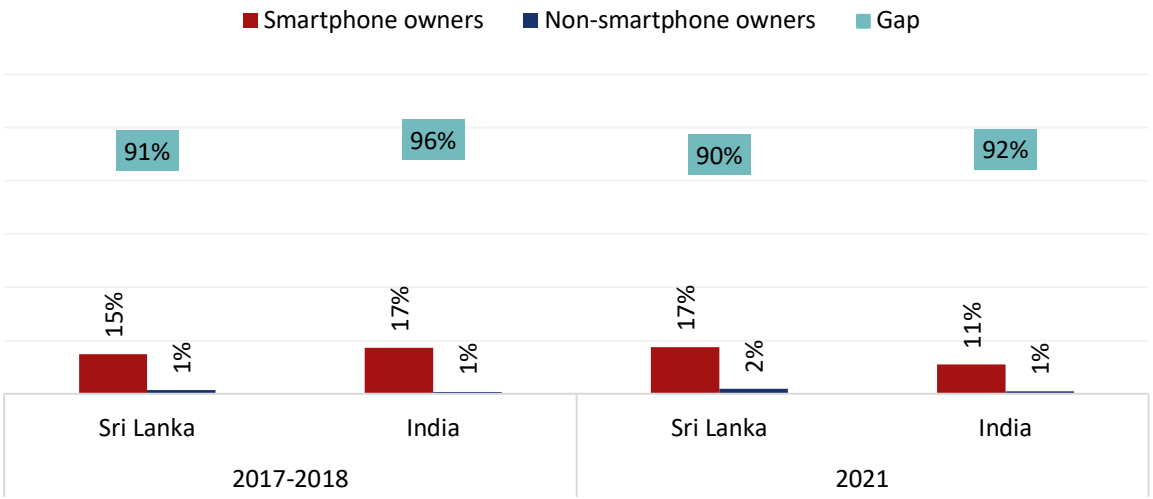


Figure 32. Use of transport or taxi platforms by smartphone ownership (percentage of age 15-65 population)



Digital skills have a strong positive relationship with both e-commerce and taxi platform usage (Figure 33 and 34).

Figure 33. Use of goods/product (e-commerce) platforms by digital skills (percentage of age 15-65 population)

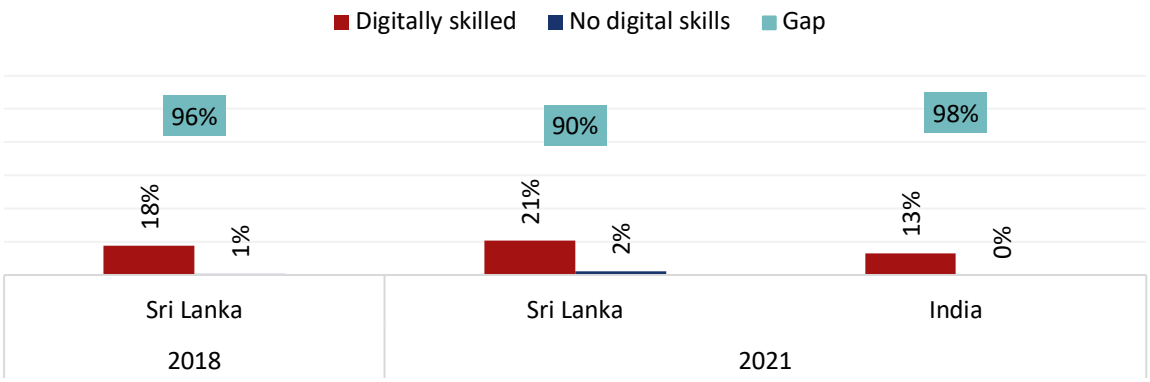
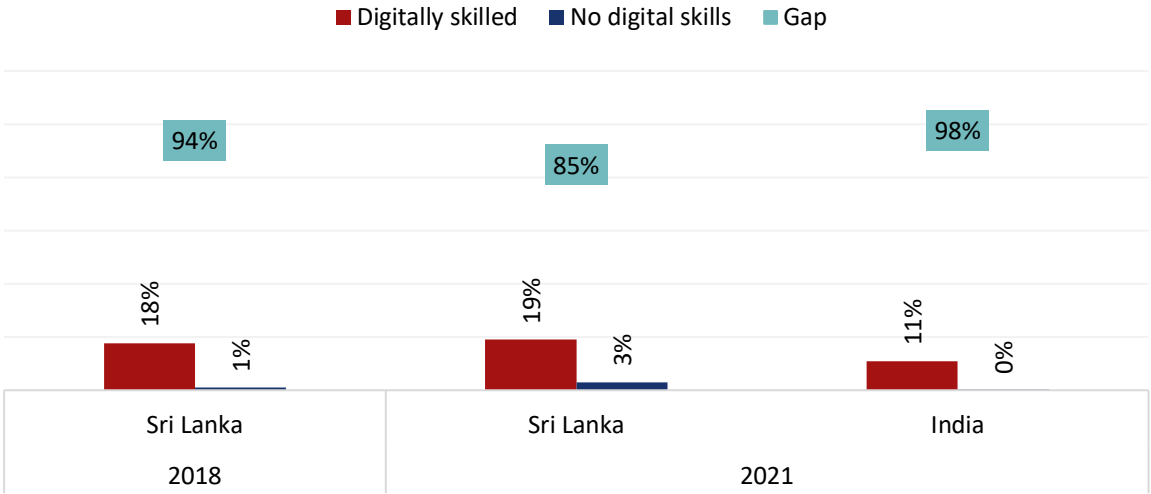


Figure 34. Use of transport or taxi platforms by digital skills (percentage of age 15-65 population)



Those who utilize cashless payment methods are more likely to use e-commerce and taxi platforms (Figure 35 and 36).

Figure 35. Use of goods/product (e-commerce) platforms by cashless payment methods (credit or debit card and mobile money) ownership (percentage of age 15-65 population)

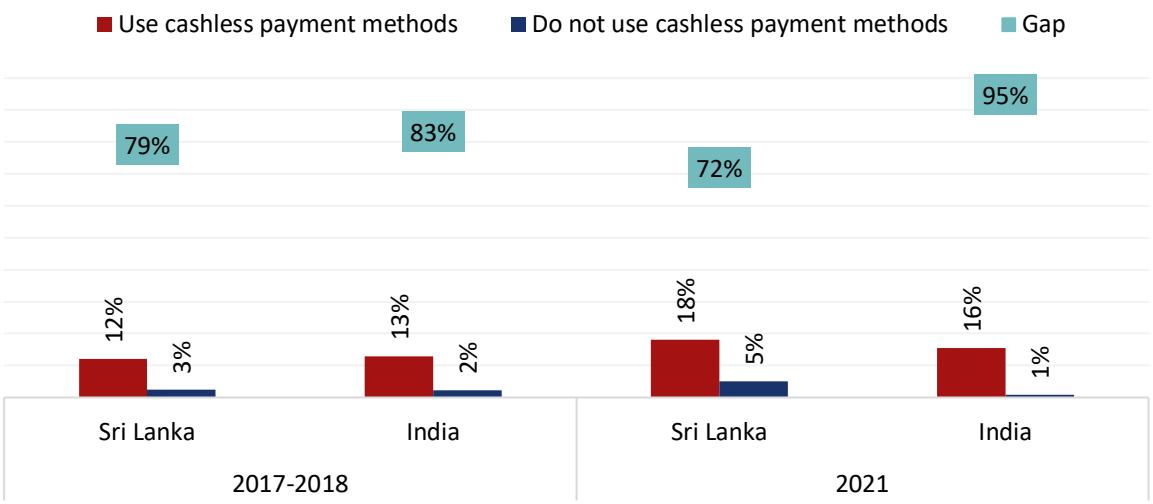
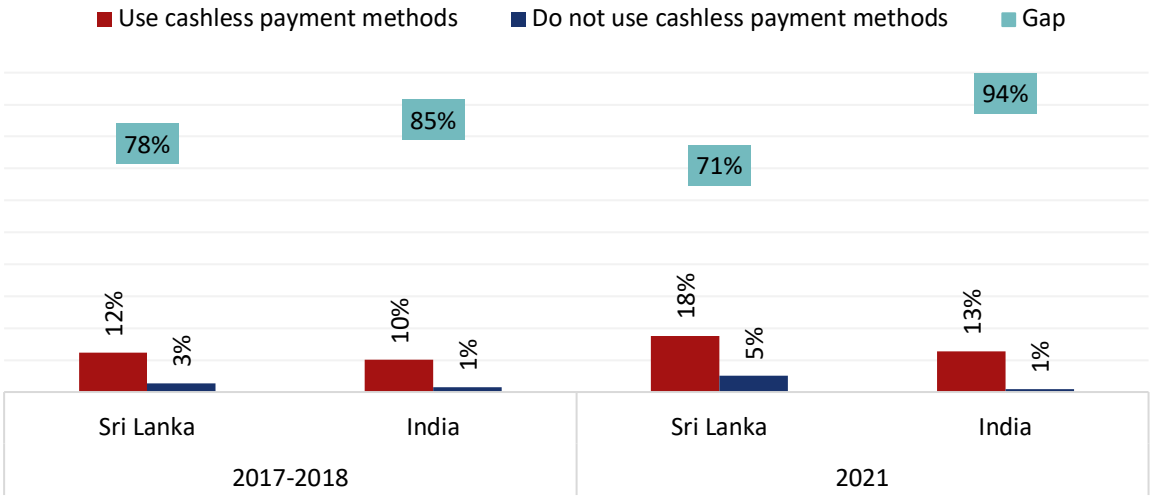


Figure 36. Use of transport or taxi platforms by cashless payment methods (credit or debit card and mobile money) ownership (percentage of age 15-65 population)



4.4. Perceived barriers to platform use

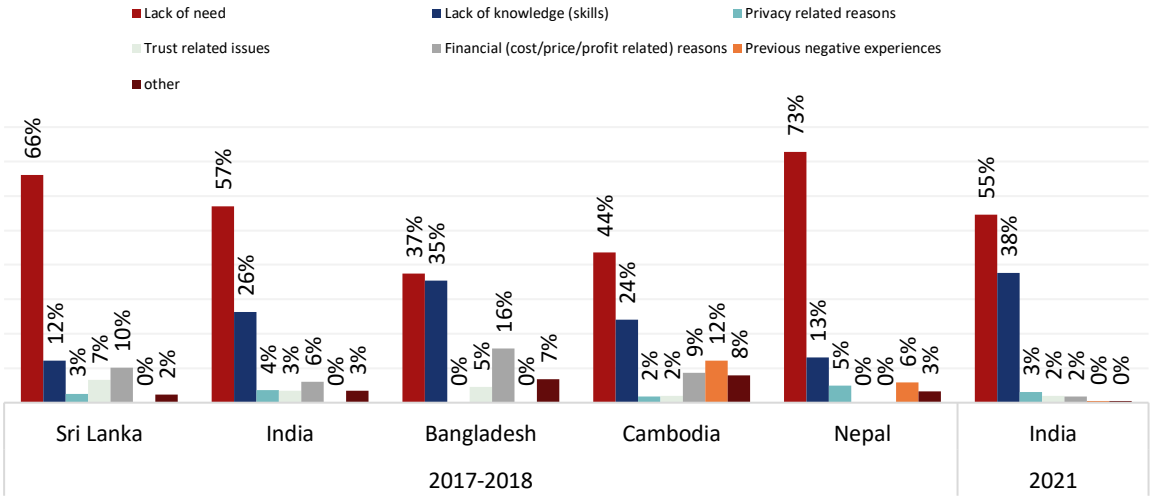
As per the previous section, there are multiple factors (demographic, digital, finance related) impacting the use of platforms positively or negatively. But individuals' perceptions too play a key

role. In this section, we analyze the role that these perceptions play in shaping platform use[27] [28] using the question that was asked of respondents of the survey.

Although skills was the main facilitator identified based on the model (Section 4.2) we see that in the respondents' minds it is not the main reasons for not using platforms (Figure 37). Termed lack of knowledge in the questionnaire, "I don't know how to use platforms" is usually the second most common reason for non-use as per the respondents. Noteworthy is that the percentage of people citing this as their main barrier to use increased in India between 2017 and 2021 from 26% to 38%. Across the six countries and across time periods, the most cited, was "I don't need to" or lack of relevance/saliency. We will see this also echoed in Section 4.4 where some who used platforms during the COVID-19 lockdowns reverted to other methods after lockdowns ended, citing a lack of need. Interestingly, the proportion of people citing the lack of need in India did not change drastically (57% in 2017 vs 55% in 2021).

While some expressed concerns around trust (lack of trust in delivery systems, payment methods, quality of products etc.)[29], this was not commonplace. In all the countries studied, more people stated financial constraints (delivery charges and online prices being too high[30]). In Bangladesh, for example, 16% of non-users stated that these were the main constraints to use. Also noteworthy is that in Cambodia, 12% of non-users that previous negative experiences (theirs or another's) impacted their choice to use platforms.

Figure 37. Main reason for not using platforms to buy or sell goods or services (percentage of age 15-65 population who are aware of the platforms but have not used for buying or selling goods or services)



[27] In the survey also we asked respondents an explicit question related to why they don't use platforms, to understand the reasons respondents might express. The respondents who were aware of the platforms but have not used for buying goods or services were asked "What is the primary reason you don't buy goods/services through the Internet or mobile apps?". Similarly, those were aware but have not used for selling goods or services were asked "What is the primary reason you don't sell goods/services through the Internet or mobile apps?". In this section, those responses are combined to see the reasons for not using platforms for both buying and selling.

[28] Reasons for not using platforms for selling goods or services were not available for Sri Lanka in 2021. Hence, Sri Lanka data is excluded from this analysis for 2021

[29] Trust related concerns include " I am not certain that I will receive the goods/services or deliver the service", " I cannot be certain of the quality of the product", " I am not certain that my payment will reach the seller" and "I am not certain that I will receive the payment"

[30] Cost related issues ("Delivery charges are too high", "Online prices of goods/services are too high" and "Charges from the website/app are too high")

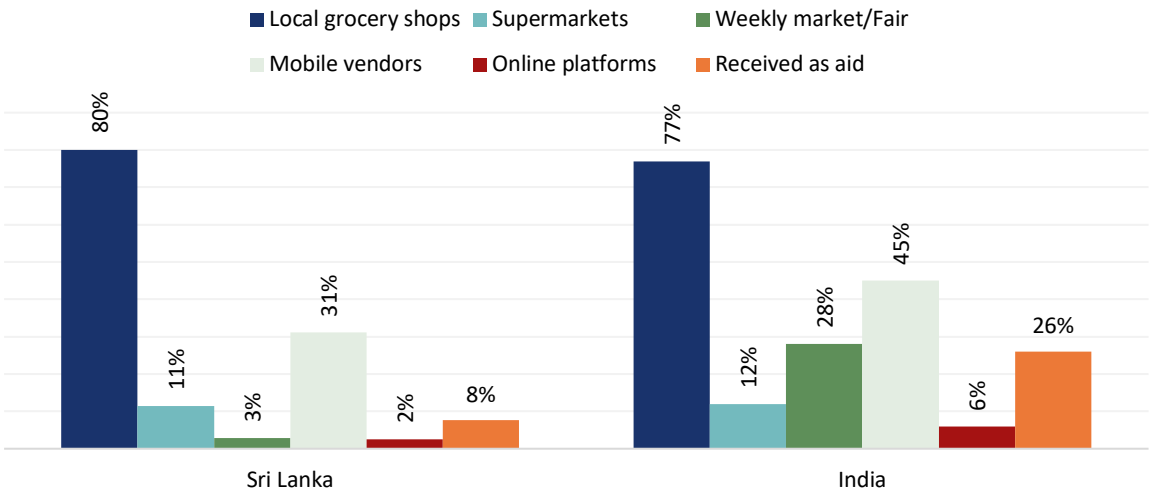
4.5. COVID-19 impacts on platform use

The disruptive impacts COVID-19 had on internet use around the world are well documented (LIRNEasia, 2021[31]; Liu & Fan, 2022[32]). We examine the use of platforms vis a vis other delivery method in India and Sri Lanka for 2 use cases – food delivery, and education.

4.5.1. Platform use for buying food and groceries for household during lockdown

Both India and Sri Lanka imposed stringent lockdowns in early 2020 with the onset of the pandemic. In our 2021 survey, we studied the different channels through which households purchased cooked food and groceries during these government enforced lockdowns[33] in 2020[34].

Figure 38. Methods used to purchase food and grocery during lockdown (percentage of households)



[31] https://lirneasia.net/wp-content/uploads/2021/12/COVID-LK_dissemination_v7.8.2.pdf
[32] https://www.unescap.org/kp/2022/digital-divide-and-covid-19-impact-socioeconomic-development-asia-and-pacific
[33] It is worth noting that the lockdown period considered to for Sri Lanka was the first lockdown period from March to June 2020. Most severe lockdown period as perceived by the household head is considered as the lockdown period for India. These definitions may have contributed for the use levels of different channels for purchasing food and groceries.
[34] The respondents were asked "Did your household purchase food and groceries from ……?"

In both countries, most households (~80%) relied on local grocery shops to purchase food during lockdowns. Second in popularity were mobile vendors delivered food to households. In contrast, only 6% of households in India, and 2% in Sri Lanka used online platforms for this purpose at this time (Figure 38).

Platform use was very concentrated in the hands of a few in Sri Lanka. A clear urban-rural divide of 87% is evident for food delivery purchases via platforms during the lockdowns (Figure 39). It is not surprising as most of the food delivery platforms are mainly available in key cities such as Colombo. Further, while a quarter of households belonging to SEC A (the wealthiest) purchased food from such platforms at this time, use was almost negligible for every other SEC (Figure 40). Although some disparities in use exist in India, it is far less pronounced.

Figure 39. Methods used to purchase food and grocery during lockdown by urbanity (percentage of households)

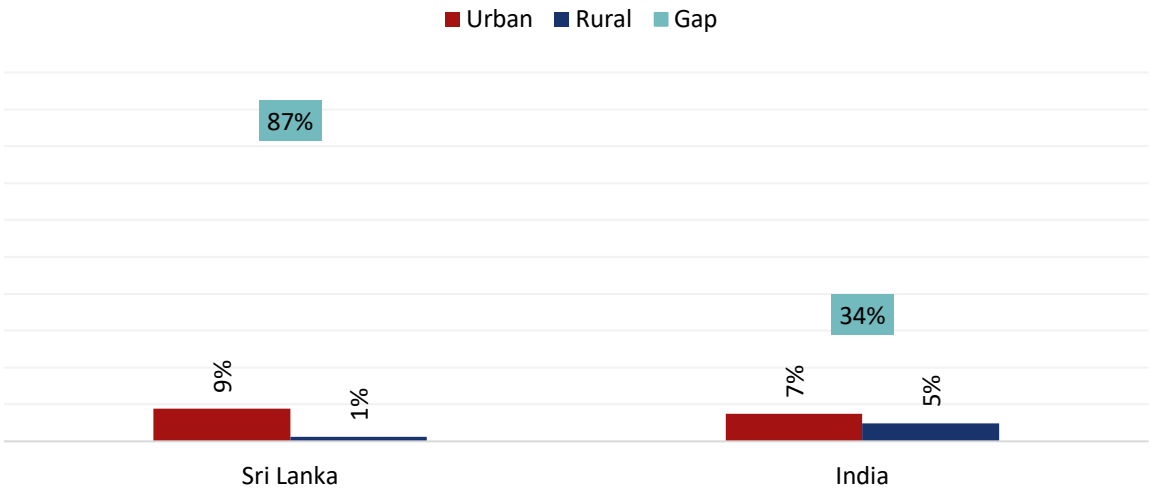
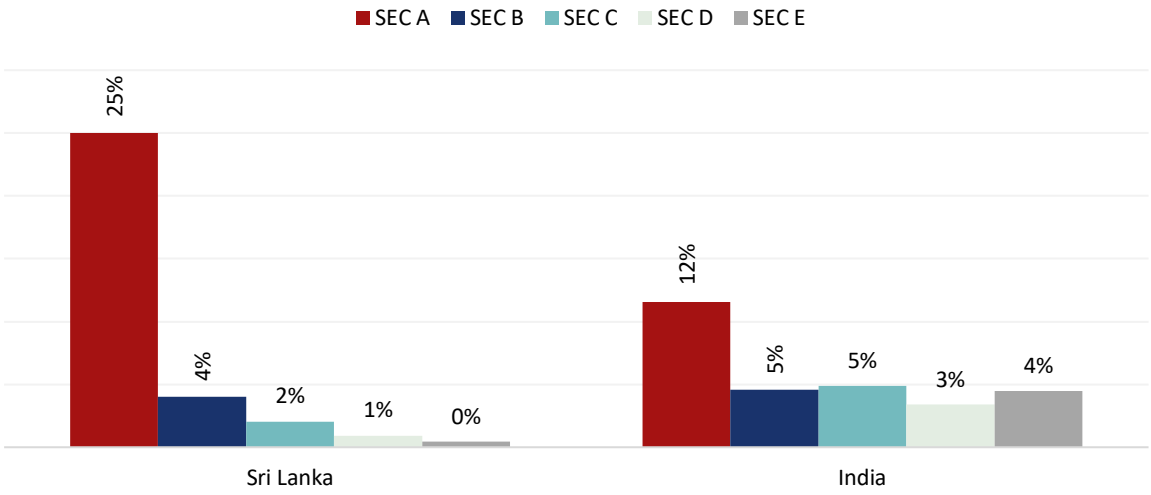


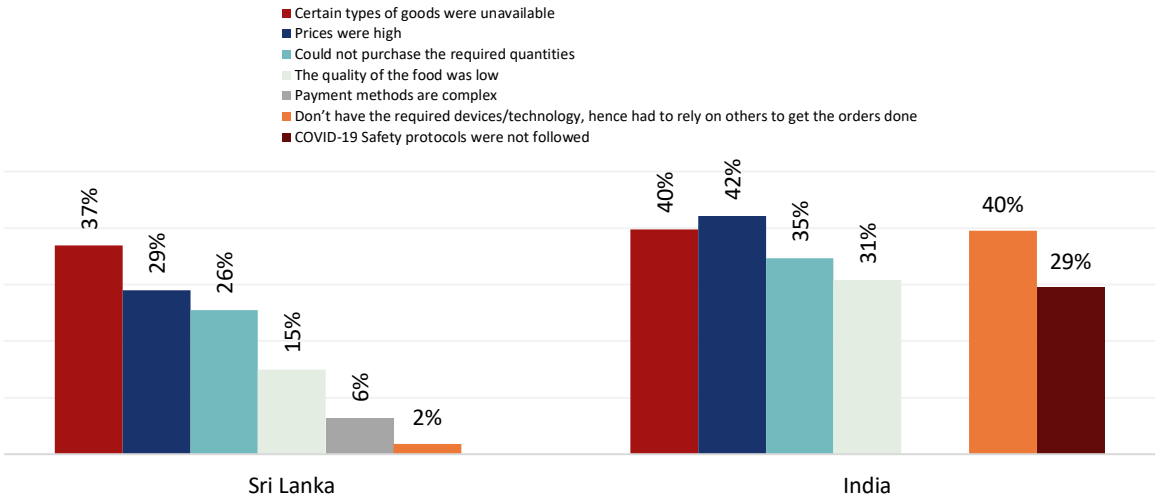
Figure 40. Methods used to purchase food and grocery during lockdown by socio-economic classification (% of households)



A study was conducted on the issues faced by food/grocery platform users when purchasing goods online. Unavailability of certain types of food and high prices were among the top two reasons in

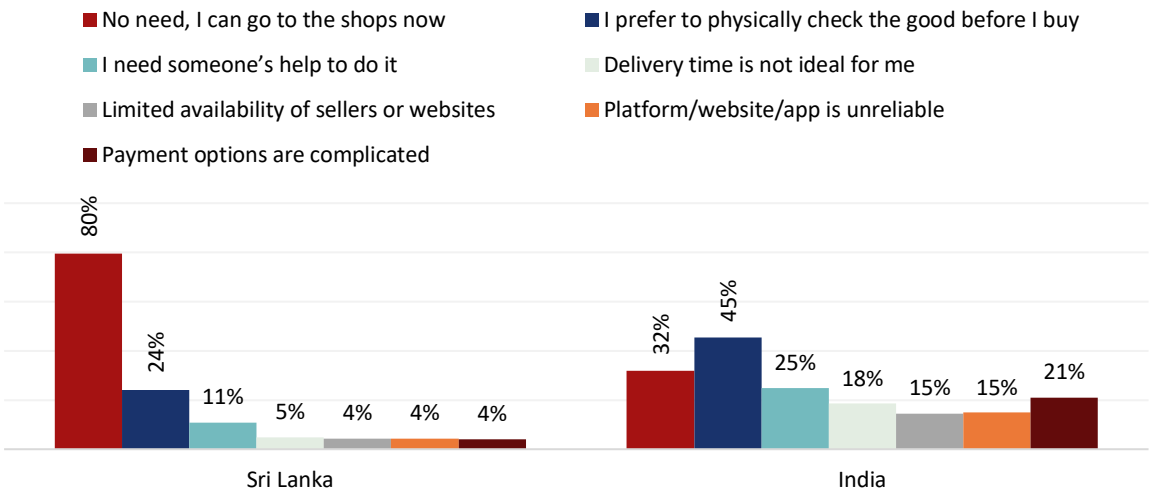
both countries. However, respondents in India also mentioned multiple other grievances including the scarcity of devices. (Figure 41).

