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Determinants of Demand in Digital Platform-Mediated Service Work in Turkey: An Empirical Study

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Abstract: Despite claims that digital platform-mediated jobs may have negative consequences for the labor market, empirical evidence supports the existence of positive effects, especially for low-paid and low-skilled service jobs. Comparative studies on the characteristics, working conditions, and earnings of workers who perform these jobs on digital platforms are becoming widespread. However, there needs to be more literature regarding the demand side of digital platform-mediated service jobs. This study aims to determine the factors affecting the demand for digital platform-mediated services using a dataset obtained from a comprehensive survey conducted by Turkish Statistical Institute (TurkStat) throughout Turkey. The study uses the probit econometric model with a qualitative dependent variable. The results show that the income level of the individuals, the characteristics of the region where they live, and the familiarity of individuals with digital platforms significantly affect the demand for digital platform-mediated services. The findings demonstrate that specifically middle-income individuals, compared to individuals in other income groups, individuals residing in areas with high population density, compared to individuals in other regions, and individuals with Internet familiarity, compared to other individuals, exhibit a higher demand for digital platform-mediated services.

Keywords: digital labor platform; digital labor demand; circular economy; sharing economy; logit/probit model; discrete dependent variable model

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1. Introduction

The digitalization process has brought a new economic change and transformation that emerged with concepts such as the "Sharing Economy", "Gig Economy", and "Platform Economy" [1]. Digital platforms, the driving forces of this process, also called the online platform economy, have emerged with different purposes and functions [2]. However, platforms, in general, consist of capital platforms such as eBay and Airbnb for the renting or buying and selling of goods, and workforce platforms that bring customers and employees together for various services such as Uber and TaskRabbit [3]; while this distinction is not perfect [4], this distinction is valid for the basic meaning of the digital labor market concept as many capital platforms also require the application of productive labor (for example, using Airbnb for room rental, which includes cleaning, maintenance, and other service functions). Digital workforce platforms refer to a system where labor supply and demand are matched online or through mobile applications. Stating that there is a triangular relationship between the workforce that produces or performs the service, the end user of the service, and the digital platforms that facilitate matching, De Stefano [5] has categorized platforms in a dual classification:

a. "Crowdwork" systems are workforce platforms where job bidding and completion can be performed through open websites, and the platform's responsibility is to bring the workforce and end users of services together.
b. This type of work, also called "working on demand" [6], includes traditional work activities that express physical tasks such as transportation and cleaning. Platforms established for this purpose are responsible for workforce selection, management, and service quality.

On the other hand, Schmid [7] distinguishes digital workforce platforms by asking two questions: "Is the job tied to a particular place?" and "Is the job tied to a particular individual?". A "cloud" job is a job that can be performed from anywhere, regardless of place. If it can be performed by anyone and given to an unknown group, it is work performed with a crowd. A gig is a job that has to be performed in a particular place and is given to a chosen person. If the work requires a place and can be given to the crowd, this is also in the scope of crowd work for gig jobs. This distinction made for gig work is mainly related to the situation in which the person who will do the work can be selected. Unlike web-based platforms, this type of digital platform-mediated work is generally for individuals, as in the examples of TaskRabbit and Uber, is performed at the local level and is usually related to concrete tasks such as transportation, delivery, and home services [8,9]. This article focuses on digital platform-mediated jobs that require a place, and in most cases, the individual who will do the job can be selected.

It is emphasized that the platforms have become an essential actor in the economic operation at the micro and macro scale in studies that position platforms in a digital ecosystem, generally as an intermediary for the producer (seller or service provider) and consumer [10,11]. Considering digital workforce platforms, the literature draws particular attention to how platforms change the nature of work and how they affect labor dynamics between employers and employees [12]. Within the scope of gig work, platforms that mediate between employers and service providers by changing the nature of work [13,14], unlike standard employment, may cause some problems [15–17]. It is stated that platform-based work inherently causes problems that have become chronic in the labor market, such as insecurity, low wages, variable income streams, and no regulation regarding social security [18–20]. Minter [21] stated that platform work without legal employment regulations and costs undermines traditional labor standards.

On the other hand, Stanford argued that platforms do not cause these non-standard working conditions, which have existed since the beginning of capitalism [22]. Accordingly, insecurity, low wages, etc., in many jobs such as seasonal work, contracted work, transportation, and personal services have occurred even before the platforms. Problems are long-standing business features. Similarly, Flanagan [23] stated that adverse working conditions such as low wages, low status, and uncertain working hours were valid, especially for home-based service workers in the 19th and 20th centuries. At this point, the innovations created by digital platforms for low-paid and insecure jobs, such as home services, may bring about some improvements. Digital platforms can allow employees to switch from one job to another without problems instead of being regular employees and determine flexible working hours or days according to them [22–24]. Some researchers have stated that platforms can provide new opportunities for unemployed individuals to find jobs and earn income, especially for the disadvantaged workforce [25,26]. At this point, platforms can offer the opportunity to find a permanent job and earn higher wages than are traditionally paid at a certain level for these low-paid jobs [27].

