Agile fusion: developing 'Eat at Right Place' sentiment analysis tool

Akash Prabhune[1,2], Vinay R Srihari[2], Neeraj Kumar Sethiya[1], Mansi Gauniyal[3]
[1]Faculty of Pharmacy, School of Pharmaceutical and Populations Health Informatics (SoPPHI), DIT University, Dehradun, India
[2]Institute of Health Management Research (IIHMR) Bangalore, Bengaluru, India
[3]Foundation of Healthcare Technology Society (FHTS), New Delhi, India

Article Info

Article history:

Received Dec 14, 2023
Revised Jan 26, 2024
Accepted Feb 4, 2024

Keywords:

Consumer reviews
Natural language processing
Scrum for mHealth
Sentiment analysis
User-centric development

ABSTRACT

This study presents the development and validation of the "Eat at Right Place Initiative," a sentiment analysis tool for restaurant reviews. Combining a user-centric approach with the Scrum framework, the mHealth agile development and evaluation framework was implemented, deviating from the initially considered Scrum framework. A multidisciplinary team navigated three phases, aligning sprints, goals, and backlogs. Phase 1 focused on product identification through interviews and surveys. Phase 2 involved development and alpha testing using a bidirectional encoder representation from transformers (BERT) rule-based sentiment analysis model. The final phase, beta testing, incorporated user feedback for usability enhancements. Ethical considerations were prioritized, ensuring participant consent and confidentiality. The study culminated in a robust aspect-based sentiment analysis model, effective in capturing nuanced insights from diverse restaurant aspects. Beta testing revealed actionable insights, marking the tool as fit for release. This sentiment analysis tool addresses consumer and owner needs, with iterative development and real-world testing laying the groundwork for future enhancements.

Corresponding Author:

Akash Prabhune
Faculty of Pharmacy, School of Pharmaceutical and Populations Health Informatics (SoPPHI)
DIT University
Dehradun, India
Email: prabhunesky@gmail.com

1. INTRODUCTION

Consumer reviews significantly impact the success of restaurants in the digital age, with platforms like Yelp, X (formerly Twitter), and Google Maps amplifying their influence [1]. However, manually analyzing these reviews is impractical for growing businesses, and existing sentiment analysis tools (VADER, TextBlob, IBM Watson) have limitations in accurately assessing restaurant-specific reviews. Studies highlight the role of online reviews in shaping restaurant success and customer perceptions. Askalidis and Malthouse [2] found a 270% increase in conversion rates with positive reviews. The existing tools like VADER [3] are quick but end users struggle with complex language; TextBlob [4] is user-friendly but limited in linguistic intricacy and cannot be contextualised to non-native english-speaking countries; IBM Watson [5] is advanced but costly for small businesses. Current sentiment analysis tools are not layman-friendly, requiring technical skills and Python environments. There's a need for a user-centric tool that simplifies sentiment analysis for restaurants and their customers.

The manuscript introduces the “Eat at right place initiative (ERPI)” tool, developed using a Scrum framework. This tool uniquely addresses the gap by providing an easy-to-use platform for both consumers and restaurant operators, focusing on sentiment analysis and visualization. The current manuscript presents a novel approach to fusing the mHealth strategies [6] for the development of software as a service platform and implementing the Scrum framework for optimised product management the manuscript details: a) adoption of the mHealth Scrum framework for ERPI, paralleling clinical research methodologies. b) Covering the phases of ERPI's development-from project identification (Phase 1), through development and alpha testing (Phase 2), to beta testing (Phase 3). The Objectives of the current study were to:

– Develop a user-centric sentiment analysis and visualization software platform for both customers and restaurant operators, aiming to describe the development process.
– Utilize the Scrum framework to systematically and timely complete the development and validation of the ERPI tool, presenting a case study for its implementation.

2. METHOD

The Scrum framework as presented by Schwaber and Sutherland [7], was explored to be used for this study as it is widely used across the industry for software development using Agile Methodologies. However, the mHealth agile development and evaluation framework was adopted as it merged the pathways of clinical development and software development. The visualization of the mHealth agile development and evaluation lifecycle framework is presented in Figure 1.