Figure 41. Issues faced when food items were ordered via platforms (percentage of households used online platforms for food delivery)



Some asserted that the use of platforms during the lockdowns would lead to high, long-lasting disruptions in the market. However, survey data show that only 65% of households continued to use platforms to purchase food post lockdown. When probed for the reasons from those that discontinued the use of platforms for this purpose, most stated that they lacked the need to do so and that the inability to physically check the quality of the food before purchasing, as key reasons holding them back (Figure 42).

Figure 42. Reasons for not continuing to use platforms to buy food and groceries after lockdowns (percentage of households continued to use online platforms for food delivery after lockdown)

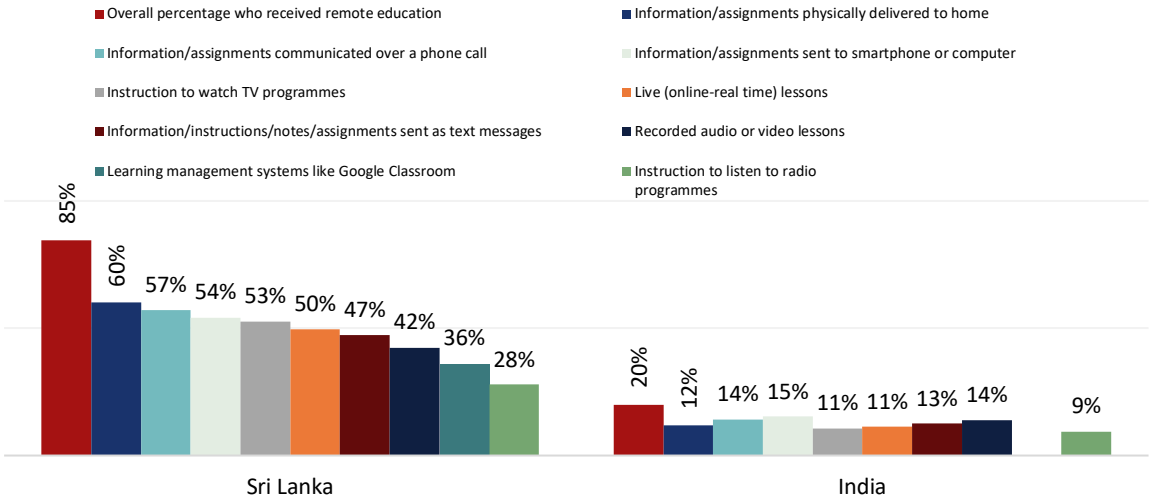


4.5.2. Platform use for remote education

We also asked households about the varied channels through which that their children received education during the lockdowns. While 60% of enrolled children in Sri Lanka used online means to

receive education during the lockdown period, only 16% of schoolchildren in India did so. We considered "online" methods as being information and assignments being sent to smartphone or computer, live (online-real time) lessons and Learning management systems like Google Classroom in the Sri Lanka survey. Information/assignments sent to smartphone (via WhatsApp, Viber etc.) and Live (online-real time) lessons were considered as online methods for India (Figure 43).

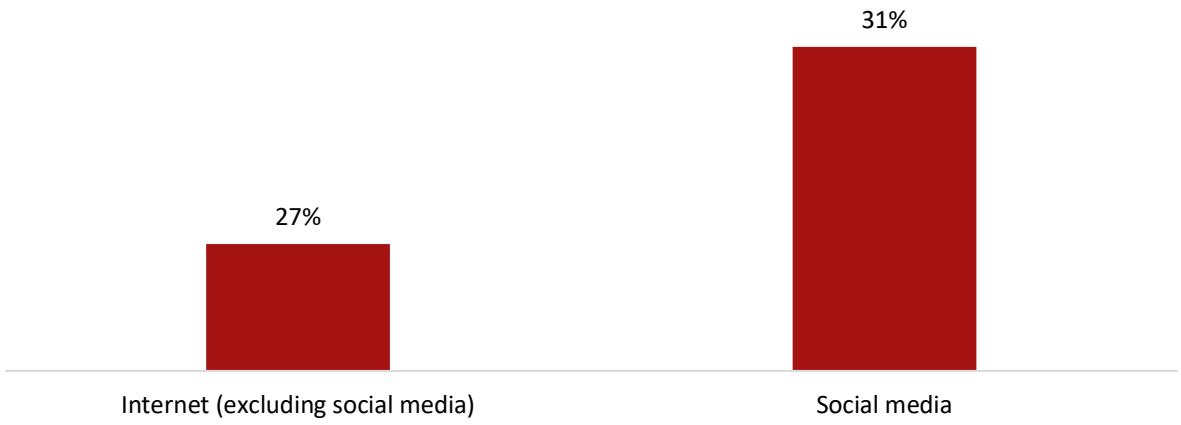
Figure 43. Channels of receiving education (percentage of enrolled school-aged children who received education)



4.6. How small and medium sized enterprises (SMEs) use internet and social media for their business activities

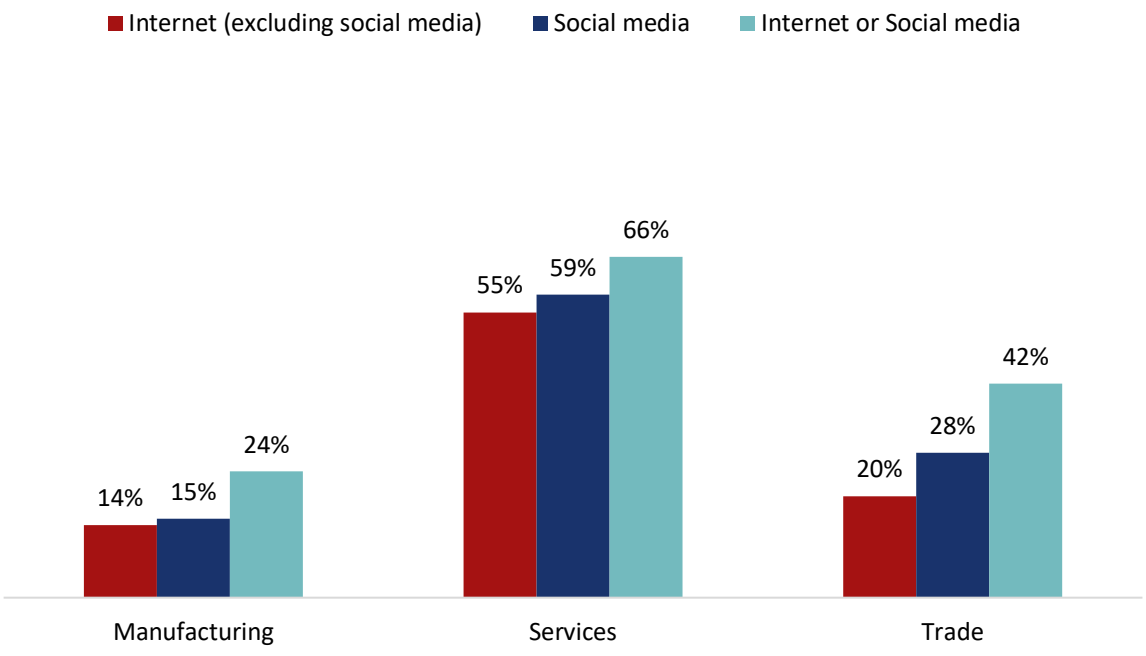
LIRNEasia's 2017 SME survey findings shows that 40% of the SMEs used internet or social media to conduct their business activities. The survey question used was "Does your enterprise use the internet or social media like Facebook, twitter, Instagram, WhatsApp, Viber, G+ for business purposes?". Figure 44 shows that internet use is driven by social media platforms in the two countries.

Figure 44. Internet and social media use for business activities (percentage of SMEs in Sri Lanka 2018)



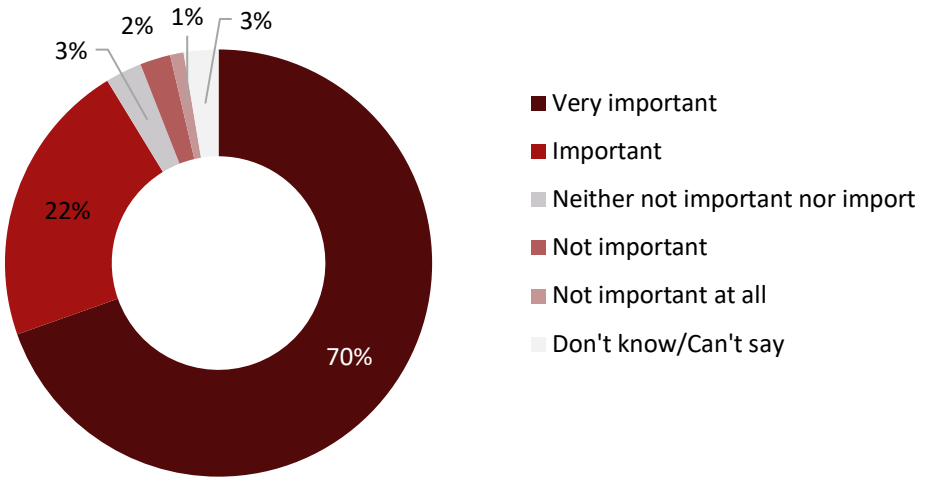
Internet use was higher among manufacturing SMEs as shown in figure 45. Our survey data further illustrates that internet use is higher among urban based SMEs.

Figure 45. Internet and social media use for business activities by enterprise sector (percentage of SMEs in Sri Lanka 2018)



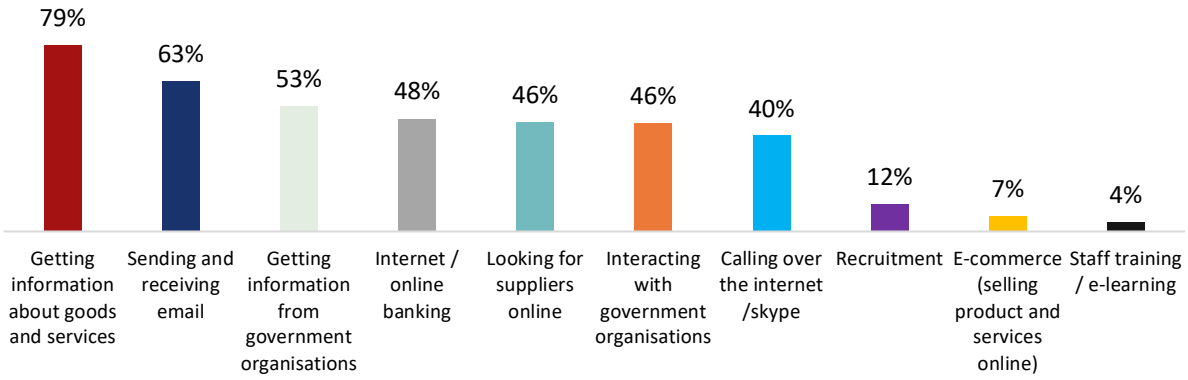
Over 90% of the SMEs that use internet or social media stated that the internet or social media use is important for their business (Figure 46).

Figure 46. Importance of internet or social media use (% of SMEs who use internet or social media)



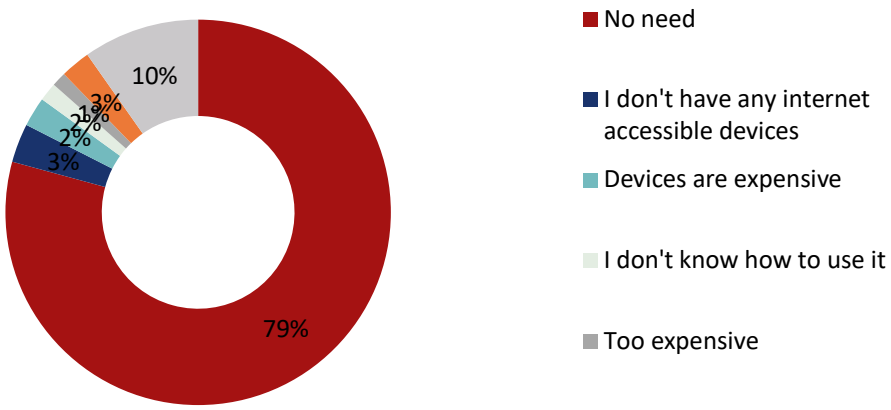
Survey findings further illustrate that the most common use of the internet and social media for SME operators is to get access to information about goods and services (Figure 47).

Figure 47. Use cases of internet and social media (% of SMEs who use internet or social media)



For those SMEs that did not opt for the use of internet and social media, feeling a lack of the need for the same was the prime reason for opting out (Figure 48).

Figure 48. Reason for not using the internet or social media (% of enterprises who don't use internet or social media)



5. Conclusions

This report explored the levels of use of various types of transactional platforms in select Asian countries. It showed that the levels of overall awareness and use were low in all countries – Sri Lanka had the highest use of platforms at just 12% of the population using a transactional platform. However, thanks in part to the impacts of COVID which imposed restrictions on people's ability to transact in traditional ways, by the end of 2021, overall use in Sri Lanka increase by 50%, to 18% of people having used a platform for buying and selling of goods/services. India nearly doubles it's usage to 12% of the population having done the same.

The use of platforms takes place in a context of overall low internet use, with both countries not having more than 50% of it's population above the age of 15 having ever used the internet. So overall internet use remains one of the main challenges to higher use of platforms. Added to this is the requirement that ease of use is facilitated by a smartphone (when compared to a basic or feature phone). We see significant gaps in platform use by smart phone owners when compared to non-smart phone owners. For example, in each of the countries studied, a smart phone owner is at least 83% more likely to have used a platform compared a non-smart phone owners. Similar usage gap exists when platform use among desktop or laptop owners is compared to those who do not own one. However, given the overall low level of laptop and desk top penetration, it is prudent to think about how to convert smart phone owners into platform users than to (at present) worry about how to convert users into desk top owners.

We then unpacked the use of platforms by type – that is platforms that enable the purchase/sale of different types of goods and services. We see that ecommerce goods platforms (Amazon, Flipkart) are popular in Sri Lanka, India and Cambodia), while transport platforms are popular in Sri Lanka, India, Pakistan. Possibly in part due to the movement restrictions due to COVID, by 2021 we see a significant rise in the use of deliver platforms (platforms that deliver goods) in Sri Lanka and India both.

The little use there is a heavily unevenly distributed. Rural dwellers are far less likely to have used platforms than urban dwellers. Men are far more likely to have used platforms than women. However, in Sri Lanka the gender gap in platform use has reduced significantly – in 2017-18 a man in Sri Lanka was 62% more likely to have used a platform than a woman. By 2021 this gap had reduced to 23%. India still has a long way to go where the gender gap reduced only marginally, from 54% to 48% between the two survey rounds we highlight. Similar gaps exist in age group – where platform use is heavily skewed towards younger demographics, the more educated, and richer individuals and households.

Digital skills is an important factor influencing the use of platforms. Overall digital skill levels are low the countries considered. And those with higher levels of skills are far more likely to have used platforms than those who are not digitally skilled. Access to financial tools such as bank accounts, but in particular cashless payments methods (e.g. credit cards) is an obvious and important differentiator too.

While the descriptive analysis of the data provides interesting insights into which factors contribute towards the use of digital transactional platforms, we explore the interactions among these factors using statistical modeling. A binary logistics model shows that the digital skills is the factor that has the highest impact on platform use: people with digital skills are five times more likely to use platforms when all other factors remain constant. Use of cashless payment methods (credit/debit cards, mobile money) was the second strongest positively related factor that drives platform use. The modeling exercise therefore is important in identifying policy and intervention priorities to

increase the use of platforms among everyone. Because as with most technologies, otherwise we are stuck in a world where the richer, more educated, and male users will dominate the use.

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Annex 1: Platform awareness

7. Awareness of platforms

This section will discuss the awareness of platforms. The internet users were asked if they are aware of the platforms[35]. The survey question used was "*Have you heard of Internet platforms or applications being available to buy and sell goods or services in the following areas?".* The local examples were provided in the questionnaire.

7.1 High level trends of platform awareness

In 2017/2018, internet users' familiarity with platforms varied significantly amongst the 6 countries studied in. 70% of internet users in Sri Lanka were aware that platforms could be used to buy/sell goods and services in at least one of the 7 areas described. In contrast, this was true for only 20% of internet users in Nepal (Figure 49).

By 2021, the number of 'platform aware' internet users increased significantly in both Sri Lanka and India. The platform aware population in Sri Lanka grew from 3.7 million to 7.1 million, while it more than doubled from 102 million in 2017 to 227 million in India (Figure 50). Needs brought about by COVID-19 (elaborated further in Section 4.7) may have contributed to the increase in awareness. While the absolute number of 'platform aware' internet users increased significantly, it's worth noting is that a smaller portion of internet users in India were aware of the existence of such platforms in 2021 vis-à-vis 2017 (48% of internet users in India were 'platform aware' in 2021 vs 62% in 2017; Figure 29). However, this must be considered in the context of the rapid growth in the base of internet users which increased 2.5x in India, as described in Section 4.2.2. As shown in Figure 31, new adopters (those who came online recently) are less likely to be online than those who have been online longer.

Familiarity with different types of platforms among internet users differed across countries. In Sri Lanka, India, Bangladesh, and Nepal the public was most aware of goods (e-commerce) platforms, closely followed by transportation/ride-hailing platforms. These trends were consistent across the two time periods in India and Sri Lanka. Pakistan was one exception, where the trend reversed (38% aware of transport platforms vs 14% aware of goods platforms in 2017. Furthermore, the public's familiarity with platforms also differed considerably in Cambodia – the only Southeast Asian country studied – with internet users being most familiar with hired help platforms (42%). (Figure 51).