As emphasized by De Stefano [5] and Schmidt [7], digital platforms, which include physical tasks such as transportation, house cleaning, and personal services and act as intermediaries for jobs that require a place, can allow the selection of the person to perform the work or are related to the selection, management, and service quality of the workforce. Moreover, the management may be responsible for the job performed under its supervision. This means a certain level of trust for service buyers. The "reputation rating systems" used by digital platforms refer to a system where employees can add information about themselves and show the quality of the work they will perform with feedback from their previous work [13]. Lehdonvirta et al. [28] stated that this system could be a signal source for both the employee and the service requester. Tanz proposed a similar idea and stated that rating systems establish trust for service providers and users and that digital platforms are the "currency" [29]. On the other hand, digital platforms can allow the price of the task to be determined for employees based on an algorithm, unlike traditional companies and, in some cases, at a higher level [27]. It is understood that digital platforms are inevitable for economic functioning and may not necessarily cause negativities for the labor market under all circumstances. Within this scope, it is understood that digital platforms provide certain advantages such as influencing pricing and offering flexible working hours, which are particularly beneficial for low-paid jobs with relatively poor working conditions such as house cleaning and personal care. When accepting these advantages offered by digital platforms, the research question of this study emerges as follows: What are the factors that platforms or workers aiming to provide services through digital platforms need to consider in order to reach a larger audience? Unlike the existing literature, this research question can be addressed by obtaining important insights related to the demand side of digital platform-mediated jobs. In fact, the literature primarily focuses on the characteristics of those providing these services. This study presents an important novelty by focusing on the demand side. When theoretically discussing the influential factors regarding the demand for service through digital platforms, certain key features come to the forefront. Among these, economic characteristics are of utmost importance [30]. The demand for these services is associated with the utility individuals can derive from them, particularly in relation to the price of the relevant service. Individuals are motivated to use these platforms because they can obtain the services in question through new business models, which offer more flexibility and pricing options, thus emphasizing the economic benefit [31,32]. In this context, considering income, it is believed that individuals with moderate income levels may have a higher demand for digital intermediary services compared to those with low or high incomes. Another important feature is related to the geographical region individuals reside in. In regions with high population density, both the supply and demand levels are high, allowing individuals to have more choices and demand a greater variety of services [33]. Within the scope of this article, it is also believed that regions in Turkey with high population density may exhibit higher demand for digital platform-mediated services. Other naturally expected features that may influence demand in digital platform-mediated jobs are related to familiarity with e-commerce. The interest individuals have in e-commerce and the frequency of their transactions, both in terms of economic value and quantity, indicate a high level of familiarity with digital platforms and suggest that this familiarity can lead to increased demand [34]. Consequently, individuals who engage more in e-commerce are presumed to have a higher level of demand for digital intermediary services.

Considering the increasing unemployment rates and low wages, especially in developing countries such as Turkey, it is understood that digital platform-mediated jobs can have significant economic contributions. The primary purpose of this article is to identify the factors affecting the demand for these digital platform-mediated service works and to develop recommendations for service providers. Furthermore, digital platforms serve as important facilitators of the transition to a circular economy, which leads to better environmental and social outcomes in addition to economic impacts [35]. In this context, another aim of the article is to develop recommendations for policymakers by promoting digital platform-mediated service work.

In the subsequent sections of the study, under the title of "Literature Review", empirical studies related to the topic are discussed, and how this study can fill the gap in the literature is explained. The study used binary choice models due to the qualitative and binary structure of the dependent variable. Among these models, the binary probit model was determined to be suitable considering the criteria for model preference. The dependent variable in the study is the individuals' utilization of digital platform-mediated services, which is dichotomous, indicating whether they engage in such services or not. As explanatory variables, various demographic characteristics of households (such as gender, education level, age, and geographical location), socio-economic attributes (household income, employment status), and variables related to Internet usage (e-commerce activities, social media usage, etc.) were included. This study, which specifically utilizes a rich dataset, distinguishes itself from previous literature by focusing on binary qualitative choice models. Within this framework, the following sections of the study provide information about digital platforms operating in Turkey, followed by a description of the data and research methodology. The results of the conducted analyses are then presented. These findings are discussed in connection with the literature, from a theoretical perspective, in the discussion section. The conclusion section summarizes the overall findings of the article and provides recommendations for service providers and future research endeavors.

2. Literature Review

As stated above, this article focuses on digital platform-mediated service jobs that require a place and involve physical tasks. These on-demand jobs generally appear as low-skilled and low-paid jobs [6]. Empirical evidence on the characteristics of employees on popular digital workforce platforms (Uber, TaskRabbit, Upwork) established for on-demand work reveals that the employees on these platforms attach great importance to determining their work hours and are more profitable in terms of earnings [36–38]. Wu et al. [39] emphasized that earnings and platform valuation systems are essential for those who use Uber as their sole source of livelihood. Flexible working hours are essential for drivers with other jobs who use Uber to earn additional income. Ticona and Mateescu [40] carried out content analysis on platforms for maintenance work. The platforms assumed a role in an attempt to formalize the previously unofficial maintenance work. Studies focusing on determining the demographic characteristics of employees on digital platforms have stated that service providers generally have a high level of education and full-time jobs [41] and aim to earn additional income by working low-income jobs [42]. Chernykh [43], on the other hand, investigated the demographic characteristics of employees on 55 platforms serving in the USA, EU, and Russia. Accordingly, on average, those working on the platforms are ten years younger than those working in traditional jobs, and the proportion of men is higher than women. On the other hand, Bissell [44] claimed that platform usage is mainly related to geographical and urban features. Unlike other authors, Li and Wen [45] conducted an empirical study on the supply and demand aspects of the digital labor market. In their study, it was revealed that low-wage jobs are more advantageous than the traditional method via platforms. Therefore, traditional firms demanding low-paid jobs must compete because they lack a labor supply. In the empirical studies mentioned, it is seen that empirical evidence is generally obtained using interviews, questionnaires, and content analyses (secondary data are used in very few of them). The paucity of empirical studies on digital workforce platforms is mainly due to the lack of sufficient and comparable data for empirical applications [46].