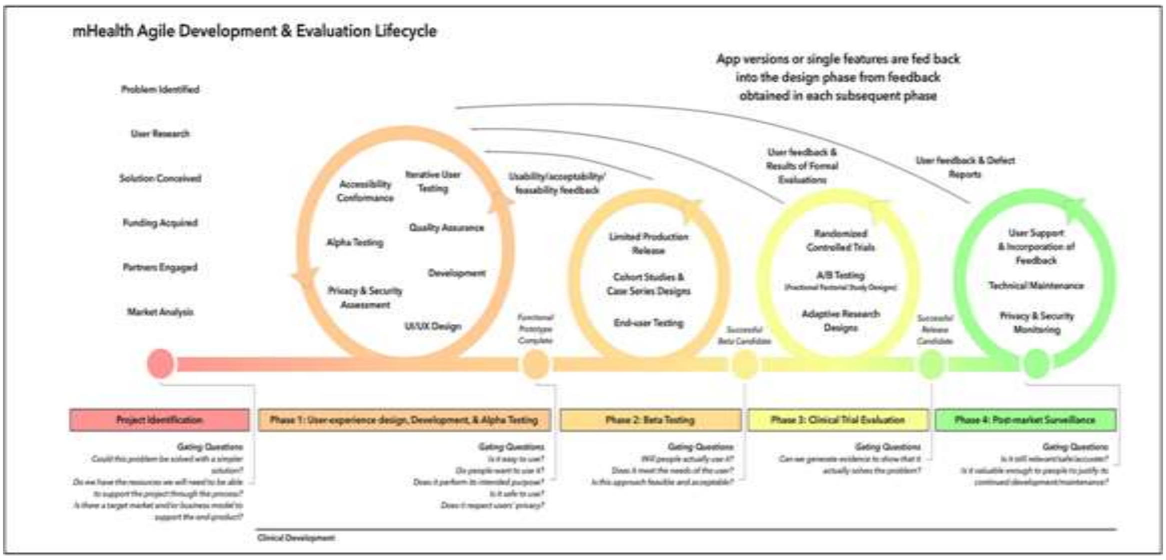

Figure 1. mHealth agile development and evaluation lifecycle [6]

As prerequisites for the implementation of the Scrum framework, we defined the Scrum team and the role of each member, defined the number of sprints, defined sprint goals, and product backlog (Artifact). Considering the multidisciplinary nature of the project a small yet multidisciplinary team was formulated as follows:

– Product owner: a research fellow in population health informatics responsible for overseeing and managing the overall project activities within the Scrum framework.
– Scrum master: a professional with a master in artificial and machine learning, experienced in managing ML projects, tasked with overseeing the technology development within the Scrum framework.

Developers: two public health researchers and one social worker assigned roles focusing on data collection, stakeholder engagement, and reporting, all operating within the Scrum framework. From the research and implementation perspective, the project was divided into three phases, thus we aligned the sprints, sprint goals and product backlog with the three phases.

2.1. Phase 1 - product identification phase

In the "product identification phase" of our study, we employed the Scrum framework a widely recognized agile methodology in software development over eight weeks from April to mid-May 2023. This phase was meticulously divided into four sprints, with each sprint spanning two weeks and focused on distinct objectives aimed at developing a customer-centric software tool for sentiment analysis in the restaurant industry.

During sprint 1 (restaurant owners' needs assessment), our primary objective was to comprehensively understand restaurant owners' expectations and requirements for sentiment analysis. To this end, we meticulously crafted an interview guide that would delve into the intricacies of their needs. restaurants were classified into five distinct service categories fine dining, casual dining, quick service, buffets, and Pop-Ups/food trucks to ensure a broad spectrum of insights. We then conducted thematic interviews with owners who had a substantial online presence, indicated by over 1000 reviews on social media platforms, and were willing to participate. The data gathered from these interviews underwent a thorough thematic analysis, through which we identified prevailing themes and specific challenges faced by the owners. These insights were pivotal in shaping the direction of our project, allowing us to tailor the sentiment analysis tool to meet the nuanced demands of the restaurant sector.

