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Exploring Post–COVID–19 Workforce Dynamics: An Experimental Study on Factors Affecting Job Acceptance in Goa

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Abstract: In the post-COVID-19 era, the dynamics of labor market participation and job acceptance have shifted significantly, driven by the development of societal and psychological factors. The study highlights the intricate interplay of psychological, societal, and economic factors influencing job acceptance in the post-pandemic labor market. It investigates the determinants of job acceptance, emphasizing the roles of risk aversion, marital status, and job attributes in Goa's labor market. Using primary data collected from respondents aged 21-55, through stratified sampling, the study applies the Cragg Hurdle Model for analysis. Key findings reveal that job attributes, including flexible working hours, job security, commuting distance, promotion opportunities, and housing conditions, play a critical role in influencing job acceptance. Risk aversion emerged as a crucial psychological factor. Risk-averse individuals strongly preferred stable and predictable jobs, whereas risk-takers were more likely to accept positions with longer hours or fewer guarantees of security. During the pandemic, risk-averse individuals avoided roles involving higher perceived risks. Marital status positively influenced engagement, with married individuals displaying higher job acceptance rates due to the need for financial security and family stability. Marginalized groups experienced disparities in job acceptance due to socio-economic challenges and limited access to resources. Notably, job acceptance was affected by practical considerations, such as commuting time and accommodation conditions. While findings provide valuable insights into Goa's labor market, limitations include the regional focus, which may restrict broader applicability. Policymakers should prioritize bridging the urban-rural divide and employers must design more flexible, stable, and growth-oriented roles to foster workforce engagement. Future research should employ longitudinal methods to capture changing labor market trends across wider contexts.

Introduction

The COVID–19 pandemic brought unprecedented disruptions to labor markets worldwide, fundamentally altering job seekers' priorities and behaviors. Goa, a state heavily reliant on its vibrant tourism sector, felt these changes acutely. With widespread layoffs, furloughs, and a steep decline in foreign tourist arrival – approximately 60% lower than pre-pandemic levels (Desk, 2024). Goa's labor market experienced a paradigm shift. Job seekers in the state began emphasizing stability, flexibility, and health safety measures, highlighting a broader global trend of recalibrating work-life priorities. This paper explores the evolving dynamics of willingness to work and job acceptance post-pandemic, particularly focusing on Goa, and examines how individual–level and job–specific factors influence employment decisions.

Before the pandemic, labor market participation in Goa was closely tied to the state's tourism-driven economy. The hospitality sector accounted for a significant proportion of jobs, drawing in local and migrant workers. However, the pandemic–induced lockdowns and travel restrictions crippled the sector, leaving thousands unemployed. Goa's unemployment rate surged to 8.7%, nearly double the national average of 4.5% (Herald Team, 2024). This alarming statistic underscores the severity of the State's economic

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downturn and highlights the challenges faced by its workforce. As the economy began recovering, job seekers became increasingly selective about the roles they pursued, prioritizing stability, flexible working conditions, and long-term growth prospects.

The shift in job seekers' attitudes post-pandemic is tied to several critical factors. Risk aversion, for instance, has emerged as a significant determinant in labor market participation. Individuals who experienced job losses, wage cuts, or health risks during the pandemic now exhibit a cautious approach to re-entering the workforce. Many prioritize job security and stable employment conditions over other considerations (Cech and Hiltner, 2022; Baluku et al., 2020). Established companies with a proven track record of employee support during crises are often preferred, as they provide a sense of reliability in uncertain times.

Educational qualifications have also gained prominence in the post-pandemic labor market. Higher educational attainment equips individuals with diverse skill sets, enabling them to access a wider array of job opportunities and exercise greater selectivity in their choices. This trend is particularly significant in Goa, where the workforce is transitioning from traditional, tourism-dependent roles to more diversified employment avenues, including remote work and digital economy jobs. The rapid advancement of digital infrastructure and the growing acceptance of virtual collaboration tools have facilitated this transition, with remote work becoming a mainstream expectation for many job seekers.

Job–specific characteristics play a pivotal role in shaping willingness to accept job offers. Factors such as working hours, job duration, commuting distance, promotion opportunities, local employment opportunities, and accommodation availability significantly influence job acceptance decisions (Van Landeghem et al., 2024). For instance, flexible working hours and longer job durations are associated with higher job satisfaction and stability, making such roles particularly attractive to potential employees. Conversely, jobs requiring long commutes or offering limited local employment opportunities can deter job acceptance, regardless of individuals' overall willingness to work.

In Goa, these dynamics are particularly pronounced. With the hospitality sector gradually recovering, job seekers are now weighing practical considerations more heavily. Accommodation availability, for example, is a critical factor for individuals in sectors like tourism and hospitality, where jobs often require employees to relocate. Similarly, local employment opportunities influence the decisions of workers who prefer to avoid lengthy commutes or uprooting their families. The pandemic has further emphasized the importance of health and safety measures in workplaces, with many job seekers prioritizing roles in companies that adhere to robust health protocols.

The willingness to work and willingness to accept a job offer are interconnected yet distinct concepts. Willingness to work reflects an individual's motivation and readiness to participate in labor market activities, influenced by personal factors such as risk aversion, marital status, and social background (Benrazavi et al., 2013). On the other hand, willingness to accept job offers hinges on job-specific characteristics that determine the perceived attractiveness and suitability. For instance, individuals with higher risk aversion may prioritize job security and stability over potentially lucrative but uncertain roles. (Abraham et al., 2013).

Job–specific factors such as working hours and promotion opportunities further shape job acceptance decisions. In Goa's context, where tourism jobs often involve irregular hours and limited career growth, these factors become critical in determining the attractiveness of such roles. Flexible working hours, for example, are increasingly valued by employees seeking better work-life balance. Promotion opportunities also play a crucial role, offering prospects for career advancement that align with employees' long-term goals.