Although the debate on the positive or negative effects of digital platforms on the labor market continues, it is stated that it offers some improvements, especially for digitally mediated low-wage jobs. As discussed by Stanford [22] and Flanagan [23], it is accepted that especially non-standard working conditions for these jobs are not a novelty brought by platforms. These conditions have become features of these jobs, while digital platforms are not yet. On the contrary, digital platforms may perform an essential function in a formalization attempt against traditional works [40]. Platform-mediated jobs are primarily flexible, autonomous, and well paid. These relative advantages encourage individuals with low-skilled or low-paying jobs to work on digital platforms [45].

On the other hand, it is stated that digital platforms may have opportunities such as self-employment and gaining prestige through platforms for this workforce group [46]. For these reasons, it is essential to understand how to work on demand [37]. To understand the operation of these platforms, evidence is needed on three issues; the features of the platforms are the characteristics of the service providers (the supply side of digital labor markets), and the end users of the services are the customers (the demand side of the digital intermediary businesses). There is little evidence of the characteristics of digital platforms and the supply side of digital labor markets. Empirical studies investigating the characteristics of demand in digital platforms are generally in the context of elements of the sharing economy, such as room sharing and car calling, which do not require service and work [30,34,45,47–49].

In contrast, there is a lack of empirical evidence on the demand side of digitally mediated jobs, also called "work on demand". This study explores the comprehensive survey data collected by TurkStat in Turkey, including factors affecting demand for digitally mediated, localized home services (such as cleaning, babysitting, repair work, and gardening). As the dataset in question includes data on demand for services directly mediated by digital platforms without distinction between platforms, it also considers capital platforms that require the application of productive labor, as discussed by Stewart and Stanford [4]. The large dataset of the study addresses an essential deficiency that the literature also draws attention to [46,50]. This study, with this dataset, profoundly contributes to the literature by empirically examining the factors affecting the demand for digital platform-mediated service work.

On the other hand, it is essential for both the literature and the entrepreneurial service providers to reveal the determinants of demand for digital platform-mediated service businesses that are still in the entrepreneurial stage in Turkey. The success of services offered through digital platforms depends on demand-priority policies. For these services to be successful, the customers' needs and expectations must be considered [30]. It is emphasized that the services offered through digital platforms are directly related to customer demand and that customer demand affects the success of these services. Li and Srinivasan [51], in their study examining the behavior of Airbnb users, state that customer demand is an essential factor for the platform's success. This study provides digital platform-mediated service providers with important information about the demand for this service. As emphasized above, previous studies have predominantly focused on the characteristics of those providing services in digital platform-mediated jobs. In contrast, this article fills the gap in the literature by focusing on the characteristics of individuals who demand these service jobs.

3. Digital Platforms Used for Gig Working in Turkey

In Turkey, there are platforms used for the digital mediation of physical tasks and localities. In this context, the world-famous Uber transportation service has been operating in Turkey since 2014. Uber operates in Istanbul, Ankara, and Izmir in Turkey. According to Uber data, users in Turkey opened the application 9.2 million times in 2021 [52]. Airbnb started its activities in Turkey in 2010 and launched its Turkish website in 2012, and it was used thousands of times for house rentals [53].

There are also some domestic platforms used for home services and maintenance works in Turkey. "Evdeki bakicim" is a platform used for many services from baby and elderly care to housekeeping. An advertisement is placed for the service needed on the platform, allowing service providers to apply. The person requesting the service has the opportunity to make a choice by examining the profiles of the service providers that apply. On the other hand, with the fast support system received from the platform, the platform can match you with the service providers you need [54]. The Mutlubiev platform, which was established in 2014, is a platform that is used especially for house cleaning and provides services such as furniture assembly and transportation. It is reported that more than 15,000 service providers are registered and receive more than 100,000 service requests per month. The operation of the platform is quite similar to that of Evdeki bakicim. In the promotion of this platform, there are statements indicating safety and responsibility such as "Referenced cleaning professionals whose criminal records are checked and regularly trained. All cleaning professionals serve at home in a manner that fulfills their legal responsibilities" [55]. Both platforms provide service all over Turkey. The Armut platform is also reported to receive more than 110,000 service requests per month and provides services such as home repair, cleaning, and transportation. It is an intermediary platform for many services. Although its operation is the same as the other two platforms, Armut operates in ten cities in total, including Istanbul, Ankara, and Izmir [56]. YARS is a platform established especially for home repair and renovation services, and its operation is quite similar to that of other platforms [57]; in addition, in general, it covers second-hand goods, cars, etc. Platforms such as sahibinden.com and Letgo.com, which aim to sell digital mediation services, also mediate home services [58,59].

4. Material and Methods

4.1. Data

The dataset used in the study is the survey data of 2021 from the module of the "Household Information Technologies Usage Survey" carried out longitudinally by TurkStat [60]; these data were taken from the module in question because the problem related to the service demand through the digital platform, which is discussed within the scope of the study, was only included in this module. In the module, the question "Have you received services for households (cleaning, baby care, repair work, gardening, etc.) for private use through the website or mobile applications in the last three months?" was used as a dependent variable in order to determine the characteristics of the service demand mediated by the digital platform. The module in question was applied to 30,530 people in total throughout. In the study, the STATA program was used to perform econometric analyses.

4.2. Logit and Probit Models for Binary Response

The cumulative distribution functions commonly used to explain the behavior of the dependent variable in binary choice models are logistic and normal cumulative distribution functions [61].