Figure 49: Overall awareness of platforms (percentage of 15-65 internet users)

[35] The numbers have converted to age 15-65 base

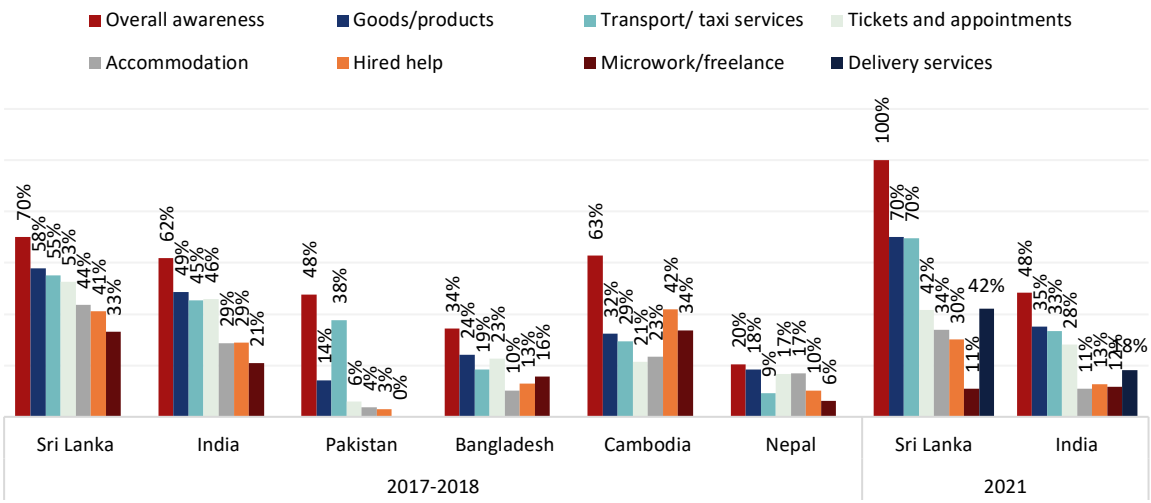


Figure 50. Overall market size for platform awareness (age 15-65 population)

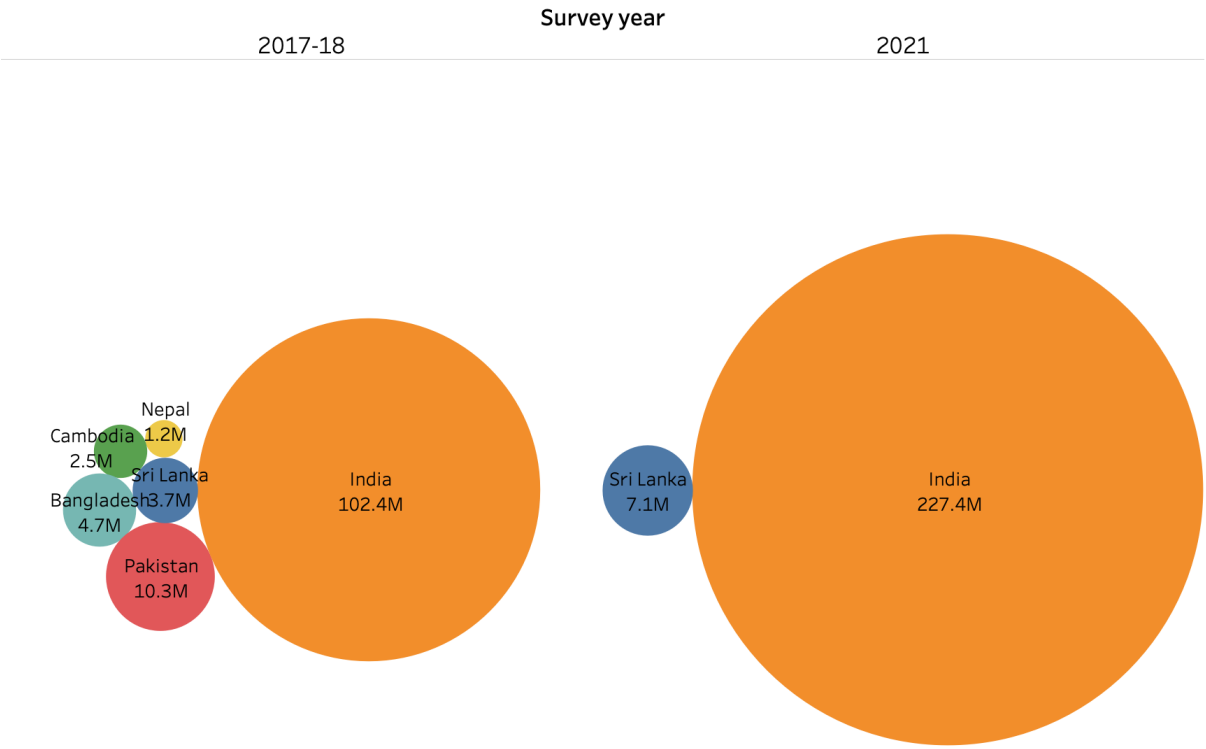
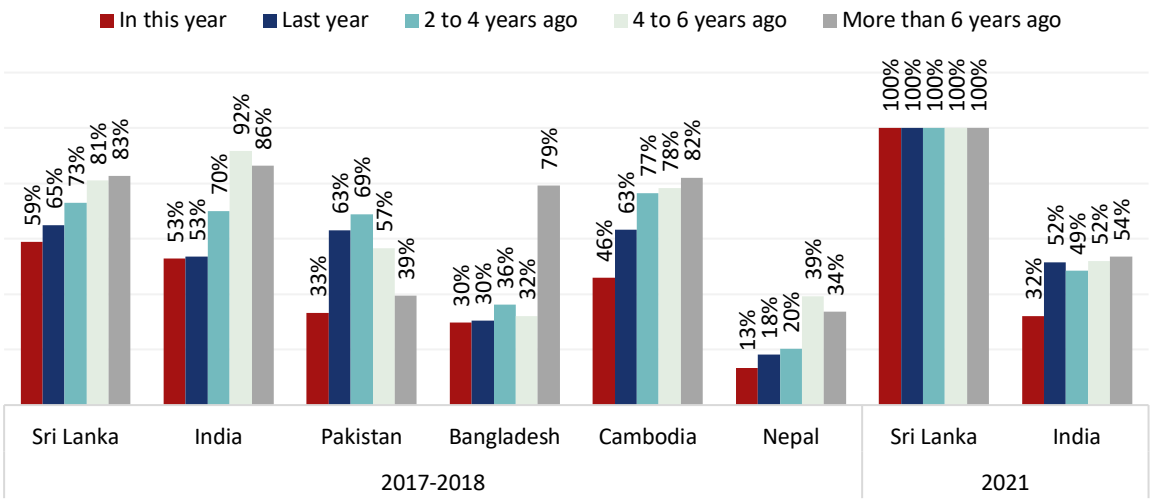


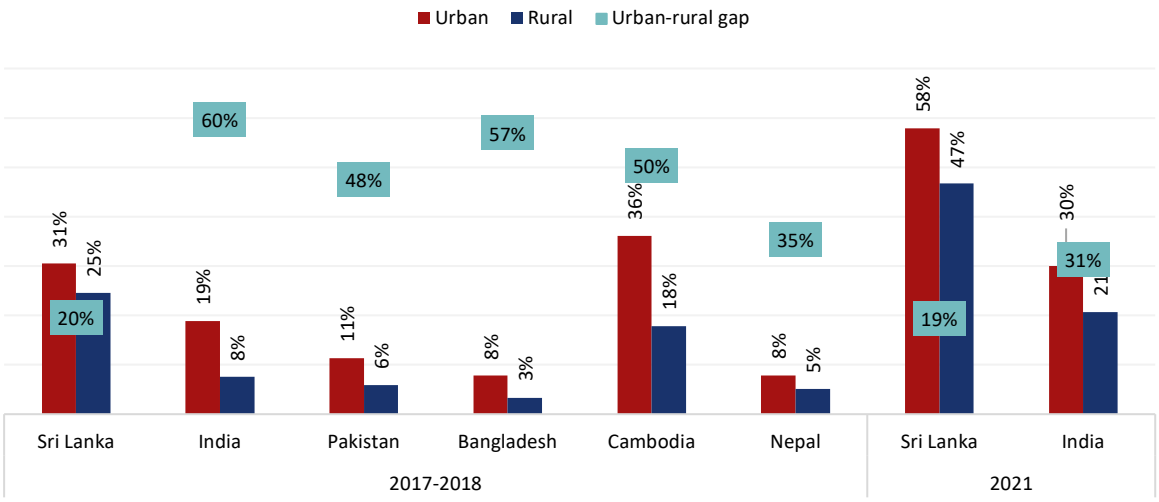
Figure 51. Awareness of the platforms by time since first ever internet use (percentage of age 15-65 internet users)



7.2 Socio-demographic and other drivers of platform awareness

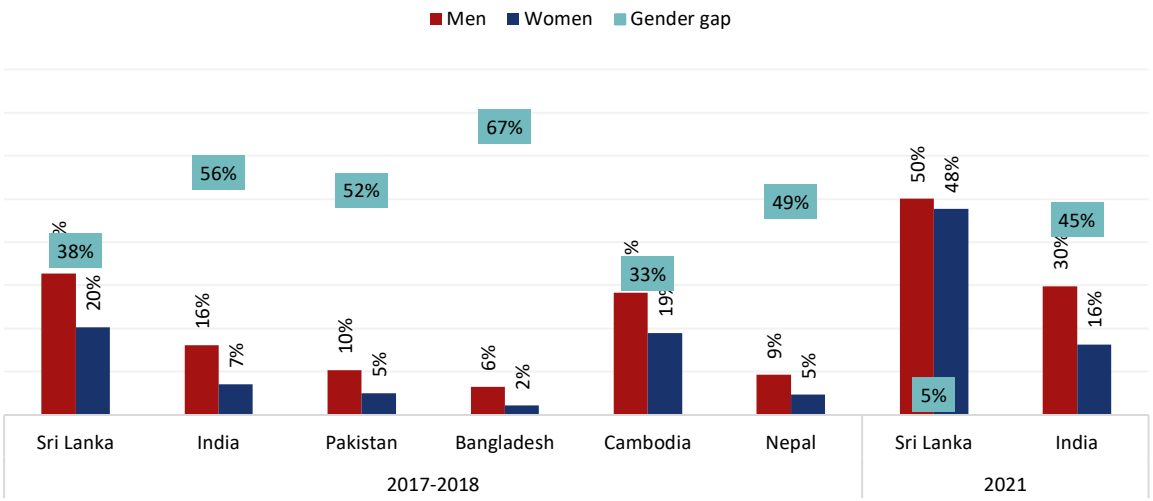
In 2017-18, the overall platform awareness was considerably higher among the urban dwellers compared to the rural dwellers. The huge urban rural gap observed in India in 2017 (60%) has reduced to nearly a half of it by 2021. The urban-rural gap remained at a similar level for in Sri Lanka (Figure 52).

Figure 52. Overall awareness of the platforms by urbanity (percentage of age 15-65 population)



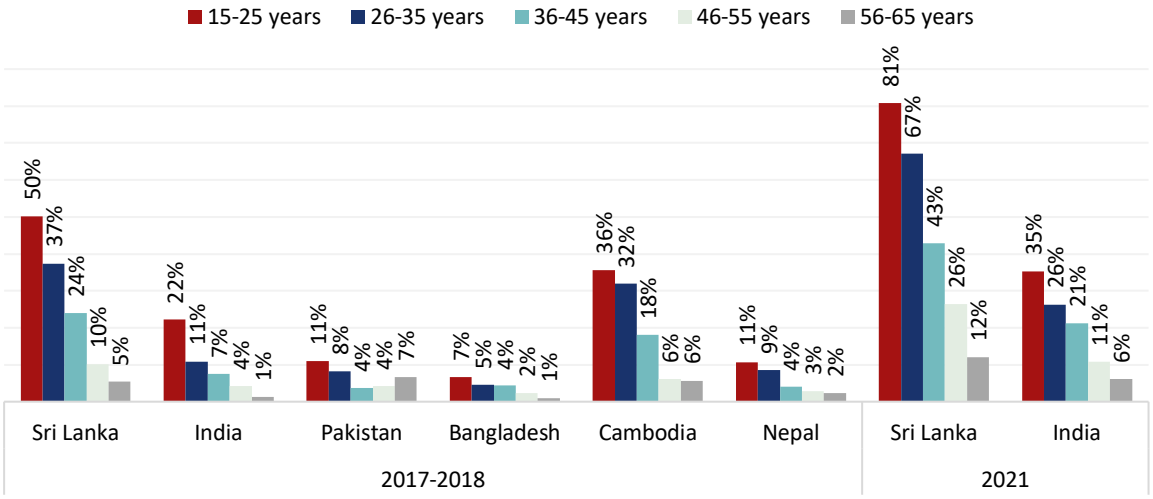
The six Asian countries were among the countries with the highest gender gap in internet use among the 23 countries studied under the 2017-18 AfterAccess global south level project (LIRNEasia, 2019). Not surprisingly, a similar gender gap was observable with platform awareness in 2017-18 for all the countries. In all the countries studied, the gender gap in platform awareness was greater than 30%. In 2021, the gender gap in platform awareness in India remained at a level as high as 45%. Contrastingly, Sri Lanka has drastically reduced the gender gap in platform awareness (Figure 53).

Figure 53. Overall awareness of the platforms by gender (percentage of age 15-65 population)



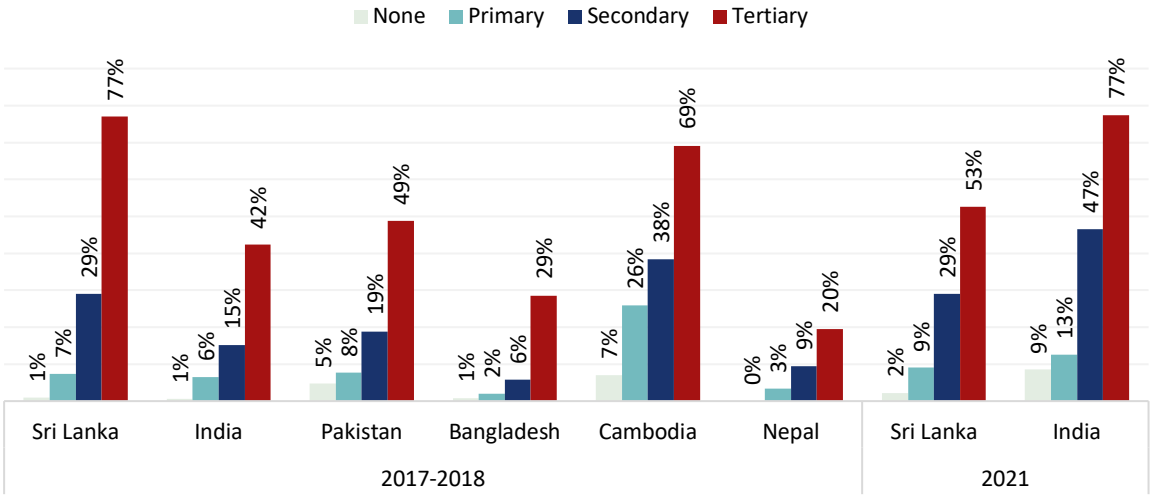
The younger population had a higher platform awareness across the six countries studied in 2017-18. The same pattern is evident in 2021 for both Sri Lanka and India. The older population lagged to grasp the opportunities platforms brought about to the Asian region countries (Figure 54).

Figure 54. Overall awareness of the platforms by age (percentage of age 15-65 population)



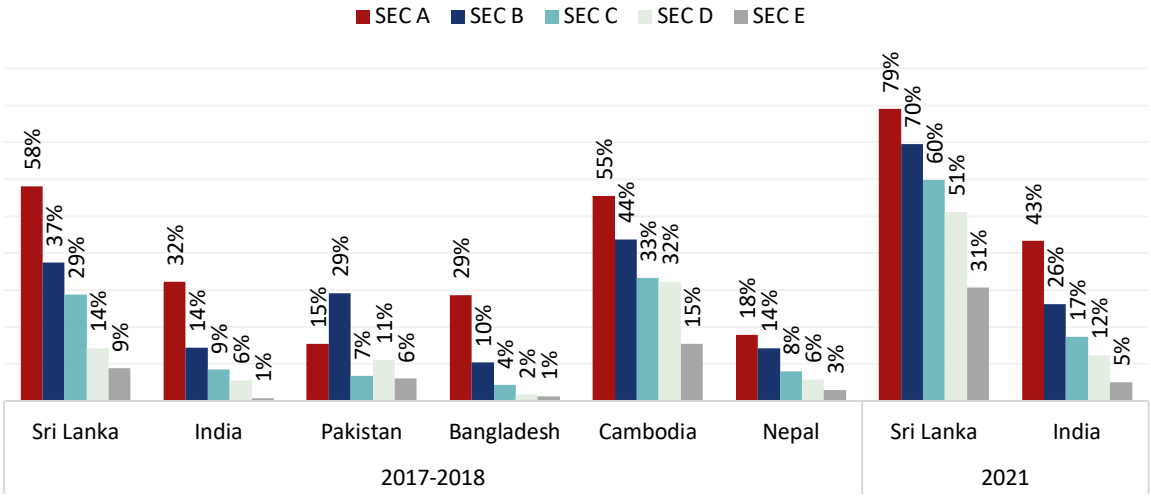
There is a clear relationship that can be observed between the platform awareness and the level of education of the population. Those who had received tertiary education had a higher platform awareness in both 2017-18 and 2021. Interestingly, the platform awareness has doubled among the population with secondary education in Sri Lanka while the awareness among the tertiary educated population remained the same. A considerable increase in the level of platform awareness is evident among the more educated Indians in the 15-65 population category. Measures may be needed to improve platform awareness levels among the less educated (Figure 55).

Figure 55. Overall awareness of the platforms by the level of education (percentage of age 15-65 population)



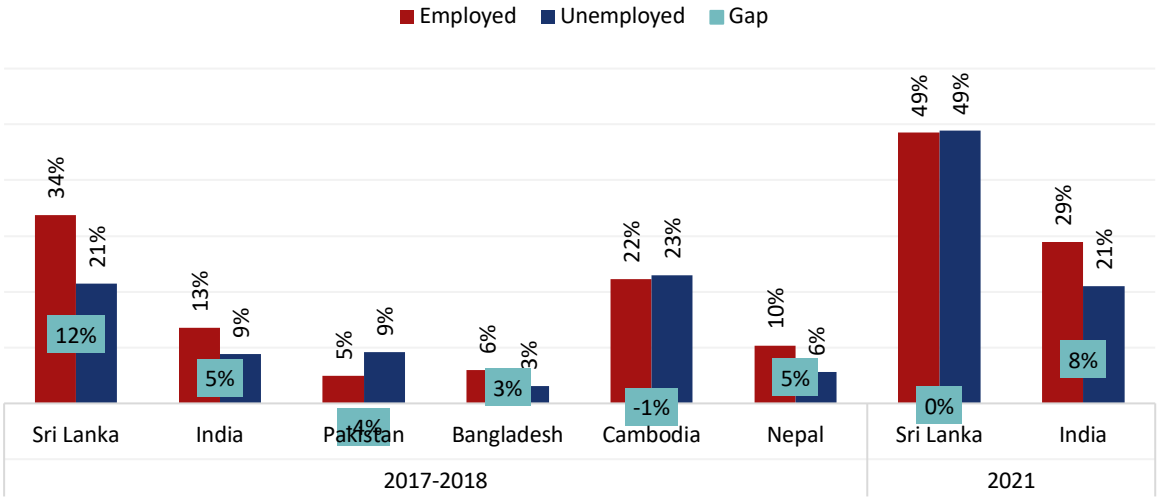
Platform awareness levels can be seen deteriorating with the level of SEC. Higher SEC levels evidently exhibit higher platform awareness while the while the reverse is true for lower SEC levels. The pattern has remained constant for 2017-18 and in 2021 for both Sri Lanka and India. A slightly different pattern can be observed in the Pakistan data for 2017. This can be interpreted as the poorer people individuals being left behind, unaware of even without knowing the opportunities present via the online platforms (Figure 56).

Figure 56. Overall awareness of the platforms by socio economic classification (percentage of age 15-65 population)



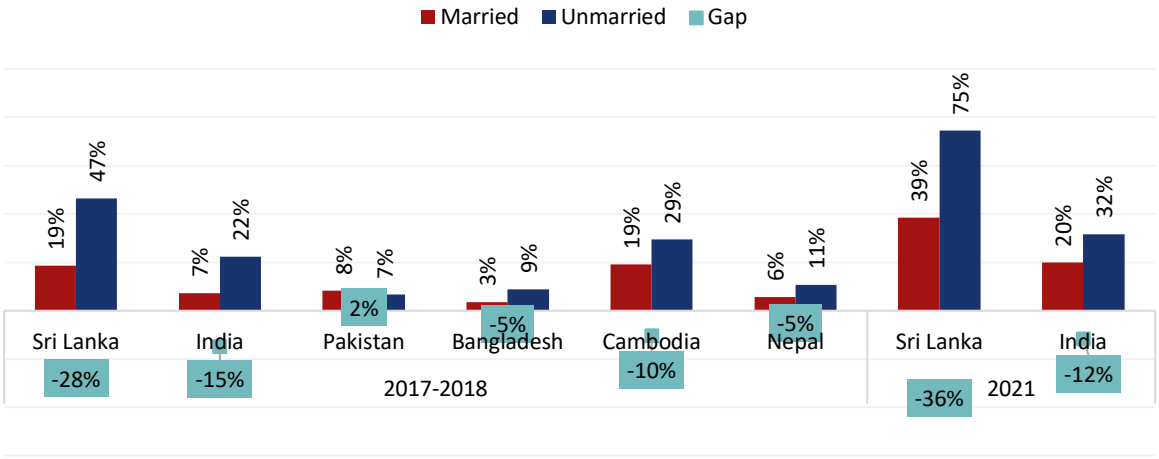
Except for Pakistan and Cambodia, those employed had a slightly higher level of awareness compared to the unemployed population in 2017-18. Interestingly, the stark difference in platform awareness between the employed and unemployed populations in Sri Lanka has dissipated by 2021 (Figure 57).

Figure 57. Overall awareness of the platforms by employment status (percentage of age 15-65 population)



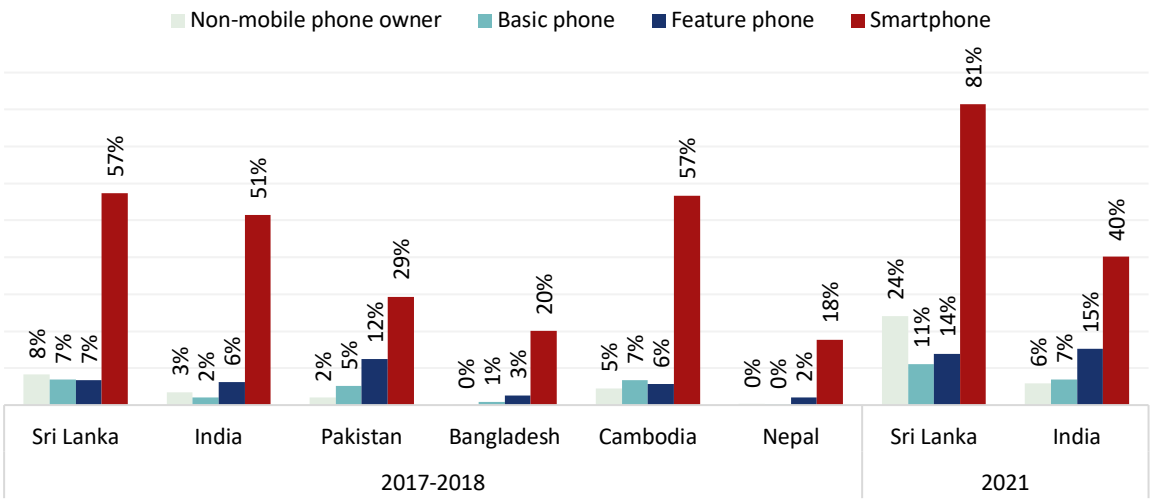
Platform awareness was higher among the unmarried population in both 2017-18 and 2021. Similar levels of platform awareness was observed for both population types in Pakistan (Figure 58).

