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What drives the ICT adoption in unorganized firms in India: An application of ordinal probit models

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Abstract

This study identifies the key drivers of Information and Communication Technologies (ICT) adoption in India's unorganised sector across four major industries. We employ an ordinal probit regression model to analyse microdata from the recent round of the Annual Survey of Unincorporated Sector Enterprises (2023). Our findings highlight that various individual, firm-level, and aggregate-level factors significantly influence the likelihood of ICT adoption. Moreover, this adoption varies across industries. The results further indicate that establishments led by educated owners and those with access to finance exhibit a higher propensity to adopt ICT. Additionally, younger enterprises and those located in urban areas are more likely to integrate ICT into their operations.

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1. Introduction

Technological advancements in recent decades have significantly transformed the production economy (Paul et al., 2024). Among these, Information and Communication Technology (ICT) has emerged as a key driver of economic growth and plays an increasingly central role in enhancing firm-level performance in the manufacturing sector in general, and the informal sector in particular (Abraham, 2021; Bhattacharya, 2019; Paul, 2016). Despite its growing influence on firm operations, a central question remains: what factors influence firms to adopt ICT in their operations, especially in the informal sector? Are these factors the same across various industries within the informal sector? This study seeks to explore these questions.

Existing studies present a one-sided picture, suggesting that several firm-level factors influence the adoption of ICT in their operations, especially for formal enterprises (Bayo-Moriones & Lera-López, 2007; Giotopoulos et al., 2017; Haller & Siedschlag, 2011; Mushtaq et al., 2022). Moreover, in a country like India, a significant share of the production economy is characterised by unregistered, unorganised, and small-scale enterprises that largely rely on family labour, traditional tools or equipment, and, most critically, operate with minimal capital resources. (Chakrabarti, 2016; Ghosh & Mitra, 2023; Paul et al., 2017). These tiny unregistered firms are characteristically very diverse from each other, so it would be difficult to direct to all types of industries. Existing literature clearly indicates that unorganised firms, which represent a substantial share of the production economy, are increasingly reaping the benefits of technological advancements (Dutta et al., 2023). This raises a pertinent question: what factors influence entrepreneurs in these unorganised firms to adopt ICT in their operational processes? These unorganised firms often experience a financial shortage during their operations (Bečicová & Blažek, 2015).

Given this complex milieu, the study aims to investigate the factors that drive unorganised firms to adopt ICT in their operational processes across four diverse industries, i.e., Manufacturing, Hospitality, Wholesale & retail, and Construction & Real Estate. For this analysis, we used recent Annual Survey of Unincorporated Sector Enterprises (ASUSE 2023) microdata for Indian unorganised enterprises.

This study makes two main contributions. First, it provides a comprehensive view of ICT adoption by examining the varied characteristics, operations, and locations of India's informal sector. Second, it identifies factors driving ICT adoption in four major industries, showing how enterprise type, operational nature, and technology use differ within the unorganised sector.

The paper is organized as follows: Section 2 provides a brief theoretical and conceptual framework for the study. Section 3 presents the modelling framework, including the theoretical foundation, the econometric model, and a description of the data used. Section 4 discusses the results, followed by Sections 5 and 6, which provide the conclusion, limitations, and policy recommendations.

2. Theoretical and Conceptual Framework

The decision to adopt ICT in an enterprise's operations is influenced by variables across three broad dimensions: enterprise-level factors, individual-level factors, and aggregate or state-level factors. Paul (2016) considered both enterprise and individual-level indicators in his paper. This study adopted those indicators, as well as incorporated other variables and state-level aggregate variables, to construct a more holistic picture in this scenario. Available studies also focused on the impact of ICT in Indian manufacturing sector (Abraham, 2021; Bhattacharya, 2019).

Unincorporated enterprises exhibit considerable diversity in terms of their operations, enterprise structure, ownership type, and geographical location, which ultimately impacts their performance and decisions regarding ICT adoption (Paul, 2016). However, the decision to adopt ICT in operations, especially for unincorporated enterprises, is influenced not only by firm-level indicators but also by broader socio-cultural and geographical contexts. This study presents a comprehensive and practical framework that incorporates individual-, enterprise-, and macro-level indicators to understand the determinants of ICT adoption among these enterprises in their operations.

