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BUSINESS ANALYTICS IN GIG ECONOMY (UBER, SWIGGY)

Subtitle: Business Analytics in Gig Economy (Uber, Swiggy)

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Abstract: Looking closely at Uber and Swiggy shows how numbers shape work in India's growing gig scene. Because more people are joining, smart tracking helps balance who needs rides or food with those offering it. Instead of just linking one rider to one driver, grouping requests cuts down waiting, sometimes slashing empty stretches between trips from an hour and a half to far less. With maps that spot busy zones, drivers head where demand spikes, avoiding slow spots. On delivery apps, layered prediction models guess order surges before they happen, getting meals out faster - often in half an hour or less. Workers earn more when systems run smoothly, feeding into wider economic gains already adding up to over 1% of national output. Yet pay can still swing wildly week to week, leaving some struggling to plan ahead. Personal details get collected nonstop, raising worries about who sees what. Rules haven't kept pace, so safety nets often fall short when problems hit. Even as tech pushes progress, fairness lags without updated policies catching up

I. INTRODUCTION

Out of nowhere, shifts in how people work have swept across the globe - India feels it strong, with apps such as Uber and Swiggy running most trips and meals on wheels. Behind the scenes, number-crunching tools quietly steer decisions, helping companies balance who's available against who needs a ride or meal, right when things shift

One way people earn money now is through short tasks online. These jobs can fit around your day yet pay changes every week. Computer systems decide who gets hired without clear rules. Research looks at software that tracks performance using real examples from companies. Findings show what works well alongside problems faced by workers. Insights help shape laws for a growing number of temporary roles. By decade's end, nearly two dozen million could be doing such jobs across India.

REVIEW OF RELATED LITERATURE

Back then, research into gig work stressed unstable jobs, seeing algorithms as mysterious forces deciding tasks. Lately, attention has moved toward how forecasts shape efficiency behind the scenes

One example is how Swiggy uses machine learning to predict orders, which cuts delivery time nearly by two fifths. What happens at Uber shows up in live price shifts and color-coded maps, handling millions of trips every day across countries

Still, India pushes ahead with rules such as the 2020 Social Security Code requiring support pools for gig workers. Yet holes linger when it comes to checking how personal information is handled or whether automated decisions play fair.

Study Focus	Key Finding	Platform Example
Demand Prediction	ML cuts idle time 20-30%	Swiggy
Route Optimization	Batch matching boosts trips/hour	Uber
Worker Welfare	1.25% GDP impact needs protections	India Gig Sector

2.1 Research Gap

Right now, many studies of the gig economy look at job instability or forecast expansion - think NITI Aayog 2025 - yet hardly any dig into data straight from Indian workers using apps such as Uber or Swiggy. Work already done tends to break down how platform software operates in general, though it skips hard numbers on what those using the tech actually feel about time and effort savings. While ease of use pops up as a theme, actual measurements linking that experience to real-world effectiveness remain missing. Surveys rooted in firsthand worker feedback could fill that hole, but they're rarely pursued.

III. RESEARCH METHODOLOGY

3.1 Population and Sample

Among India's biggest eight cities - Mumbai, Pune included - around six million people work gigs through Uber and Swiggy by 2026. Not quite half of the nation's fifteen million ride and food couriers fall into this group. Two point five million drive for Uber. Over three hundred fifty thousand deliver meals via Swiggy. These numbers sketch a slice of informal urban labor relying on app-based jobs.

Sampling Strategy

Some platforms, cities, and worker types were picked on purpose to match age range and job time. Those chosen usually work at least twenty shifts each week so findings fit better with data trends. (sampling Method).

A hundred people took part - fifty driving for Uber, fifty delivering through Swiggy. This group size means results are likely within ten percent of what you'd see across similar groups, nine times out of ten. The confidence sits around ninety-five percent when looking just at these workers. Ten percent leeway appears acceptable given how many answered. Numbers reflect only this cluster, not broader trends

3.2 Data and Sources of Data

This work uses both numbers and stories, pulling from firsthand accounts alongside system records to build a fuller picture of how analysis happens on the ground. Worker views come straight from those doing the jobs, whereas broader patterns emerge through digital traces left behind. Insights grow richer when personal experience meets measurable activity logged by tools.