Figure 58. Overall awareness of the platforms by marital status (percentage of age 15-65 population)



Mobile phones are the most common methods used to access the internet. Owning an internet capable device that can connect to the internet allows people to use the internet and that can have a higher chance of being aware of platforms as demonstrated in the chart below. significant impact on platform awareness as shown in the chart below. Smartphone owners are significantly more aware of platforms compared to other type of device owners or non-mobile phone owners. The platform awareness among Sri Lankan smartphone owners increased drastically from 2018 to 2021. However, in India the platform awareness among smartphone owners fell while the platform awareness among the other type of phone owners (especially feature phone owners) increased considerably (Figure 59).

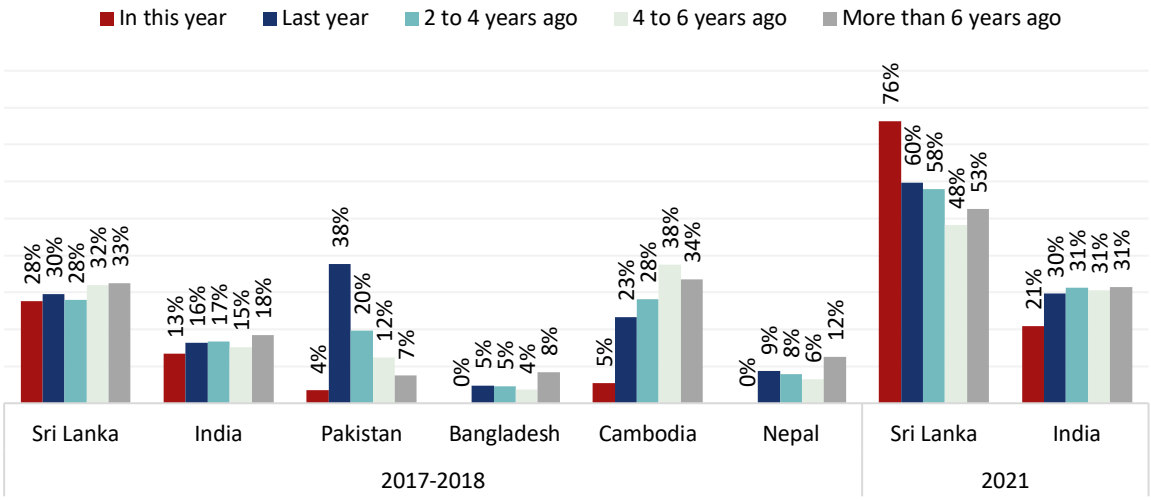
Figure 59. Awareness of the platforms by type of mobile device owned (percentage of age 15-65 population)



In 2017-18, both Sri Lanka and India had a similar pattern of having similar level of platform awareness across different time periods since their first instance of mobile ownership. In 2021, newer mobile phone owners were becoming aware of the platforms while in India the reverse was true. Notably, older mobile phone owners (in terms of when they purchased their first ever mobile phone) had a better platform awareness in 2017 for Cambodia (Figure 60).

The older internet users (not in terms of their age but the time since their first ever internet use) had a higher platform awareness across the countries studied except for Pakistan in 2017. All internet users were aware of at least one platform in Sri Lanka for 2021. In India, the platform awareness among the internet users decreased mainly due to the low awareness levels among the newer internet users

Figure 60. Awareness of the platforms by time since first ever mobile phone use (percentage of age 15-65 population)



Desktops and laptops are a better way to get a more wholesome and meaningful internet experience. Owning or having access to a desktop or a laptop is essential to engage in buying or selling of goods and services via platforms. As the below chart illustrates, it has a strong relationship with platform awareness as well. Across the countries, those who owned computers were more likely to be aware of the internet than the non-computer owners. The gap has reduced in 2021 for both Sri Lanka and India nevertheless the gap remains at a considerably high level (Figure 61).

Figure 61. Awareness of the platforms by computer ownership (percentage of age 15-65 population)

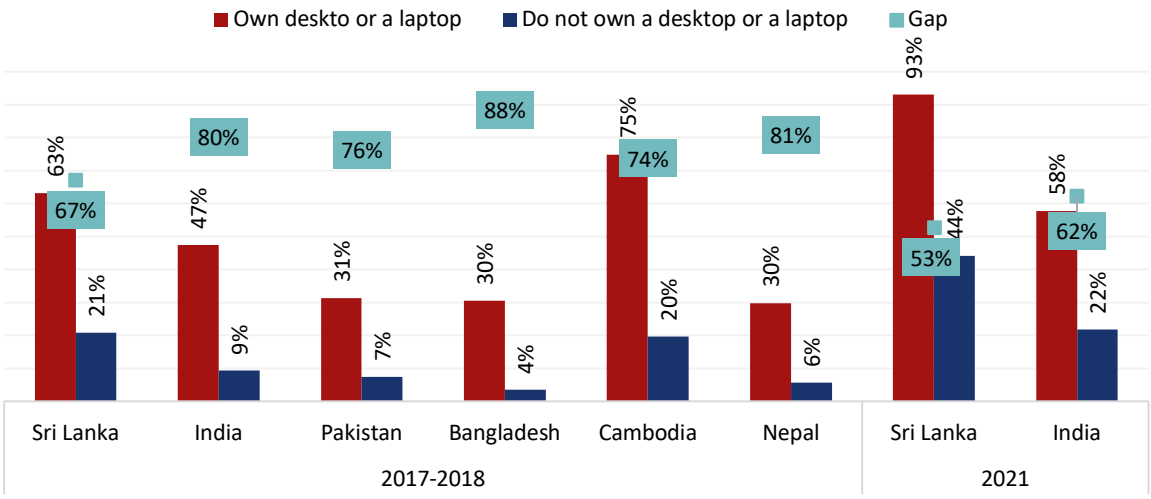
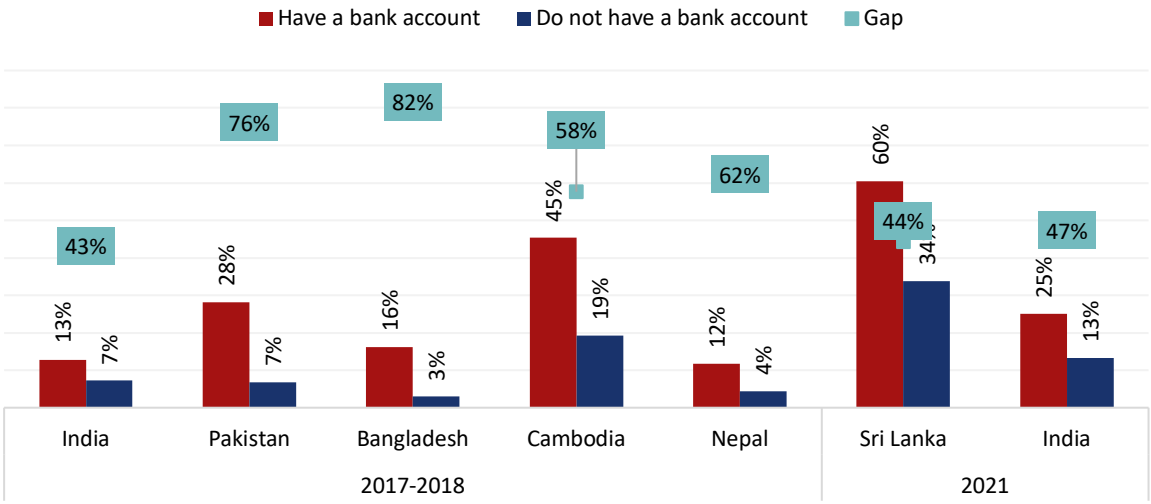


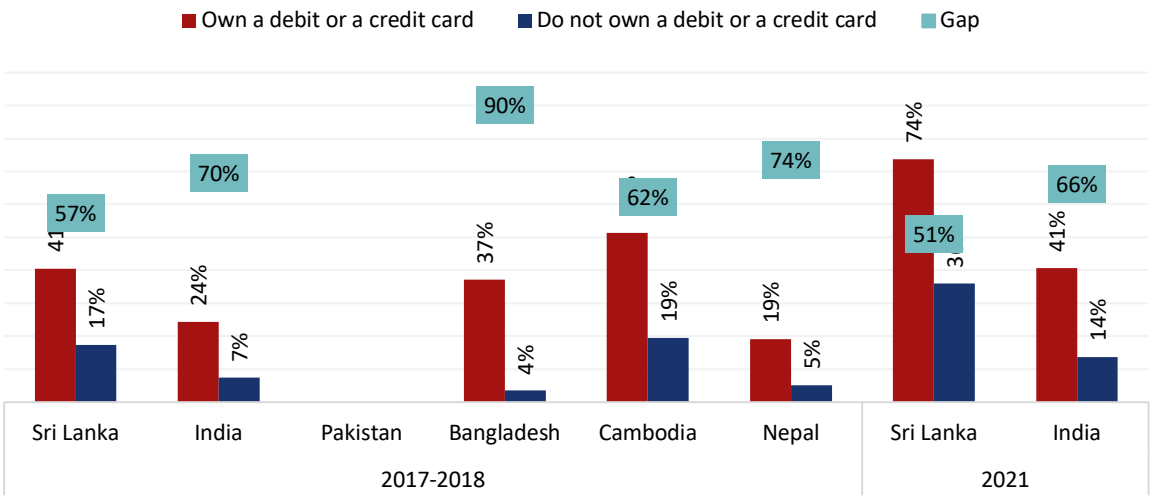
Figure 25 shows how bank account ownership is related with platform awareness. Clearly the bank account owners had a higher awareness in both time periods. (Figure 62).

Figure 62. Awareness of platforms by bank account ownership (percentage of age 15-65 population)



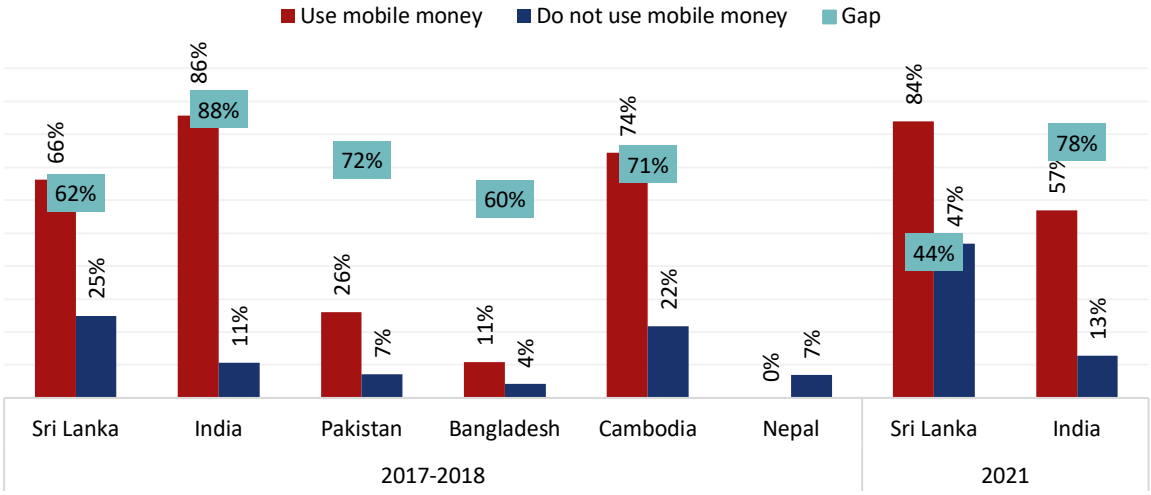
Like the bank account ownership, owning a credit or debit card too is useful for using platforms, especially in order to buy products or services online. As Figure 63 demonstrates, debit or credit card owners were more likely to be aware of the platforms in 2017-18. The gap has slightly decreased in 2021 for both Sri Lanka and India. Despite this, the gap remained at a high level.

Figure 63. Awareness of platforms by credit or debit card[36] ownership (percentage of age 15-65 population)



Mobile money is a more convenient way of making payments and receiving payments while using platforms. As the below chart illustrates it has a strong relationship with platform awareness as well. Mobile money users were highly aware of the platforms, a pattern that remained from 2018-18 to 2021 (Figure 64).

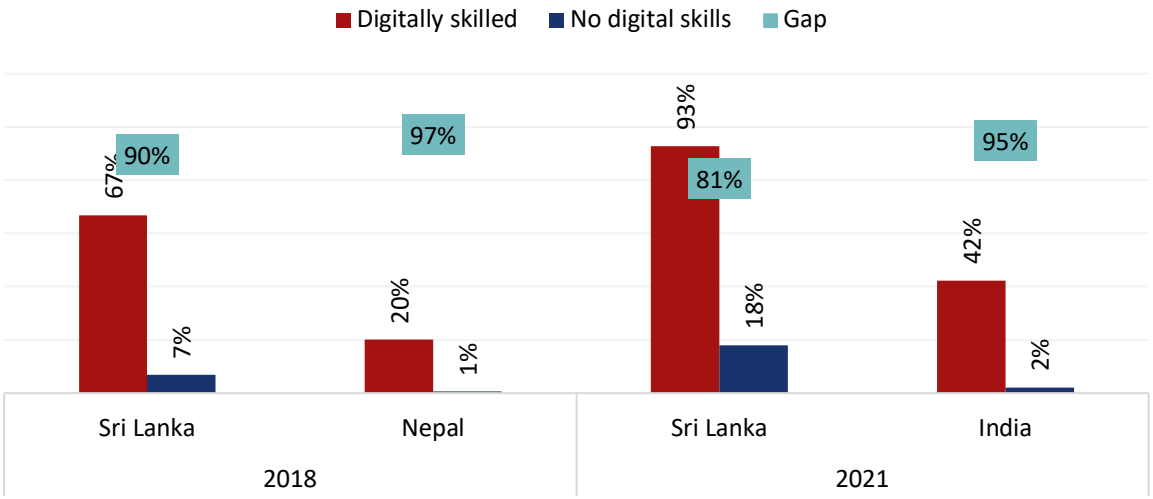
Figure 64. Awareness of platforms by mobile money use (percentage of age 15-65 population)



Those who are digitally skilled had a very high level of awareness compared to those who did not possess the digital skills (Figure 65).

[36] Credit card or debit card ownership data is not available for Pakistan

Figure 65. Awareness of platforms by digital skills (percentage of age 15-65 population)



Chi-square test was used to test the significance of the relationship between the platform awareness and the 15 facilitating factors discussed here.

As shown in Table 8, urbanity seems to have a significant relationship across the countries for both time periods. The relationship between the gender and the platform awareness is significant across the countries except for India in 2021. Factors such as Age, Education, Socio economic classification, Computer (Desktop or laptop) ownership, Time since first ever internet use, Bank account ownership and Debit or credit card ownership had statistically significant relationship with the platform awareness across the countries for both time periods.

Employment status did not have a significant relationship with the platform awareness for Cambodia and India. Pakistan was the only country that did not indicate a significant relationship between marital status and platform awareness.

Table 8.Chi-square significance for the variables discussed in the section with related to the overall platform awareness.

Variable	2017-2018						2021	
	Sri Lanka	India	Pakistan	Bangladesh	Cambodia	Nepal	Sri Lanka	India
Urbanity	**	***	***	***	***	**	***	***
Gender	***	***	***	***	***	***	***	
Age	***	***	***	**	***	***	***	***
Education	***	***	***	***	***	***	***	***
Socio economic classification	***	***	***	***	***	***	***	***
Employment status	***	***	***	***		***	***	
Marital status	***	***		***	***	***	***	***
Type of mobile phone owned	***	***	***	***	***	***	***	***
Time since first ever phone use			***	***	***	**	*	***

Computer (Desktop or laptop) ownership	***	***	***	***	***	***	***	***
Time since first ever internet use	***	***	***	***	***	***	***	***
Bank account ownership	***	***	***	***	***	***	***	***
Debit or credit card ownership	***	***	-	***	***	***	***	***
Mobile money use	***	***	***	*	***	-	***	***
Digital skills[37]	***	-	-	-	-	***	***	***
* The Chi-square statistic is significant at the .05 level. ** The Chi-square statistic is significant at the .03 level. *** The Chi-square statistic is significant at the .01 level - Data is not available								

7.3 Country-specific drivers of platform awareness

It is important to understand what these factors has contributed to the level of platform awareness in each country studied. A binary logistic regression model has been used to understand these country level drivers. The model output is available in Table 9. Next few paragraphs will be used to explain the country level findings from the models.

Sri Lanka

As per 2018 data, women, the elderly (compared to 15-25 age group) - with a declining trend (age 26- 25 being more aware than the age group 56-65), and low-tech devices owners are less likely to be aware of platforms. Out of these, women were 33% less likely to be aware of the platforms. Although in 2021, the same groups were negatively related with awareness, the gender gap reduced significantly with only 3% being less likely to be aware of platforms. When all other factors are held constant, being married was negatively related with platform awareness in both 2018 and 2021. This could be explained by the older population being less aware of platforms in relation to the younger population, assuming that the older population is more likely to be married than the younger.

Education is the biggest driver of platform awareness with those who have received a tertiary education being 13 times more likely to be aware of platforms in comparison to those who had not received a formal education. This is followed by belonging to the highest SEC (SEC A) and claiming ownership to a smart phone. These factors had the highest positively relationship with platform awareness in Sri Lanka in 2017.

In 2021, these dynamics have shifted. Although education is still a primary driver towards more platform awareness, those who acquired a tertiary education were only 2.5 times more likely to be aware of platforms. The ownership of smartphones however became a more significant factor that increased the odds of being aware of platforms - by ninefold. Other highly significant factors that drove platform awareness are the ownership of a desktop computer or laptop, owning a bank account and having access to debit or credit cards.

Interestingly, the use of mobile became a less prominent factor in increasingly likelihood of platform awareness in 2021 when compared to 2017.

[37] Those who could do the at least one of the six activities mentioned below by themselves are considered as digitally skilled.
1. Search for information or other content online
2. Install an application on mobile phone
3. Create log-in details (user) and a password to use a particular service or a website online
4. Locate and adjust settings on an application or service on mobile phone
5. Post any information on the online
6. Make a payment or complete a transaction online or by phone

India
In 2017 and 2021, women and the elderly were the groups that were less likely to be aware of platforms. Additionally, while in 2017 women were 34% less likely to be aware, this figure reduced to 24% in 2021. Although in 2017 only basic phone owners were less likely to be aware of platforms in 2017, both basic and feature phone owners were less likely to be so in 2021.

Belonging to higher SEC groups, having tertiary education, owning a smartphone, and owning a mobile money account increased the likelihood of being aware of the platforms by more than six times in 2017. In 2021, the impact of being highly educated greatly increased the odds of platform awareness. Although socio-economic classification, device type and owning a mobile money account became less significant, they remained more significant drivers of platform awareness compared to other factors.

The direction of the relationship of bank account ownership and platform awareness changed from being positive to being negative from 2017 to 2021 respectively.

Pakistan
In 2017/18, being a woman decreased the odds of being aware of platforms by 60%. Age had a negative relationship with platform awareness. Being formally employed reduced the odds of being aware of platforms by 83%. Interestingly, there existed a non-liner relationship between socio-economic classification and platform awareness. i.e., SEC B is positively related to platform awareness while SEC A is negatively related.

Owning a smartphone increased the likelihood of being aware of the platforms by 23 times. Having received tertiary education, owning mobile devices, owning a bank account, being married, and owning a desktop or laptop are factors that increase the odds of being aware of the platform by over twofold. Additionally, it was observed that being an urban dweller seemed to have an increase the odds of being aware of the platforms.

Bangladesh
In 2017/18, the factor that negatively affected platform awareness by the largest extent was being in the 56-65 age bracket (compared to the 15-25 bracket). This group had the reduced odds of being aware of platform by 75%. Being married also reduced the likelihood of being aware of platforms. Compared to the other countries surveyed in the same year, women were less aware of platforms only by a smaller margin of 2%.

Owning a smartphone was the driver with the most potent odds of platform awareness in Bangladesh – this made a Bangladeshi citizen 47 times more likely to be aware of platforms. Owning feature phones (increase the odds by 9.5 times more) and having received a tertiary education (increase the odds by 6 times) were the next two drivers with the highest potential. Additionally, receiving secondary education, owning a personal computer, and being employed increased the odds of platform awareness by over twofold.

Cambodia
Being a woman and being elderly (with age 15-25 years as the reference category) were the two factors that contributed the most towards there being lesser platform awareness in Cambodia in 2017. In fact, being a women reduced the odds by 30%. A declining trend of being platform aware was observed along with increasing age.

Smartphone ownership made an individual 13 times more likely to be aware of platforms – the biggest driver of platform awareness in the country. Following this, belonging to a SEC A household made an individual 7.6 times more likely and having a tertiary education made an individual 5.3 times more likely to be aware. The use of mobile money increased the odds of being platform aware by threefold.

Nepal

In 2018, women and the elderly were two groups that were less likely to be aware of platforms in Nepal. Being a woman reduced the odds of being aware of platforms by 29%. Interestingly, socio economic classification did not affect platform awareness by much.

Owning a smartphone was the strongest driver of platform awareness in the country – it made one 32 times more likely to be aware of platforms. This was followed by feature phone ownership and having received a tertiary education - by 4% and 3% respectively.

Table 9.Binary logistic regression model for overall platform awareness.