First, we start with individual-level indicators. In unincorporated enterprises, these indicators pertain to the proprietor or owner of the unit, as shown in Figure 1. Earlier studies identified individual-level factors such as the owner's gender, social category, and educational attainment as influencing decisions about adopting ICT in business operations. In addition, access to credit is a crucial individual-level factor for unorganised enterprises.

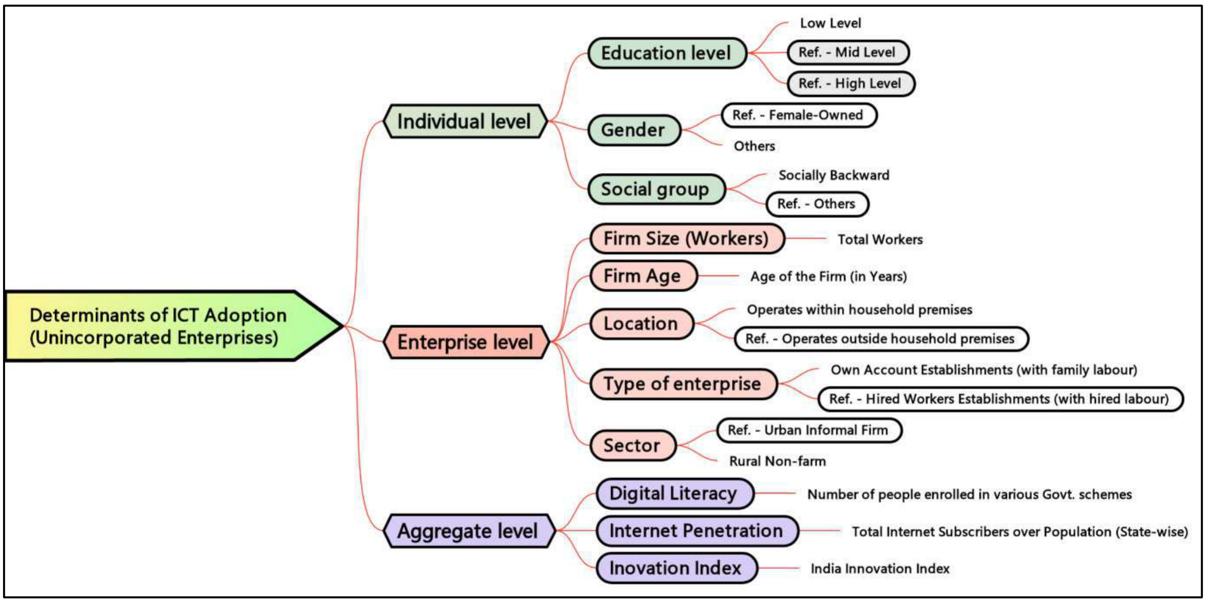

Figure 1: Conceptual Framework of ICT Adoption in the Unorganised Sector

Source: Author's creation

Alongside the individual and enterprise level, some aggregate-level region-specific factors are also playing a crucial role. State-level digital literacy, internet density, the state's performance on innovation, and the sector play a crucial role in this context. The total number of people enrolled in various digital education missions is an indicator that digital literacy can influence the ICT adoption in the unorganised sector. Similarly, the total internet subscribers of a particular state might influence the ICT adoption behaviour of a particular segment (unorganised sector) due to awareness.

3. The Modelling Framework

This section explains the theoretical background of ordinal outcome models, introduces the ordinal/ordered probit model along with its estimation approach, and briefly describes covariate or marginal effect calculation and model diagnostic measures.

3.1 Theoretical Foundation

The ordinal probit models used in this study are grounded in the theory of choice in economics, which is closely linked to the random utility framework (Luce,1959; Luce and Suppes,1965; Marschak,1960). In a basic random utility model, a rational agent selects one option from a set of mutually exclusive and exhaustive alternatives, each associated with a certain utility level. The aim of the stakeholder is to choose the alternative that maximizes their utility. While the stakeholder has full information of the utility of each option and would make the same choice if the situation were replicated, the researcher does not observe these utilities directly. Instead, the researcher observes a set of individual characteristics (such as age, gender, and income), known as the representative utility, which makes up the systematic component. The unobserved influences on utility form the stochastic component, which the researcher models using a probability distribution in order to make probabilistic statements about observed choices based on the representative utility (Mukherjee & Rahman, 2016).

