



Original Research Paper

Economic and Operational Challenges of App-Based Taxi Drivers: A Study of Selected Aggregator Platforms in Chennai City

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Abstract

The increasing cost and limited availability of fish meal have prompted the search for alternative protein ingredients in aquaculture feeds. This study evaluated the potential of dried *Moina micrura* meal as a partial fish-meal substitute in diets for common carp (*Cyprinus carpio*). Three dietary treatments were evaluated over a 100-day feeding trial: a control diet without *M. micrura* meal, a diet containing 5% *M. micrura* meal (M5), and a diet containing 10% *M. micrura* meal (M10). Growth performance, feed utilization and whole-body proximate composition were assessed. The dried *M. micrura* meal contained $51.00 \pm 0.50\%$ crude protein and $17.60 \pm 0.26\%$ crude lipid, with moisture and ash contents of $14.33 \pm 0.29\%$ and $10.53 \pm 0.06\%$, respectively. Dietary treatment significantly affected growth performance ($p < 0.001$). Final body weight increased from 2.67 ± 0.10 g in the control to 4.83 ± 0.15 g in M5 and 6.83 ± 0.15 g in M10. Similarly, weight gain increased from 1.11 ± 0.08 g in the control to 3.26 ± 0.15 g in M5 and 5.27 ± 0.16 g in M10. The M10 group exhibited the highest specific growth rate ($1.333 \pm 0.012\% \text{ day}^{-1}$) and protein efficiency ratio (1.165 ± 0.045), together with the lowest feed conversion ratio (1.90 ± 0.06). Whole-body crude protein and lipid contents increased with increasing dietary *Moina* inclusion, whereas moisture content decreased. Overall, the results demonstrate the potential of dried *M. micrura* meal as an alternative protein ingredient in common carp diets. Among the treatments evaluated, 10% inclusion was associated with the most favourable growth performance and feed utilization. Further studies using nutritionally matched diets are warranted to distinguish the effects of *Moina* inclusion from those of differences in dietary protein content.

Keywords: *Moina micrura*, cladoceran meal, Fish meal replacement, Growth performance.

1. Introduction

The transportation sector has undergone substantial transformation in recent years with the emergence of app-based aggregator taxi models such as Uber, Ola, and Rapido. By integrating digital technology with traditional transport services, these platforms offer commuters convenience, transparent pricing, real-time tracking, and improved service accessibility (Chatterjee & Ramadurai,

2015; Taiebat et al., 2022). In metropolitan cities such as Chennai, where rapid urbanization, population growth, and traffic congestion place increasing strain on conventional transport systems, aggregator platforms have become an integral part of daily mobility (Rao & Rao, 2012).

Beyond their effect on passenger travel behavior, aggregator platforms have created new earning opportunities for drivers by connecting them to customers through digital intermediation, thereby reducing idle time

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and, in principle, improving earning potential (Gupta, 2018). However, this shift has also introduced new sources of vulnerability, including algorithmically determined commission structures, intensified competition, dependency on a single digital intermediary, and the need for continual technological adaptation (Rosenblat & Stark, 2016; Surie & Koduganti, 2016). In cities such as Chennai, where traditional auto and taxi services have long formed part of daily life, the aggregator model has reshaped drivers' working patterns, income structures, and service expectations.

Recent developments in Chennai illustrate the scale of driver dissatisfaction with the aggregator model. Large-scale driver boycotts and strikes against major platforms have been reported, driven by concerns over high commission rates, long working hours, and a lack of job security (Florentyna, 2025; Sundaram, 2025; The New Indian Express Bureau, 2025). These events underscore the practical urgency of systematically documenting the economic and operational conditions under which aggregator-affiliated drivers work.

Despite a growing body of research on aggregator-based mobility, much of the existing literature has concentrated on consumer-facing outcomes — pricing strategies, service quality, and customer satisfaction (Anirvinna & Deshmukh, 2019; Samuel, 2023; Yamuna et al., 2019) — or on driver conditions in other Indian metropolitan contexts such as Bengaluru, Delhi, and Kolkata (Basu, 2019; Ilavarasan et al., 2018; Surie & Koduganti, 2016). Comparatively less empirical attention has been paid to the multidimensional structure of economic and operational hardship among aggregator drivers specifically in Chennai, and few studies have used factor-analytic methods to identify the latent dimensions underlying these challenges. This study addresses that gap.