	2017-2018						2021	
	Sri Lanka	India	Pakistan	Bangladesh	Cambodia	Nepal	Sri Lanka	India
Nagelkerke R Square	0.539	0.536	0.386	0.389	0.548	0.336	0.702	0.385
Percentage of cases correctly classified by the model	84.2	91.5	92.0	95.5	85.5	93.1	86.1	80.7
Location: Urban (vs Rural)	(-) 0.942	(+) 1.318**	(+) 1.958***	(+) 1.186	(+) 1.404*	(+) 1.081	(+) 1.283	(+) 1.185**
Gender: Female (vs Male)	(-) 0.675***	(-) 0.666***	(-) 0.402***	(-) 0.979	(-) 0.704**	(-) 0.714	(-) 0.971	(-) 0.764***
Age (15-25 years is the reference category)	***	***	***	...	***	...	***	***
26-35 years	(-) 0.478***	(-) 0.365***	(-) 0.418***	(-) 0.548	(-) 0.839	(-) 0.718	(-) 0.348***	(-) 0.581***
36-45 years	(-) 0.387***	(-) 0.309***	(-) 0.114***	(-) 0.696	(-) 0.425***	(-) 0.444**	(-) 0.104***	(-) 0.615***
46-55 years	(-) 0.227***	(-) 0.292***	(-) 0.153***	(-) 0.529	(-) 0.263***	(-) 0.652	(-) 0.062***	(-) 0.306***
56-65 years	(-) 0.126***	(-) 0.092***	(-) 0.173***	(-) 0.241	(-) 0.315***	(+) 1.431	(-) 0.033***	(-) 0.255***
Level of education (No education is the reference category)	***	***	***	***	***	**	***	***
Primary	(+) 2.285	(+) 4.192***	(+) 1.042	(+) 1.491	(+) 1.637**	(+) 1.834	(+) 0.783	(+) 3.211***
Secondary	(+) 4.5	(+) 4.783***	(+) 2.884***	(+) 2.692	(+) 2.574***		(+) 1.614	(+) 6.193***
Tertiary	(+) 12.996	(+) 8.273***	(+) 4.014***	(+) 6.146***	(+) 5.32***	(+) 2.553***	(+) 2.213	(+) 7.624***
SEC (SEC E is the reference category)	***	***	***	...	***	...	**	*
SEC A	(+) 6.467***	(+) 9.276***	(-) 0.309**	(+) 1.771	(+) 7.669***	(-) 0.908	(+) 1.953	(+) 1.821*
SEC B	(+) 5.202***	(+) 8.98***	(+) 1.673	(+) 1.715	(+) 2.342***	(+) 1.053	(+) 2.087***	(+) 1.466
SEC C	(+) 2.79***	(+) 6.117***	(-) 0.248***	(+) 1.658	(+) 1.838	(-) 0.944	(+) 1.629**	(+) 1.37
SEC D	(+) 1.543	(+) 6.098***	(-) 0.656	(+) 1.117	(+) 2.032***	(-) 0.945	(+) 1.514*	(+) 1.509
Employed	(+) 1.079	(+) 1.059	(-) 0.173***	(+) 2.143*	(+) 1.747*	(+) 1.296	(+) 1.397*	(+) 1.053

Married	(-) 0.639**	(-) 0.791	(+) 2.857***	(-) 0.766	(+) 1.112	(+) 1.202	(-) 0.547***	(+) 1.17
Type of mobile phone device owned (no mobile phone owned is the reference category)	***	***	***	***	***	***	***	***
Basic phone	(-) 0.71	(-) 0.443***	(+) 3.313***	(+) 3.209	(+) 1.153	(-) 0.26	(+) 0.552***	(+) 1.154
Feature phone	(-) 0.545	(+) 1.028	(+) 9.047***	(+) 9.573*	(+) 1.063	(+) 3.973	(+) 0.318***	(+) 1.789***
Smartphone	(+) 6.021***	(+) 7.792***	(+) 23.323***	(+) 46.988***	(+) 12.96***	(+) 32.15***	(+) 9.079***	(+) 3.133***
Own personal desktop or laptop	(+) 1.769***	(+) 2.144***	(+) 2.018	(+) 2.23	(+) 2.677***	(+) 1.627	(+) 2.117**	(+) 1.9***
Own a bank account	(+) 1.328	(+) 1.477**	(+) 3.529***	(+) 1.621	(+) 1.963	(-) 0.896	(+) 2.039***	(-) 0.891
Own debit or credit card	(+) 1.234	(+) 1.457***		(+) 1.467	(+) 1.027	(+) 1.17	(+) 3.089***	(+) 1.228**
Own a mobile money account	(+) 3.078**	(+) 6.454***	(+) 1.648	(+) 1.187	(+) 3.905		(+) 1.622	(+) 2.846***
Constant	(-) 0.032*	(-) 0.003***	(-) 0.023***	(-) 0.001***	(-) 0.026***	(-) 0.004***	(-) 0.531	(-) 0.018***

(+) Indicates a positive relationship with the dependent variable (platform awareness).
(-) Indicates a negative relationship with the dependent variable (platform awareness).
... Indicates the overall categorical variable is not significantly contributing to the model.
x Indicates that the category of the categorical variable is merged with the below category.
* The variable is significantly contributing to the model at the .05 level.
** The variable is significantly contributing to the model at the .03 level.
*** The variable is significantly contributing to the model at the .01 level.

Since the skills question was administrated only in Sri Lanka and Nepal in 2018, we looked at a separate model for Sri Lanka, Nepal in 2018 and Sri Lanka and India in 2021 including the skills. The skills variable had a big impact on platform awareness for all four instances where the skills variable was available. The model fit increased when the skill variable was introduced to the model indicating the strong relationship and explainability brought by the skills variable for platform awareness (Table 10).

Sri Lanka
Once the skills variable was introduced, it became the second most important factor driving platform awareness. Skilled people were 7.6 times more likely to be aware. It also reduced the odds of having tertiary education on platform awareness which stood at 13 times. After the skills variable was introduced, this number reduced to 10.4 times. It largely reduced the magnitude of the odds of smartphone ownership to platform awareness. In the previous model this stood at 6 times but with skills variable it reduced to 1.5 times.

India
Skills variable was only added in 2021 due to the unavailability of the skills question in 2017. When impact of skills on platform awareness was considered, it becomes the one with highest odds. Skilled Indians are 10.4 times more likely to be aware of platforms. The introduction of the skills variable reduced the importance of tertiary education which had the highest odds in the previous model (from 7.6 to 5.3) and secondary education (from 6.2 to 4.4)

Nepal
Skills variable was only added in 2018. When Skills variable was introduced to the model it become the variable with biggest odds ratio. The highest odds observed in the previous model under smartphone ownership reduced to 4.6 from 46.9. Odds of ownership of feature phones and having tertiary education on platform awareness also decreased.

Table 10.Binary logistic regression model for overall platform awareness including the digital skills variable.

	2017-2018		2021	
	Sri Lanka	Nepal	Sri Lanka	India
Nagelkerke R Square	0.588	0.369	0.775	0.444
Percentage of cases correctly classified by the model	85.7	93.1	89.4	80.8
Location: Urban (vs Rural)	(-) 0.869	(+) 1.033	(+) 1.26	(+) 1.172*
Gender: Female (vs Male)	(-) 0.785	(-) 0.726	(+) 1.048	(-) 0.83**
Age (15-25 years is the reference category)	***	...	***	***
26-35 years	(-) 0.502***	(-) 0.762	(-) 0.479**	(-) 0.664***
36-45 years	(-) 0.429***	(-) 0.541	(-) 0.174***	(-) 0.754**
46-55 years	(-) 0.294***	(-) 0.873	(-) 0.103***	(-) 0.463***
56-65 years	(-) 0.188***	(+) 2.161	(-) 0.068***	(-) 0.422***
Level of education (No education is the reference category)	***	...	...	***
Primary	(+) 2.462	(+) 1.387	(-) 0.559	(+) 2.93***
Secondary	(+) 4.325		(-) 0.933	(+) 4.426***
Tertiary	(+) 10.42	(+) 1.805	(+) 1.149	(+) 5.289***
SEC (SEC E is the reference category)	***	...	*	...
SEC A	(+) 6.539***	(-) 0.955	(+) 1.427	(+) 1.848*
SEC B	(+) 5.252***	(+) 1.209	(+) 2.125***	(+) 1.537
SEC C	(+) 2.795***	(-) 0.903	(+) 1.635*	(+) 1.5
SEC D	(+) 1.583	(+) 1.027	(+) 1.579*	(+) 1.678
Employed	(-) 0.986	(+) 1.191	(+) 1.2	(+) 1.102

Married	(-) 0.788	(+) 1.272	(-) 0.658	(+) 1.233*
Type of mobile phone device owned (no mobile phone owned is the reference category)	***	***	***	***
Basic phone	(-) 0.487***	(-) 0.211	(-) 0.733	(+) 1.506**
Feature phone	(-) 0.255***	(+) 1.401	(-) 0.553	(+) 1.46
Smartphone	(+) 1.527	(+) 7.578**	(+) 7.413***	(+) 1.668***
Own personal desktop or laptop	(+) 1.365	(+) 1.553	(-) 0.752	(+) 1.983***
Own a bank account	(+) 1.35	(-) 0.89	(+) 1.743***	(-) 0.838
Own debit or credit card	(-) 0.971	(-) 0.99	(+) 2.714***	(+) 1.117
Own a mobile money account	(+) 2.498		(+) 1.216	(+) 2.281***
Digital skills	(+) 7.622***	(+) 7.768***	(+) 14.914***	(+) 10.42***
Constant	(-) 0.025**	(-) 0.003***	(-) 0.263***	(-) 0.005***

(+) Indicates a positive relationship with the dependent variable (platform awareness).
(-) Indicates a negative relationship with the dependent variable (platform awareness).
... Indicates the overall categorical variable is not significantly contributing to the model.
x Indicates that the category of the categorical variable is merged with the below category.
* The variable is significantly contributing to the model at the .05 level.
** The variable is significantly contributing to the model at the .03 level.
*** The variable is significantly contributing to the model at the .01 level.

Annex 2: Platforms for buying goods and services

8. Platforms for buying goods and services

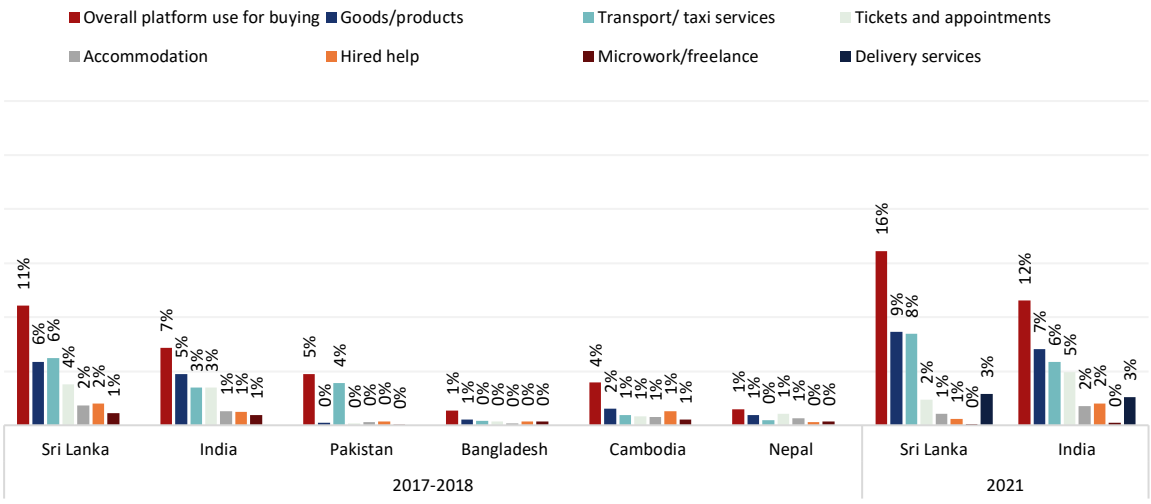
In this section we explore the extent of buying via platforms. We express the data as a percentage of the population aged 15-65 as well as a percentage of those who are familiar (i.e., aware) of digital platforms since knowing of a platform a necessary condition to using it for buying (section 4.3)[38].

We first conduct a market sizing of users of specific platform types in the 6 countries (e.g.: number of e-commerce, ride-hailing app users). Thereafter we take a high level look at descriptive statistics to ascertain variations in the use of platforms based on socio-economic and demographic characteristics, after which country specific drivers are examined using binary logistic models (See Section 3.3 & 3.4).

8.1 High level trends of platform use for buying

A very low percentage of the age group of 15-65 used platforms to buy goods or services. Sri Lanka had the highest overall platform use for buying in 2017-18. This was followed by India. E-commerce platforms selling goods and transport (taxi) service apps were the most popular apps for buying in 2017. The pattern remained constant for Sri Lanka and India in 2021 as well. There was an increase in the use of platforms for buying across most of the platforms in Sri Lanka and India. It is important to note that the margin of errors of the estimates will be higher at these levels (Figures 66 and 67).

Figure 66. Use of the platforms for buying goods or services (percentage of age 15-65 population)



73 million age 15-65 people used at least one platform once to buy goods and services across all six countries in 2017-18. In 2021, India alone had more than 110 million people (age 15-65) using platforms to buy goods and services. A platform level market sizing is available in Figure 68.

[38] The numbers have converted to age 15-65 base. The survey question used was " *Have you used Internet platforms/apps to buy goods or services of the following types?".* The local examples were provided in the questionnaire for the buying section as well. The overall use of platforms for buying goods or services included an "other platforms" category option in 2017-18, while the "Delivery services" platforms were considered in the overall use for buying for 2021.

Figure 67. Use of the platforms for buying goods or services (percentage of those who are aware of the platforms)

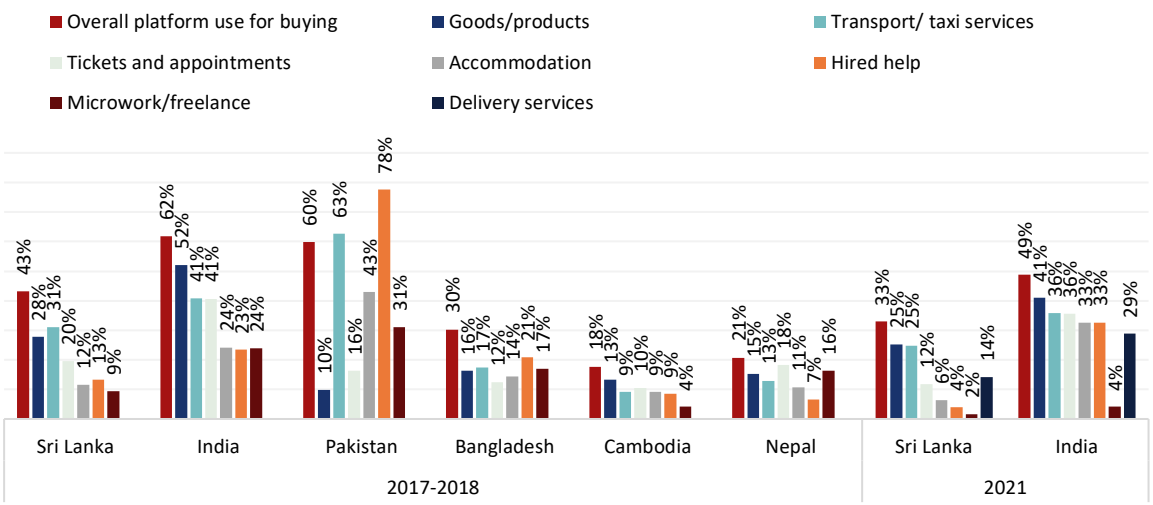
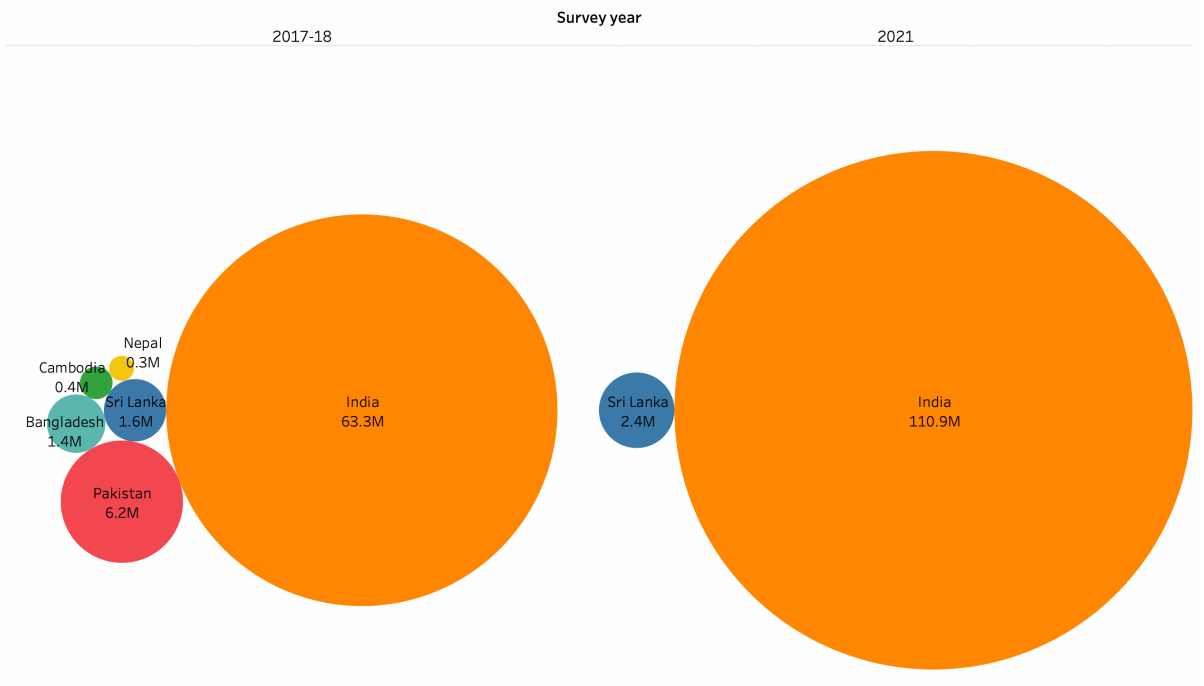


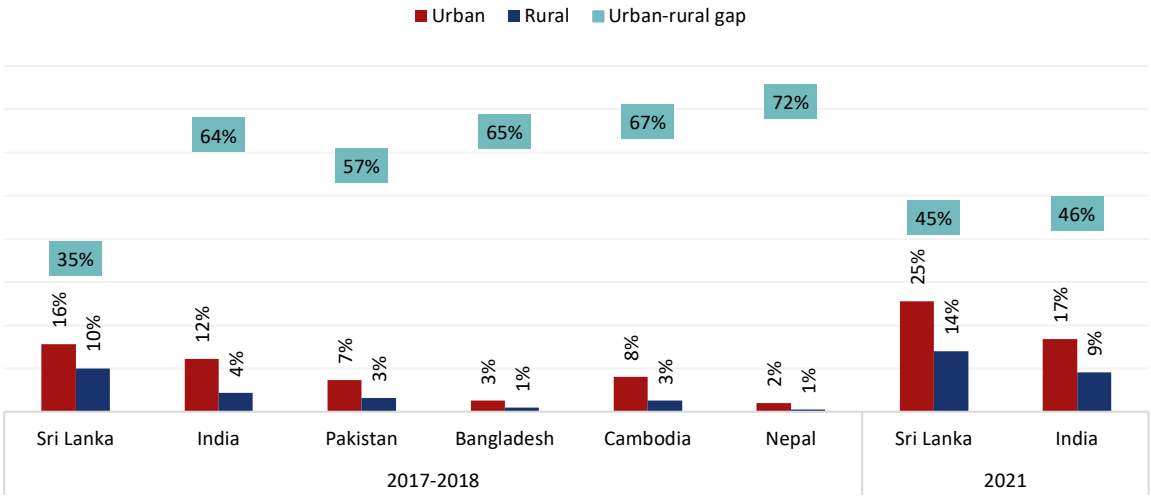
Figure 68. Overall market size for buying goods or services via platforms (age 15-65 population)



8.2 Socio-demographic and other facilitating factors of platform use for buying

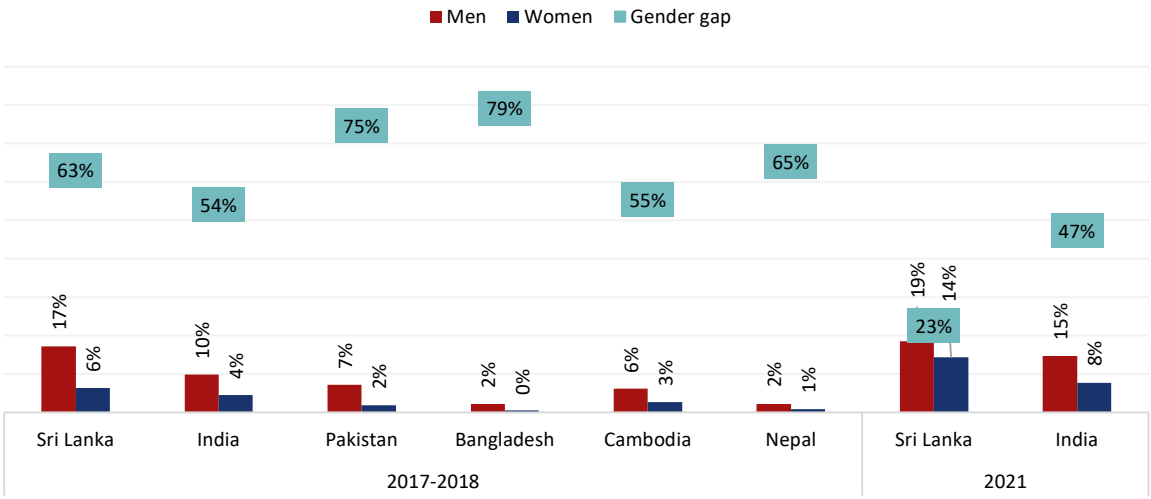
A High urban-rural divide is evident for all countries studied in 2017-18. Urban dwellers were more likely to use platforms to buy goods and services. In 2021, the urban-rural divide in India decreased significantly compared to 2017. Contrastingly, the significantly increased use of platforms for buying by urban dwellers had made the urban-rural divide larger in Sri Lanka in 2021. The urban-rural divide for India and Sri Lanka remained similar in 2021 (Figure 69).

Figure 69. Use of at least one platform for buying goods or services by urbanity (percentage of age 15-65 population)



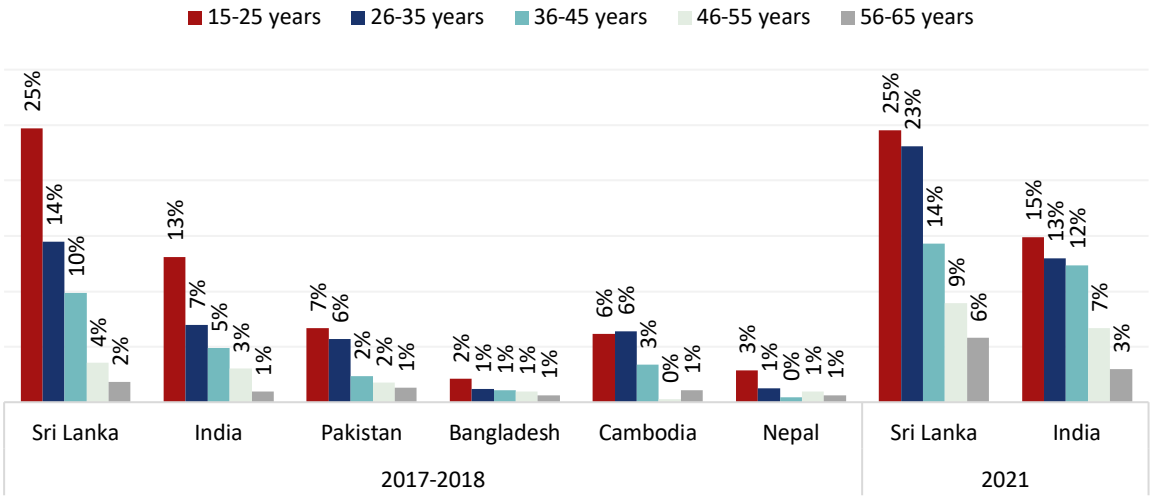
Women were less likely to use platforms to buy goods and services across the countries studied in 2017 with all countries having a gender gap greater than 50%. There is a drastic decrease in the gender gap in Sri Lanka and a relatively smaller decrease in India by 2021. This pattern was observed with other indicators such as internet use and social media use (LIRNEasia, 2021). Despite the reduction in the gender gap compared to 2017, the gender gap overall is high, especially in India where women are nearly 50% less likely to have used a platform to purchase goods or services (Figure 70).