In sprint 2 (customer needs assessment), running concurrently with the first, our focus was a cross-sectional study to gauge how customers use online reviews to choose restaurants. We launched a meticulously designed and expert-validated questionnaire to more than 1,000 members of the Indian Google local guides community, targeting those who used reviews for restaurant selection in the past month. With a calculated sample size of approximately 280 based on a 30% expected response rate, we achieved 232 complete responses, which were then analysed using descriptive statistics. This analysis uncovered key patterns and preferences related to how cleanliness, pricing, and food quality ratings influence dining decisions, providing vital data for the development of user experience specifications for the sentiment analysis tool. Formula used for sample size calculation formula.

$$n = \frac{E^2 \cdot N \cdot Z^2 \cdot p \cdot (1-p)}{}$$

Where N=1000 (expected invitations), Z≈1.282 for an 80% confidence level, p=0.3 (assuming a 30% response rate), and E=0.05 (5% margin of error). The calculation yielded 279.3 samples which was rounded off to 280 participants.

Top of form in sprint 3 (user experience specification), the emphasis was on converting the insights from the earlier sprints into concrete user experience specifications for our product. We began by distilling the various needs and challenges identified by restaurant owners into a detailed set of product specifications. Building on this foundation, we crafted a user experience framework, which involved defining distinct user personas reflective of the diverse stakeholders, as gleaned from our earlier research phases. This step was instrumental in identifying and integrating critical features that would address the specific requirements of both restaurant owners and customers into a holistic user experience design, ensuring the tool’s relevance and usability across different user groups.

In sprint 4 (finalization of user experience specifications), the culminating phase of our process, we focused on finalizing the user experience specifications for our sentiment analysis tool. This involved a comprehensive integration of feedback from various stakeholders, a critical step that ensured the product design was in complete alignment with the overarching goals of the project. Through this collaborative approach, we developed and thoroughly validated a detailed document that clearly outlined all user experience requirements. This document not only served as a blueprint for the upcoming development phase but also established a set of success criteria, ensuring that the final product would meet the nuanced needs of our diverse user base.

Throughout this phase, we adhered to the Scrum framework's emphasis on iterative progress, transparency, and adaptability. Our approach was justified by the Scrum framework's success in software development, ensuring a structured yet flexible process. The detailed algorithms and techniques employed, such as thematic analysis for interview data and descriptive statistics for survey data, provide a replicable model for similar studies. This comprehensive methodology not only achieves the study's objectives but also serves as a "how-to" guide for future research endeavours, offering the necessary details to replicate our findings.

2.2. Phase 2 - development and alpha testing

This phase started in mid of May 2023 and ended by the end of July 2023 with five sprints each lasting for two weeks. For the finalisation of the Sentiment analysis model, we explored the GitHub repository. It presented nine models around sentiment analysis focused on restaurant reviews [8]–[16]. The bidirectional encoder representations from transformers (BERT) model and rule-based aspect assignment approaches were selected because.

During the Sprint 5 (sentiment analysis model development) development of sentiment analysis model was undertaken utilizing the BERT model, recognized for its state-of-the-art capabilities in natural language processing (NLP) and deep learning. Pre-trained on extensive text data, the BERT model offers the flexibility of fine-tuning for specific tasks like sentiment analysis. We chose scala consultant's aspect-based-sentiment-analysis (ASBA) [17] model, an open-source version of BERT, which is accessible for both commercial and non-commercial use. This choice was guided by the need for a sophisticated tool capable of understanding and processing complex linguistic patterns found in restaurant reviews.

Alongside the BERT model, we incorporated a rule-based aspect assignment approach, which allowed for a more targeted analysis of sentiment related to distinct aspects of restaurant services. This method's strength lies in its ability to dissect customer feedback into categorized sentiments, such as service quality or food taste. By applying this approach, we were able to systematically identify and analyse sentiment patterns tied to specific aspects, enhancing the granularity and focus of our sentiment analysis.