The unsystematic component is usually assumed to follow a continuous distribution, and a continuous latent random variable (or a continuous latent utility) is believed to underlie the observed discrete outcomes. When the available alternatives or outcomes are inherently ordered, an individual's choice can be interpreted as the latent variable crossing a specific threshold or cut-point. This threshold-crossing framework effectively links individual choice behaviour with ordinal data models. Beyond its theoretical appeal, the latent variable approach also facilitates the estimation process. It is important to note that while the theoretical foundation is rooted in choice theory and random utility models, the econometric methods used are general and applicable whenever the data meet the conditions of ordinal ranking.

3.2 Econometric models

Ordinal data models are used when the dependent variable has more than two discrete, inherently ordered values (Mukherjee & Rahman, 2016). In this study we have used ASUSE microdata, ICT adoption is coded as 1 for 'No Adoption', 2 for 'Partial Adoption', and 3 for 'Full Adoption'; reflecting order without implying equal intervals between categories. This econometric model is largely adopted from Mukherjee and Rahman (2016) with some modification.

The response variable in this model is ICT Adoption represented by a discrete variable $\boldsymbol{y}$, and we assume the existence of continuous latent variable $\mathbf{M}$ that represents the degree of support for ICT Adoption. The model is specified as a function of covariates as follows:

$$\boldsymbol{M_i = x_i'\beta + C_i, \quad \forall\, i = 1, \ldots, N,} \tag{1}$$

Here, $\boldsymbol{x_i}$ denotes a $\boldsymbol{k\times 1}$ vector of covariates, $\boldsymbol{\beta}$ is a corresponding $\boldsymbol{k\times 1}$ vector of unknown parameters, N represents the total number of observations, and ϵ_i follows a specified probability distribution. The choice of distribution for $\boldsymbol{\epsilon_i}$ determines the type of ordinal model used. In most practical cases, the error term $\boldsymbol{\epsilon_i}$ is assumed to be Independently and Identically Distributed (IID) and normally distributed with mean zero and unit variance, thereby yielding the ordinal probit specification. The unobserved latent variable $\mathbf{M}_i$ is related to the observed discrete outcome $\boldsymbol{y_i}$ as follows:

$$\boldsymbol{\gamma_{j-1} < M_i \leq \gamma_j \Rightarrow y_i = j, \quad \forall\, i = 1, \ldots, N;\ \forall\, j = 1, \ldots, J,} \tag{2}$$

where $-\infty = \gamma_0 < \gamma_1 \cdots < \gamma_{j-1} < \gamma_j = \infty$ represent the cut-points (or thresholds) and $\boldsymbol{y_i}$ is assumed to have $\boldsymbol{J}$ categories. These thresholds define the relationship between the continuous latent variable $\boldsymbol{M}$ and the observed dependent variable $\boldsymbol{y}$. To uniquely identify the model parameters, location and scale restrictions are also required. Location restriction is imposed by setting γ_1= 0 and scale restriction by assuming a constant variance, which is fixed at 1 in the ordinal probit model. Given the data vector $y = (\boldsymbol{y_1} \dots \boldsymbol{y_N})'$, the full likelihood function of the ordinal probit model in terms of the unknown parameters $(\boldsymbol{\beta},\boldsymbol{\gamma})$, is expressed as follows,

$$\boldsymbol{l}\,(\boldsymbol{\beta},\boldsymbol{\gamma};\boldsymbol{y}) = \prod_{i=1}^{N}\prod_{j=1}^{J}\boldsymbol{P}(\boldsymbol{y_i}=\boldsymbol{j}|\boldsymbol{\beta},\boldsymbol{\gamma})^{\boldsymbol{I}(\boldsymbol{y_i}=\boldsymbol{j})},$$

$$= \prod_{i=1}^{N}\prod_{j=1}^{J}[\Phi(\boldsymbol{\gamma_j}-\boldsymbol{x_i'\beta})-\Phi(\boldsymbol{\gamma_{j-1}}-\boldsymbol{x_i'\beta})]^{\boldsymbol{I}(\boldsymbol{y_i}=\boldsymbol{j})}, \qquad \textbf{(3)}$$

Here, $\Phi(\cdot)$ corresponds to the cumulative distribution function of the standard normal distribution, and I $(y_i = j)$ is an indicator variable equal to 1 if the condition $y_i = j$ holds, and 0 otherwise. The parameters are obtained by applying Maximum Likelihood Estimation (MLE) to the log-likelihood function (iii).