This study aims to contribute to understanding these dynamics in a post-pandemic context, focusing on Goa's labor market. Specifically, it investigates whether individuals with a greater willingness to work are also more likely to accept job offers and examines how job-specific factors influence these decisions. By adopting a dual approach that includes both descriptive analyses and advanced econometric models like the Cragg Hurdle Model, the study seeks to provide nuanced insights into the interplay of individual motivations and job characteristics.

Willingness to work and accept job offers has been extensively studied in labor economics, where it is recognized as a fundamental aspect of workforce participation and employment decisions. Researchers have explored various factors that influence an individual's willingness to work, including economic conditions, personal motivations, and demographic characteristics. Factors such as risk aversion, marital status, and social category have also been identified as significant moderators of job acceptance behavior. In recent years, the post-pandemic labor market has also prompted a shift in employment preferences,

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emphasizing stability, flexibility, and security. It is a key concept in labor economics, reflecting an individual's readiness to engage in the labor market. Several factors influence this willingness, including socio-economic status, family responsibilities, and personal motivations (Carneiro et al., 2003; Heckman et al., 2006). On the other hand, willingness to accept a job offer is not solely dependent on the desire to work but also on the characteristics of the job itself. The job offers' attributes, such as compensation, security, and stability, play a significant role in whether an individual chooses to accept it (Mortensen, 1986; Van den Berg and Gorter, 1997).

Risk aversion is a critical psychological trait that affects economic decisions, including job search behavior. Individuals who are more risk–averse tend to avoid uncertainty, which includes being cautious about accepting job offers that appear risky (Caliendo et al., 2011). Dohmen et al. (2011) argue that risk-averse individuals prefer stable and secure employment, and this preference shapes their job search and decision-making. Risk aversion mediates the relationship between willingness to work and job acceptance, as individuals' concerns about job security and stability play a crucial role in whether they choose to accept an offer.

Marital status and social category also significantly influence the willingness of risk-averse individuals to accept job offers. Married individuals with higher risk aversion, especially from those SC/St categories, tend to prioritize stable and secure job offers to ensure family well-being and address socio-economic challenges. On the other hand, single, risk-averse individuals from General/OBC categories may be more open to taking calculated risks in pursuit of career advancement. This interplay between marital status and social category impacts decision–making, with job security being a common priority for risk–averse individuals across various contexts (Nagargoje et al., 2022; Di Mauro and Musumeci, 2011; Sawyer, 2022; Deb, 2019).

The specific characteristic of job offers play a crucial role in shaping an individual's willingness to accept them. Flexible working hours are positively associated with job acceptance, as they cater to personal and family needs, providing work-life balance (Golden, 2001; Tausig and Fenwick, 2001). Permanent positions or those with longer durations are generally preferred due to their stability and benefits (Van den Berg and Van der Klaauw, 2006; Baydur and Mukoyama, 2020; Abraham et al., 1987). Longer commuting distances negatively impact job acceptance, as they increase time and financial burdens (Stutzer and Frey, 2004; Dickerson et al., 2014; Clark et al., 2019). Jobs with clear promotion paths are more attractive, offering career growth and higher future earnings (Ng et al., 2005; De Souza, 2002; Garba and Idris, 2021). The abundance of local job opportunities can decrease the urgency to accept specific offers, as individuals may prefer exploring other options (Simpsons, 1987; Shields and Swenson, 2000; Molho, 2001). Job offers that include accommodations provisions are particularly attractive in regions with high living costs, as they reduce the financial burden on workers (Zhao, 2005; Wang and Dong, 2021; Mullan et al., 2011).

The Impact of the Pandemic on Goa's Economy

The post-pandemic labor market has seen shifts in employment preferences, with workers now prioritizing job security, flexible work arrangements, and healthy safety protocols, driven by the vulnerabilities exposed during the COVID-19 pandemic. Risk aversion has increased, with many job seekers choosing stable roles over high–paying but riskier opportunities. Furthermore, once considered a perk, remote work has become an expectation (Kavya et al., 2024; Eriksson and Petrosian, 2020). These trends are particularly evident in regions like Goa, where tourism, a highly volatile sector, significantly influences the labor market (Chaudhary et al., 2010; Škare et al., 2020; Siddhartha and Naleen Chandra, 2024)

Both economic and psychological factors have shaped the post-pandemic labor market. The search and matching theory (Mortensen and Pissarides, 2011; Mortensen and Pissarides, 1999) suggests that workers and employers search for optimal matches influenced by key job attributes like security, duration and flexibility. The pandemic has intensified these dynamics, with workers prioritizing stability and health-related assurances (Gupta et al., 2021; Reynolds et al., 2022). Psychological theories like Risk Aversion Behavior (Dohmen et al., 2011) further emphasize how individuals' responses to uncertainty influence their willingness to accept jobs, particularly in regions like Goa, which are vulnerable to economic stability.

Job Acceptance in Goa: A Model for Other Tourism–Dependent Regions

Goa's economy suffered significantly during the pandemic due to its dependence on tourism, leading to widespread layoffs, reduced incomes, and greater economic insecurity. The pandemic's disruption of the tourism sector led to massive job losses and increased economic vulnerability. According to Becker's Human Capital Theory (Blaug, 1974; The Editors of Encyclopaedia Britannica, 2024), individuals with higher education or skills may seek remote or digital jobs, while

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those with fewer job opportunities may opt for stable local employment. This aligns with findings suggesting that workers in volatile sectors prioritize roles offering greater predictability (Cech and Hiltner, 2022). Additionally, psychological factors such as Maslow's Hierarchy of Needs emphasize the importance of safety and security during times of crisis, further shaping job choices in Goa's labor market (Kendra Cherry, 2024)

Understanding job acceptance factors in this region is critical for several reasons. First, Goa's demographic profile includes both urban and rural labor markets, each with distinct needs and preferences. The urban population tends to favor remote or digital work opportunities, while rural workers, constrained by limited digital infrastructure, often prefer stable, local employment (Gillette, 2023). Second, Goa's reliance on seasonal industries like hospitality highlights the importance of job-specific factors such as job duration, commuting distance, and promotion opportunities in shaping employment decisions. The insights gained from such studies can help inform policies that promote workforce stability, diversify job opportunities, and enhance resilience in Goa's economy. Finally, the state's recovery offers valuable insights into how tourism-dependent economies can strengthen their resilience and develop more diversified and stable labor markets (Pascariu et al., 2021). These findings can also serve as a model for other tourism-dependent regions seeking to recover from similar disruption.