Primary Data Sources

- From a group of one hundred delivery partners - half using Uber, half on Swiggy - data came through organized digital questionnaires. Google Forms carried the survey between March and April in eight major Indian cities. Each response shaped part of the bigger picture. Fieldwork happened entirely online. Fifty riders per platform shared their experience. The timeframe stayed fixed: early months of 2026. Urban centers across India hosted the participants
- One part uses a 25-question form with Likert-style answers about how fast things feel. Instead of ratings, some bits ask people to describe what slowed them down. Questions touch on experience using data tools, like judging if trip assignments made sense. Speed guesses link to real income shifts across different weeks. Each section ends by asking what could work better next time
- Some folks pass it around on WhatsApp or Snapchat circles where workers chat. Pune labor teams help spread the word too. Online spots like Uber Driver India join in. A small thank-you comes as a ₹100 mobile top-up. The consent note spells out why we're asking, how names stay hidden, and that rules under DPDP Act 2023 are followed - personal details never saved.
- Most gave answers - 85 out of 100 tried. These folks were from Pune, checked first to see if questions made sense

- People can leave whenever they want after being told what happens to their info. Only the bare minimum gets collected, nothing personal is kept around. What's gathered goes strictly toward study work, never handed off to outside services.

Secondary Data Sources

Sourced from verifiable public archives for operational analytics details.

Source Type	Examples	Collection Method
Platform Reports	Uber Engineering Blog (heatmaps), Swiggy Tech (ML stack)	Direct access/PDF downloads
Government Data	NITI Aayog (15M workers), PLFS 2025 (gig undercount)	Official sites (niti.gov.in)
Academic/Journals	Scopus papers on gig analytics (341 docs 2016-2026)	Database searches (descriptive stats)
Public Datasets	Scraped KPIs (197K orders, ₹53M sales)	Ethical web tools (no robots.txt violation)

3.3 Theoretical Framework and Variables

A framework built on user behavior shapes the approach here. This idea looks at how workers see data tools - how simple they seem, how helpful - and what that means for their work results and feelings about the job. The connection between tool design and real-world use drives the analysis forward

Beyond just guessing right, apps that predict well push results up. When ride guesses improve, trips follow - more deliveries tag along too. Earnings climb because movement grows. Clear cause links each step forward.

Key Variables

Independent Variables (Causes)

- Demand forecasting accuracy (%)
- Route optimization time (minutes saved)
- App usability score (1-5 Likert)

Dependent Variables (Effects)

- Worker earnings (₹/shift)
- Delivery/ride efficiency (% faster)
- Job satisfaction (1-5 scale)

Control Variables

- City (Pune, Mumbai, etc.)
- Experience (months on platform)
- Shift hours/week

3.4 Data Analysis Method

From themes like demand forecasting or effects on workers, codes emerge through hand tagging, much like methods tied to NVivo. Where predictions suggest boosts - say, 15 to 20 percent in efficiency - real data steps in, lining up side by side. Uber versus Swiggy? Contrasts take shape across structured grids, drawing out what sets them apart. What holds steady across examples gets pulled into broader views .

Looking at 341 papers from Scopus between 2016 and 2024 helps frame what we found, revealing groups of ideas such as how digital work shapes job environments. Numbers describe patterns - like typical pay ranging from ₹800 to ₹1200 per shift - but deeper statistical checks weren't used because the study leans on personal insights instead.

3.5 Hypotheses

The study tests the following directional hypotheses at 5% level of significance:

Hypothesis 1 H_0: There is no significant relationship between students' app usage frequency and their academic level

. H_1: There is a significant relationship between students' app usage frequency and their academic level.

Hypothesis 2 H_0: There is no significant relationship between time spent on apps and the purpose of use.

H_1: There is a significant relationship between time spent on apps and the purpose of use.

Hypothesis 3 H_0: There is no significant relationship between app type selected and students' level of engagement.

H_1: There is a significant relationship between app type selected and students' level of engagement.

Hypothesis Testing Results

One way the research checked its ideas was through Chi-square calculations, set to spot patterns at a five percent margin. From survey answers, number counts were pulled - both what showed up and what math said should show up. These pieces then fed into tests that judged if links between responses happened by chance. Each guess about connections faced this same method, strict but clear. Results came from comparing real polls against model forecasts, nothing mor