The ordinal probit model uses a non-linear and non-monotonic link function, as such the coefficients by themselves do not give the covariate effect. For a continuous regressor $\mathbf{x_k}$, the covariate effect is calculated as, $\partial \Pr\,(y_i = j\,)/\partial x_{i,k} = -\beta_k[\Phi(\gamma_j - x_i'\beta) - \Phi(\gamma_{j-1} - x_i'\beta)]$. The average covariate effect is obtained by substituting the estimated coefficients $\hat{\beta}$ and averaging across all observations. While the independent variable is an indicator variable, the covariate effect is calculated as follows: $\Pr(y_i = j|x_{i,-k}, x_{i,k} = 1) - Pr(y_i = j|x_{i,-k}, x_{i,k} = 0)$ and similarly, the average effect is found by averaging this difference across all observations. To evaluate the goodness of fit for these models, the paper uses two measures: likelihood ratio (LR) test statistic and McFadden's R-square.

3.3 Data

The study uses the Annual Survey of Unincorporated Sector Enterprises (ASUSE 2023) microdata, collected by the National Sample Survey Organisation, for Indian unorganised enterprises. The ASUSE is the only firm-level dataset available for the unorganised sector in India. The total number of observations in the sample is 5,37,199. As per the objective of this study, we have selected four major industries, i.e. manufacturing (1,27,202), hospitality (46,629), wholesale & retail (1,67,184), and construction & real estate (51,888), for our analysis. In addition, we have used three aggregate/state-level indicators: 'Digital Literacy'[1] and 'Internet Subscribers[2],' both collected from the Rajya Sabha (2024), and the Innovation Index, collected from the India Innovation Index report (2020).

The dependent variable, ICT_ADOPT (ICT adoption), originates from the answer to the question: "Does this establishment adopt ICT in its operations?". The variable takes the value two if the establishment has adopted both full ICT (both internet and computer), one if the firm adopted partial ICT (either internet or computer), and zero otherwise). As per availability of the indicators in respective dataset, this three Individual-level and five firm-level variable are used in the model: EDUCATION (= 2 if the owner has completed graduate-level education or higher, = 1 if the owner's education is equal to or above primary but below graduate level, and otherwise 0); GENDER (= 1 if the owner is Female otherwise 0); SOCIAL_GRP (= 1 if the

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[1] The source of this data is Rajya Sabha Session - 267 Unstarred Question No 549 Answered On, 7th February 2025 (https://www.data.gov.in/resource/stateut-wise-number-candidates-enrolled-and-trained-under-national-digital-literacy)

[2] The source of this data is Rajya Sabha Session - 267 Unstarred Question No 265 Answered On, 1st August 2024 (https://www.data.gov.in/resource/stateut-wise-details-internet-penetration-internet-subscribers-100-population-urbanrural)

establishment owner belongs to a non-backward social group, and 0 otherwise); FIRMSIZE (the size of the firm determined by the total workers as proxy); FIRMAGE (age of the firm in years); LOCATION (= 1 if the enterprise operates outside household premises otherwise 0) ENTP_TYPE (= 1 if the enterprise operates with hired labour otherwise 0) and SECTOR (= 1 if the enterprise is located in Urban otherwise 0).

Table I: Data Description of factors for unorganised enterprises

Part A: Descriptive Statistics of indicators for four different industries

	Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Manufacturing	Worker	127202	2.45	4.64	1	257
	Firm Age	127202	11.65	8.80	1	78
	Digital Literacy	127202	571574.74	361217.90	135	1033441
	Subscriber per capita	125313	65.28	21.67	36.43	204.39
	Innovation Index	127202	14.28	2.69	0	27.88
Hospitality Service	Worker	46629	1.13	0.73	1	42
	Firm Age	46629	9.91	6.75	1	78
	Digital Literacy	46629	509723.52	352228.58	135	1033441
	Subscriber per capita	44886	64.39	18.90	36.43	204.39
	Innovation Index	46629	14.94	3.49	0	27.88
Wholesale & Retail	Worker	167184	1.78	2.08	1	154
	Firm Age	167184	10.57	7.82	1	78
	Digital Literacy	167184	555701.22	369463.38	135	1033441
	Subscriber per capita	163881	64.57	21.60	36.43	204.39
	Innovation Index	167184	14.29	2.96	0	27.88
Construction & Real Estate	Worker	51888	2.73	3.67	1	203
	Firm Age	51888	10.49	8.25	1	75
	Digital Literacy	51888	555705.30	363811.39	135	1033441
	Subscriber per capita	50947	65.26	22.36	36.43	204.39
	Innovation Index	51888	14.38	2.88	0	27.88