Sprint 6 (model setup and benchmarking) Running concurrently with first sprint, the practical application of these methodologies involved an extensive data collection and analysis process. We began by gathering 3596 reviews from 26 Bengaluru-based restaurants, dividing this dataset into training and testing segments. Collaborating with scala consultants, we fine-tuned their ASBA model with keywords pertinent to the Indian restaurant scene. The model's efficacy was further validated using additional data from restaurants in Dehradun, Pune, and Bhubaneshwar. This dual approach, combining web scraping with aspect-based sentiment analysis (ABSA), allowed us to test the model on various aspects such as "service, food, price, ambiance," initially on 500 reviews to gauge baseline performance. Subsequently, we expanded the rule-based system to include a broader range of aspects, encompassing "ambiance, hygiene, service, time, food, variety, price, and accessibility," and utilized 3096 labelled reviews for this purpose. The resulting adapted model showed marked improvements in precision, recall, specificity, and sensitivity, indicating its successful adaptation to the nuances of Indian consumer sentiment across different cities.

Our findings indicated that the adapted model achieved high precision, recall, and F square values across multiple aspects, demonstrating its robustness and suitability for the Indian context. Notably, the model's average F square value of 0.86 exceeded those of similar commercial models, underscoring the effectiveness of our tailored approach. The model's accuracy was significantly bolstered by the rule-based component, which was enhanced with a carefully crafted keyword dictionary. This amalgamation of advanced NLP techniques and meticulous rule-based categorization ensures that our model stands as a reliable and efficient tool for sentiment analysis in the Indian restaurant industry. The detailed methodology for model development is published in the IEEE conference proceeding [17]. Figure 2 presents the outline of methodology.

Sprint 7 (model validation and automation) and sprint 8 (internal testing and reliability assessment) the development of the tool involved a comprehensive, multi-step process to create a robust sentiment analysis system for restaurant reviews. The core of this development was a structured data pipeline that integrated data acquisition, pre-processing, sentiment analysis modelling, and visualization. This pipeline was meticulously tested and validated, including unit testing of individual components and integration testing to ensure seamless data flow and accurate sentiment representation.

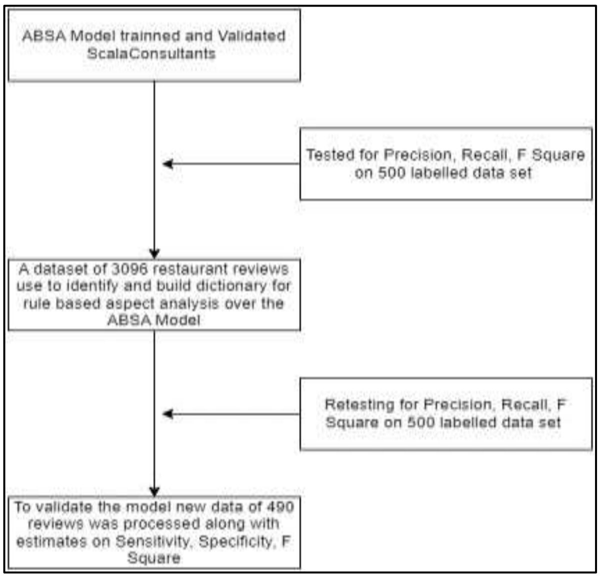

Figure 2. Process flow of the BERT Rule based sentiment analysis model [17]

Key steps in the pipeline included acquiring consent from restaurant 10 owners to use over 1000 reviews, employing sophisticated tools such as AWS EC2, Cloud9, Docker, and PostgreSQL for data handling and storage, and utilizing the Out-scrapper API for data retrieval. Figure 3 visualises the flow of data through the pipeline. The sentiment analysis was conducted using an ABSA model, fine-tuned to interpret various aspects like service, food, and hygiene. The results were then visualized through Python-generated bar plots, offering clear insights into customer sentiments.

Sprint 9 (user experience and alpha testing inputs) the effectiveness of the tool was further enhanced by focused group discussions (FGDs) involving restaurant owners and consumers, which provided valuable feedback on the tool's visualization outputs and usability. These discussions, along with rigorous testing, ensured that the tool was not only technologically sound but also aligned with the needs and preferences of its end-users, marking a significant stride in the realm of customer-centric software development for the restaurant industry.

A total of three FGDs were conducted two for consumers and one for restaurant owners. Two groups of six participants were involved in consumer FGDs, and four restaurant owners were part of the restaurant owners FGD. The FGDs were themed around understanding the preferences of the consumers and restaurant owners about the final visualisation output. Another theme was what interpretations were derived by the stakeholders looking at the visualisation output, additional information needed to be added to aid in decision-making for both stakeholders. At the end of Phase 2, the initiative was christened as the ERPI.