Although the linear probability model is simple to predict and use, it has disadvantages. The two most important disadvantages are that the fitted probabilities can be less than 0 or greater than 1, and the partial effect of any explanatory variable (appearing in level form) is constant. These problems, which can occur in the linear probability model, can be solved using logit and probit models [62]. In binary choice models, the interest is primarily in the probability of realization of the desired event. The dependent variable can take the value of "0" or "1"; the observed result is often called "occurrence of the event" ("non-occurrence of the event") and is usually coded as 1 (0).

$$P(y = 1|x) = P(y = 1|x_1, x_2, \ldots, x_k) \quad (1)$$

where x shows all the explanatory variables in the model. Considering the model as follows, where the dependent variable is binary:

$$P(y = 1|x) = G(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k) = G(\beta_0 + x\beta) \quad (2)$$

G is a function having values strictly between 0 and 1: $0 < G(z) < 1$ for all real numbers z [62]. This ensures that the estimated response probabilities are strictly between 0 and 1. Alternative nonlinear functions have been suggested for function G to ensure that the probabilities are between 0 and 1. Logit and probit models, which will be mentioned below, are frequently used in applications.

In the logit model, G is the logistic function

$$G(z) = \frac{exp(z)}{[1 + exp(z)]} = \Lambda(z), \quad (3)$$

and is between 0 and 1 for all real numbers z. This is a standard logistic random variable's cumulative distribution function (cdf) [63].

In the probit model, G is the standard normal cdf, which is expressed as an integral:

$$G(z) = \Phi(z) = \int_{-\infty}^{z} \phi(v)dv, \tag{4}$$

where $\phi(z)$ is the standard normal density,

$$\phi(z) = (2\pi)^{-1/2}\exp\left(-\frac{z^2}{2}\right). \tag{5}$$

This choice of G again ensures that (2) is strictly between 0 and 1 for all values of the parameters and the x_j [63]. The probit model is more prevalent in econometrics than the logit model, as economists tend to prefer the assumption of normality for the error term [62].

The maximum likelihood method (MLE) can be used to find parameter estimates of logit and probit models. The advantage of using this method is that MLE is based on the distribution of y given x, and the heteroskedasticity in Var($y_i \mid x_i$) is automatically accounted for.

The maximum likelihood method is the most widely used estimation method for estimating binary choice models [62]. Since the cumulative normal transformation approach is nonlinear, the standard least squares method is not accepted as a suitable estimation method for estimating the probit model [64]. Since the dependent variable is discrete, the likelihood function cannot be defined as a combined density function. In this case, the likelihood function has to be defined as the probability in which a probability value is observed. With this new definition, the sum of the likelihood values of possible values is equal to 1 [63].

In a random sample of size n, when x is given to the explanatory variables to obtain the maximum likelihood estimator conditionally, the density of y is needed.

$$f(y|x_i;\beta) = [G(x_i\beta)]^y[1 - G(x_i\beta)]^{1-y}, y = 0, 1 \tag{6}$$

The log-likelihood function for the observation i is a function of the parameters and (x_i,y_i) data and is obtained by taking the logarithm of Equation (4).

$$l_i(\beta) = y_i\log\left[G(x_i\beta)\right] + (1 - y_i)\log[1 - G(x_i\beta)] \tag{7}$$

where x_i denotes the independent variable matrix, y_i represents the dependent variable, and β represents the coefficient vector. Since $G(.)$ for logit and probit is strictly between 0 and 1, l_i (β) is well defined for all values of β. The log-likelihood function for a sample of size N is obtained by summing Equation (5) for all observations. If $G(.)$ is the standard logit cumulative distribution function, it shows the logit estimator. However, if $G(.)$ is the standard normal cumulative distribution function, β indicates the probit estimator [65].

Coefficient interpretations for discrete choice models cannot be performed directly through the coefficients in the model estimation results. Since the dependent variable of these models is discrete, there is a need for possibilities to choose alternatives. Therefore, after the estimates of the coefficients are obtained, the marginal effects should be calculated in order to perform their interpretation [62]. The marginal effect shows the effect of a change in the value of one dependent variable on the probability of different alternatives. The increase or decrease due to the positive marginal effect function is determined by the sign of the parameter. When the value of this parameter is positive, an increase in the independent variable increases the probability value of the category of the dependent variable, while an increase in the independent variable with a negative value of the parameter decreases the probability value of the category of the dependent variable [66].

5. Results

Table 1 shows the frequency values of the variables, their percentages in e-service purchases in parentheses, and the probability value of Pearson chi-square (χ^2) test statistics at the end of the table. In the first three columns of the table, the frequencies of the independent variables according to the categories of the dependent variable and the percentage values in parentheses are given. In the last column, the probability value of the Pearson χ^2 (chi-square) test, which investigates whether there is a relationship between the dependent variable and the independent variables, is given.

Table 1. Frequency (%) Information of Variables.