Part B: Data Description of Indicators for four different industries

	Manufacturing	Hospitality Service	Wholesale & Retail	Construction & Real Estate
Partial ICT Adoption	19.2%	14.4%	27.6%	30.4%
Full ICT Adoption	3.3%	10.7%	5.4%	11.1%
Low Level	15.9%	9.4%	13.9%	15.8%
Mid-Level Education	75.3%	65%	73.2%	69.5%
High Level Education	8.8%	25.6%	12.9%	14.8%
Socially Backward	72.5%	61.7%	67.6%	67.9%
Non-Backward	27.5%	38.3%	32.4%	32.1%
Female-Owned	45.9%	14.8%	10%	11.5%
Access to Finance	7%	2.3%	13.1%	10.6%
Registered Firm	26.3%	25.7%	57.1%	46.6%
Establishment	24.3%	4.3%	20.1%	32.4%
Outside HH	42.9%	28.4%	84%	86.2%
Urban	43.1%	68.8%	45.4%	47.6%

Source: Author's creation

Additionally, this study incorporated three aggregate-level variables, and we have imputed across states in the empirical model: DIG_LIT (state-wise digital literacy denoted by the number of people enrolled in various government schemes); INT_PENT (state-wise internet penetration denoted by the total number of internet subscribers over population), and INNOVATION (state-wise innovation index).

Table II: Determinants of ICT Adoption Among unorganized firms across Four Major Industries in India

Dependent variable: ICT_ADOPT	***Ordinal Probit Model***				***Ordinal Logit Model***			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
EDUCATION	0.07***	0.10***	0.08***	0.10***	0.12***	0.17***	0.13***	0.17***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SOCIAL_GRP	0.12***	-0.05***	0.12***	0.07***	0.22***	-0.08***	0.22***	0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)
GENDER	-0.17***	-0.22***	-0.15***	-0.33***	-0.30***	-0.40***	-0.27***	-0.56***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)
FIRMAGE	-0.07***	-0.14***	-0.05***	-0.01*	-0.14***	-0.26***	-0.08***	-0.03**
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
FIRMSIZE	0.32***	0.93***	0.63***	0.21***	0.55***	1.72***	1.12***	0.40***
	(0.01)	(0.05)	(0.01)	(0.01)	(0.02)	(0.09)	(0.02)	(0.02)
ENTP_TYPE	0.12***	0.42***	0.18***	0.21***	0.17***	0.71***	0.24***	0.33***
	(0.01)	(0.05)	(0.01)	(0.02)	(0.03)	(0.10)	(0.02)	(0.03)
LOCATION	0.45***	0.75***	0.23***	0.11***	0.80***	1.29***	0.42***	0.22***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
DIG_LIT	-0.02***	0.02***	0.01***	0.01***	-0.04***	0.05***	0.02***	0.02***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
SECTOR	0.21***	-0.21***	0.20***	0.23***	0.38***	-0.35***	0.36***	0.40***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)
INT_PENT	0.01***	-0.00***	0.01***	0.01***	0.01***	-0.00***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
INNOVATION	0.08***	0.08***	0.06***	0.05***	0.14***	0.15***	0.11***	0.09***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Cut point 1	2.99***	3.05***	3.30***	3.10***	5.37***	5.50***	5.81***	5.33***
	(0.06)	(0.10)	(0.04)	(0.07)	(0.11)	(0.18)	(0.08)	(0.13)
Cut point 2	4.41***	3.83***	4.80***	4.35***	7.95***	6.88***	8.47***	7.49***
	(0.06)	(0.10)	(0.05)	(0.08)	(0.11)	(0.18)	(0.08)	(0.13)
LR (χ^2) Statistics	23552.73	9486.52	33499.41	11734.76	20058.44	8316.46	29511.28	10476.61
MacFadden's R^2	0.186	0.207	0.167	0.153	0.177	0.2	0.16	0.149
Observations	125,313	44,886	163,881	50,947	125,313	44,886	163,881	50,947
Industry	Manufacturing	Hospitality	Wholesale & Retail	Construction & Real Estate	Manufacturing	Hospitality	Wholesale & Retail	Construction & Real Estate