The study of job acceptance in Goa is vital due to its unique demographic and economic landscape. It can provide critical insights for policymakers regarding regional labor dynamics. Findings from such studies can guide targeted interventions aimed at improving job security, enhancing digital infrastructure, and diversifying employment opportunities. This approach will aid Goa's economic recovery and prepare it to withstand future disruptions (Aleem et al., 2022; Besbris et al., 2024). The insights gained from such studies can help inform policies that promote workforce stability, diversify job opportunities, and enhance resilience in Goa's economy. These findings can also serve as a model for other tourism-dependent regions seeking to recover from similar disruptions.

Materials and Methods

The study employed a stratified random sampling method to ensure a representative sample of the working-age population in Goa, focussing on individuals aged 21 to 55 years. A total of 163 participants were included, capturing diverse demographic and socioeconomic profiles. Participants were stratified based on geographical location, age, educational background, and employment status to achieve a balanced representation. Geographical stratification included both urban areas, such as Panaji, Margao, Vasco, and Mapusa, and rural regions such as Aldona, Bicholim and Quepem. Age groups were divided into four brackets: 21-30, 31-40, 41 -50, and 51-55 years. Educational backgrounds ranged from high school graduates to postgraduates, encompassing technical and non-technical qualifications, diploma holders, and individuals with vocational training.

Within each stratum, participants were randomly selected to minimize bias. The study also considered employment status, including both employed and unemployed individuals. Occupations represented in the sample included professionals, service workers, clerical staff, contractual employees, and self-employed individuals. Gender representation was balanced to examine disparities in job acceptance trends. By including urban and rural populations, the study captured the unique challenges and preferences of different segments of Goa's workforce, such as the urban inclination toward remote work and the rural preference for locally stable jobs. This stratified approach ensured the findings reflected the broader labor market dynamics in Goa, enhancing the study's validity and applicability.

The study employed a carefully designed experimental setup to explore the factors influencing job acceptance in Goa's post-pandemic labor market. Data were collected using a structured, self-evaluated survey administered to a stratified random sampling of 163 participants aged 21-55 years. The survey captured demographic information, job-specific attributes, and psychological factors such as risk aversion. Responses were analyzed using the Cragg Hurdle Model, a two-step approach that first examined participants' willingness to work and then assessed their willingness to accept specific job offers. Control variables, including age gender, marital status, education level, geographical location, and employment status, were incorporated to isolate their effects on job acceptance decisions. This ensured that variations in the dependent variable could be attributed to the independent variables of interest rather than external factors.

To minimize potential biases, several measures were implemented. Stratified sampling ensured equal representation of diverse population subgroups, reducing selection bias. The survey design was rigorously pilot tested, with neutrally worded questions to eliminate response bias. Participants were assured anonymity to encourage honest and uninfluenced feedback.

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Additionally, survey administrators were trained to ensure consistency during data collection, thereby minimizing interviewer bias. Key constructs such as risk aversion and job preferences were measured using standardized and validated scales, enhancing the reliability and comparability of the findings. These methodological precautions ensured robust and credible results, providing a nuanced understanding of job acceptance dynamics in Goa's labor market.

The study applied the Cragg Hurdle Model, also known as the Double-Hurdle Model, a statistical approach used to analyze datasets with two distinct decision processes. Developed by John G. Cragg in 1971, this model is particularly useful in situations where individuals first decide whether to participate in an activity and then determine the extent of their participation. It addresses the limitations of traditional Tobit models, which assume that the same process determines the decision to participate and the level of participation.

In the Cragg Hurdle Model, the first "hurdle" involves a binary choice model, typically a probit or logit model, to estimate the probability that an individual will engage in the activity. For example, in the context of Job seekers, this step would analyze whether a Job seeker displays some magnitude of risk attribute when he chooses to accept the job offer or not. Once the first hurdle is crossed, the second hurdle uses a truncated regression model to examine the extent of participation, such as his marital status and category influencing his decision about whether to choose. This two-part approach allows for greater flexibility and more accurate modeling of real-world behaviors where different factors influence the decision to participate and the level of participation (García, 2013; Jones, 1989; Engel and Moffatt, 2014).

By separating these two processes, the Cragg Hurdle Model provides a more nuanced understanding of behaviors and can yield better policy and business insights. For instance, policymakers can identify different factors affecting the likelihood and intensity of participation separately, allowing for targeted interventions. Similarly, businesses can tailor marketing strategies based on factors that influence initial purchase decisions and those that affect the purchase quantity. The model's ability to handle zero-inflated data and provide detailed insights makes it a valuable tool in fields like economics, marketing, and health sciences.

Hypothesis Testing

H0: There is no significant relationship between an individual's risk attitude (risk taker, peacemaker, and risk-averse) and their likelihood of engagement across various work-related factors (hours worked, promotion opportunities, job type, travel distance, local employment opportunities, and accommodation conditions).

H1: An individual's risk attitude (risk taker, peacemaker, and risk-averse) significantly influences their likelihood of engagement across various work-related factors (hours worked, promotion opportunities, job type, travel distance, local employment opportunities, and accommodation conditions). Specifically, risk-takers are likelier to engage in the activity than peacemakers and risk-averse individuals.