II. REVIEW OF LITERATURE

Rising urban population and travel demand have historically outpaced the capacity of conventional public transport in Indian metropolitan cities, creating conditions favorable to alternative mobility solutions (Chatterjee & Ramadurai, 2015; Rao & Rao, 2012). Large-scale analyses of ride-hailing datasets confirm that app-based mobility services have grown rapidly in urban areas because of the convenience and cost advantages they offer over traditional taxis (Taiebat et al., 2022). Gupta (2018) similarly found that increasing smartphone penetration has been a principal driver of ride-sharing adoption across Indian cities. However, these studies focus primarily on aggregate mobility trends and passenger-side adoption rather than on the conditions experienced by the drivers who supply these services. A substantial body of work documents the precarious working conditions of aggregator-affiliated drivers. Rosenblat and Stark (2016) showed that Uber's algorithmic management — encompassing rating systems, dynamic pricing, and automated work allocation — affords drivers limited control over their earnings and schedules,

generating persistent income uncertainty. Comparable findings emerged from Surie and Koduganti's (2016) qualitative study of Uber and Ola drivers in Bengaluru, which found that platform-based work offered only temporary income stability alongside heightened exposure to flexible-work risk. Raval and Pal (2019) similarly reported that Indian gig-economy drivers experience income uncertainty, long working hours, and high dependence on aggregator companies, while Kumar and Ramesh (2019) and Srinivas and Prasad (2021) documented job insecurity and commission-related dissatisfaction among gig workers and app-based transport drivers, respectively, in South Indian cities.

Commission structures and dynamic pricing mechanisms feature prominently as sources of driver grievance. Sawant et al. (2025) compared fare structures across Ola, Uber, and Rapido and found that surge pricing and commission deductions materially affect driver earnings. Anirvinna and Deshmukh (2019) explained surge pricing as a revenue-management strategy that balances demand and supply but raises transparency concerns for drivers and regulators alike. Devda and Attri (2019) identified delayed wallet settlements and high cancellation charges as further sources of dissatisfaction, while Mahalingam's (2006) earlier analysis of Chennai auto-rickshaw fare structures underscored the importance of scientifically designed, distance- and duration-based pricing models for fairness and stakeholder satisfaction — an insight that remains relevant to contemporary aggregator commission design. Recent journalistic and empirical accounts document escalating driver unrest in Chennai. Florentyna (2025) reported a large-scale boycott of aggregator platforms driven by high commission rates, long working hours, and lack of job security, while Sundaram (2025) and The New Indian Express Bureau (2025) similarly reported strikes by auto and cab drivers demanding fairer fare regulation and income stability. Reddy (2022) extended this discussion by showing that traditional auto drivers in South India experience income loss due to platform-based competition, further intensifying tension within the sector. A parallel literature examines aggregator services from the customer's perspective. Verma et al. (2021) found that driver professionalism and behavior strongly shape passenger satisfaction, while Samuel (2023) and Yamuna et al. (2019) identified convenience, affordability, and technological features as key drivers of customer adoption, tempered by concerns over surge pricing and cancellations. Basu (2019) and Bishnoi and Bhardwaj (2019) reported comparable patterns in Kolkata and pan-India contexts, respectively. At the policy level, Ilavarasan et al. (2018) emphasized the need for supportive licensing and market-based pricing policies to strengthen digital taxi platforms in New Delhi, and Chandratreya and Kulkarni (2024), Mehta et al. (2022), Goel and Sahil (2024), and Nallasivam and Selvaraj (2021) collectively call attention to regulatory

compliance gaps, stakeholder inequities, and the need for balanced policy frameworks governing the cab-aggregation industry.

