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WORKWAVE 2.0: A Trust-Centric Micro-GIG Economy Connector Using Behavioural Analytics

Ms. Vishruthi K B, Ms. Vijaya Lakshmi S

Department of M.Tech Computer science and engineering,

Sri Krishna College of Engineering and Technology, Kuniamuthur, Coimbatore, Tamil Nadu - 641008

Assistant Professor,

Department of M.Tech Computer science and engineering,

Sri Krishna College of Engineering and Technology, Kuniamuthur, Coimbatore, Tamil Nadu - 641008

Abstract

The hyper-extension of hyperlocal micro-gig platforms reconstituted the access to household and personal services, but the majority of them have not passed the trust-safety-service reliability trilemma. They employ most of them with the use of the static rating mechanism that fails to characterize the consistency of behaviour and accountability in real-time. A micro-gig economy connector called WORKWAVE 2.0, proposed in this paper, is a trust-based micro-gig economy connector that dynamically assesses service providers with behavioural analytics and community-tested interactions. In this case, a mixed trust assessment system is suggested, which implements the history of fulfilling tasks, punctuality, customer feedback, and patterns of interaction. It is the graph based trust propagation model that gives the trust the ability to develop automatically by means of confirmed user worker relationship, and it is also the GPS based location tracking that improves the transparency and also permits the ability to check on the punctuality. The fact that anomaly-aware trust adjustment decreases the chance of presenting unreliable or dishonest behaviour even further. It has been experimentally tested that the proposed method enhances trust and service reliability and the accuracy of gig matching as compared to traditional rating-based methods. WORKWAVE 2.0 offers a scalable and explainable model of the development of far safer and reliable hyperlocal gig platforms.

Keywords: Behavioural Analytics, Graph-Based Trust, GPS Tracking, Micro-Gig Economy, Trust Modelling.

1. Introduction

The hyper-local micro gig economy has sprung up to bring about a fundamentally new way in how such local services as funding would be available tuition, 'cooking the works and more would come at home doing house-keeping in your presence. They enable on-demand services by connecting people who need a products/service with local businesses that share it mobile or web app. The micro-gig economy has become popular because it's flexible, cost-effective and can fulfil on-demand service. But as these environments increasingly grant access to people's private and sensitive spaces we believe the more important reliable trust mechanisms are.

Even as gig economy models continue to gain spectacular traction, they are plagued by root trust, safety, and service accountability challenges. Most of such platforms rely on user-rating and textual reviews to assess the service providers. Despite coming with such solutions, none of these techniques can be trusted due to biased feedback, non-genuine reviews and unreliable user dynamics. The household related services, where the personal safety and time are crucial require a particular risk-mitigated approach to end-users' trust decrease and service operational risks increase.

It is further made worse by static rating-based reputation models treating trust as a fixed attribute, rather than a behaviourally evolved end state. Furthermore, the assigned ratings are typically unchangeable. The rating values may fail to represent current performance, consistency in behaviour or external factors as on time and quality of service provision. The bottom-line is: contract can be awarded to incompetent service providers while qualified workers may not get their salaries

Figure. 1.Behavioural Data Sources for Trust Modelling

paid accordingly. This is the limitation of naive reputation systems in terms of the representation of real-life service trustworthiness.

With such disadvantages, there is now a potential demand to have trust-based service matching systems that are capable of dynamically assessing the performance of services based on credible and verifiable experiential evidences. Behavioural analytics, community-endorsed interactions and real-time contextual information can dramatically improve the precision in which trust is estimated. This contributes to better transparency and accountability, as well as reduced manipulation and cold-start effects that are frequently present in gig platforms.

In this way, WORKWAVE 2.0 is a further evolution of the above-described micro-gig economy connector with design that focuses trust for overcoming challenges identified in traditional gig platforms. The systems constructs a hybrid trust assessment model by combining behavioural consistency, anomaly detection, graph-based trust dissemination and GPS-based accountability. Contributions of this paper are: (i) the design of dynamic and explainable trust model; (ii) improved gig matching reliability, as compared to that in [4]; (iii) a scalable system architecture for deployment in practice hyperlocal service settings.