Note: In model testing R4 : 0- Risk taker (reference category) and 1 – Peacemaker & Risk averse.

Result and Discussion

Table 1. Descriptive Statistics.

Variable	Mean	Standard deviation
W1	0.816	0.389
WA2	3.877	2.119
Risk	0.638	0.438
WA5	1.908	0.744
Work_Hr	2.239	0.567
Promotion	2.350	0.468
Job_type	2.624	0.490
Travel_Dist	2.186	0.513
LocEmpOpp	2.252	0.511
Accommodat~n	2.213	0.520

Source: Author's compilation based on data obtained from the Primary survey

Table 1 presents descriptive statistics for various variables related to the study. The mean values indicate the central tendency of the data, while the standard deviation measures the variability. The mean value of W1 (Willingness to Work) is 0.82 with a standard deviation of 0.39, suggesting a generally high willingness to work among respondents but with considerable variability. With a mean of 3.88 and a standard deviation of 2.12, WA2 (Willingness to Accept a Job Offer) shows substantial variability in how attractive job offers are perceived. The mean of Risk (Risk Aversion) is 0.64 with a standard deviation of 0.44, indicating moderate risk aversion among respondents. A mean of 1.91 and a standard deviation of 0.74 inWA5 (Willingness to Accept a Job Offer with Specific Conditions) show variability in acceptance depending on specific job conditions.

The mean of Work_Hr (Work Hours) is 2.24 with a standard deviation of 0.57, indicating a moderate preference for certain work hours. Promotion (Promotion

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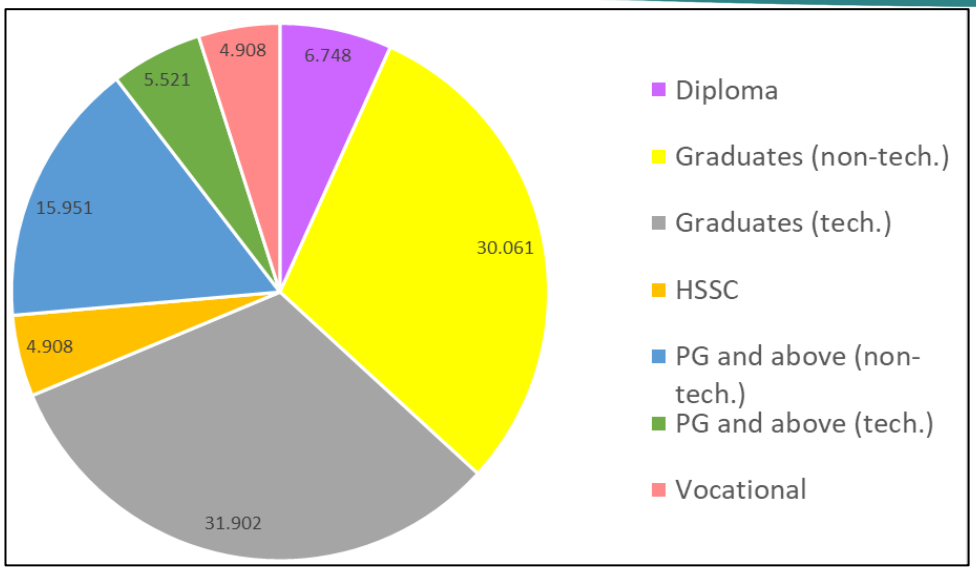

Figure 1. Sample composition by nature and level of education [Source: Author's compilation based on data obtained from the Primary survey].

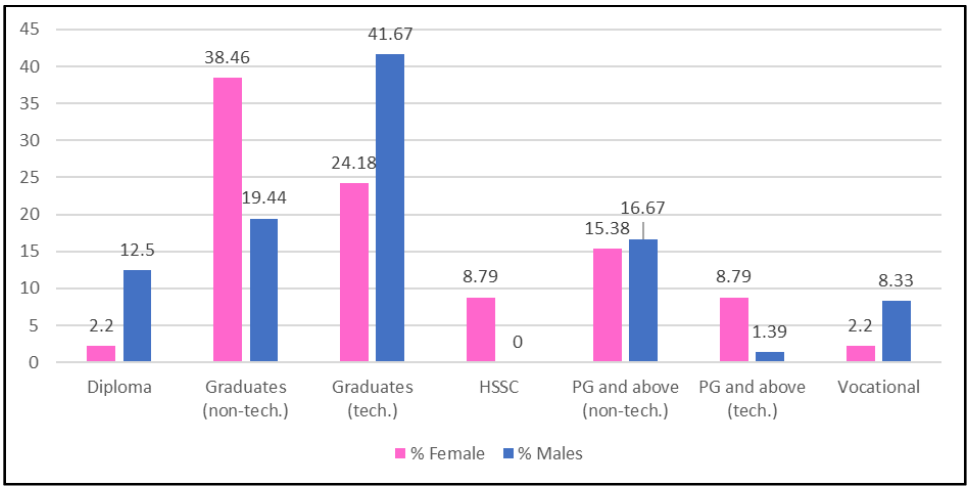

Figure 2. Sample composition by Gender and level of education [Source: Author's compilation based on data obtained from the Primary survey].