Figure 70. Use of least one platform for buying goods or services by gender (percentage of age 15-65 population)



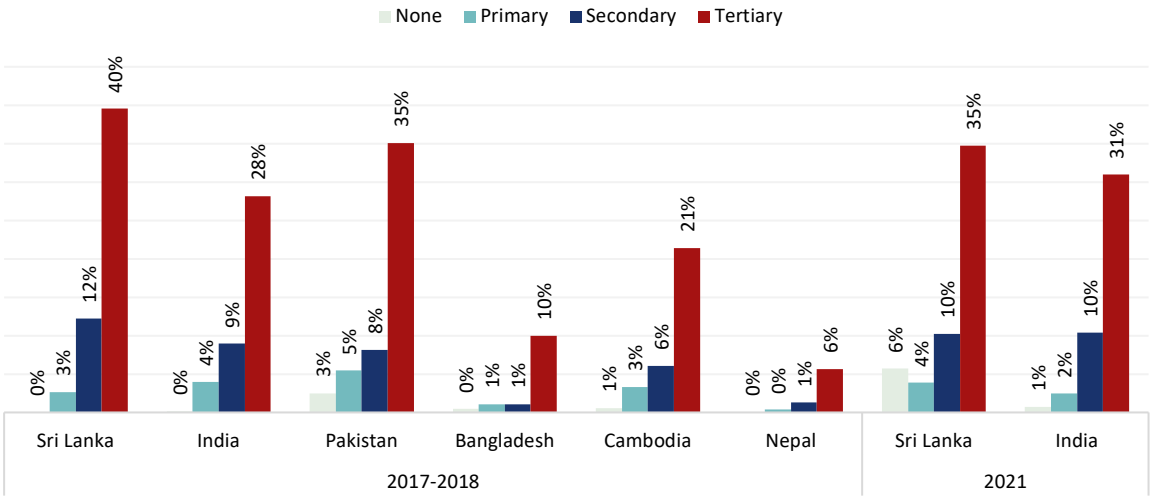
Similar to platform awareness, a high percentage of the young population used platforms for buying in 2017-18. This pattern was also observed in 2021 for Sri Lanka and India. The age 15-25 and 26-35 groups showed somewhat similar levels of use. Only a negligible percentage of older population used platforms for buying (Figure 71).

Figure 71. Use of at least one platform for buying goods or services by age (percentage of age 15-65 population)



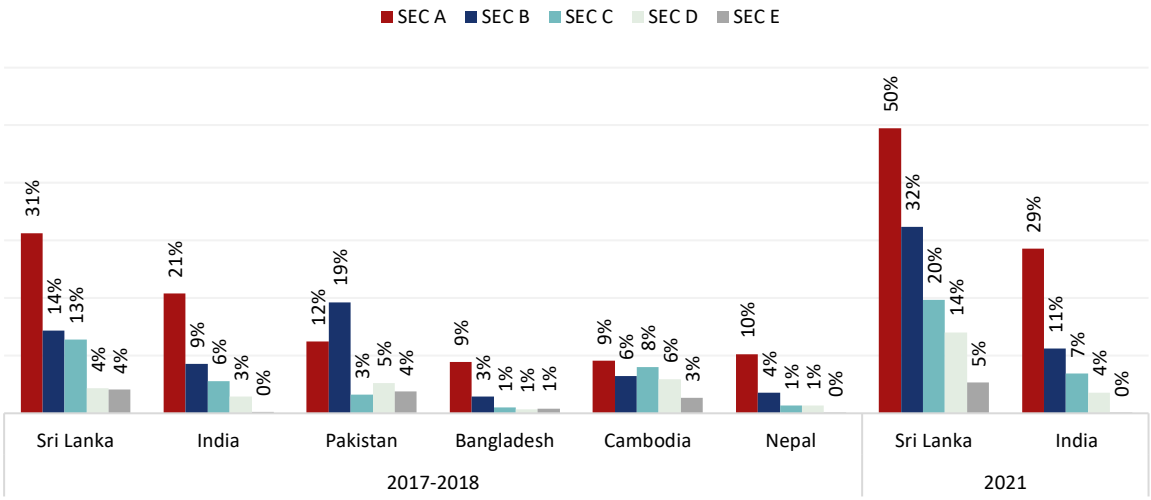
A clear relationship is observable between the level of education and the use of platforms to buy goods or services. Higher the level of educational attainment, higher the This was evident for all the countries studied in 2017-18. Even though the similar pattern was there for Sri Lanka and India in 2021, platform use level decreased for the population with tertiary education for Sri Lanka. Furthermore, there is a noticeable increase in platform use for buying among the population with no formal education (Figure 72).

Figure 72. Use of at least one platform for buying goods or services by the level of education (percentage of age 15-65 population)



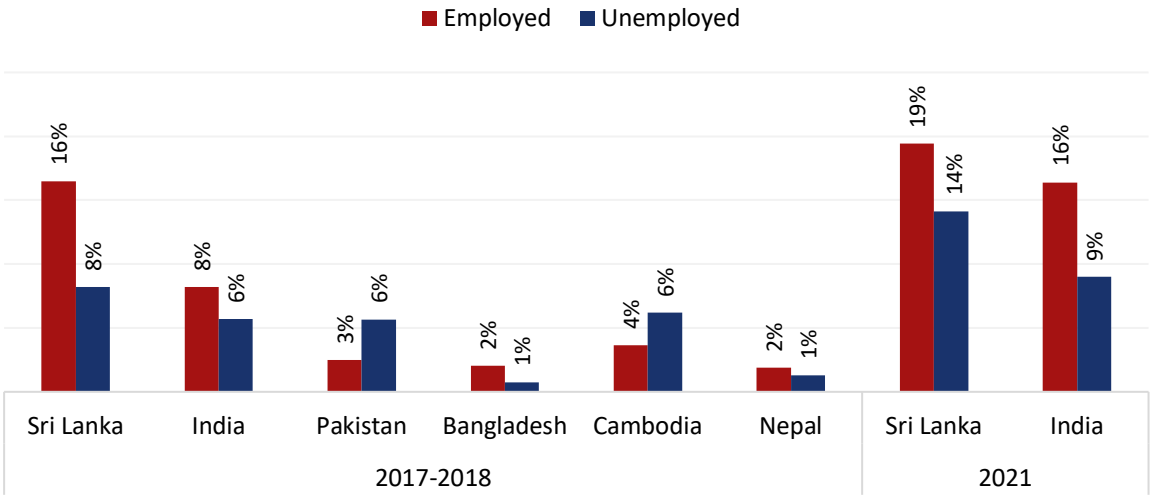
With Pakistan being the exception, a higher percentage of people from wealthy households used platforms to buy goods or services in 2017-18. The same pattern can be observed for Sri Lanka and India in 2021. There is a clear pattern demarcating a difference between SEC groups in terms of platform use for buying (Figure 73).

Figure 73. Use of at least one platform for buying goods or services by socio economic classification (percentage of age 15-65 population)



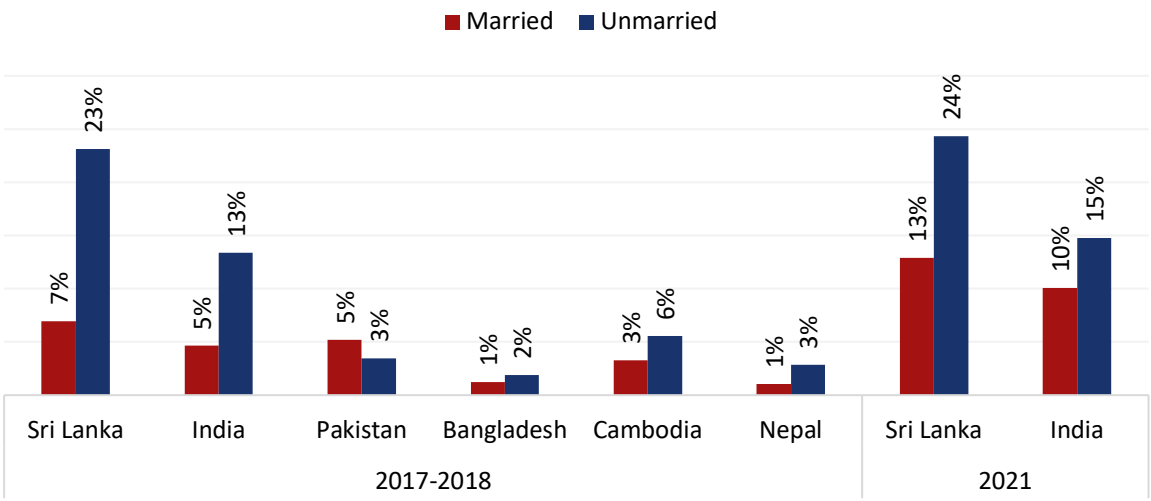
Employed population aged 15-65 were using platforms more for buying goods or services in all the countries studies except for Pakistan and Cambodia in 2017-18. It is important to note that the use of platforms for buying is very low in countries like Pakistan, Bangladesh, Cambodia, and Nepal In terms of the gap in platform use for buying within employed and unemployed population groups, Sri Lanka has seen a decrease in 2021, while India has experienced an increase in the same year (Figure 74).

Figure 74. Use of at least one platform for buying goods or services by employment status (percentage of age 15-65 population)



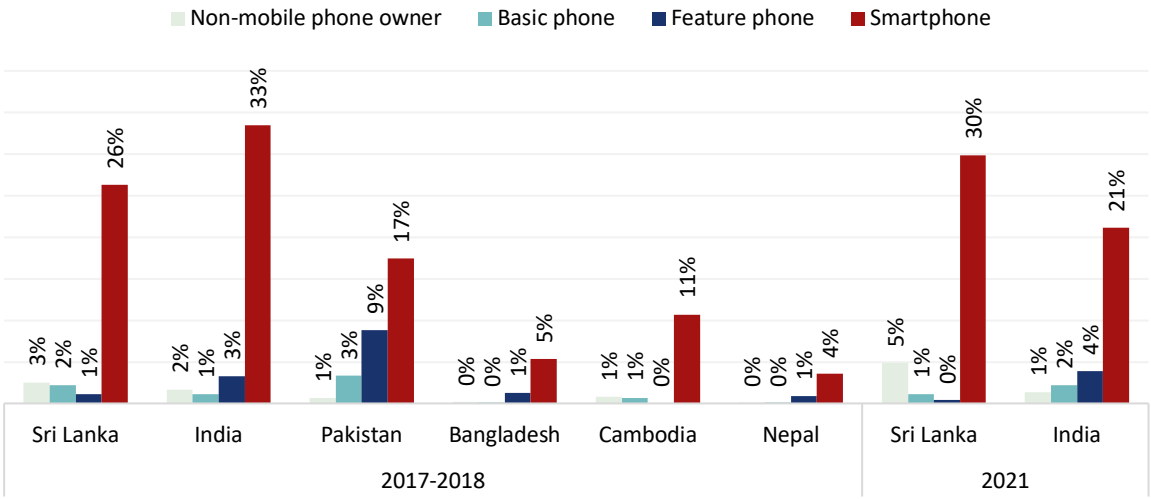
Unmarried people were more likely to use platforms for buying goods and services in both Sri Lanka and India in 2017-18. Unmarried people were also significantly more likely to use platforms to buy goods or services. The differences observed were marginal mainly due to the low use numbers for Pakistan, Bangladesh, Cambodia, and Nepal. The gap between the two has reduced in 2021 for both Sri Lanka and India (Figure 75).

Figure 75. Use of at least one platform for buying goods or services by marital status (percentage of age 15-65 population)



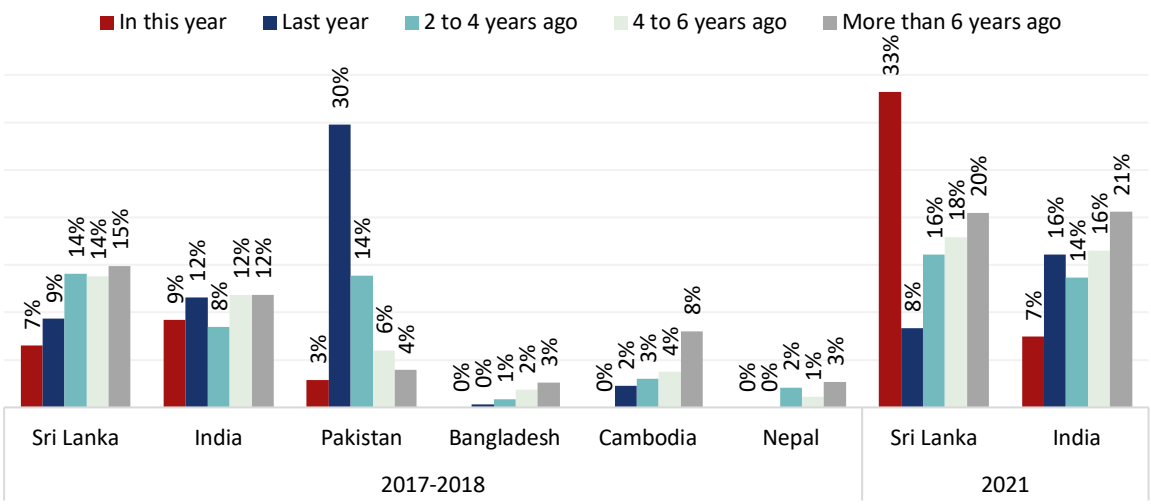
The type of mobile device owned is a critical factor for access online platforms. As mentioned before, smartphone owners generally have a higher level of digital literacy as well. Thus, the next chart shows a strong relationship with platform use for buying goods and services and the type of mobile device owned. The strong relationship was evident in all countries studied in 2017-18 even with the low usage levels for some countries. A similar pattern was observed in 2021. However, the percentage that used platforms for buying has reduced for India in 2021 (Figure 76).

Figure 76. Use of at least one platform for buying goods or services by type of mobile device owned (percentage of age 15-65 internet users)



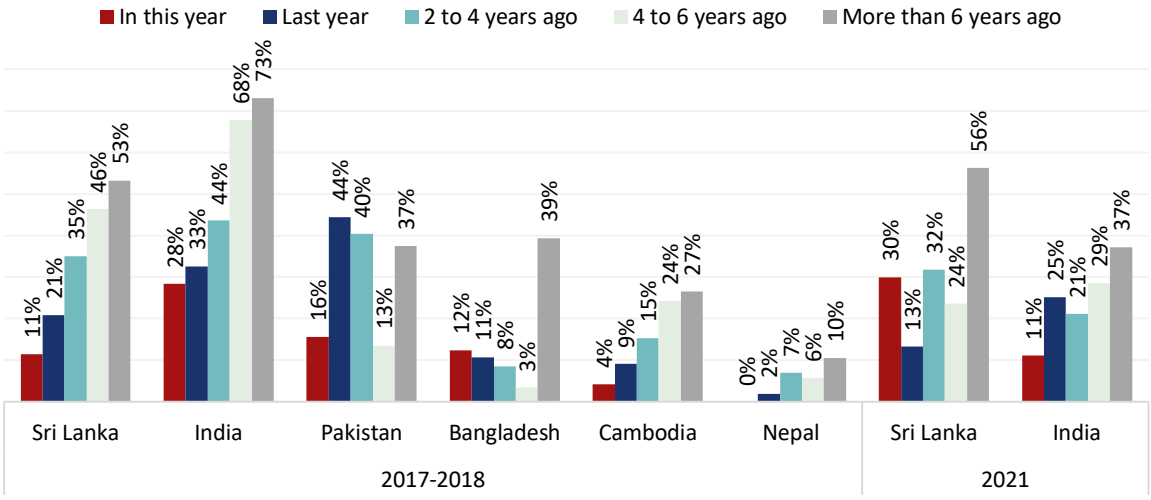
The length of time a person has owned a phone seemed to also be an important factor in their likelihood of having used a platform. In all countries except Pakistan, the longer a person owns a mobile, more likely he/she to have used at least one platform in 2017. However, in 2021 more than one third of the mobile phone users who bought their first ever mobile phone in the same year had used platforms to buy goods or services. This may indicate that the pandemic increased the demand for using platforms and also that some of the new phone owners bought a phone in order to use a platform (Figure 77).

Figure 77. Use of at least one platform for buying goods or services by time since first ever mobile phone use (percentage of age 15-65 mobile phone owners)



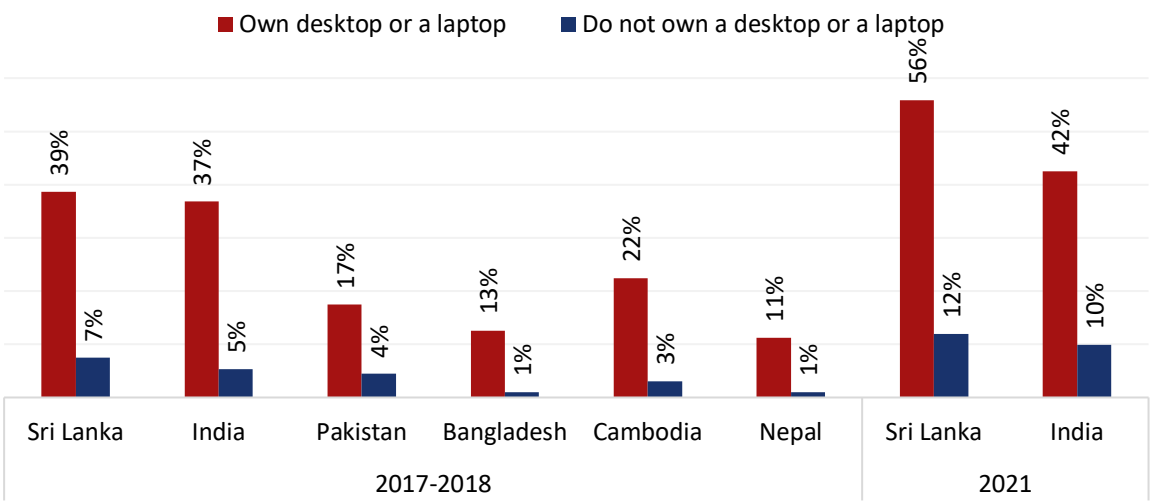
Experience with the internet also turns out to important, in addition to experience with a mobile phone. The length of ownership of a phone is important as seen. But so is the experience of the internet. With Pakistan and Bangladesh being the exceptions, a higher percentage of those who were using internet for a longer period of time had used platforms for buying goods or services in 2017-18. The same can be observed for India in 2021. However, Sri Lankan internet users exhibit a slightly different pattern in 2021 compared to 2018 (Figure 78).

Figure 78. Use of at least one platform for buying goods or services by time since first ever internet use (percentage of age 15-65 internet users)



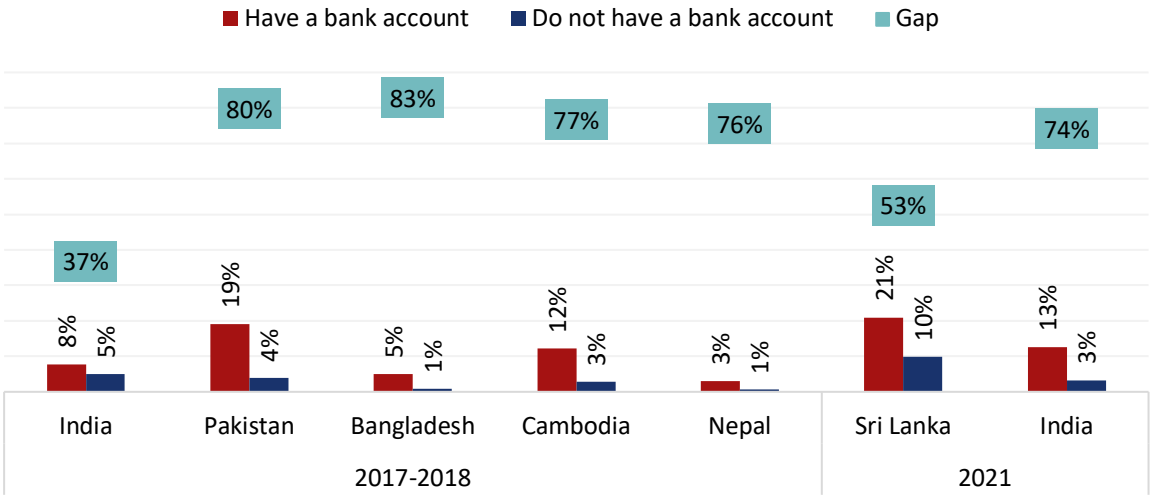
Those who owned desktop or laptop computers were significantly more likely to use platforms for buying goods or services via platforms in 2017-18. It is not surprising to see this relationship as computers are a better and convenient way to access the internet and platforms. Computer owners are also more tech savvy with a higher level of digital skills compared to the non-computer owners. The pattern remained the same in 2021 for both Sri Lanka and India (Figure 79).