2. Related Works

Resnick et al. (2000) presented one of the earliest formal treatments of reputation systems in online markets, and proposed methods for aggregating feedback on sellers given by buyers after successful transactions. In reality, on platforms like eBay it is observed that sellers with better ratings sell more. Shortcomings are feedback bias and slow trust correction, which emphasized the challenge of reconciling recent behavioral change.

Dellarocas (2003) studied word-of-mouth in online reputation systems for the level of digitization it involved and considered its vulnerability to manipulation, strategic feedback and scalability. Control and filtering mechanisms were considered for noise reduction, whereas unregulated feedback was found to lead to reputation inflation. Dynamic, adaptive improvements were found to be necessary for trustworthy reputation systems.

McDonald and Slawson (2002) investigated the impact of reputation on online auctions, showing that sellers who had good reputations were able to secure an 8–10% price premium. Yet, reputation effects decayed over time with ratings saturation and static feedback mechanisms seem to lose salience after a market matures.

Search and Collusion in Online Hiring Kato and Jin (2006) look at Moral Hazard and Adverse Selection that arise for firms using online hiring platforms. They discovered that reputation system reduced 20% adverse selection, but could not solve the moral hazard completely because of late feedback and incomplete monitoring, thus it needs to a continuous trust maintenance way.

Brown and Morgan (2006) consider the manipulation of reputation, and by endogenously providing strategic feedback and fake reviews sellers can inflate their reputations, inflating transaction rates at most temporarily 15%.

Bolton et al. (2013) concentrated on incentive mechanisms, and they demonstrated that sound incentives increased honest feedback by 25%, however many times, to agree users would provide an inflated rating that reinforced reputation inflation.

The issue of reputation inflation was examined by Horton and Golden in 2015 in the context of work on online labor platforms. The writers demonstrated that workers received higher "grades" which were not reflective of reality because the average score was greater than 4.5/5 and predictive to future performance declined. Their research has demonstrated that a static rating system has its shortcomings.

Ert et al. (2016) explored the development of trust in the sharing economy, revealing that hosts with profile photos were 12% more likely to be

considered trustworthy. But the optics were not a reliable indicator of service or long-term quality.

Livan et al. (2016) to study the reputation distortion caused by over reciprocity in online social networks. They concluded that scores were inflated by approximately 30% due to reciprocate-report-loops, and therefore if they wanted to prevent trust inflation, they should take into consideration interaction patterns.

Nosko and Tadelis 2015: investigated biases in feedback system, The most powerful positivity bias was found such that over 98% of buyers left a positive rating which then bind the system's ability to effectively signal poor performance.

Abawajy and Goscinski suggested a social network oriented reputation model for web services, which also provided propagation of trust in service interaction graph. Simulation gave an increase of 18% for the trust accuracy, but did not account for real-time behavioural traces.

Singer and Hillebrand (2015) introduced a belief-based reputation system which incorporated user cognition in a strong type of trust metric. The computing results have proved that this way has stronger difference in trust distinguishing but built on the user interaction data, and lacks of validation based on the context.

Yashkina et al. presented a time-dependent trust model using the interaction frequency, where most recent interactions exhibited greater impact on leap of faith, but this work did not discuss about ABehaD.

Xu et al. (2015) have studied fake reputation markets. They proposed to apply anomaly detection related to the review-time and the behaviour of reviewers. The findings of their evaluation showed that fraudulent review could be reduced by 35% with historical data.

Corten et al. (2023) explored digital identity and reputation in shared economics. They discovered that verification cues increased perceived trustworthiness by 22% and decreased risk perceptions, but actual performance did not always correspond to perception.

Zloteanu et al., in their study, analyse trust and reputation signals on decision making; the findings indicate that participants rely heavily on reputation in decisions even when performance data is made explicitly available, which emphasizes the importance of transparent trust measures.

Lehdonvirta (2023) is one level of analysis: that at macro-level where trust governance on digital platforms operates by taking over the centralized control, it calls for open and transparent initiatives based on a framework that places trust in accountability.

b Tadelis (2023) surveyed trust and reputation systems, identifying a number of common problems such as slow update to trusts and bias as well as manipulation; focusing on behaviour-based and context-aware models.