Variable	**Digital Platform-Mediated Service Procurement**		**Sum**	χ^2_p
	No	**Yes**		
Gender				
Male	4390 (48.5)	195 (50.9)	4585 (48.6)	0.375
Female	4665 (51.5)	188 (49.1)	4853 (51.4)	
Generation				
Generation Z	1377 (15.2)	42 (11.0)	1419 (15.0)	0.069 *
Generation Y	3754 (41.5)	172 (44.9)	3926 (41.6)	
Generation X	1989 (22.0)	94 (24.5)	2083 (22.1)	
Generation Baby Boomer	1935 (21.4)	75 (19.6)	2010 (21.3)	
Education				
Illiterate	582 (6.4)	15 (4.2)	598 (6.3)	0.161
Primary School	2412 (26.6)	100 (26.1)	2512 (26.6)	
Secondary School or Primary School	1435 (15.8)	59 (15.4)	1494 (15.8)	
High School	2288 (25.3)	87 (22.7)	2375 (25.2)	
Associate Degree	626 (6.9)	32 (8.4)	658 (7.0)	
Undergraduate	1432 (15.8)	72 (18.8)	1504 (15.9)	
Postgraduate	280 (3.1)	17 (4.4)	297 (3.1)	
Statistical Region Unit Classification (IBBS)				
TR1	1606 (17.7)	107 (27.9)	1713 (18.2)	0.000 ***
TR2	553 (6.1)	24 (6.3)	577 (6.1)	
TR3	1082 (11.9)	34 (8.9)	1116 (11.8)	
TR4	970 (10.7)	52 (13.6)	1022 (10.8)	
TR5	1042 (11.5)	57 (14.9)	1099 (11.6)	
TR6	845 (9.3)	21 (5.5)	866 (9.2)	
TR7	556 (6.1)	12 (3.1)	568 (6.0)	
TR8	539 (6.0)	18 (4.7)	557 (5.9)	
TR9	476 (5.3)	12 (3.1)	568 (6.0)	
TRA	310 (3.4)	21 (5.5)	331 (3.5)	
TRB	476 (5.3)	9 (2.3)	485 (5.1)	
TRC	600 (6.6)	16 (4.2)	616 (6.5)	
Frequency of Internet use in the last three months				
Less than once a week or every two to three weeks	62 (0.8)	2 (0.6)	64 (0.8)	0.865
At least once a week	325 (4.2)	13 (3.8)	338 (4.2)	
Almost every day	7734 (95.0)	338 (95.6)	7670 (95.0)	
Spending on online purchases				
Not spending	2908 (32.1)	122 (31.9)	3030 (32.1)	0.000 ***
Less than TRY 450	3621 (40.0)	65 (17.0)	3686 (39.1)	
Between TRY 451 and TRY 2699	1148 (12.7)	57 (14.9)	1205 (12.8)	
TRY 2700 and above	1378 (15.2)	139 (36.3)	1517 (16.1)	

Table 1. *Cont.*

Variable	Digital Platform-Mediated Service Procurement		Sum	χ_p^2
	No	Yes		
Internet sales of goods and services				
No	6778 (87.6)	280 (82.8)	7058 (87.4)	0.012 **
Yes	956 (12.4)	58 (17.2)	1014 (12.6)	
Searching for a job online or applying for a job				
No	6934 (89.7)	316 (93.5)	7250 (89.8)	0.021 **
Yes	800 (10.3)	22 (6.5)	822 (10.2)	
Social media use				
No	1995 (25.8)	93 (27.5)	2088 (25.9)	0.485
Yes	5739 (74.2)	245 (72.5)	5984 (74.1)	
Working Status				
Not working	5285 (58.4)	199 (52.0)	5484 (58.1)	0.015 **
Working	3770 (41.6)	184 (48.0)	3954 (41.9)	
Monthly Income				
TRY 0–1000	2094 (23.1)	62 (16.2)	2156 (22.8)	0.004 ***
TRY 1001–2000	3523 (38.9)	140 (36.6)	3663 (38.8)	
TRY 2001–3000	1577 (17.4)	80 (20.9)	1657 (17.6)	
TRY 3001–4000	715 (7.9)	31 (8.1)	746 (7.9)	
TRY 4001–5000	507 (5.6)	33 (8.6)	540 (5.7)	
TRY 5001–6000	161 (1.8)	9 (2.3)	170 (1.8)	
TRY 6001–7000	119 (1.3)	5 (1.3)	124 (1.3)	
TRY 7001 and above	359 (4.0)	23 (6.0)	382 (4.0)	

Note: * 10%, ** 5%, and *** 1% denote significance at the significance level. χ_p^2 shows the probability value of the chi-square test statistic.

Regarding gender, 51% of individuals using e-services are male, and 49.1% are female. In addition, 11% of the participants in the Z generation, 45% in the Y generation, 25% in the X generation, and 20% in the Baby Boomer generation stated that they received e-services. While 4.2% of individuals using e-services are illiterate, 41% are primary school graduates, 23% are high school graduates, 8% have associate degrees, 19% have undergraduate degrees, and 4% have postgraduate degrees.

Thirty percent of individuals receiving e-services live in TR1, 6% in TR2, 9% in TR3, 14% in TR4, 15% in TR5, 6% in TR6, 3% in TR7, 5% in TR8, 3% in TR9, 6% in TRA, 2% in TRB, and 4% in the TRC region. Ninety-six percent of individuals who receive e-services said that they use the Internet almost every day.

It has been determined that 36% of individuals who buy e-services spend TRY 2700 or more for online purchases. It was found that 17% of individuals who sell goods and services online and 7% who search for a job or apply for a job on the Internet purchase e-services. It has been determined that 73% of individuals who purchase e-services use social media. Forty-eight percent of working individuals receive e-services. It has been determined that 73.7% of individuals with an income level of TRY 0–3000 benefit from e-services, while 27.6% of individuals with an income level of 3001 and above benefit from e-services.

Before including the independent variables to be used in the study in the model, whether the dependent variables are related or not was examined using the chi-square test statistic. According to the Pearson chi-square relationship measures in Table 1, benefiting from e-service purchase and age group, region of residence, spending on Internet purchases, selling goods and services over the Internet, searching for a job or applying for a job on the Internet, working status, and monthly income per capita variables were found to be statistically significant at various significance levels.

In the study, the estimation of both the logit and probit models was performed, and it was seen that the values of both the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) for the probit model given in Table 2 were lower than those for the logistic model. The probit model was preferred, and the analyses were continued. It is also seen that the model has adequate goodness-of-fit measures. Findings regarding the probit model are shown in Table 2. In econometric models where there is more than one independent variable, the high-order relationship between the independent variables reveals the multicollinearity problem. Finding multicollinearity can lead to biased parameter estimates. Variance inflation factor (VIF) values were obtained to evaluate the multicollinearity problem between the independent variables of the predicted probit model. If VIF values are greater than 10, the model has a multicollinearity problem. When the values given in the last column of Table 2 are examined, it is seen that none of the VIF values of the independent variables is greater than 10. There is no multicollinearity problem in the estimated model.