III. SIGNIFICANCE AND SCOPE OF THE STUDY

The study is confined to Chennai city and focuses on drivers affiliated with app-based aggregator platforms, examining economic aspects (earnings, costs, commissions, and incentives) alongside operational aspects (competition, fare structures, technology use, and regulatory issues). The findings are intended to inform driver unions, transport policymakers, platform operators, and researchers examining gig-economy labor conditions in the Global South.

IV. RESEARCH GAP AND CONTRIBUTION OF THE PRESENT STUDY

Although the reviewed literature establishes that aggregator drivers across Indian cities face income instability, algorithmic control, and inconsistent regulatory protection, most studies rely on qualitative interviews, secondary fare data, or single-city case studies outside Chennai. Few studies have empirically modeled the latent dimensional structure of economic and operational hardship among Chennai's aggregator drivers using quantitative multivariate techniques. The present study addresses this gap by applying exploratory factor analysis to survey data from 223 drivers to identify the dominant underlying dimensions of hardship, thereby providing an empirically grounded basis for targeted policy intervention.

V. OBJECTIVES OF THE STUDY

This study was guided by the following objectives:

1. To identify the underlying dominant dimensions of economic and operational challenges faced by taxi drivers operating through aggregator models in Chennai city.
2. To examine the influence of aggregator policies on driver income stability and job satisfaction.
3. To explore the reasons behind recurring strikes, boycotts, and protests among aggregator drivers in Chennai.

VI RESEARCH METHODOLOGY

This study adopted a descriptive, cross-sectional research design to examine the economic and operational challenges faced by aggregator-affiliated taxi drivers. The

design was selected to enable systematic quantification of driver-reported challenges and their underlying dimensional structure through statistical analysis. A total of 223 aggregator-affiliated drivers in Chennai participated in the study, comprising Car Taxi, Auto Taxi, and Bike Taxi drivers operating under Ola, Uber, and Rapido. Participants were recruited using non-probability convenience sampling because of time and access constraints; 103 responses were collected via an online Google Forms questionnaire and 120 via a physical structured questionnaire administered in person. Data were collected using a structured questionnaire comprising three sections. Section I captured demographic and work-profile information (age, gender, educational qualification, vehicle type, aggregator platform, driving experience, average working hours, average monthly income, and vehicle ownership status). Section II measured 12 items assessing economic and operational challenges (e.g., unfair commission charges, ride cancellations, technical glitches, safety concerns, language barriers) on a 5-point Likert scale ranging from Strongly Disagree to Strongly Agree. Section III measured seven items assessing drivers' perceptions of aggregator policies (e.g., commission fairness, incentive transparency, grievance redressal) using the same 5-point Likert format. The Section II scale demonstrated acceptable internal consistency, Cronbach's $\alpha = .859$ (12 items). The Section III scale demonstrated acceptable internal consistency, Cronbach's $\alpha = .823$ (7 items).

VII. RESULTS AND DISCUSSION

Data were analyzed using percentage analysis for demographic profiling, descriptive statistics (means and standard deviations) for the challenge items, and exploratory factor analysis with principal component extraction and varimax rotation to identify the latent dimensions of economic and operational challenges. Sampling adequacy was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. Mean-based ranking was used to evaluate drivers' relative perceptions of aggregator policy items. All statistical analyses were performed using IBM SPSS Statistics, version 22.

Table 1 summarizes the demographic and work-profile characteristics of the 223 respondents.

Table 1 Demographic and Work Profile of Respondents (N = 223)

Characteristics	N	%
Age		
Below 25 years	79	35.4
25–34 years	71	31.8
35–44 years	45	20.2

Characteristics	N	%
45 years and above	28	12.6
Gender		
Male	190	85.2
Female	33	14.8
Educational Qualification		
No formal education	18	8.1
Primary education	30	13.5
Secondary education	43	19.3
Higher secondary	52	23.3
Graduate and above	80	35.9
Type of Vehicle Operated		
Car Taxi	81	36.3
Auto Taxi	66	29.6
Bike Taxi	76	34.1
Aggregator Platform Used		
Ola	74	33.2
Uber	79	35.4
Rapido	70	31.4
Driving Experience under Aggregators		
Less than 1 year	61	27.4
1–3 years	68	30.5
3–5 years	47	21.1
More than 5 years	47	21.1
Average Working Hours per Day		
Less than 8 hours	68	30.5
8–10 hours	79	35.4
10–12 hours	61	27.4
More than 12 hours	15	6.7
Average Monthly Income from Aggregator Driving		
Below ₹15,000	104	46.6
₹15,000–₹30,000	86	38.6