Figure 79. Use of at least one platform for buying goods or services by computer ownership (percentage of age 15-65 population)



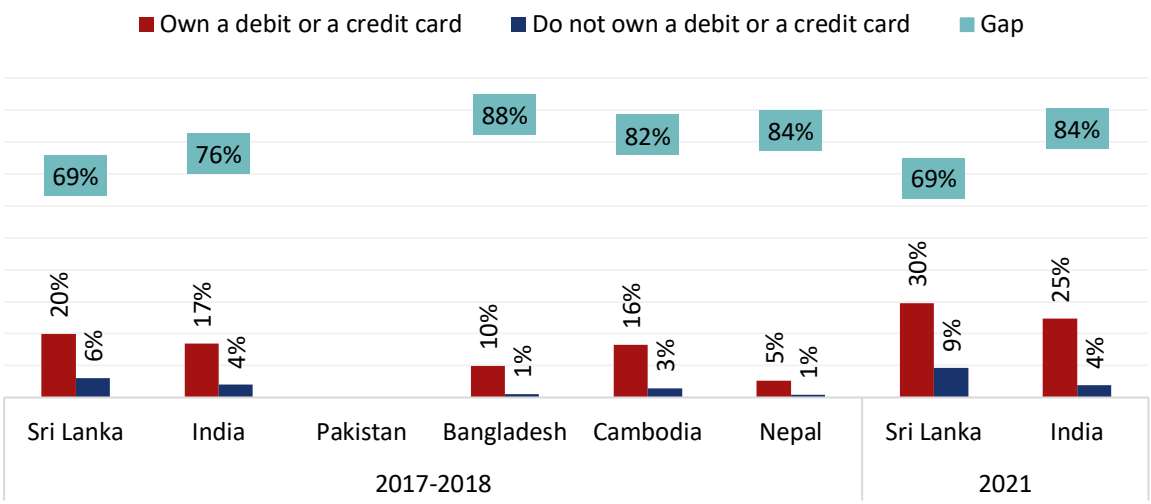
Owning a bank account is a crucial factor to make payments when purchasing goods or services online. The gap in buying product or services were very high among the countries studied which had low levels of bank account ownership in 2017-18. However, this gap has increased for India in 2021. These two countries had a high level of bank account ownership levels in 2017-18 as well as in 2021(Figure 80).

Figure 80. Use of at least one platform for buying goods or services by bank account ownership (percentage of age 15-65 population)



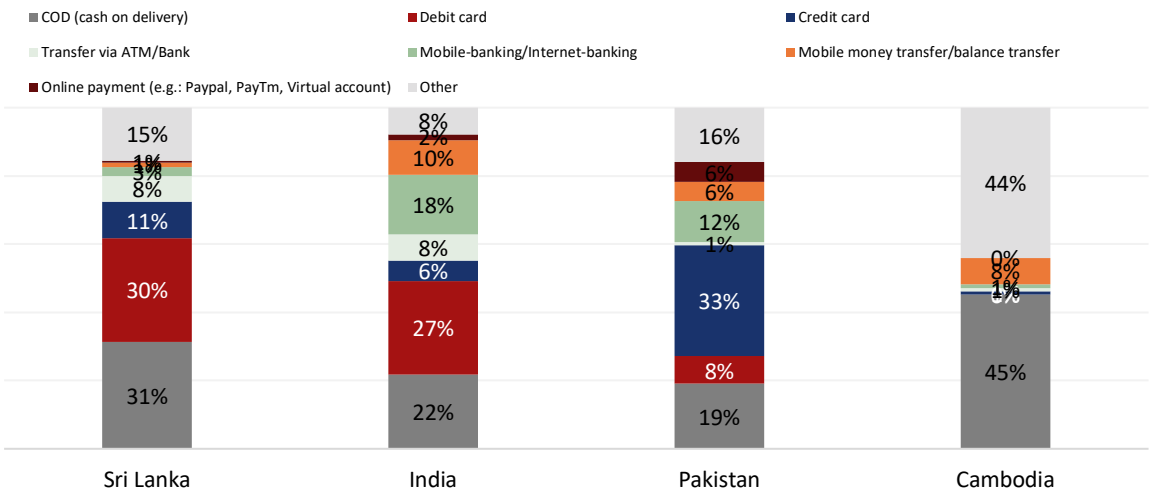
Owning a debit or credit card is an even more important when buying goods or services online. This is evident by the high platform use levels for buying among the debit or credit card owners across the countries studied in 2017-18. A similar gap is observed in 2021 confirming the importance of debit or credit cards for buying goods or services via platforms (Figure 81).

Figure 81. Use of at least one platform for buying goods or services by credit or debit card ownership (percentage of age 15-65 population)



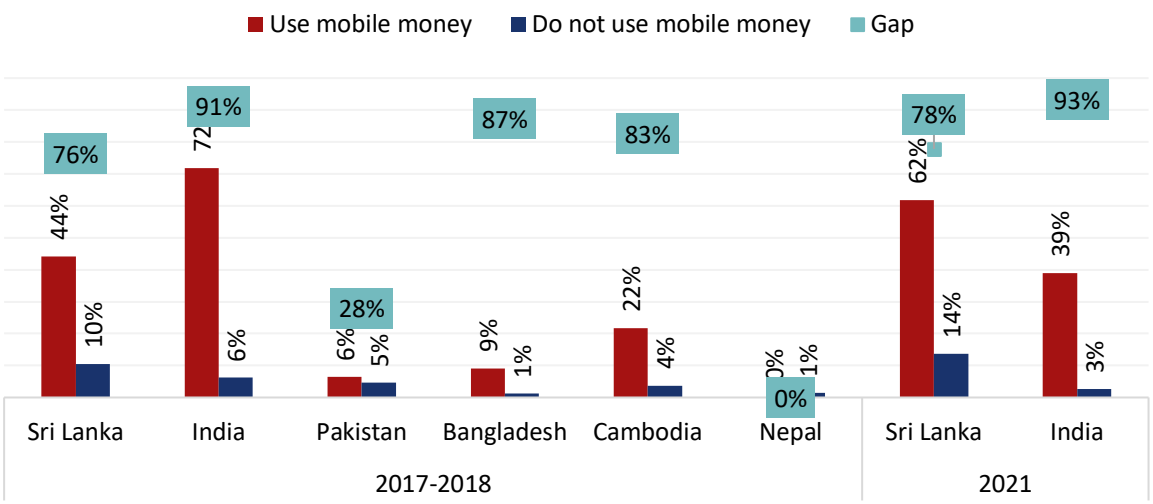
Debit and credit cards were among the most commonly used methods of making payments when transactions were facilitated via platforms (Figure 82).

Figure 82. Usual payment method for buying goods or services via at least one platform in 2017-18 (percentage of age 15-65 population who bought goods or services via platforms)



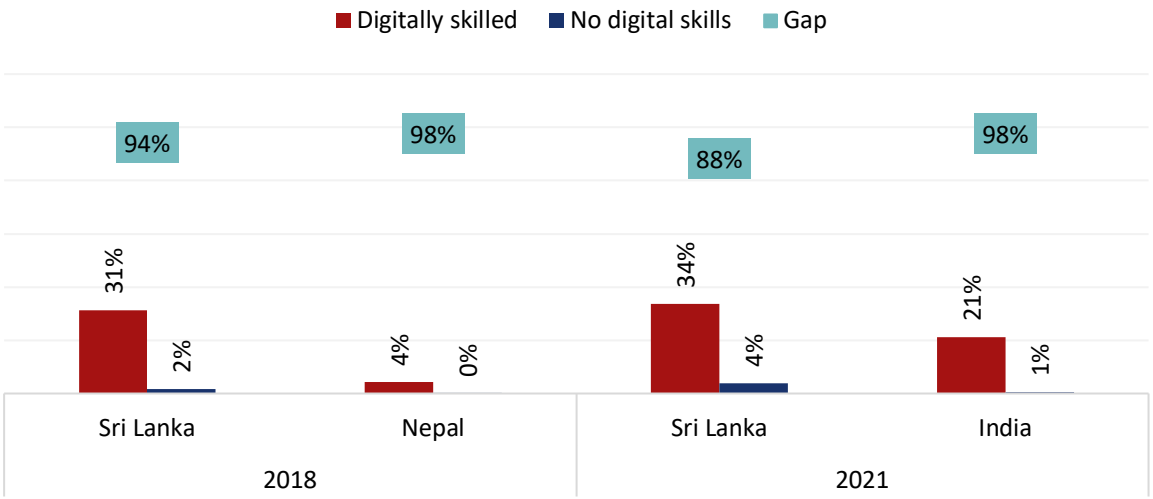
Mobile money too is a convenient way to make payments when buying goods and services via platforms. There was a clear distinction in platform use for buying between mobile money users and non-mobile money users. The gap remained at a similar level for Sri Lanka and India for 2021 as well(Figure 83).

Figure 83. Use of at least one platform for buying goods or services by mobile money use (percentage of age 15-65 population)



Digital skills are very important for buy goods or services online as it always required completing some digital tasks. As the below chart explains, people with digital skills are highly likely to use platforms compared to people without digital skills (Figure 84).

Figure 84. Use of at least one platform for buying goods or services by digital skills (percentage of age 15-65 population)



Chi-square test was used to test the significance of the relationship between the platform use for buying goods or services and the 15 facilitating factors discussed in the previously. Table 11 shows the results of the Chi-square test.

Education, SEC, type of device owned, computer ownership and time since first ever internet use has significant relationship with the platform use for buying across the countries. Digital skills is also significantly related to the instances where the variable is available.

Urbanity was not significantly related with platform use for buying in 2018 Sri Lanka and Pakistan in 2017. Gender was not a significant factor for Pakistan, Bangladesh and Cambodia. Employment status was not significant in Pakistan, Bangladesh, Cambodia and Nepal in 2017-18. Marital status is also not significant in Pakistan, Bangladesh and Cambodia. Pakistan is the only country where owning a bank account is not significantly related to platform use for buying goods or services.

Table 11. Chi-square significance for the variables discussed in the section with related to the overall use of platforms for buying goods or services.

Variable	2017-2018						2021	
	Sri Lanka	India	Pakistan	Bangladesh	Cambodia	Nepal	Sri Lanka	India
Urbanity		***		***	***	*	***	***
Gender	***	***				***	***	
Age	***	***			***		***	***
Education	***	***	***	***	***	***	***	***
Socio economic classification	***	***	***	***	***	***	***	***
Employment status	***	*					***	***
Marital status	***	***				***	***	***
Type of mobile phone owned	***	***	***	***	***	***	***	***
Time since first ever phone use		**					***	**
Computer (Desktop or Laptop) ownership	***	***	***	***	***	***	***	***
Time since first ever internet use	***	***	***	***	***	***	***	***
Bank account ownership	***	***		***	***	***	***	***
Debit or credit card ownership	***	***	-	***	***	***	***	***
Mobile money use	***	***		***			***	***
Digital skills	***	-	-	-	-	***	***	***

* The Chi-square statistic is significant at the .05 level.
** The Chi-square statistic is significant at the .03 level.
*** The Chi-square statistic is significant at the .01 level
- Data is not available

8.3 Country level drivers for platform use for buying

A binary logistic regression model has been used to understand the country level drivers. The model output is available in Table 12. The next few paragraphs explain the country level findings derived from the models.

Sri Lanka

In 2018, women were 56% less likely to buy goods or services via platforms. In 2021, this number has reduced to women being 30% less likely to use platforms for buy in 2021. Age also negatively related to platform use for buying in both 2018 and 2021. However, this was by a lesser margin in 2021. Owners of less sophisticated phones such as basic or feature phones were less likely to buy via platforms in both 2018 and 2021. The ownership of a bank account owners was less significant in driving purchasing via platforms in 2018, compared to being 20% more likely in 2021. Being married made individuals less likely to purchase goods via platforms in both 2018 and 2021.

Belonging to a SEC A household increased the odds of buying goods or services online by 3.6 times. The second biggest driver was owning a smartphone followed by owning mobile money account, desktop, or laptop ownership. Owning a mobile money account was the factor with highest odds related to buying goods or services online (5.8 times more), followed by belong to SEC A households, owning smartphones and desktop or laptops. having tertiary education increased the odds by 2.3 times in 2017 but changed to a negative relationship in 2021.

India

Being a woman slightly reduced (by 8%) the likelihood of buying goods or services via platforms in 2017. However, in 2021, this relationship flipped into a positive relationship where being a woman made an individual more likely to buy goods and services via platforms. Being elderly and being married reduced the likelihood to buy via platforms both in 2017 and 2021. Formally employed people were less likely to buy via platforms in 2017 but 40% more likely in 2021.

Tertiary education was the strongest indicator of the likelihood to buy through platforms – increasing the odds by 21 times. Having acquired a secondary education and at least having had a primary education increased the odds of using platforms for buying by more than 14 times. Socio economic classification is also positively related to buying via platforms in 2017. In 2021, the impact on buying of education reduced in but the impact on buying via platforms of socio-economic classification increased.

Pakistan

Being a women decreased the odds of buying goods and services via platforms by 85% in 2017/18. Being employed reduced the likelihood by 90%. Age too was negatively related with platform use for buying. Higher SEC had a similarly negative relationship, along with a low likelihood. Using a mobile money account was another factor that had a negative relationship with buying via platforms.

On the other hand, smartphone ownership increased the odds of buying by almost 50 times. Owning a feature phone was the second most potent factor, increasing the likelihood of buying by 21 times. This was followed bank account ownership that increased the likelihood by 6.5 times. Education too had a strong positive relationship. The tertiary educated were 5 times more likely to buy goods or services via platforms.

Cambodia

Being a woman made individuals in Cambodia 45% less likely to make purchases via platforms. The elderly was similarly less likely to buy goods and services through platforms.

Smartphone ownership increased the likelihood by 7.2 times. Tertiary educated increased the same by 7.14. Additional positive drivers of platform awareness were ownership of a mobile money account (5 times) and bank account ownership (2 times).

Nepal

In 2017/18, women in Nepal were 50% less likely to make purchases via platforms. The middle-aged population from the age bracket of 26 -45 were also less likely to do the same.

Belonging to SEC A made an individual 11 times more likely of utilizing platforms to make purchases. While this was the strongest driver, it was followed by smartphone ownership, which increased the likelihood by almost 7%.

Table 12. Binary logistic regression model for overall platform use for buying goods or services.

	2017-2018						2021	
	Sri Lanka	India	Pakistan	Bangladesh	Cambodia	Nepal	Sri Lanka	India
Nagelkerke R Square	0.419	0.463	0.442	0.307	0.366	0.288	0.430	0.425
Percentage of cases correctly classified by the model	90.1	93.6	95.2	98.6	96.5	98.5	87.1	89.4
Location: Urban (vs Rural)	(+) 1.264	(+) 1.33*	(+) 2.728***	(+) 1.482	(+) 1.579	(+) 2.181	(+) 1.668***	(+) 1.26**
Gender: Female (vs Male)	(-) 0.449***	(-) 0.92	(-) 0.147***	(-) 0.534	(-) 0.55*	(-) 0.499	(-) 0.7**	(+) 1.072
Age (15-25 years is the reference category)	***	***	***	...	...	...	***	***
26-35 years	(-) 0.498**	(-) 0.552***	(-) 0.378***	(-) 0.282*	(-) 0.775	(-) 0.302*	(-) 0.757	(-) 0.812
36-45 years	(-) 0.463***	(-) 0.501***	(-) 0.096***	(-) 0.275	(-) 0.536	(-) 0.141**	(-) 0.486***	(+) 1.245
46-55 years	(-) 0.293***	(-) 0.585	(-) 0.083***	(-) 0.344	(-) 0.118	(-) 0.618	(-) 0.361***	(-) 0.82
56-65 years	(-) 0.188***	(-) 0.239***	(-) 0.02***	(-) 0.187	(-) 0.527	(-) 0.719	(-) 0.367***	(-) 0.531*
Level of education (No education is the reference category)	...	***	*	...	***	...	***	***
Primary	(+) 1.88	(+) 14.265***	(+) 1.699	(+) 1.477	(+) 1.964	(+) 1.655	(-) 0.379	(+) 2.157*
Secondary		(+) 15.134***	(+) 2.798**	(-) 0.81	(+) 2.809*		(-) 0.289**	(+) 4.634***
Tertiary	(+) 2.304	(+) 21.293***	(+) 5.027***	(+) 4.104	(+) 7.148***	(+) 3.019	(-) 0.508	(+) 4.569***
SEC (SEC E is the reference category)	***	*	***	...	...	...	***	***
SEC A	(+) 3.618***	(+) 7.644***	(-) 0.319*	(-) 0.394	(+) 2.19	(+) 11.354*	(+) 4.313***	(+) 23.798*
SEC B	(+) 2.142*	(+) 9.279***	(-) 0.881	(-) 0.646	(-) 0.814	(+) 5.148	(+) 2.83***	(+) 15.093
SEC C	(+) 2.255**	(+) 8.558***	(-) 0.194***	(-) 0.657	(+) 1.299	(+) 4.099	(+) 2.237***	(+) 17.154
SEC D	(-) 0.829	(+) 6.94**	(-) 0.283***	(-) 0.694	(+) 1.282	(+) 5.263	(+) 1.972***	(+) 17.587
Employed	(+) 1.257	(-) 0.937	(-) 0.108***	(+) 1.873	(-) 0.978	(-) 0.92	(+) 1.403*	(+) 1.212

Married	(-) 0.652	(-) 0.827	(+) 4.162***	(+) 1.931	(+) 1.469	(+) 1.154	(-) 0.884	(-) 0.922
Type of mobile phone device owned (no mobile phone owned is the reference category)	***	***	***	**	***	...	***	**
Basic phone	(-) 0.657	(-) 0.488**	(+) 5.984***	(-) 0.47	(-) 0.774	(-) 0.737	(-) 0.238***	(+) 1.312
Feature phone	(-) 0.283	(+) 1.166	(+) 21.537***	(+) 3.436	(-) 0	(+) 3.497	(-) 0.014**	(-) 0.87
Smartphone	(+) 3.52***	(+) 8.022***	(+) 49.951***	(+) 9.814	(+) 7.288***	(+) 6.71	(+) 2.914***	(+) 1.759**
Own personal desktop or laptop	(+) 2.659***	(+) 2.85***	(+) 2.309	(+) 5.883***	(+) 1.632	(+) 2.045	(+) 2.445***	(+) 2.084***
Own a bank account	(-) 0.662	(-) 0.875	(+) 6.492***	(+) 2.144	(+) 2.445	(+) 1.065	(+) 1.204	(-) 0.872
Own debit or credit card	(+) 1.809***	(+) 2.018***		(-) 0.513	(-) 0.828	(+) 1.34	(+) 1.463**	(+) 1.801***
Own a mobile money account	(+) 3.026**	(+) 5.092***	(-) 0.263*	(+) 6.18***	(+) 4.905***		(+) 5.816***	(+) 9.169***
Constant	(-) 0.052***	(-) 0***	(-) 0.006***	(-) 0.002***	(-) 0.005***	(-) 0.001***	(-) 0.134***	(-) 0***

(+) Indicates a positive relationship with the dependent variable (platform use for buying).
(-) Indicates a negative relationship with the dependent variable (platform use for buying).
... Indicates the overall categorical variable is not significantly contributing to the model.
x Indicates that the category of the categorical variable is merged with the below category.
* The variable is significantly contributing to the model at the .05 level.
** The variable is significantly contributing to the model at the .03 level.
*** The variable is significantly contributing to the model at the .01 level.

Like the awareness model, introduction of the skills variable increased the model fit in each instance and had both positive and negative effects on the magnitude of the odds with other factors. The results of this model is available in Table 13.

Sri Lanka

Once the skills variable was introduced, digitals skills became the variable with the highest odds. The skilled were 5.8 times more likely to buy goods or services via platforms in 2018. Introduction of the digital skills variable resulted in a negative relationship for smartphone owners in 2018. In 2021, the skills were an important factor, but it was not the most influential.

India

In 2021, skills seem to have a stronger relationship as the skilled were 10 times more likely to buy via platforms. However, introduction of the skills variable increased the odds of wealthier (higher SECs) making purchases via platforms. It also reduced the odds of mobile money account owners from 9 times to 7.6.

Nepal

Digital skills were the biggest factor driving buying on platforms in Nepal. Like Sri Lanka in 2018, it made a directional change to the smartphone ownership variable. Which is to say, when all other factors remained constant (this includes skills - i.e., when skills variable was at 0 or non-skilled) smartphone owners were 32% less likely to buy goods or services online.

Table 13. Binary logistic regression model for overall platform use for buying goods or services including the skills variable

	2017-2018		2021	
	Sri Lanka	Nepal	Sri Lanka	India
Nagelkerke R Square	0.445	0.312	0.448	0.447
Percentage of cases correctly classified by the model	90.2	98.5	87.1	89.4
Location: Urban (vs Rural)	(+) 1.252	(+) 2.086	(+) 1.664***	(+) 1.241**
Gender: Female (vs Male)	(-) 0.477***	(-) 0.511	(-) 0.703**	(+) 1.123
Age (15-25 years is the reference category)	**	...	...	***
26-35 years	(-) 0.53**	(-) 0.317	(-) 0.863	(-) 0.87
36-45 years	(-) 0.511**	(-) 0.166*	(-) 0.639	(+) 1.385*
46-55 years	(-) 0.38**	(-) 0.756	(-) 0.491**	(+) 1.017
56-65 years	(-) 0.253***	(-) 0.785	(-) 0.546	(-) 0.684
Level of education (No education is the reference category)	...	...	***	***
Primary			(-) 0.35	(+) 1.924
Secondary	(+) 1.688	(+) 1.213	(-) 0.226***	(+) 3.263***
Tertiary	(+) 1.977	(+) 1.875	(-) 0.38	(+) 3.194***
SEC (SEC E is the reference category)	***	...	***	***
SEC A	(+) 3.177***	(+) 12.3*	(+) 3.952***	(+) 25.14*
SEC B	(+) 1.911	(+) 5.94	(+) 2.601***	(+) 16.241
SEC C	(+) 2.119**	(+) 4.072	(+) 2.072***	(+) 18.805
SEC D	(-) 0.805	(+) 5.517	(+) 1.891***	(+) 19.348
Employed	(+) 1.177	(-) 0.85	(+) 1.293	(+) 1.238*
Married	(-) 0.752	(+) 1.182	(-) 0.908	(-) 0.924

Type of mobile phone device owned (no mobile phone owned is the reference category)	**	...	***	*
Basic phone	(-) 0.407*	(-) 0.368	(-) 0.285***	(+) 1.67
Feature phone	(-) 0.129*	(-) 0.528	(-) 0.013**	(-) 0.574
Smartphone	(-) 0.904	(-) 0.681	(+) 2.337***	(-) 0.916
Own personal desktop or laptop	(+) 2.299***	(+) 1.939	(+) 2.096***	(+) 2.108***
Own a bank account	(-) 0.652	(+) 1.12	(+) 1.088	(-) 0.861
Own debit or credit card	(+) 1.575*	(+) 1.192	(+) 1.348	(+) 1.694***
Own a mobile money account	(+) 2.598*	(+) 0	(+) 5.657***	(+) 7.61***
Digital skills	(+) 5.869***	(+) 15.819	(+) 2.957***	(+) 10.274***
Constant	(-) 0.051***	(-) 0.001***	(-) 0.101***	(+) 0***

(+) Indicates a positive relationship with the dependent variable (platform use for buying).
(-) Indicates a negative relationship with the dependent variable (platform use for buying).
... Indicates the overall categorical variable is not significantly contributing to the model.
x Indicates that the category of the categorical variable is merged with the below category.
* The variable is significantly contributing to the model at the .05 level.
** The variable is significantly contributing to the model at the .03 level.
*** The variable is significantly contributing to the model at the .01 level.