Table 2. Binary Probit Model Estimation Results.

Variable	Coefficient	Std. Error	z	$p > \lvert z \rvert$	VIF
Monthly Income (Ref. Cat: TRY 0–1000)					
TRY 1001–2000	0.127	0.080	1.580	0.114	
TRY 2001–3000	0.142	0.090	1.570	0.116	
TRY 3001–4000	0.048	0.114	0.420	0.673	
TRY 4001–5000	0.250	0.121	2.070	0.038	1.40
TRY 5001–6000	0.197	0.186	1.060	0.291	
TRY 6001–7000	0.095	0.226	0.420	0.674	
TRY 7001 and above	0.141	0.131	1.080	0.280	
Working Status (Ref. Cat: Not working)					
Working	0.041	0.063	0.650	0.515	1.31
IBBS (Ref. Cat: TR1)					
TR2	−0.057	0.115	−0.490	0.623	
TR3	−0.319	0.100	−3.170	0.001	
TR4	0.021	0.088	0.230	0.815	
TR5	−0.017	0.086	−0.200	0.845	
TR6	−0.333	0.118	−2.820	0.005	
TR7	−0.402	0.138	−2.920	0.004	1.03
TR8	−0.200	0.129	−1.550	0.120	
TR9	−0.342	0.152	−2.260	0.024	
TRA	−0.297	0.138	2.150	0.032	
TRB	−0.285	0.152	−1.870	0.061	
TRC	−0.126	0.128	−0.990	0.323	
Education (Ref. Cat: Illiterate)					
Illiterate	0.304	0.247	1.230	0.219	
Primary School	0.315	0.251	1.250	0.210	
Secondary School or Primary School	0.184	0.251	0.730	0.463	1.50
High School	0.340	0.259	1.320	0.188	
Associate Degree	0.210	0.257	0.820	0.413	
Undergraduate	0.208	0.277	0.750	0.453	
Generation (Ref. Cat: Generation Z)					
Generation Y	0.111	0.087	1.280	0.199	
Generation X	0.156	0.097	1.610	0.107	1.22
Baby Boomer	0.140	0.116	1.200	0.231	

Table 2. *Cont.*

Variable	Coefficient	Std. Error	z	$p > \|z\|$	VIF
Gender (Ref. Cat: Female)					
Male	−0.046	0.057	−0.820	0.413	1.18
Frequency of Internet use in the last three months (Ref. Cat: Less than once a week or once every two to three weeks)					
At least once a week	0.046	0.345	0.130	0.894	1.08
Almost every day	0.054	0.319	0.170	0.867	
Searching for a job online, applying for a job (Ref. Cat: No)					
Yes	−0.262	0.101	−2.580	0.010	1.08
Spending for online purchase (Ref. Cat: No spending)					
Less than TRY 450	−0.324	0.071	−4.590	0.000	1.06
Between TRY 451 and TRY 2699	0.105	0.080	1.300	0.193	
TRY 2700 and above	0.430	0.066	6.480	0.000	
Order period made for private use over the Internet (Ref. Cat: Never used)					
In the last three months	0.117	0.076	1.540	0.122	1.20
Between three months and one year	0.173	0.101	1.720	0.086	
More than a year	0.086	0.128	0.680	0.499	
Internet sales of goods and services (Ref. Cat: No)					
Yes	0.161	0.074	2.170	0.030	1.02
Social media use (Reference Category: No)					
Yes	−0.069	0.064	−1.080	0.282	1.11
Constant	−2.149	0.426	−5.050	0.000	
Fit Test Results					

Number of observations = 8072. LR χ^2 (40) = 199.839; p = 0.000. Pseudo-R^2 = 0.0712. Wald χ^2(40) = 189.70; p = 0.000. Log-Lik Intercept Only: −1403.334. Log-Lik Full Model: −1303.414. AIC: 0.335, BIC: −69,578.332. Pearson χ^2 (6993) = 7070.60; p = 0.2548. Hosmer–Lemeshow χ^2 (8) = 10.95; p = 0.2045. Correctly classified = 95.81%.

Since the probability value for the Pearson χ^2 statistic (p= 0.2548 > 0.05) and Hosmer–Lemeshow χ^2 statistic (p = 0.2045 > 0.05) is greater than 5%, it has been decided that there is no identification error in the estimated model. It is seen that the correct prediction success of the predicted probit model is 95.81%. The pseudo-R^2 value of the model is 0.0710. Although the pseudo-R^2 value is relatively low, it is not a problem for the success of the model. Greene [62] stated that pseudo-R^2 is not an appropriate measure for evaluating model prediction success and that these and similar values do not provide information about the explained variance ratio. In addition, it was stated that there was no effect on the evaluation of the model's predictive ability. It has been stated that the pseudo-R^2 value is useful in comparing one model with another in nested models. Long and Freese [67] stated that it could be used to select the model with the maximum pseudo-R^2 value, and no convincing evidence shows that the model evaluated according to these criteria is the most appropriate. Martin [68] stated that pseudo-R^2 measurements are of little value and that likelihood ratio tests are more informative for comparing nested models than pseudo-R^2 statistics. For the above reasons, the analysis was conducted by choosing the most suitable model, considering the log-likelihood criterion.

Table 2 shows the estimation results of the binary probit model. According to the results obtained, the variables income, region of residence, job search or job application on the Internet, time spent on online shopping, time of ordering from the Internet for private use, and selling goods and services over the Internet were found to be statistically significant at the 5% significance level according to the probability value of the calculated Z test statistics ($p < 0.05$).