Characteristics	N	%
₹30,001–₹45,000	24	10.8
Above ₹45,000	9	4.0
Vehicle Ownership Status		
Own vehicle	117	79.4
Rented / leased vehicle	46	20.6

Note. Percentages within some categories do not sum exactly to 100.0 due to rounding.

Table 1 shows that respondents were predominantly young and male: 35.4% were below 25 years of age and 85.2% were male. Most respondents (35.9%) held a graduate qualification or above. Car taxis were the most common vehicle type operated (36.3%), and Uber was the most frequently used platform (35.4%), followed closely by Ola (33.2%) and Rapido (31.4%). A majority of drivers (65.9%) worked 8 or more hours per day, yet 46.6% earned below ₹15,000 per month and only 4.0% earned above ₹45,000, indicating a pronounced mismatch between time invested and income earned. Most drivers (79.4%) operated their own vehicle rather than a rented or leased one.

Table 2 presents the means and standard deviations for the 12 items measuring economic and operational challenges (Cronbach's $\alpha = 0.859$).

Table 2 Descriptive Statistics on Economic and Operational Challenges Faced by Drivers

Item	M	SD
Unfair commission charges reduce my overall income significantly.	4.40	0.752
Frequent last-minute ride cancellations impact my daily earnings.	4.38	0.840
Language barriers create communication difficulties with customers.	4.36	0.799
Irregular incentives from aggregators affect my financial stability.	4.32	0.760
GPS mismatch in pickup and drop locations causes operational issues.	4.28	0.872
Unfamiliar customers create safety concerns for me during rides.	4.24	0.790
Inappropriate behaviour of customers affects my job satisfaction.	4.20	0.794
Lack of proper legal support increases my insecurity while working.	4.17	0.797
Time pressure to complete rides quickly creates work stress.	4.10	0.785
Lack of insurance coverage increases my financial risk.	4.09	0.842
Unpredictable demand makes it difficult to maintain steady income.	3.72	0.836
Technical glitches in the app interrupt my work frequently.	3.67	0.842

Note. Scale: 1 = Strongly Disagree to 5 = Strongly Agree. Items are sorted in descending order of mean agreement.

Table 3

KMO and Bartlett's Test

Measure	Value
Kaiser–Meyer–Olkin measure of sampling adequacy	0.819
Bartlett's test of sphericity — Approx. χ^2	933.273
df	66

Measure	Value
Sig. (p)	< .001

Table 3 shows that the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was .819, exceeding the recommended threshold of .60, and Bartlett's test of sphericity was significant, $\chi^2(66) = 933.27$, $p < .001$, confirming that the correlation matrix was not an identity matrix and that the data were suitable for factor analysis.

Table 4

Total Variance Explained by the Three Extracted Components

Component	Eigenvalue	% of Variance	Cumulative %
1 — Operational Challenges	4.728	39.40 (rotated: 22.42)	39.40
2 — Economic Challenges	1.235	10.29 (rotated: 19.39)	49.69
3 — Safety Concerns	1.113	9.28 (rotated: 17.16)	58.97

Note. Extraction method: Principal component analysis; Rotation method: Varimax with Kaiser normalization. Percentages in parentheses reflect the rotated (post-varimax) variance apportioned to each component.

Table 4 shows that communalities for all 12 items ranged from 0.40 to 0.76, and Measure of Sampling Adequacy (MSA) values for individual items all exceeded 0.70, confirming that each item was well represented by the extracted factor solution and suitable for inclusion. Principal component analysis with varimax rotation extracted three components with eigenvalues greater than 1.0, jointly accounting for 58.97% of total variance (Table 4). Rotation converged in five iterations.