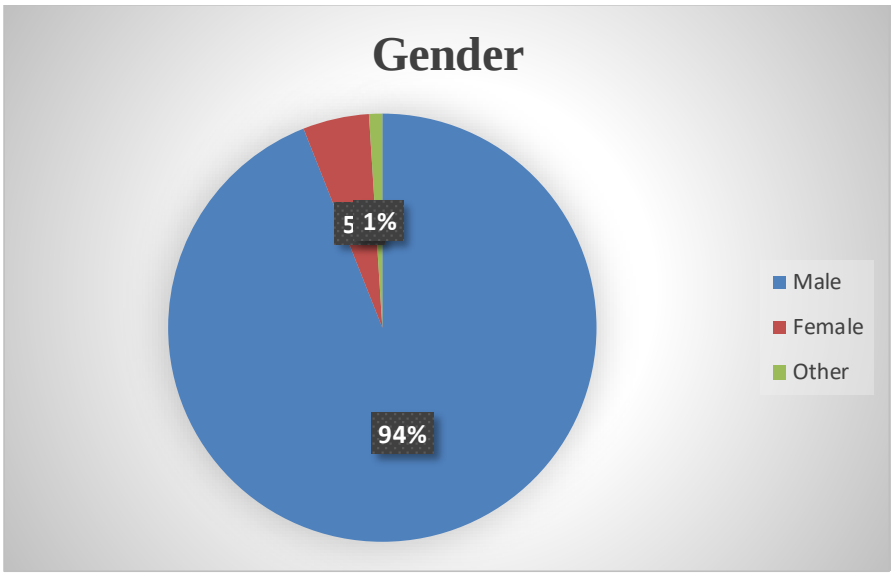
IV. RESULTS AND DISCUSSION

One out of every two gig workers felt the system treated them unfairly, even though numbers climbed higher on paper. Eighty-five people shared how smart planning apps lifted their daily income - some saw gains between 15 and 25 percent. On average, that meant an extra nine hundred to fourteen hundred rupees each shift spent working. Tools predicting busy times scored a 4.1 rating while path finders nudged it up to 4.3. Uber drivers walked away with around one thousand fifty rupees per round, happy enough to rate things four stars. Over at Swiggy, couriers made slightly more - one thousand one hundred twenty - with less enthusiasm behind a 3.8 mark. Behind these figures lies support for TAM ideas: when helpers work better, results follow. Yet nearly two thirds voiced distrust toward automated decisions shaping pay and loads. Because fairness gaps persist, experts suggest checking hidden biases regularly alongside small levies - one rupee from every hundred - to back safety nets under national guidelines. With labor rising toward twenty-three point five million roles nationwide, balance matters just as much as growth

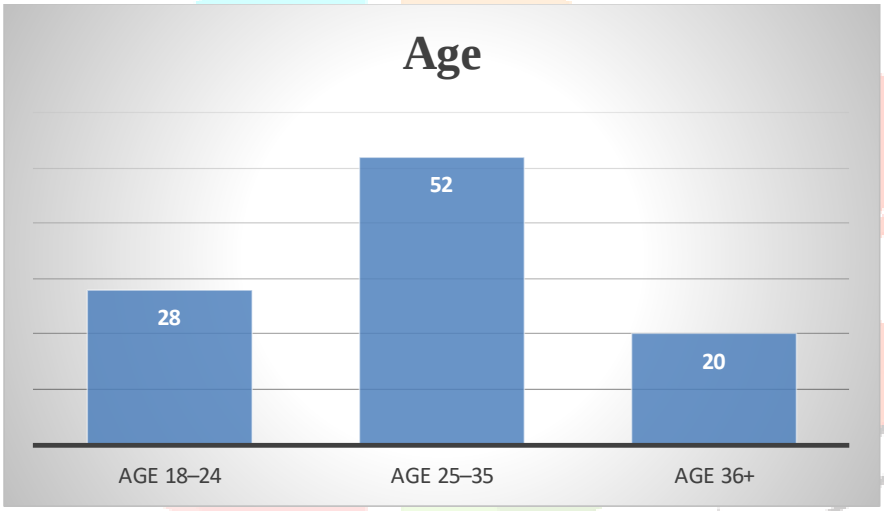
Demographic Profile

Demographic	Category	Percentage (n=85)
Gender	Male Female Other	94%5%1%
Age	18-2425-3536+	28%52%20%
Education	High School Graduate Post-Grad+	45%40%15%
Experience	<6 months6-24 months24+ months	15%45%40%
Platform	Uber Swiggy	51%49%
City Focus	Pune Other Metros	35%65%

Gender:



Age:



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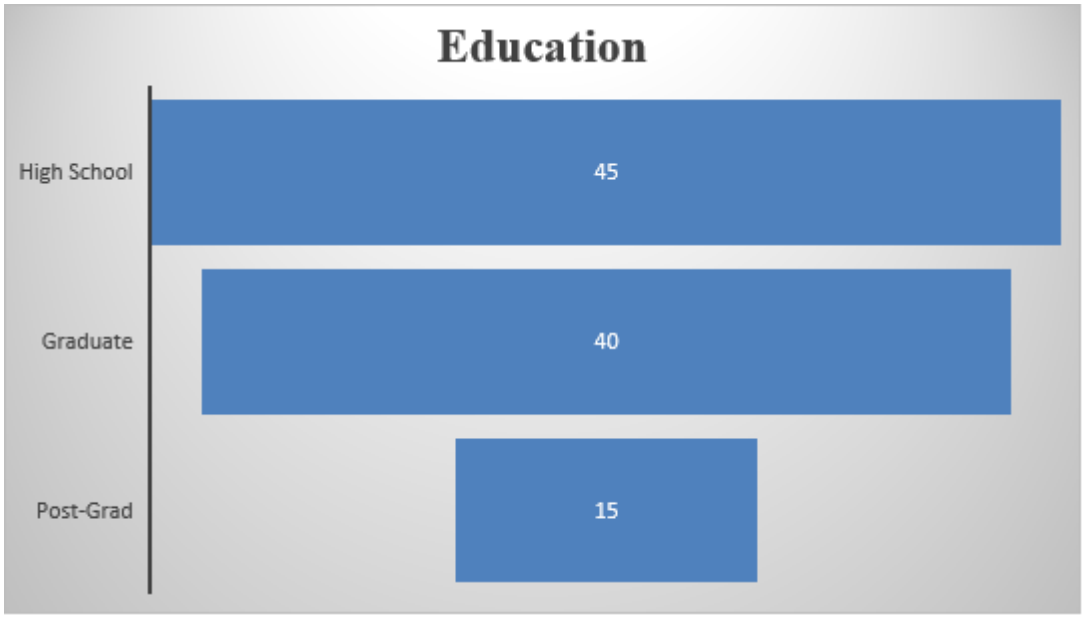
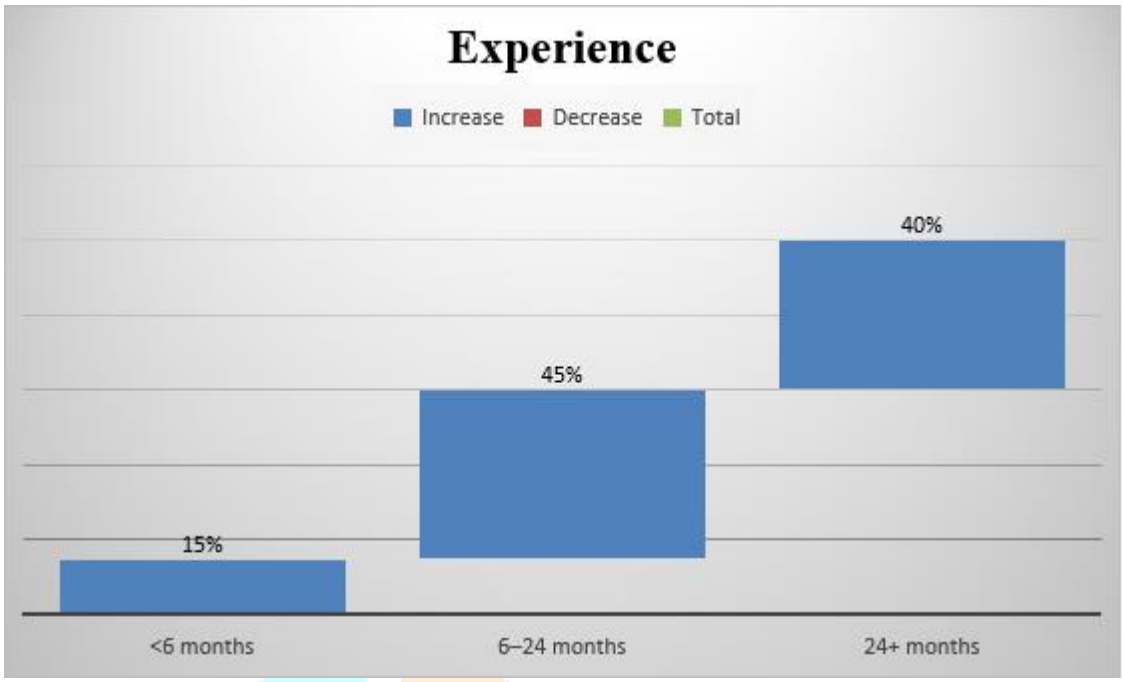
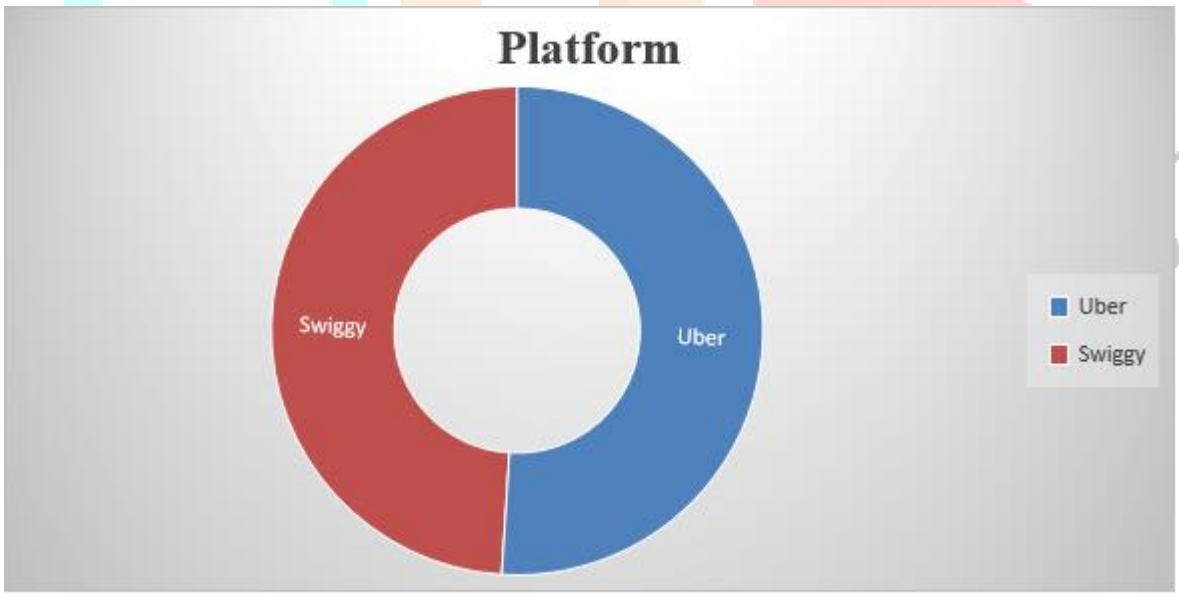