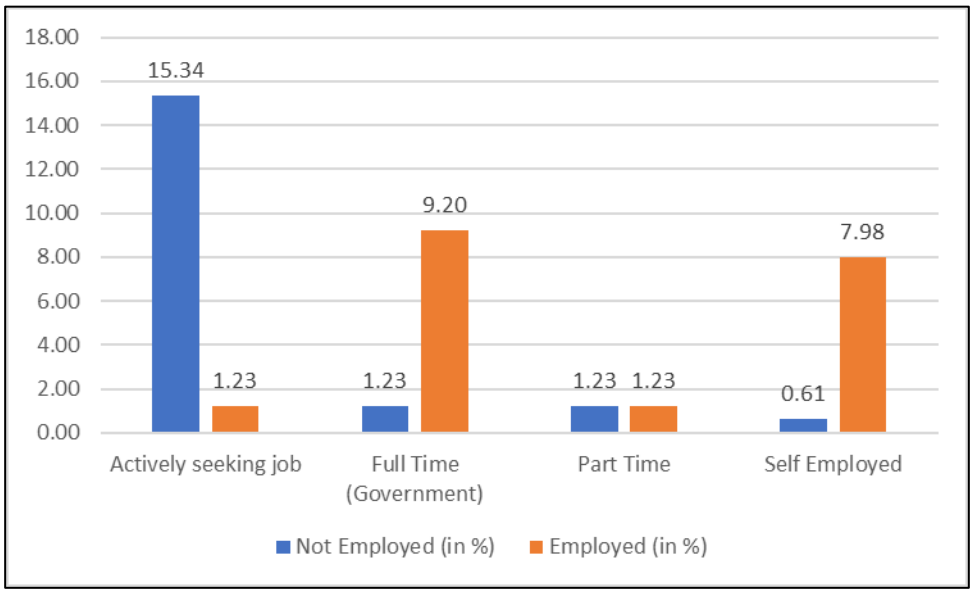

Figure 3. Sample composition by Occupational status [Source: Author's compilation based on data obtained from the Primary survey].

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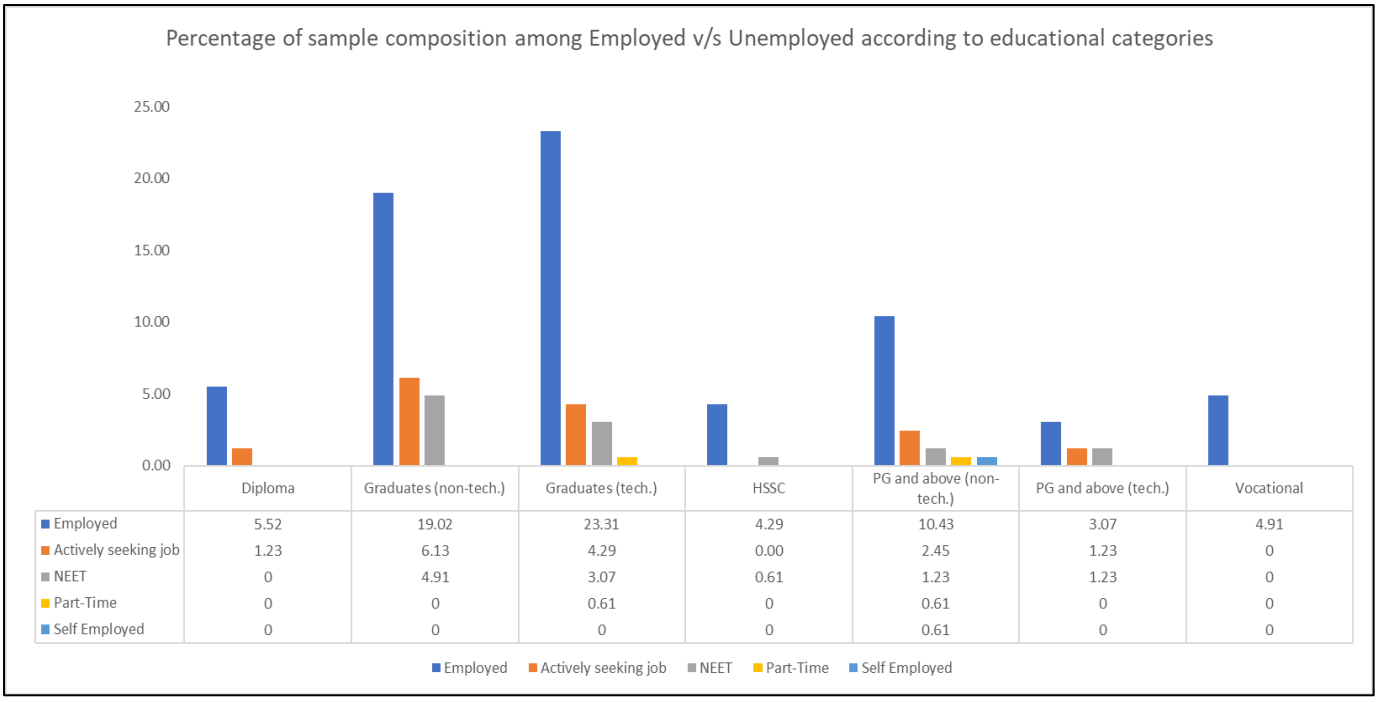

	Diploma	Graduates (non-tech.)	Graduates (tech.)	HSSC	PG and above (non-tech.)	PG and above (tech.)	Vocational
Employed	5.52	19.02	23.31	4.29	10.43	3.07	4.91
Actively seeking job	1.23	6.13	4.29	0.00	2.45	1.23	0
NEET	0	4.91	3.07	0.61	1.23	1.23	0
Part-Time	0	0	0.61	0	0.61	0	0
Self Employed	0	0	0	0	0.61	0	0

Figure 4. Sample composition Employed v/s Unemployed with educational categories [Source: Author's compilation based on data obtained from the Primary survey].

Opportunities) mean value of 2.35 with a standard deviation of 0.47 suggests that promotion opportunities are moderately valued.

Job_type (Job Type) mean value of 2.62 with a standard deviation of 0.49 reflects a moderate preference for certain types of jobs. Travel_Dist (Travel Distance) mean value of 2.19 and a standard deviation of 0.51 indicate moderate concern about commuting distances. LocEmpOpp (Local Employment Opportunities) mean value is 2.25 with a standard deviation of 0.51, showing moderate satisfaction with local employment opportunities. Accommodat~n (Accommodation Availability) mean value of 2.21 and a standard deviation of 0.52, there is a moderate level of concern regarding accommodation availability.