Utz et al. (2023) research block chain-driven reputation systems for business services, indicating greater transparency although with a computational overhead and integration complexity.

Olariu et al. (2024) introduced the trust and reputation as a service model in decentralized marketplaces to solve information asymmetry and manipulation of reputation in digital ecosystems. The authors proposed block chain enabled trust architecture where seller reputation based on the rating and feedback are generated as smart contracts providing enhanced defence against malicious feedback along with transparency.

3. Proposed System

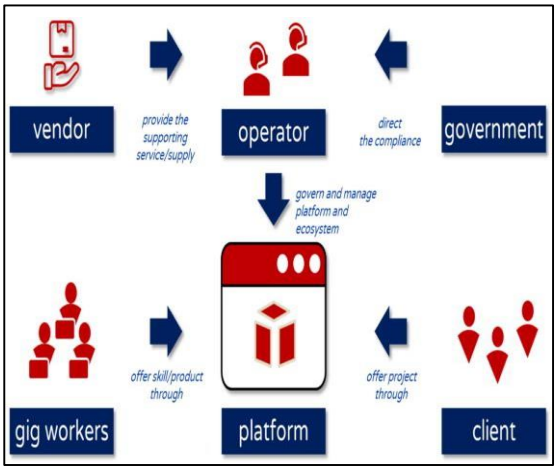

Figure. 2. System Architecture of the Trust-Centric Micro-Gig Platform (WORKWAVE 2.0)

WORKWAVE 2.0 is presented as a trust-based micro-gig economy enabler, and its goal is to enhance the

trustworthiness, security, accountability of hyperlocal service delivery. Its purpose is to complement All-Trust by capturing trust as a dynamic, evolving factor that originates from actual experience with services, rather than settling for traditional rating-based reputation models. By facilitating micro-gig connections at the household level, it assesses reliability of a provider in real-time based on behaviour and context. The design includes trust evaluation in the system architecture and does not treat it as a side feature. Service vendors rated by rational behavioural characteristics – timely completion of tasks, accuracy, feedback from customers and history of interaction. These scores are updated in real time as Perform Live makes her decisions to play a gig or not, so the Trust Scores are an accurate reflection of recent activity. This model provide for more responsibility in quality of care provision. The heart of WORKWAVE 2.0 is a hybrid trust evaluation analysis constructed on the weighted trust scoring, behavioural based anomaly detection and interaction-based trust adaptation. These delivery boys Restaurants in New York Let Delivery Workers Strike cartoonish high with every completed run; if anything is off — a cancellation, arriving late too many times — their trust score starts to fall. This model offer dynamic evaluation on resistivity against manipulations and reasoning of trust computation. To enhance trust, there also exists a community driven trust propagation model which is built on the basis of positively confirmed user-worker interactions. Trust can also trickle down to new providers, or the “little brother” parties starting out small next to the big ones: grow your good reputation through repeat business with someone who is already trusted. Meanwhile, the reputation formation for high-trust or unhesitating users should be less influenced by low trust or suspicious ones to prevent biased or untrue feedback. GPS enabled accountability parameters in the implementation of services that bring about transparency and ensure rights on time. Using real time location tracking, we can validate in how much time a worker arrived at the location and performed the service which are objective parameters for determining punctuality. Thanks to this context, trust is directly computed leading to a greater user confidence and operational reliability, especially with respect to the sensitive household services. WORKWAVE 2.0 adopts a trust-aware gig matching scheme in which the service allocation is made by considering both the trust score as well as geographical location of a worker. To improve service quality, customer satisfaction and positive reinforcing behaviours over platform, the matching is balanced such that high-trust providers with good history get more visibility while new and moderate-trust workers get fair chances.

4. Methodology

4.1 User Registration and Authentication

It begins with the approach to secure user registration and authentication for customers, service providers and other participants. They have add a profile (with the essentials) and verified info, if they choose, to build enough trust in the system. Then it is normal authentication for safe use of the system to avoid unauthorized use. This includes skill categories based profile creation and availability for gig matching, creating the call to action from day one.