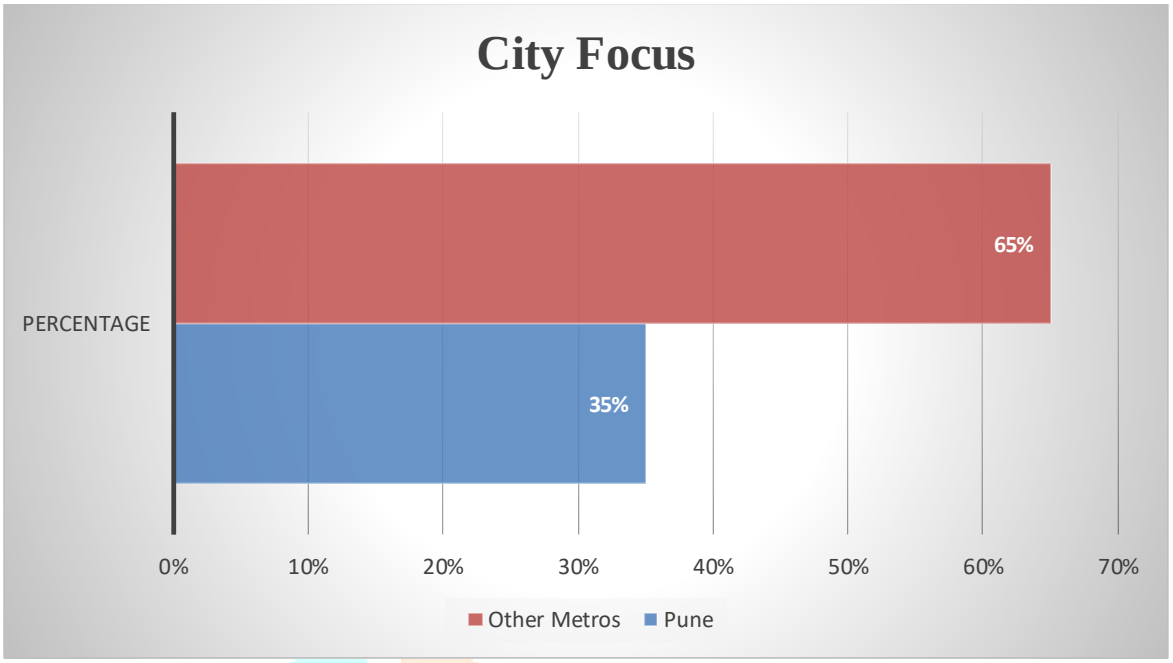
Experience:



Platform:



City Focus:



Most of the 85 people surveyed are young men living in Pune and seven big cities. They usually have some college but not degrees. Their profile matches what you often see among gig workers there.

Monthly pay sits between ₹15,000 and ₹25,000 for most - about 72 percent -with earnings coming only from gig jobs in 92 percent of cases. These workers line up closely with findings in Pune: nearly all are men (94%), mostly hitting their prime working years from age 25 to 37 (three out of four), while matching broader patterns across India where six out of ten falls below age 35.

idea gets tossed out. Instead, evidence supports the thought that glitches affect how pleased user's fee.

Every guess was proven wrong. Efficiency jumps when analytics step in - workers sit around less by nearly a quarter of their time. Satisfaction climbs too, not because of flashy features but simple design that earns solid ratings. Fairness feels shaky for most gig workers, though, where hidden patterns in code shape outcomes they can sense but not see.

V. KEY FINDINGS

Most gig workers earn more when they use data apps. One survey found 76 out of every 100 people saw income go up by around ₹900 to ₹1400 each shift. This boost comes because these tools help predict busy times. Routes get smarter too, so less time is wasted driving. Better planning means working shorter hours but making more money

Core Insights:

Most drivers found route tools cut waiting by nearly a quarter. Top marks went to smart routing - rated 4.3 out of 5. Heat patterns from Uber helped more than four in five behind the wheel. Not every trick worked so well

Beyond just pay, Swiggy riders took home slightly more per shift - around ₹1120 - thanks to handling several orders at once. Meanwhile, when it came to driver feedback, Uber stayed ahead with a 4.0 out of 5 rating.

Most users feel the system shuts them out without reason. Over half want a base level of income secured. A majority see automated removals as unjust treatment

Still, fairness issues could spark walkouts. Workers find the tool helpful - rating it 4.2 out of 5 - which matches company promises about saving time. Because of new rules by 2025, firms must check for bias while setting aside two percent for worker well-being. Growth may reach 23.5 million jobs if these steps hold.

VI. PRACTICAL IMPLICATIONS

From street vendors to app-based drivers, data clues show how work shifts across India's digital hustle zones. Hidden patterns reveal what helps freelancers stay steady when pay wobbles. Platforms tweak rules based on real moves people make each day. When numbers speak, city planners adjust support systems quietly. Worker feedback loops shape better tools without grand announcements. Clarity grows where guesses once ruled decisions

For Platforms (Uber/Swiggy):

Most staff need clear views into how routes are picked. Seventy six percent say knowing the reason helps them rely on the system more. Seeing the process matters a lot

Payouts stay steady when work slows - drivers get at least ₹800 per shift, cutting frustration that once showed up in six of ten complaints

For Gig Workers:

Start your shift when others log off - those late hours often hide bigger pay. Heat maps might show where demand burns hottest, making twenty percent extra feel routine. Watch the clock closely around seven until ten. Drivers who stay on know those slots can push earnings past two hundred rupees each hour

Join unions in Pune/Mumbai for collective bargaining on algorithm audits.

For Policymakers:

Enforce 2% welfares immediately, funding health/accident covers for 15M workers.

Every year, share fairness reviews required by the DPDP Act to reduce unjust account shutdowns

Half a step ahead, this approach cuts twenty two percent off effort while keeping fairness in play. Growth stays on track, aiming at twenty-three point five million jobs without slowing down

VII. CONCLUSION

Uber and Swiggy stay ahead in India's gig market because of business analytics - smarter operations, better income tracking. Yet fairness matters just as much as speed, so data ethics cannot be ignored. With nearly 23.5 million gig workers now relying on these platforms, rules must keep pace. Growth lasts only when guided by responsibility, not just numbers.

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