Figure 1 shows the distribution of respondents by their educational qualifications. The largest group comprises graduates with technical degrees (31.90%), followed by non-technical graduates (30.06%). Post-graduate degrees (both technical and non-technical) are less common, with a combined percentage of around 21.47%. Diploma holders and vocational training participants are relatively fewer, representing only 11.67% of the sample. The distribution indicates a well-educated sample with a strong representation of graduates and post-graduates.

Figure 2 illustrates the gender distribution across different educational levels. Female representation is notably low among technical graduates (24.18%) and diploma holders (2.20%). Non-technical graduates have a higher female percentage (38.46%). Female participation is minimal in fields like HSSC and vocational training, indicating potential gender disparities in certain educational sectors.

Figure 3 compares employment and non-employment percentages across four job categories: actively seeking jobs, full-time government positions, part-time jobs, and self-employment. The highest percentage of non–employed individuals (15.34%) are actively seeking jobs, while only 1.23% of this group are employed. Full time government jobs have a significantly higher employment percentage (9.20%), while part–time jobs and self-employment show relatively low percentages of non-employed individuals (1.23% and 0.61%, respectively). Self-employment accounts for 7.98% of the employed category, indicating its growing importance. This highlights employment distribution disparities across job types.

Figure 4 illustrates the percentage distribution of employed and unemployed individuals across various educational categories. Graduates (non–technical) have the highest representation among employed (19.02%) and actively seeking jobs (6.13%). Post-graduates and above (non–technical) show moderate employment (10.43%), while vocational education accounts for a smaller but notable share of employment (4.91%). NEET (Not in education, employment, or training) percentages are higher among graduates, particularly non–technical (4.91%), indicating job search challenges. Part-time and self-employment percentages remain minimal across all educational categories, highlighting a preference for full–time roles among the workforces.

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Table 2. Cragg hurdle regression.

RA4	Variables	Coefficient	p-value	Significance
Working Hours (Model 1)	WAJO	0.0461 (0.23)	0.045	*
	10 hours	-0.2901 (0.091)	0.001	**
	20 hours	0.1276 (0.085)	0.131	
	30 hours	-0.1516 (0.075)	0.044	*
Promotion opportunities (Model 2)	WAJO	0.0483 (0.024)	0.043	*
	Fewer internal promotions	-0.1920 (0.068)	0.005	**
	None internal promotions	-0.0160 (0.062)	0.795	
	Many internal promotions	0.0303 (0.078)	0.697	
Job Duration (Job_Type) (Model 3)	WAJO	0.0422 (0.022)	0.060	
	Permanent	-0.3247 (0.102)	0.001	***
	Limited to 01 year	0.0763 (0.081)	0.347	
	Limited to 03 year	-0.1940 (0.072)	0.007	**
Commuting Distance (Travel_Dist) (Model 4)	WAJO	0.0543 (0.023)	0.020	*
	01 hour	-0.2883 (0.132)	0.030	*
	04 hour	-0.0829 (0.076)	0.273	
	06 hour	0.0789 (0.079)	0.316	
Local Employment Opportunities (LocEmpOpp) (Model 5)	WAJO	0.0654 (0.023)	0.005	**
	Worse compared with the current place of residence	0.0432 (0.061)	0.477	
	Similar compared with the current place of residence	-0.0304 (0.077)	0.694	
	Better than compared with the current place of residence	-0.0575 (0.075)	0.443	

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Accommodation Availability (Model 6)	WAJO	0.0500 (0.023)	0.032	*
	Very easy in finding adequate housing	-0.2305 (0.084)	0.006	**
	Some efforts need to find adequate housing	0.0600 (0.074)	0.415	
	Considerable efforts need to be put into finding an adequate housing	-0.0248 (0.064)	0.699	

Variables	**No. of Obs.**	**Log-likelihood**	**Pseudo R2**
Hours	163	-158.707	0.097
Promotion	163	-161.048	0.083
Job_Type	163	-154.632	0.120
Travel_Dist	163	-161.908	0.078
LocEmpOpp	163	-164.406	0.064
Accommodation	163	-161.568	0.080
Source: Analysis based on data obtained from the Primary Questionnaire.			
Notes: 1) *, **, * represent significance levels of 10 percent, 5 percent, and 1 percent; 2) Standard error reported in parenthesis; 3) WAJO refers to willingness to accept job offers.**			

Table 3. Margins.

Avg Marginal Effects			**No. of Obs**	**163**
Model	**VCE**	**OIM**		
Expression	**Conditional mean estimates of dependent variable, predict()**			
	Delta-method			
	dy/dx	**SE**	**z**	**P>|z|**
Mar_S	0.230	0.090	2.55	0.011 **
Cate	0.114	0.050	2.27	0.023 *
Source: Analysis based on data obtained from the Primary Questionnaire.				
Notes: *, **, * represent significance levels of 10 percent, 5 percent, and 1 percent**				

Table 2 presents results from a Cragg Hurdle regression analysis across six different models, examining various factors' effects on a dependent variable.

Hours (Model 1)

In Model 1, WAJO (likely a variable representing Willingness to accept job offers) has a positive and significant coefficient (0.046, p=0.045), indicating that higher WAJO is associated with an increased likelihood of the outcome. The variable "10 hours" has a negative and significant effect (-0.290, p=0.001), while "30 hours" also shows a negative impact (-0.152, p=0.044). The constant term (_cons) is positive and highly significant (1.987, p=0.000). The sigma term indicates the dispersion parameter of the model.

Promotion (Model 2)

In Model 2, WAJO has a similar positive effect (0.048, p=0.043). "Fewer internal promotions" is negatively associated with the outcome (-0.192, p=0.005), while other promotion variables are not significant. The constant term is significant and positive (1.601, p=0.000), with sigma values indicating the model's fit.