Table 3 gives the marginal effects of the predicted binary probit model. Accordingly, individuals with a monthly income level of TRY 4001–5000 per capita are 25% more likely to purchase e-services than individuals with a monthly income of TRY 0–1000. Compared to individuals living in TR1, the probability of purchasing e-services is 31% less in TR3, 33.3% less in TR6, 40.2% less in TR7, 34% less in TR9, 29.7% less in TRA, and 28.5% less in TRB. Individuals who search for or apply for a job online are 26.2% less likely to purchase e-services than those who do not. It has been determined that individuals who spend less than TRY 450 on the Internet are 32.4% less likely to receive e-services than those who do not spend. It has been determined that individuals who spend TRY 2700 or more on the Internet are 43% more likely to purchase e-services than those who do not spend at all. It has been determined that individuals who ordered over the Internet for private use in the last three months to one year are 17.3% more likely to purchase e-services compared to individuals who have never placed an order. Individuals who sell goods and services over the Internet are 16.1% more likely to receive e-services than those who do not.

Table 3. Marginal Effects.

Variable	dy/dx	Std. Error	z	$p > \mid z \mid$
Monthly Income (Reference Category: TRY 0–1000)				
TRY 1001–2000	0.127	0.080	1.580	0.114
TRY 2001–3000	0.142	0.090	1.570	0.116
TRY 3001–4000	0.048	0.114	0.420	0.673
TRY 4001–5000	0.250	0.121	2.070	0.038
TRY 5001–6000	0.197	0.186	1.060	0.291
TRY 6001–7000	0.095	0.226	0.420	0.674
TRY 7001 and above	0.141	0.131	1.080	0.280
Working Status (Reference Category: Not working)				
Working	0.041	0.063	0.650	0.515
Statistical Region Units Classification (Reference Category: TR1)				
TR2	−0.057	0.115	−0.490	0.623
TR3	−0.319	0.100	−3.170	0.001
TR4	0.021	0.088	0.230	0.815
TR5	−0.017	0.086	−0.200	0.845
TR6	−0.333	0.118	−2.820	0.005
TR7	−0.402	0.138	−2.920	0.004
TR8	−0.200	0.129	−1.550	0.120
TR9	−0.342	0.152	−2.260	0.024
TRA	−0.297	0.138	2.150	0.032
TRB	−0.285	0.152	−1.870	0.061
TRC	−0.126	0.128	−0.990	0.323
Education (Reference Category: Illiterate)				
Primary School	0.304	0.247	1.230	0.219
Secondary School or Primary School	0.315	0.251	1.250	0.210
Secondary School	0.184	0.251	0.730	0.463
Associate Degree	0.340	0.259	1.320	0.188
Bachelor	0.210	0.257	0.820	0.413
Master′s or Doctorate	0.208	0.277	0.750	0.453
Generation (Reference Category: Generation Z)				
Generation Y	0.111	0.087	1.280	0.199
Generation X	0.156	0.097	1.610	0.107
Generation Baby Boomer	0.140	0.116	1.200	0.231
Gender (Reference Category: Female)				
Male	−0.046	0.057	−0.820	0.413

Table 3. *Cont.*

Variable	dy/dx	Std. Error	z	$p > \|z\|$
Frequency of Internet use in the last three months (Reference Category: Less than once a week or once every two to three weeks)				
At least once a week	0.046	0.345	0.130	0.894
Almost every day	0.054	0.319	0.170	0.867
Searching for a job online or applying for a job (Reference Category: No)				
Yes	−0.262	0.101	−2.580	0.010
Spending for online purchase (Reference Category: No spending)				
Less than TRY 450	−0.324	0.071	−4.590	0.000
Between TRY 451 and TRY 2699	0.105	0.080	1.300	0.193
TRY 2700 and above	0.430	0.066	6.480	0.000
Order period made for private use over the Internet (Reference Category: Never used)				
In the last three months	0.117	0.076	1.540	0.122
Between three months and one year	0.173	0.101	1.720	0.086
More than a year	0.086	0.128	0.680	0.499
Internet sales of goods and services (Reference Category: No)				
Yes	0.161	0.074	2.170	0.030
Social media use (Reference Category: No)				
Yes	−0.069	0.064	−1.080	0.282
Constant	−2.149	0.426	−5.050	0.000

6. Discussion

When the effects of income on digitally mediated service demand are examined, it is seen that the results are generally insignificant, but significant results are obtained for a single category. Theoretically, considering the effect of income, it is wrong to make definite prejudices about the positive or negative effects of digitally mediated service demand. In this study, it was found that the middle-income group within the sample group demanded digital platform-mediated services approximately 25% more than other groups. As highlighted by Hamari et al. [30], economic benefit is one of the most significant motivators for users of digital platforms. Indeed, in the literature, pricing and economic advantages emerge as particularly noteworthy factors within the context of the sharing economy [69]. Some studies conclude that affordable advertisements are among the most important sources of motivation in the use of digital platforms by sharing economy customers [30–32,45]. The obtained results of the study are consistent with the literature. Indeed, it is difficult for low-income individuals to demand services through digital platforms. On the other hand, high-income individuals are less likely to consider economic benefits in these service jobs. Therefore, it can be expected that individuals with moderate income levels would have a higher demand for these services by using digital platforms and considering economic benefits. Similarly, it is acceptable to acknowledge that besides income, the price of services offered on platforms can significantly influence the demand for digital intermediary services. One of the most critical limitations of the study is the lack of data pertaining to information about service operation on digital platforms.