Source: ASUSE (2023-24); Author's Calculation

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table I (part A) represents the describe statistics of the enterprise and aggregate level variables, i.e., total workers, firm age, digital literacy, subscribers, and innovation index. The table is self-explanatory. Similarly, part B portrays the individual and enterprise level information mainly categorically, with two or more categories taken from the latest round of ASUSE microdata. Here, the dependent variable of this model is the degree of ICT adoption with three categories such as No ICT adoption, partial ICT adoption, and Full ICT adoption.

4. Result and Discussion

Table II shows the proposed model's estimation results comprises all four selected industries (model 1-4). The key enterprise-level factors influencing ICT adoption are firm size and firm age, both behaving as expected. Bigger firms are more likely to adopt ICTs, while younger firms tend to adopt ICT more readily than older ones.

Individual-level factors have a moderate impact on the adoption of ICT. The owner's educational attainment exerts a significantly positive influence on a firm's decision to adopt ICT. As highlighted in the existing literature, women-owned enterprises often face adverse conditions, and ICT adoption is no exception. Our findings indicate that women-owned enterprises exhibit lower levels of ICT adoption in comparison to others.

Similarly, newly established enterprises are more likely to adopt ICT in their operations. While newer firms aim to capture market share, older firms are already well-established. In the same way, larger firms, those employing hired labour, and urban informal enterprises are more inclined to adopt ICT in their operations.

Finally, aggregate-level factors show a diverse picture. States that are advanced in terms of innovation have a positive impact on ICT adoption. Similarly, overall digital literacy has positive impact except manufacturing firms (model 1). Similarly, states that have higher internet density intend to adopt ICT, except the firms in the hospitality industry within the unorganised sector (model 2). Here, it is clear that, in the manufacturing sector, higher digital literacy does not necessarily translate into ICT adoption within the informal counterpart. This adverse result may be caused by structural rigidities, skill mismatches, and path dependence in the production economy, as highlighted in earlier studies. Also existing studies mentioned that the use of ICT is significantly influence digital inclusion at all sphere whereas, ICT access does not (Adam & Dzang Alhassan, 2021). Similarly, for the hospitality sector, the result shows an adverse interlinkage with internet penetration, possibly due to customer heterogeneity, sectoral diversity, market saturation, and varying levels of ICT adoption across firm sizes. Furthermore, to strengthen our results, we conducted robustness checks by applying an alternative methodological approach: ordinal logistic regression in models 5-8. While the coefficients differ in magnitude, their directions remain consistent with those obtained from our main ordinal probit model, thereby reaffirming the robustness of our findings.

5. Conclusion

Despite the diverse nature of the Indian unorganised sector, ICT adoption is becoming increasingly widespread. Many individual-level, enterprise-level, and aggregate-level factors are influencing the firm to adopt ICT in their operations. The education level of the owner and location of the enterprises (especially urban informal firms) play a significant role in facilitating ICT adoption in business operations. Enterprise-level factors, such as newly established firms and larger firms, are more inclined to adopt ICT. At the aggregate level, the picture is more varied. Digital literacy has a positive impact on ICT adoption across most industries, with the exception of the manufacturing sector. While innovation consistently shows a positive influence, internet density also has a favourable effect, except in the hospitality industry in the post-COVID scenario. In a nutshell, we can clearly state that in the manufacturing sector, higher digital literacy does not necessarily translate into ICT adoption in the informal counterpart due to structural rigidities, skills mismatch, and path dependence in production systems, which has also been highlighted in prior studies. In a similar manner, the hospitality sector also has shown a negative association with internet penetration may be explained by factors such as customer heterogeneity, market saturation, and differential adoption of ICT across firm sizes.

6. Limitation and Policy Recommendation

Our study primarily focused on identifying the drivers of the degree of ICT use in the Indian unorganised manufacturing enterprises. Despite conducting a comprehensive analysis, certain factors such as the cost of ICT adoption, experience of the owner, and export orientation, which could significantly influence adoption, are not captured in the dataset. Nevertheless, the analysis provides a more in-depth understanding that can help policymakers formulate concrete strategies to strengthen overall ICT adoption while addressing spatial disparities and sectoral imbalances.

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