Job Type (Model 3)

In Model 3, WAJO's effect is marginally significant (0.042, p=0.060). "Permanent" job types have a

significant negative association (-0.325, p=0.001), and "Limited to 03 years" also shows a negative effect (-0.194, p=0.007). The constant is positive and significant (2.405, p=0.000).

Travel Distance (Model 4)

Model 4, WAJO with a significant positive effect (0.054, p=0.020). "01-hour" travel distance has a significant negative effect (-0.288, p=0.030), while other travel distances are not significant. The constant term is positive and significant (2.004, p=0.000).

Local Employment Opportunities (Model 5)

In Model 5, WAJO is positively associated with the outcome (0.065, p=0.005). Other variables related to employment opportunities do not show significant effects. The constant is significant (1.250, p=0.000).

Accommodation (Model 6)

Model 6, WAJO displays a positive and significant coefficient (0.050, p=0.032) in Model 6. "Very easy in finding adequate housing" is negatively associated with the outcome (-0.231, p=0.006). Other accommodation variables are not significant. The constant term is positive and significant (1.686, p=0.000).

Selection Model

The selection model includes marital status (Mar_S) and social category (Cate – General, OBC, SC, ST). Mar_S has a positive and significant effect (0.491, p=0.015), and Cate also has a significant positive effect (0.244, p=0.029). The constant term is negative and significant (-0.874, p=0.032).

Model Statistics

Each model has a different number of observations (163) and varying likelihood ratio chi-squared values, all significant at p=0.000, indicating that the models fit the data well. The pseudo-R-squared values range from 0.064 to 0.120, indicating the proportion of variance explained by the models.

In Table 3, the marginal effects of Mar_S and Cate (Marital Status and Social Category) are positive and significant. A change in marital status shows an increase in the expected value of the dependent variable (RA4) by out 0.231 units, which means that the higher the probability that the job seeker is married shows that his response to willingly accept the job offer (taking the risk) increases by 0.231 units. In the case of CATE (social category), we observe a similar pattern where we understand that those falling into the category of general (unreserved) will exhibit a 0.11 chance of willingly accepting the job offer.

Risk Takers (represented by WAJO) tend to show a positive engagement across most models, indicating they are more likely to participate in or contribute to the dependent variable. Peacemakers and Risk Averse tend to exhibit behaviors aligned with stability (e.g., preference for permanent jobs) and avoidance of extensive engagement (e.g., fewer hours worked, shorter travel distances, easier housing conditions). The significance of variables like marital status and category (General, OBC, SC, ST) also suggests these factors interact with risk attitudes, influencing overall outcomes.

The statistical analysis employed the Cragg Hurdle Model, which provided a two-step evaluation of willingness to work and job acceptance factors. Results indicate that job-specific attributes, such as flexible working hours, job security, and proximity to employment locations, significantly influence job acceptance decisions. Key findings include a significant positive effect of willingness to accept job offers (WAJO) across multiple models, with coefficients ranging from 0.046 (p=0.045) in the hours worked model to 0.065 (p=0.005) in the local employment opportunities model. Similarly, risk aversion demonstrated a negative association with accepting jobs requiring long commuting distances or minimal job security. For instance, the variable “10 hours” exhibited a negative coefficient of -0.290 (p=0.001), indicating a significant deterrent effect of longer working hours for risk-averse individuals. Marital status (0.231, p=0.011) and social category (0.115, p=0.023) were found to significantly moderate job acceptance, highlighting the role of demographic factors. These results underscore the multifaceted influences on job decisions and validate the reliability of the model with a pseudo-R2 range of 0.064 to 0.120 across the tested models.

To summarise, the Cragg Hurdle regression results suggest that WAJO is a significant predictor across most models, while other variables like hours worked, job type, travel distance, local employment opportunities, and accommodation conditions also play important roles in determining the outcomes, with varying degrees of significance. RA4's categorization into risk taker, peacemaker, and risk-averse provides a meaningful lens through which to interpret the effects of other variables, highlighting how risk attitudes influence engagement and contributions to the outcome measured in the models.

Comparison with Broader Research

The study’s findings align with broader research on job acceptance factors, particularly those emphasizing the importance of job-specific attributes and individuals’ risk preferences. For example, Dohnmen et al. (2011) similarly found that higher risk aversion correlated with a preference for stable, secure jobs. However, this study adds a regional dimension by focusing on Goa, where

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reliance on the tourism sector and a significant urban-rural divide creates unique employment challenges. Compared to national studies like Rao and Naik (2020), which highlight the role of digital infrastructure in job preferences, this study finds a greater emphasis on traditional job attributes such as commuting distance and promotion opportunities, reflecting Goa's economic reliance on face-to-face industries. Furthermore, while global studies note a universal shift toward remote work post-pandemic, this study reveals that such trends are moderated by local infrastructural constraints, especially in rural areas. These comparisons place the findings within a broader context while highlighting Goa's distinctive labor market dynamics, underscoring the importance of localized strategies for workforce engagement (Jansen et al., 2024; Kaur, 2024).

Conclusion

In the post-COVID-19 era, the dynamics of the job market have significantly shifted, influencing individuals' willingness to accept job offers and their overall willingness to work. This paper examined whether risk-averse individuals differ from risk-takers and others in their willingness to accept job offers. This inquiry is crucial to understanding interregional disparities in unemployment and labor mobility. Theoretically, a risk-averse individual might be less likely to relocate for a job in another region due to their preference for stability and lower perceived risk.

Our study employs the Cragg Hurdle regression model to investigate the impact of various factors on engagement in work-related activities, categorizing individuals into risk-takers, peacemakers, and risk-averse. The analysis sheds light on the significant role of risk attitudes, marital status, and social category in decision-making, especially in COVID-19 dynamics, and their influence on labor behavior.