8.4 Main reason for not using platforms for buying

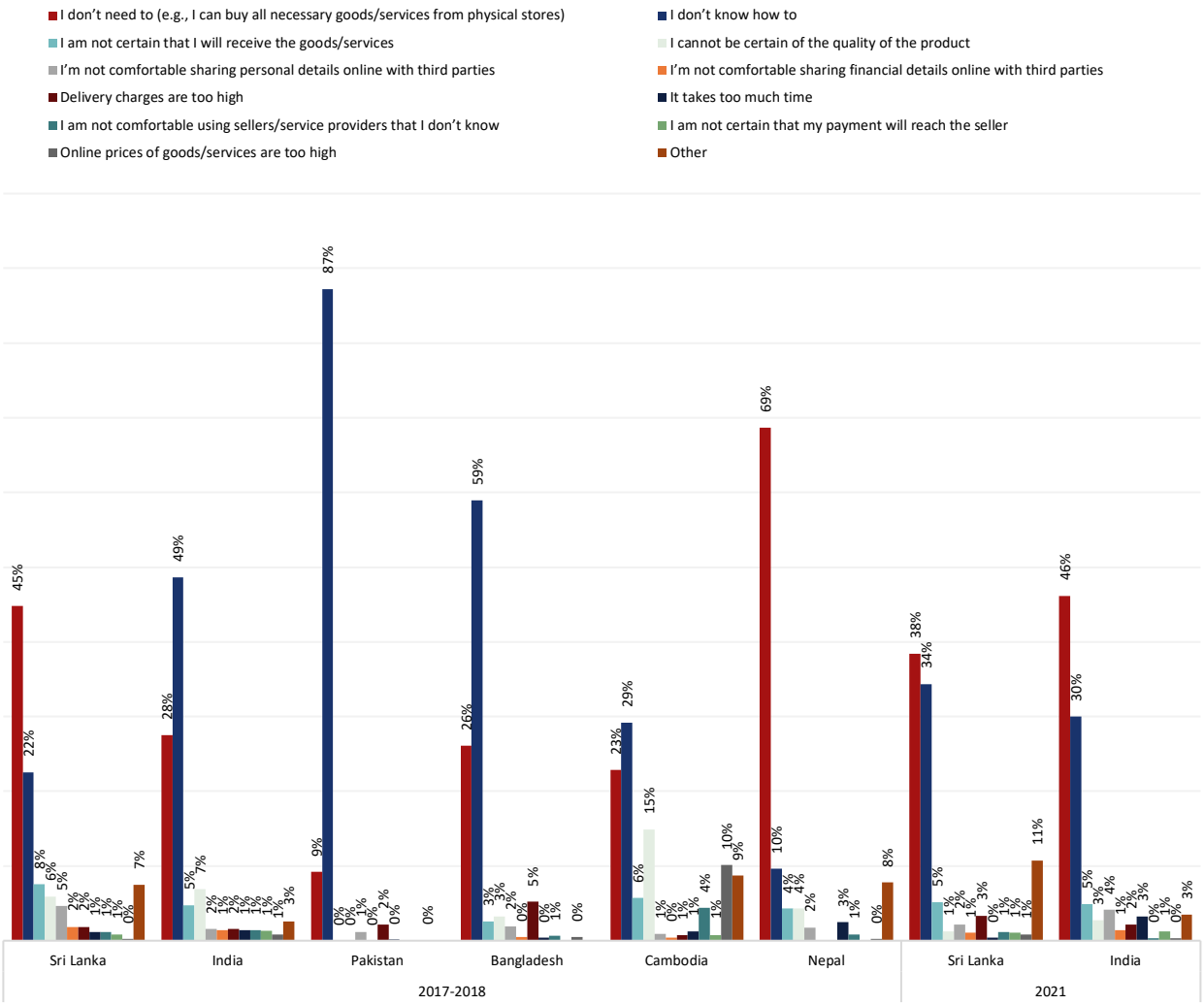
The respondents who were aware of the platforms but have not used for buying goods or services were asked " What is the primary reason you don’t buy goods/services through the Internet or mobile apps?".

Lack of knowledge on how to make the purchase was the main reason for not buying goods or services online for India, Pakistan, Bangladesh and Cambodia in 2017. Lack of need was the main reason for non-use for Sri Lanka and Nepal in 2018. These two were the top two reasons for not using platforms for buying products and services for all countries studied in 2017-18.

Lack of need was cited by less percentage of non-users (compared to 2018) for Sri Lanka in 2021, and the lack of knowledge reason was cited by a higher percentage of non-users (compared to 2018) in 2021. This can indicate an increase in the need to use among non-users as well as lacking the knowledge to do so. The lack of need was cited by a higher percentage of non-users (compared to 2017) and the lack of knowledge was cited by a lesser percentage of non-users (compared to 2017) for India in 2021 (Figure 85).

Lack of trust and concerns about the quality of the products is also evident across the countries studied in 2017-18 as well as in 2021.

Figure 85. Main reason for not using platforms to buy goods or services (percentage of age 15-65 population who are aware of the platforms but have not used for buying product or services)



Annex 3: Platforms for selling goods and services

9. Platforms for selling goods and services

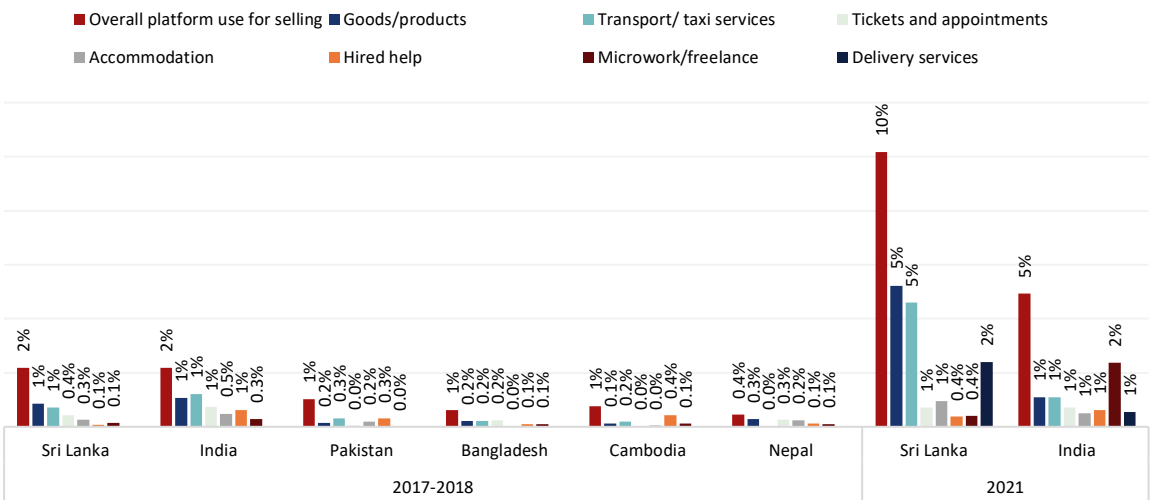
Digital platforms also provide an opportunity for individuals to sell goods and services and earn an income. In this section we look to understand trends around selling on digital platforms. We do this using a survey question, in which we asked those who claimed they were aware of the platforms if they have used the platforms for selling goods or service[39]. This enables us to understand how many sellers (e.g.: drivers, micro workers) are selling services using digital platforms in the 6 countries. We then take a high level look at descriptive statistics to understand variations based on socio-economic and demographic characteristics, after which country specific drivers are examined using binary logistic models (See Section 3.3 & 3.4). Sri Lanka data is not available for 2021.

It is important to note that not all the users we discussed here are current platform users who are using it to sell product or services. Therefore, the results can be a bit harder to explain.

9.1. High level trends of platform use for selling

As Figure 86 shows, platform use for selling goods or services was very low across the 6 countries studied in 2017-18.

Figure 86. Use of the platforms for selling goods or services (percentage of age 15-65 population)



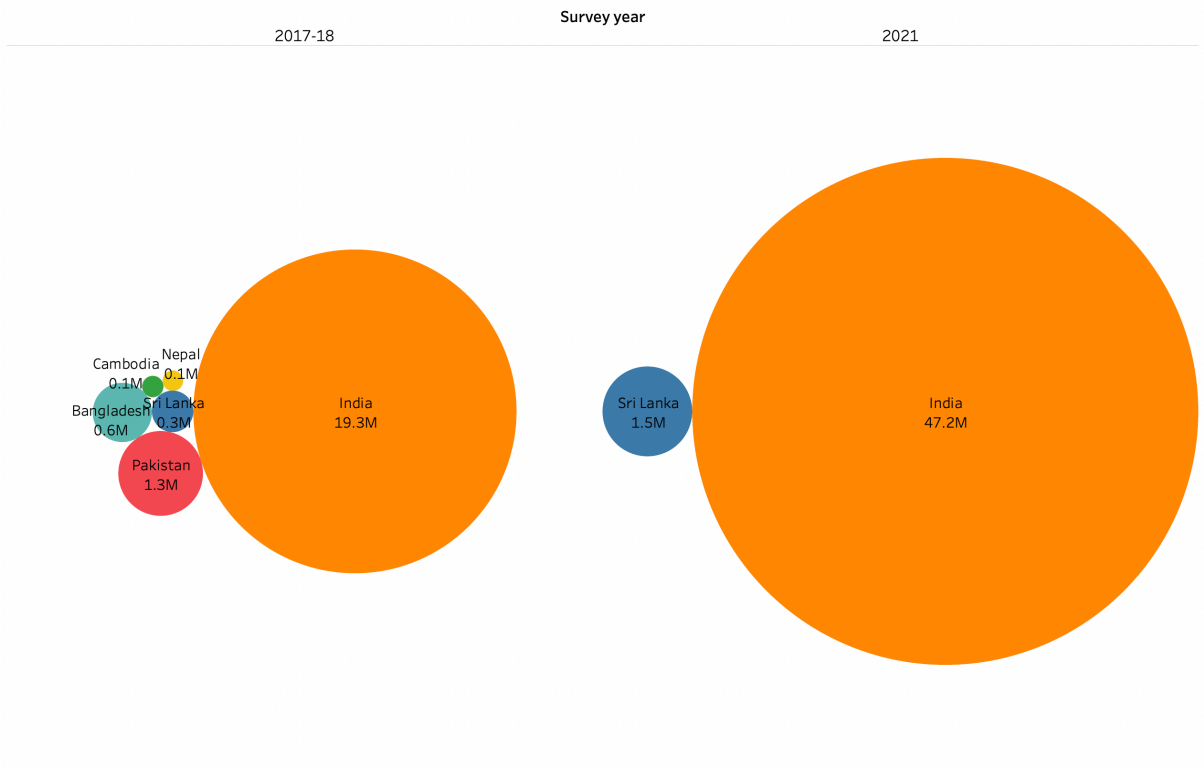
As shown in Figure 86, only one percent of the population in Pakistan, Bangladesh & Cambodia were selling goods and services of platforms in 2017/2018. Even in Bangladesh, a country with a population of ~ 160 million, this amounted to less than one million people (Figure 87). This was true of about 1.3 million people in Pakistan.

Two percent of the population in India and Sri Lanka were using platforms to sell goods in 2017/2018. This amounted to over 19 million individuals in India, given its large population size.

[39] The numbers have converted to age 15-65 base. The survey question used was " Have you used Internet platforms/apps to sell goods or services of the following types?". The local examples were provided in the questionnaire for the buying section as well. The overall use of platforms for selling goods or services included an "other platforms" category option in 2017-18, while the "Delivery services" platforms were considered in the overall use for buying for 2021.

ASSOCHAM (2020)[40] also reported that this market in India is valued at ~USD 1 billion. Meanwhile the global market was valued at between USD 2 and 3 billion. Furthermore, this is an area in which India has seen much growth, with the number of digital platform workers more than doubling to 42 million by 2021 (5% of the population aged 15-65). This growth in India was mainly driven by the growth in the service offerings of microwork and freelance platforms -- in 2021, 23 million people aged 15-65 were working on microwork and freelancing platforms.

Figure 87. Overall market size for selling goods or services via platforms (age 15-65 population)



It was difficult for use to derive meaningful findings for the selling section due to the low bases. Hence, further descriptive analysis as well as the logistic regression modeling will not be carried out for platform use for selling.

9.2. Main reason for not using platforms for selling

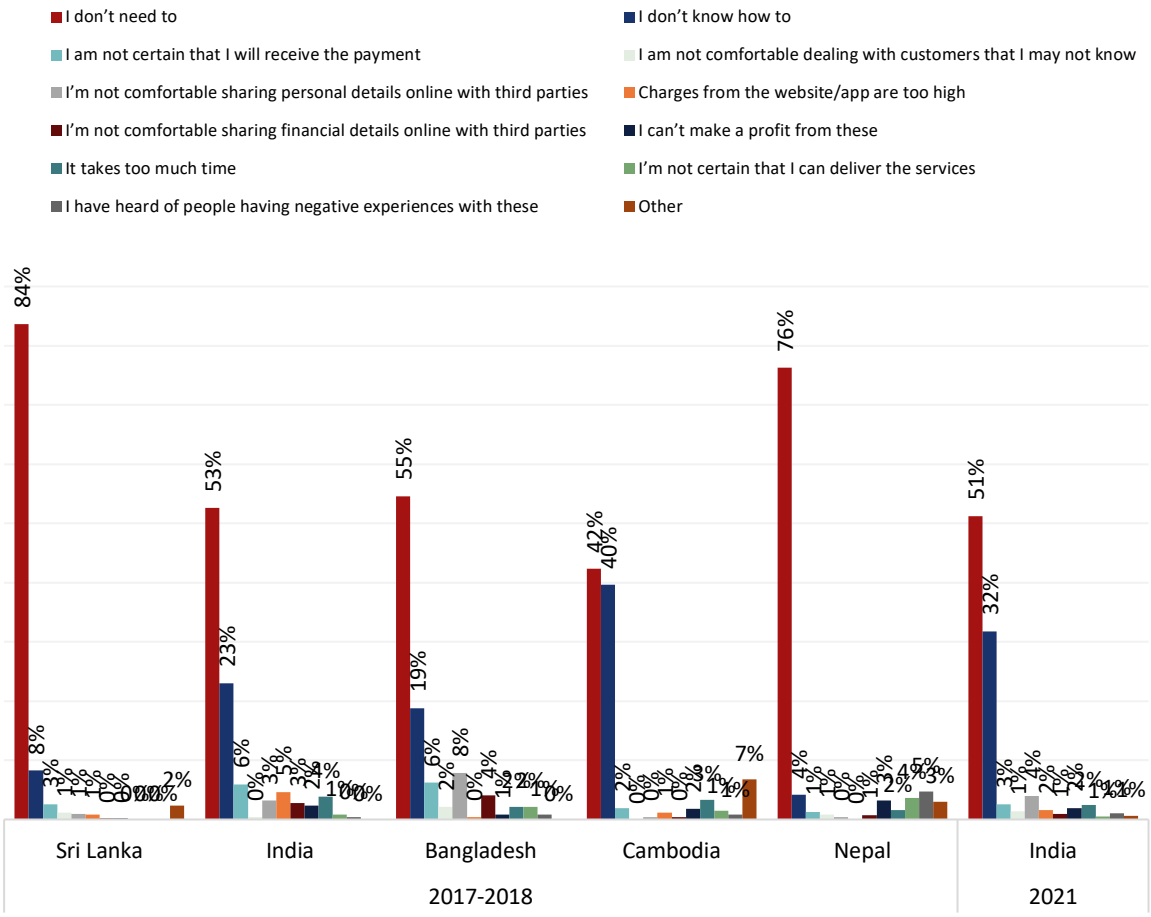
Those who are not using platforms for selling products or services were asked " What is the primary reason you don't sell goods/services through the Internet or mobile apps?".

As per the stated primary reason shown in Figure 88, the non-use of platforms for selling goods and services is mainly driven by the lack of need for all countries. Lack of knowledge had a similar importance for Cambodia in 2017. The lack of need was remained in a similar level for India in 2021. However, lack of knowledge has become the primary reason for a higher percentage of Indian non-users in 2021.

Trust related issues ("I am not certain that I will receive the payment") and privacy related issues such as sharing personal information are also among the cited reasons compared to others. It is worth to note that the percentages for these categories are still less than 10%.

[40] https://www.assocham.org/uploads/files/1628143386.pdf

Figure 88. Main reason for not using platforms to sell goods or services (percentage of age 15-65 population who are aware of the platforms but have not used for selling product or services)[41]



[41] Data is not available for Pakistan in 2017 and Sri Lanka in 2021

Annex 4: Platforms use model with gender interactions

10. Platform use model with gender interaction terms

When we look at the gender interaction terms, the trends are similar within each gender. For example - both urban men and women were more likely to use platforms in comparison to their rural counterparts. The more educated of both the genders were more likely to use platforms. Those who were in possession of digital skills were more likely to use platforms. Nevertheless, when both genders were compared, i.e, compared at the reference category (who are men without access to facilitating factors), it was observable that women were severely less likely to use platforms.

A few examples are given below.

- Digitally skilled men were 5 times more likely to use platforms compared to men with no digital skills. Digitally skilled women had similar odds of using platform as men with no digital skills.
- Men from SEC A households were 2.6 times more likely to use platforms than men from SEC A households. However, women from SEC A households were 40% less likely to use platforms as SEC A men.
- Owning a smartphone increased the odds of men using platforms by 1.4 times compared to men that do not use a mobile phone. However, women that own smartphones were 36% less likely to use platforms compared to men that do not use smartphones.
- Tertiary educated men were two times more likely to use platforms compared to men without the same. However, tertiary educated women were 40% less likely to use platforms compared to non-tertiary educated men.
- Men who use cashless payment methods were 4.3 times more likely to use platforms compared to men who do not use cashless payment methods. However, Women who use cashless payment methods are 48% less likely to use platforms when compared with men who do not use cashless payment methods.

Table 14. Binary logistic regression model for overall platform use with gender interaction term for all variables.

Nagelkerke R Square	0.396
Percentage of cases correctly classified by the model	88.1
Location: Urban (vs Rural)	(+) 1.345***
Gender: Female (vs Male)	(-) 0.215**
Location*Geneder interaction	(+) 1.211
Age (15-25 years is the reference category)	***
26-35 years	(-) 0.718**
36-45 years	(+) 1.031
46-55 years	(-) 0.603**
56-65 years	(-) 0.42***
Age*Gender interaction	**
26-35 years*Gender interaction	(+) 1.733**
36-45 years*Gender interaction	(+) 1.055

46-55 years*Gender interaction	(+) 1.812
56-65 years*Gender interaction	(+) 2.55*
Level of education (No education is the reference category)	***
Primary	(+) 1.232
Secondary	(+) 1.518
Tertiary	(+) 2.154**
Level of education*Gender interaction	*
Primary*Gender interaction	(+) 1.292
Secondary*Gender interaction	(+) 2.047
Tertiary*Gender interaction	(+) 1.317
SEC (SEC E is the reference category)	***
SEC A	(+) 2.685***
SEC B	(+) 1.477
SEC C	(+) 1.404
SEC D	(+) 1.417
SEC*Gender interaction	...
SEC A*Gender interaction	(+) 1.035
SEC B*Gender interaction	(+) 1.209
SEC C*Gender interaction	(+) 1.232
SEC D*Gender interaction	(-) 0.917
Employed	(+) 1.218
Employment status*Gender interaction	(-) 0.917
Married	(+) 1.061
Martital status*Gender interaction	(-) 0.668
Type of mobile phone device owned (no mobile phone owned is the reference category)	***
Basic or feature phone	(-) 0.491**
Smartphone	(+) 1.405
Type of mobile phone device owned*Gender interaction	...
Basic or feature phone*Gender interaction	(+) 1.766
Smartphone*Gender interaction	(+) 2.118**
Own personal desktop or laptop	(+) 2.297***
Personal desktop or laptop ownership*Gender interaction	(+) 1.089

Own a bank account	(-) 0.741
Bank account ownership*Gender interaction	(+) 1.664*
Use cashless payment method (mobile money or credit/debit cards)	(+) 4.272***
Cashless payment method*Gender interaction	(-) 0.618**
Digital skills	(+) 5.053***
Digital skills*Gender interaction	(-) 0.925
India	(-) 0.3***
Country*Gender interaction	(+) 1.001
Constant	(-) 0.018***
(+) Indicates a positive relationship with the dependent variable (platform use for buying). (-) Indicates a negative relationship with the dependent variable (platform use for buying). ... Indicates the overall categorical variable is not significantly contributing to the model. * The variable is significantly contributing to the model at the .05 level. ** The variable is significantly contributing to the model at the .03 level. *** The variable is significantly contributing to the model at the .01 level.	

Table 15. Contingency table for odds ratios for gender interaction terms

Variable	Sub-category	Men	Women
Location: Urban (vs Rural)	Rural	1	0.215
	Urban	1.345	0.350
Age	15-25 years	1	0.215
	26-35 years	0.718	0.267
	36-45 years	1.031	0.234
	46-55 years	0.603	0.235
	56-65 years	0.420	0.230
Level of education	No education	1	0.215
	Primary	1.232	0.342
	Secondary	1.518	0.668
	Tertiary	2.154	0.610
SEC	SEC E	1	0.215
	SEC A	2.685	0.597
	SEC B	1.477	0.384
	SEC C	1.404	0.372
	SEC D	1.417	0.279
Employment status	Unemployed	1	0.215
	Employed	1.218	0.240
Marital status	Unmarried	1	0.215
	Married	1.061	0.152
Type of mobile phone device owned	No mobile phone	1	0.215
	Basic or feature phone	0.491	0.186
	Smartphone	1.405	0.639

Desktop or laptop ownership	No	1	0.215
	Yes	2.297	0.538
Bank account ownership	No	1	0.215
	Yes	0.741	0.265
Use cashless payment method (mobile money or credit/debit cards)	No	1	0.215
	Yes	4.272	0.568
Digital skills	Not digitally skilled	1	0.215
	Digitally skilled	5.053	1.005
Country	Sri Lanka	1	0.215
	India	0.300	0.065