Regional differences were analyzed concerning the TR1 region (Istanbul Province) [70], which has the highest indicators in terms of population and economic factors in Turkey. The results confirm that platform usage is mainly related to geographic and urban features [44] and provide evidence that demand for digital platform-mediated services declines as population density decreases across regions. As emphasized by Cullen and Farronato [33], this situation can be attributed to primary reasons such as geographically close demand, a high number of supplies, and easier access to various services demanded due to density. The results of Hoffren for the Netherlands revealed that the rate of demand for services through a digital platform in provinces with high population density is significantly higher than that in provinces with lower population density [71].

Selected as independent variables within the scope of the study, the variables of spending for online shopping, frequency of ordering, selling goods and services over the Internet, and searching for a job or applying for a job over the Internet were combined and interpreted under the concept of "familiarity" emphasized by Möhlmann [34]. The variables in question show the characteristics of individuals' use of information technologies. This provides information on how relevant individuals are to digital platforms. The results show that when the money spent on online shopping increases, the probability of individuals requesting digital platform-mediated services increases. This result aligns with the study of Barbu et al. [72], which concluded that satisfaction with purchasing goods and services through platforms increases digitally mediated demand. It is an acceptable situation that the level of satisfaction can positively affect the amount of spending. It has been concluded that the increase in the frequency of ordering for private use over the Internet and the sale of goods and services through the platforms can increase the demand for services through a digital platform. This result supports the evidence [34,73] that familiarity with platforms can increase customer demand within the scope of the sharing economy.

Similarly, the results of Shaw et al. [74] showing that workers who perform digital platform-mediated jobs are more skilled Internet users also support the results showing that familiarity with platforms can increase demand. The result of Wiertz and Ruyter [75] showing that the most important determinant of customer loyalty in online platforms is the tendency of online interaction supports the assumption that familiarity with digital platforms can increase the demand for platform-mediated services. On the other hand, the results show that job seekers' demand for digital mediation services over the Internet is lower than the demand of those who do not search for jobs. This result contradicts the assumption that digital platform familiarity will increase demand for digital platform-mediated services. However, considering that younger people primarily use the Internet resource as a job search channel [76], it may be that the individuals in question may not need the digital platform-mediated services (cleaning, babysitting, repair work, gardening, etc.) considered in this study.

This study is in line with the theoretical expectations regarding the demand for service jobs through digital platforms, based on its obtained results. From an economic perspective, it has been confirmed that these jobs are more likely to be demanded by middle-income individuals. Considering living spaces, the expectation of high demand for digital platform service jobs in densely populated cities, where both supply and demand are high, has also been confirmed. Furthermore, the theoretical expectation that individuals who are more engaged in e-commerce would demand these services more has been verified. In this context, the study makes significant contributions to the developing theoretical framework of service jobs through digital platforms. Additionally, as the first study to comprehensively investigate the demand for service jobs through digital platforms, it provides an important contribution to the literature, as mentioned above.

7. Conclusions

Discussions on the impact of digital platforms on economic functioning in general, and their consequences on labor markets in particular, have been primarily driven by theoretical discussions and conceptualization efforts over the last decade. Empirical studies on the subject are relatively few due to the need for more statistical data [46]. The lack of empirical evidence on the demand side of digital platform-mediated service businesses points to a significant shortcoming of this discussion. It is vital to understand the functioning of digital platforms, given that they will become an increasingly important actor in economic functioning and may have more and more tangible implications for the labor market. Therefore, it is vital to determine the characteristics of individuals who form one of the three primary aspects of the said process and demand digital services. As much as determining the reasons that encourage individuals to participate in collaborative use within the scope of the sharing economy is necessary for the needs of users and the continuation of the operation in the entire sector [45], it is essential and necessary to determine the characteristics of the demand for digital mediation works within the scope of the sharing economy.

On the other hand, it is strongly argued that performing service jobs, which are generally considered low-paid and low-skilled, through digital platforms provides various advantages [36,37,42]. This will increase the number of individuals supplying the workforce with low-skilled service jobs through digital platforms. In this context, it is crucial to know the characteristics of the digitally mediated service demand for the workforce group in question. Based on the empirical findings obtained in this study, some important recommendations can be made. The conclusion on the impact of revenue on demand for platform-mediated service businesses provides essential insights for service providers. Accordingly, service demand is not related to an increase in customer revenue. It is more attractive to relatively middle-income customers. This underlines that service providers should adjust their prices according to the income group. According to another result, the demand for services via digital platforms is higher in areas with high population density. This indicates that service providers should target incredibly densely populated regions or cities. The other specific result shows that those who shop more on the Internet demand these services more. In this direction, service providers can use data related to e-commerce and offer special services to cities, districts, or neighborhoods where e-commerce is intense. Based on the literature within the scope of the study, some suggestions can be made for policymakers. It is understood that digitalization will have essential effects on the labor market in all areas of society. Policymakers must make adequate adjustments to adapt labor market policies to this change. Based on demand-side inferences, governments should make legal arrangements that protect the basic order of society, and appropriate legal arrangements should be made regarding the digital labor market.

The study's results about the characteristics of demand in digital platform-mediated service jobs are generally compatible with the literature. However, the most critical limitation of the study is that the data obtained do not include information on service announcements on digital platforms and satisfaction with the said digitally mediated services. Considering that statistical data on digital platforms will become increasingly functional and more accessible, it is thought that future studies can overcome these limitations and reach more comprehensive results. In future studies utilizing the mentioned data, the characteristics of advertisements related to services offered on digital platforms and the impact of satisfaction with these services on demand can be determined. Furthermore, other studies on this topic can focus on the beneficial features of digital platforms in terms of the continuity of sustainability in the circular economy and its social and environmental benefits [77].

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