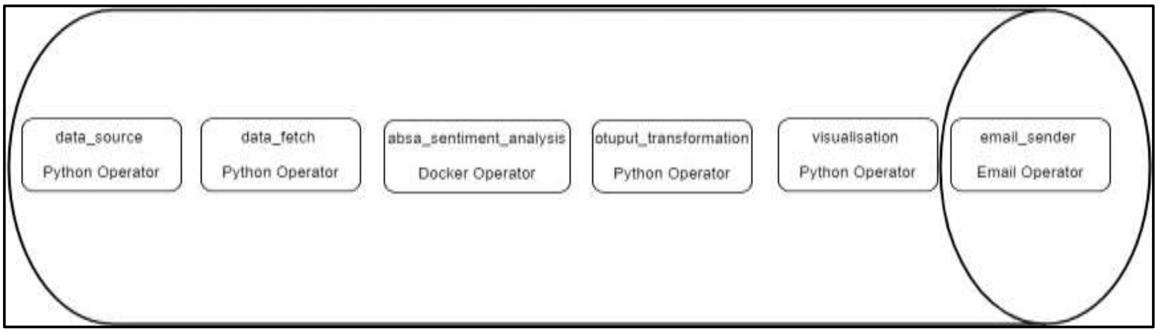

Figure 3. Proposed data pipeline with components and connections

2.3. Phase 3 - beta testing

This phase started in August 2023 and ended by the middle of August 2023 with one sprint lasting for two weeks. For sprint 10 (user feedback integration) we contacted consumer volunteers across the cities of Bengaluru, and Dehradun, the volunteers were asked to list of restaurants they visited in the last 2 weeks and the sentiment analysis of all the restaurants listed (N = 6) by the consumer volunteers was carried out and a semi-structured questionnaire was administered to the consumer volunteers and they were asked to recall their experiences and state on the scale of 1 to 5 the findings of ERPI Analysis relates with their experience.

The questions for consumers were:

- How close was your experience to the findings of the ERPI analysis?
- Do you have any specific observations about any of the aspects reported?
- Has the ERPI analysis missed anything obvious about the restaurant?
- Is the information provided from the ERPI analysis sufficient for you to make decisions on visiting the restaurant?
- Is the information clear, do you see any confusing or conflicting information?

The questions for restaurant owners or managers were:

- Do you think the ERPI analysis has correctly represented customer reviews of your restaurant?
- Is the information provided from the tool helpful for you?
- Are you planning to make any management-level decisions based on ERPI analysis?

The questions were tailored to suit the ERPI analysis findings from each restaurant and shared via Google Forms for a total of 8 consumer volunteers. The consumer volunteers were recruited through snowballing from the references provided by participants of Phase 2 FGDs. The restaurant owners, the same restaurant owners who participated in Phase 2 for focussed group discussion were contacted to share their views on the findings of the sentiment analysis.

2.4. Ethical considerations

The study was approved by the Institutional Review Board of DIT University Dehradun, vide letter number DITU/UREC/2022/04/16. The researchers have obtained written informed consent from all the participants in the study. The primary and secondary data collected for the study purpose were stored and analysed after removing any personal identifiers. All the participants were informed about their right to confidentiality and privacy. For the restaurants only geographic identifiers were preserved. The flow of participants across the three phases of the study is visualised in Figure 4. During the three phases of the study, the team utilized different types of data, the type of data (primary or secondary), and linkages with the sprint goal are presented in Figure 5.