4.2 Gig Posting and Service Provider Selection

The service workflow is initialized and controlled by the customer, who submits a gig request indicating service category, location and time. These additionally are submitted to backend for save and process. Relevant Services Suitable service providers are matched for service and location. Selection is not only based on availability, but also trust scores, for the right distribution of service.

4.3 Gig Acceptance and Location Tracking

After getting shortlisted, the gigs could be accepted by the service providers using platform interface. If hired, it would enable GPS based location tracking for the duration that workers are in route performing on the job. This leads us to an estimate of time of arrival, and consequently a level of punctuality which boosts user’s confidence in the system.

4.4 Behavioural Data Collection in Execution of Service

While performing the gig, the system collects behavioural information about how a service is performed. This is with regards to factors such as

the task achievements, the timeliness of performing the task, number of times a user cancels a task and the statements in customer feedback. Anything that's oddball or doesn't follow the scheme is noted for close scrutiny.

4.5 Dynamic Calculation of Trust Score

After the performance of a gig, their uploaded behavioural data is processed by the hybrid trust evaluation technique. The weighted trust scoring method evaluates the reliability of the server with regard to its behaviour and depending on a detection mechanism of anomaly modulates the trust score taking into account an abnormal activity. The community trust propagation method refines this score by considering the confirmations of interaction history.

4.6 Trust Update and Storage Mechanism

This round information are securely stored into the system database and used in real-time to fatten future gigs and rank the providers. That is to say, providers' trust profiles are updated over time.

5. Experimental & Implementation Details

5.1 System Architecture and Technology Stack

A flexible and extensible solution, WORKWAVE is built on a modular client-server architecture as to be both scalable for large enterprise production environments and feature rich with the ability for real-time trust analysis. For the task posting, the task assignment and status updating, we developed an Android mobile application as GUI. RESTful interfaces are a popular option in backend applications for secure client-server interaction. User profiles, task data, behaviour logs, trust scores and GPS coordinates are stored in a NoSQL database.

5.2 Implementation of Trust Evaluation

All algorithms are used in trust evaluation function. A weighted trust scoring mechanism to calculate their dependability on the basis of task completion rate, punctuality, customer rating and interaction with each other by normalizing every variable and taking into account various aspects of reliability by assigning weight to these measures has used. A behavioural anomaly detection aspect identifies trends including continuous cancellations and lateness. Besides, the trust propagation component of graph-based uses reliability in community level from verified worker-user interaction that increases the robustness about assessment based on the trust measure.

5.3 Simulation Environment & Experimental Setup

The system has already been tested in a simulated environment which emulates a hyperlocal micro-gig economy. A simulation set-up of 500 customers and 200 service providers is used, under which the service providers are defined as belonging to different categories of services. We conducted a simulation several rounds, with 5,000 gig n round each for studying the trust formation process and service allocation. The GPS data is synthesized to mimic the typical pathway and arrival duration. The relationship specifics for each gig have been logged by respondents to allow a detailed analysis of trust.

5.4 Evaluation Metrics and Parameters

The performance analysis for WORKWAVE 2.0 is presented with several quantitative parameters. Variance of scores across gigs was used to check the stability of trust scores. The trustworthiness of the service was provided by the successful-execution probability and on-time delivery probability. Anomaly detection performance has been measured in the decrease of the service-fail rate. The response time and successful service’s rate were used to evaluate the efficiency of gig assignment.

5.5 Dataset and Behavioural Scenarios Considered

The experimental data consisted of structured traces derived during the simulation. Organized tracks were formed using gig information, service time, feedback score, cancellation events and GPS traces. The range of behavioural traces included normal service delivery, a moderate level of variation in levels of performance and also anomalous patterns of delays/cancellations. Simply, behaviour traces enabled to examine on if the system would have been able to differentiate trustworthy providers from untrustworthy ones and whether or not (if) it was possible to give validity to a trust based framework. 6. Results and Discussion
6.1 Analysis on the Evolution of Trust Score

6. Results and Discussion

6.1 Trust Score Evolution Analysis

Trust This time dynamic trust evaluation in WORKWAVE 2.0 model demonstrated significant reactions to provider behaviour across several gig contracts. Providers who consistently fulfilled tasks, were on time and workman like made their trust grow in a steady manner whereas the opposite resulted in a constant decay. More than 5,000 simulated gigs Reliable providers increased their average trusting score from 0.62 to 0.88 after 20 completed gig offers. Suppliers with repeated late arrival or gig cancellations decreased from 0.65 to 0.41.