Table 5

Rotated Component Matrix: Factor Loadings for Economic and Operational Challenges

Item	Loading
Factor 1: Operational Challenges (22.42% of variance)	
GPS mismatch in pickup and drop locations causes operational issues.	0.798
Language barriers create communication difficulties with customers.	0.732
Inappropriate behaviour of customers affects my job satisfaction.	0.691
Time pressure to complete rides quickly creates work stress.	0.542
Factor 2: Economic Challenges (19.39% of variance)	
Unpredictable demand makes it difficult to maintain steady income.	0.832
Technical glitches in the app interrupt my work frequently.	0.795
Lack of proper legal support increases my insecurity while working.	0.520
Factor 3: Safety Concerns (17.16% of variance)	
Irregular incentives from aggregators affect my financial stability.	0.795
Unfamiliar customers create safety concerns for me during rides.	0.741
Unfair commission charges reduce my overall income significantly.	0.662

Table indicates that unfair commission charges received the highest mean agreement ($M = 4.40$, $SD = 0.75$), indicating that it is the single most salient challenge affecting driver income, followed closely by frequent ride cancellations ($M = 4.38$) and language barriers with customers ($M = 4.36$). Technical glitches in the application ($M = 3.67$) and unpredictable demand ($M = 3.72$) were rated as comparatively less severe, though still substantial sources of difficulty. Prior to factor extraction, sampling adequacy was assessed. The three-factor solution indicates that driver hardship under aggregator platforms is not

unidimensional but instead reflects distinct operational, economic, and safety-related sources of strain, with operational frictions (technology and interpersonal service delivery) accounting for the largest share of variance. Table 6 presents the mean-based ranking of drivers' agreement with statements describing aggregator policy performance.

Table 6
Mean-Based Ranking of Aggregator Policies for Using the Platforms

Policy Statement	M	SD	Rank
Aggregator companies provide adequate support during accidents or vehicle breakdowns.	3.09	1.031	1
Aggregator policies provide sufficient flexibility to choose routes or end trips conveniently.	3.06	1.171	2
Overall, I am satisfied with working under the aggregator model.	3.02	1.133	3
Aggregator policies positively influence my income stability.	2.75	1.247	4
The incentive policies of aggregators are transparent.	2.63	1.241	5
The pricing and fare regulation system is satisfactory.	2.49	1.423	6
Aggregator companies address driver grievances promptly and fairly.	2.33	1.478	7
The commission structure of aggregators is fair and reasonable.	2.31	1.495	8

Table 6 indicates that drivers rated accident/breakdown support most favorably ($M = 3.09$), followed by route/trip flexibility ($M = 3.06$) and overall satisfaction with the aggregator model ($M = 3.02$). By contrast, fairness of the commission structure received the lowest mean rating of all eight items ($M = 2.31$, Rank 8), consistent with its identification as the highest-agreement challenge item in Table 2. Grievance redressal ($M = 2.33$) and fare regulation satisfaction ($M = 2.49$) were similarly rated poorly, suggesting that drivers perceive aggregator platforms as more responsive to logistical/operational support than to core economic fairness.

VIII. MANAGERIAL IMPLICATIONS

This study examined the economic and operational challenges faced by 223 taxi drivers operating under aggregator platforms in Chennai. Consistent with the study's first objective, exploratory factor analysis identified three distinct underlying dimensions of driver hardship — operational challenges, economic challenges, and safety concerns — jointly explaining approximately 59% of total variance. This multidimensional structure extends prior descriptive accounts of aggregator-driver hardship (e.g., Raval & Pal, 2019; Srinivas & Prasad, 2021) by empirically demonstrating that these difficulties cluster into separable, statistically distinguishable domains rather than forming a single undifferentiated construct.