The regression results demonstrate that risk aversion significantly influences engagement levels. Risk-takers are likelier to engage in work-related activities, while risk-averse individuals show lower engagement levels. This trend is consistent across several models, indicating that risk attitudes are a crucial determinant in the likelihood of engaging in activities that require time commitment, job mobility, or adaptability to different working conditions. During the COVID-19 pandemic, risk aversion played a pivotal role in shaping individuals' willingness to accept job offers, with risk-averse individuals preferring more secure and stable job opportunities amidst the uncertainties. The pandemic heightened concerns about health and economic stability, leading risk-averse individuals to avoid positions with higher perceived risks, such as those requiring physical presence or extensive travel.

Marital status (MAR_S) is another critical factor influencing engagement. The marginal effects analysis reveals that marital status has a positive and significant outcome on the dependent variable indicating that married individuals or those in stable relationships are more likely to engage in work-related activities compared to their single counterparts. The stability and support provided by a marital relationship could contribute to higher engagement levels, as individuals may feel more secure and motivated to participate in various activities. The COVID-19 pandemic further accentuated this trend, as married individuals might have sought stable employment to ensure financial security for their families. The need to balance work and family responsibilities also became more pronounced during the pandemic, influencing job acceptance decisions and engagement levels.

Social category (CATE) also plays a significant role in decision-making. The marginal effect suggested that individuals from different social categories (e.g., General, OBC, SC, ST) have varying levels of engagement. This variation could be attributed to socioeconomic factors, use of resources, and differing social expectations. For example, individuals from marginalized groups might face additional barriers that impact their engagement levels. The COVID-19 pandemic exacerbated these disparities, as marginalized groups often experienced more significant economic hardships, affecting their willingness to accept job offers and their overall engagement in the labor market. These groups may have been disproportionately affected by job losses, reduced working hours, and limited access to remote work opportunities, further widening the engagement gap.

Furthermore, the model's detailed breakdown across different work-related factors such as hours worked, promotion opportunities, job type, travel distance, local employment opportunities, and accommodation conditions provides nuanced insights. For example, in the hours worked model, risk-averse individuals are less likely to work longer hours, suggesting a preference for stable and predictable work schedules. In the promotion opportunities model, fewer internal promotions correlate with higher engagement among risk-takers, while risk-averse individuals might be less responsive to promotion opportunities due to their preference for stability.

The travel distance model reveals that longer travel times negatively impact engagement, particularly for risk-averse individuals who might avoid jobs requiring

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extensive commuting during the pandemic. The accommodation conditions model shows that ease of finding adequate housing significantly affects engagement, with better housing conditions correlating with higher engagement levels. Therefore, we find that risk aversion, marital status, and social category significantly influence engagement in work-related activities, with the COVID-19 pandemic adding a layer of complexity to these dynamics. Risk-takers are more likely to engage actively, while risk-averse individuals prefer stability.

This study highlights critical insights into factors influencing job acceptance in Goa's post-pandemic labor market. Job–specific attributes such as flexible working hours, job security, commuting distance, and promotion opportunities significantly affect individuals' willingness to accept job offers. Risk aversion emerged as a key psychological factor, with risk-averse individuals showing a preference for stable and predictable employment. Additionally, demographic factors like marital status and social category moderated job acceptance, emphasizing the role of personal and socio-economic contexts. These findings suggest that employers and policymakers must consider a multidimensional approach to addressing employment challenges in regions like Goa, which is heavily reliant on tourism and characterized by an urban-rural divide.

To enhance workforce engagement, policymakers should prioritize strengthening digital infrastructure in rural areas to expand access to remote and hybrid job opportunities. Introducing policies like subsidized digital training programs can equip rural workers with skills needed for digitally mediated jobs, bridging the urban-rural divide. Employers can focus on designing roles that emphasize flexibility, stability, and career growth, such as offering part-time or remote options for workers with family responsibilities. Policymakers could also implement employment guarantee schemes tailored to Goa's economic context, ensuring job security for workers in volatile sectors like tourism (Ahmed et al., 2020).

Additionally, targeted incentives such as tax benefits for companies providing employee housing or commuting allowances can mitigate barriers like high living costs and long travel distances, making job offers more attractive. By adopting these recommendations, employers and policymakers can create a resilient labor market that aligns with workers' evolving preferences, fostering sustained economic recovery and growth in the post-pandemic era (Williams and Baláž, 2020; Mishra, 2014).

While the study provides valuable insights into factors influencing job acceptance in Goa's post-pandemic labor market, it is not without its limitations. One notable limitation is the sample size, which, although sufficient for statistical analysis, comprises only 163 participants. This relatively small sample may limit the generalizability of the findings, particularly in capturing the diversity of job seeker's preferences and behaviors across larger or more heterogeneous populations.

Additionally, the regional focus of the study, confined to Goa, restricts its applicability to other regions with differing economic, cultural, and labor market conditions. Goa's heavy reliance on the tourism industry and its unique demographic profile, including a significant urban-rural divide, may result in findings that are not directly transferable to areas with more industrial or agricultural economies.

Another limitation lies in the study's cross-sectional design, which captures data at a single point in time. This approach does not account for dynamic changes in job preferences or employment conditions that may occur over a longer period, particularly as the labor market continues to recover from the pandemic. Lastly, while steps were taken to minimize biases, such as anonymous surveys and stratified sampling, self-reported data inherently carries the risk of social desirability bias, where participants might respond to what they perceive as favourable rather than fully accurate.

These limitations suggest that while the findings are valuable for understanding job acceptance dynamics in Goa, caution should be taken when applying them to broader contexts. Future research could address these limitations by including a larger, more diverse sample, expanding the geographic scope, and employing longitudinal methods to capture evolving labor market trends.

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Conflict of Interest

The authors declare that there is no conflict of interest.

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