Table 1: Trust Score Evolution across Gig Interactions

Worker Category	Initial Trust	Trust After 10 Gigs	Trust After 20 Gigs
Consistent	0.62	0.79	0.88
Moderate	0.60	0.68	0.72
Anomalous	0.65	0.50	0.41

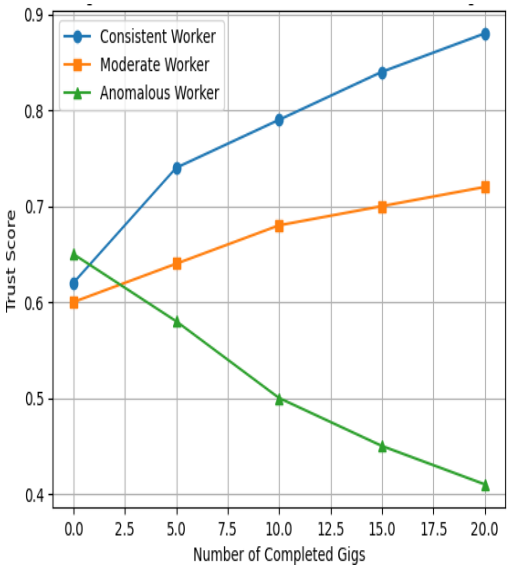

Figure. 3. Trust Score Evolution across Successive Gigs

6.2. Community-Driven Trust Propagation Boosts Effectiveness

The graph-based approach for propagating trust significantly smoothed the estimate of trust, especially for newly added service providers. New workers who did gigs for high-trust users established credibility much more rapidly than those whose only option was to depend on disconnected evaluations. When community propagation was on, new providers' trust scores rose 32%, on average, in their first eight gigs. It also managed to decrease the impact of low-trust users on reputation to 41%, which contributed to contain biased/malicious feedback.

Table 2: Impact of Trust Propagation on New Workers

Metric	Without Propagation	With Propagation
Average Trust After 5 Gigs	0.58	0.72
Cold-Start Resolution Time	15 gigs	8 gigs
Impact of Low-Trust Feedback	High	Low

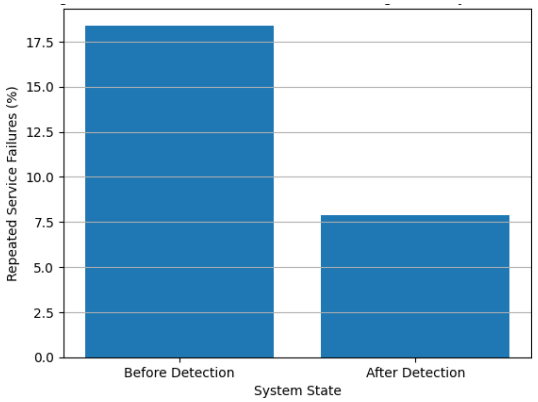

Figure. 4. Reduction in Service Failure Using Anomaly Detection

6.3 Implication of Anomaly Detection on Service Reliability

The behaviour-driven anomaly detection module effectively identified the out of line service patterns that we know, such as cancellations and late arrivals. At the start of the pandemic, workers flagged by this model saw their future gig work fall by 46% — increasing overall reliability. Anomaly-aware trust adjustments decreased repeated service outage from 18.4% to 7.9 and demonstrated the preventive nature of the system against untrustworthiness and preserving QoS.