With respect to the second objective, the finding that unfair commission charges were both the most strongly endorsed challenge item ($M = 4.40$) and the lowest-rated aggregator policy dimension ($M = 2.31$, ranked last of eight) directly corroborates prior work identifying commission structures as a central driver of income instability (Anirvinna & Deshmukh, 2019; Devda & Attri, 2019; Sawant et al., 2025). Notably, despite the fact that 65.9% of drivers reported working 8 or more hours per day, 46.6% earned below ₹15,000 monthly — a pattern consistent with

Rosenblat and Stark's (2016) argument that algorithmic commission and pricing control limits drivers' ability to convert labor time into proportional earnings.

The prominence of frequent ride cancellations and language barriers as top-rated operational challenges aligns with, and adds specificity to, Verma et al.'s (2021) finding that driver–customer interaction quality shapes service outcomes; the present results suggest this interaction is a two-way source of strain, affecting drivers' income (through cancellations) and workplace comfort (through communication difficulties) as much as it affects passenger satisfaction. Regarding the third objective, these economic and interpersonal frictions — particularly unfair commission structures and inadequate grievance redressal ($M = 2.33$, second-lowest-rated policy item) — offer a plausible empirical explanation for the driver boycotts and strikes documented in Chennai during 2025 (Florentyna, 2025; Sundaram, 2025; The New Indian Express Bureau, 2025): the present data show that dissatisfaction with exactly these policy domains is widespread and severe among active drivers, not confined to protest organizers. Concerning the fourth objective, drivers' comparatively low ratings of fare-regulation satisfaction ($M = 2.49$) and the identification of a distinct Safety Concerns factor —

encompassing unfamiliar-customer risk, irregular incentives, and commission unfairness — point to gaps in the existing regulatory and insurance framework. This is consistent with calls in the literature for stronger licensing oversight, market-based pricing regulation, and insurance protections for platform-based drivers (Ilavarasan et al., 2018; Kumar & Ramesh, 2019). Encouragingly, drivers rated accident/breakdown support and route flexibility relatively favorably, suggesting that aggregator companies' operational support systems are perceived as more functional than their economic and grievance-related policies — a distinction with direct implications for where policy reform should be targeted.

IX. CONCLUSION

This study examined the economic and operational challenges faced by 223 taxi drivers working under aggregator platforms — Uber, Ola, and Rapido — in Chennai. The findings show that despite long working hours, a majority of drivers earn modest monthly incomes, and that their hardship is structured along three empirically distinct dimensions: operational challenges, economic challenges, and safety concerns. Unfair commission charges emerged as the single most pressing concern, rated both as the most strongly endorsed challenge and the most poorly regarded aggregator policy. These results indicate that while aggregator platforms have expanded flexible earning opportunities and improved certain operational supports (e.g., accident assistance, route flexibility), meaningful improvements in commission transparency, grievance redressal, technical reliability, and legal/insurance protection are needed to enhance driver welfare and to support the long-term, sustainable functioning of aggregator-based taxi services in Chennai and comparable urban contexts.

X. LIMITATIONS

Several limitations should be considered when interpreting these findings. First, the use of non-probability convenience sampling limits the statistical generalizability of the results to the broader population of Chennai's aggregator drivers; future studies should consider stratified or platform-proportionate probability sampling. Second, the cross-sectional design captures driver perceptions at a single point in time and cannot establish causal relationships between aggregator policies and economic outcomes. Third, self-reported income data may be subject to recall or reporting bias, particularly given drivers' reluctance to disclose exact earnings. Fourth, the study is geographically confined to Chennai and may not generalize to aggregator markets in other Indian cities with different regulatory environments or competitive dynamics. Finally, rapid changes in aggregator commission and incentive policies mean that the specific figures reported here may shift over time, even if the underlying structural challenges persist.

XI. DIRECTIONS FOR FUTURE RESEARCH

Future research could adopt probability-based sampling across multiple Indian cities to test the generalizability of the three-factor structure identified here, employ longitudinal designs to track driver income and satisfaction as aggregator policies evolve, and incorporate platform-verified earnings data to reduce self-report bias. Comparative studies examining differences across vehicle types (car, auto, bike taxi) and platforms (Ola, Uber, Rapido) would also help clarify whether these challenges are uniform or platform-specific.

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