Table 3: Service Reliability Before and After Anomaly Detection

Metric	Before Detection	After Detection
Repeated Cancellations (%)	18.4	7.9
Late Arrival Incidents (%)	21.2	9.6

Successful Task Completion (%)	78.5	91.3

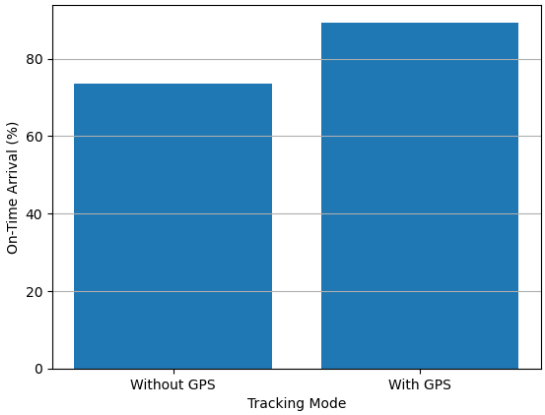

Figure. 5. Improvement in Service Punctuality Using GPS Tracking

6.4 The Role of GPS-Based Accountability

For instance, the utilization of GPS for tracing one location has fundamentally lead to transparency and helped proof-read delivery timing. Apologize now. This was monitoring in clock time-reality, so that you could actually compare arrival times and then 'do good' by feeding the information directly back into the calculus of trust. For on-time arrivals (which were 73.6% with no GPS and 89.4% with), customer complaints of delays fell 38%, so perhaps perception and factual measure are coming apart rather dramatically here.

Table 4: Effect of GPS Tracking on Service Timeliness

Metric	Without GPS	With GPS
On-Time Arrival (%)	73.6	89.4
Delay-Related Complaints	112	69
Trust Score Accuracy	Moderate	High

6.5 Performance Compared to Traditional Rating Systems

Comparing the traditional rating-driven gig allocation (benchmarking purpose) with WORKWAVE 2.0 demonstrates an insight to see improvements. The trust model was effective in all those dimensions worth mentioning: gig completions successfully served grew by 13.8% and service disputes decreased by 35%. Unlike fixed rating systems which do not track one's evolving behaviours over time, WORKWAVE 2.0 was able to observe improvements in performance within a GIG cycle.

Table 5: Comparison with Traditional Rating-Based Systems

Metric	Rating-Based System	WORKWAVE 2.0
Successful Completion (%)	77.5	91.3
On-Time Arrival (%)	74.2	89.4
Service Disputes (%)	14.6	9.5
Trust Update Latency	High	Low

6.6 Scalability and Real-World Deployment

The model is based on the WORKWave 2.0 modular architecture, which makes the model scalable and ready for practical application. It was able to process larger gig sizes without a loss in trust calculation or matching speed. Trust scores are calculated and updated, with an average latency of less than 120 ms per transaction. Elastic scaling of service types and regions was supported through NoSQL storage and lightweight algorithms. These findings confirm that we can apply the proposed trust-centric framework in real world large-scale hyperlocal gig platforms with reliability & transparency.

7. Conclusion and Future Work

It's also launched WORKWAVE 2.0 — a trust-based on-ramp to the hyperlocal micro-gig economy that was created to solve the problems associated with information truth, safety and accountability around local service marketplaces. Our findings suggest that a dynamic model of trust mediated by behavioural analytics results in more timely and accurate information on the quality of providers compared to ratings. Signs scores fluctuated with observed behaviour; they reliably .segmented high from low reliable providers. With GPS accountability, timeliness and verifiability went up even more; anomaly detection meant less frequent, less severe service failures and always higher quality. The core contribution is a hybrid trust management framework that integrates behavioural indications and community based trust propagation and the real-time context in which they are formed in one single platform. Rather than trusting a rating, WORKWAVE 2.0 removes the trust

issue that emerges from having a static rating and facilitates better gig matching, discourages gaming of ratings, & solves the cold-start problem for providers. This model has real-world implications for sensitive household services–where trust is essential. But there are limits to the contrasts. The review was conducted in a controlled simulation; real-world user behaviour could bring more variability. The use of GPS tracking is increasing accountability; however, privacy issues must be addressed through informed consent and data-protection provisions going forward, we aim to validate the performance of the system at scale in real- world conditions with operational data. We anticipate that models beyond logistic-regression or post-processing techniques (e.g., graph neural networks) will be developed to model more complex interaction and influence patters, as well as exploration of privacy-preserving methods to improve user trust and satisfy regulation. Two promising extensions of the framework are introducing an incentive mechanism and making platforms portable across apps.

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