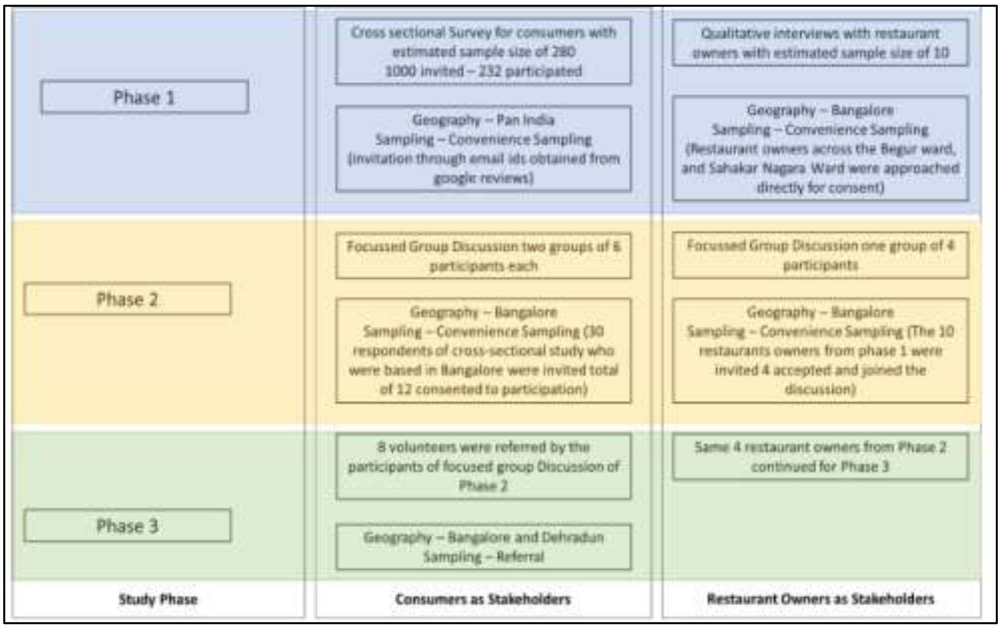

Figure 4. Visualisation of methods, sample size, sampling, and geography of the study population across the three phases of the study

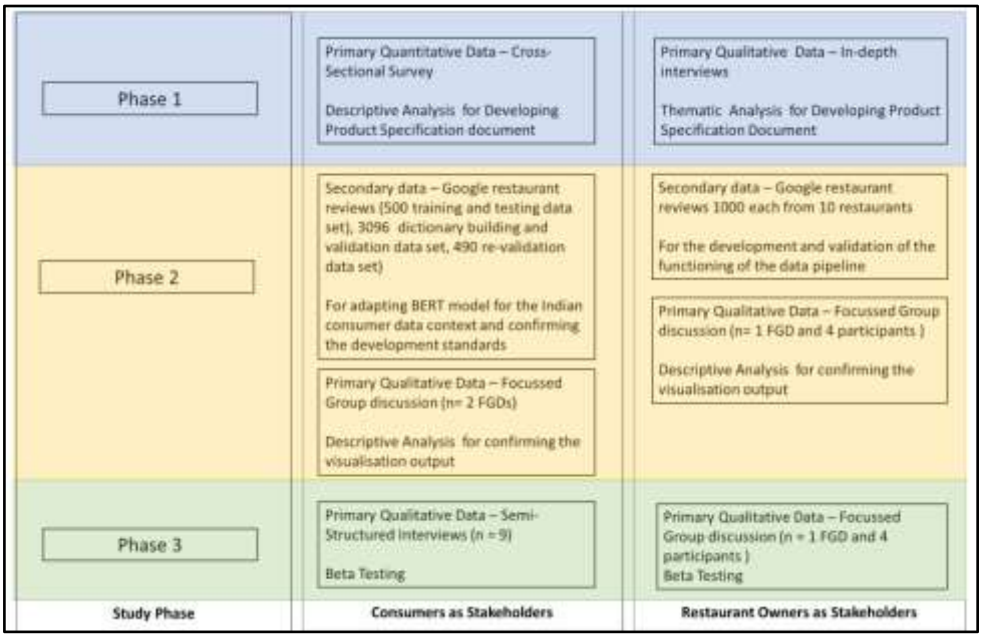

Figure 5. Visualisation of research methods employed, type of data collected, type of analysis undertaken and outcome across the three phases of study

3. RESULTS

The total study duration was five months (20 weeks) with a total of 10 sprints. We have presented the results Phase-wise and commented on the achievement of the sprint goals, if the goal was not achieved how was it managed? Throughout the study, while not all sprint goals were met on the original timeline, the agile approach allowed for flexibility and adaptability. Challenges were managed through strategic adjustments, additional resources, and enhanced coordination efforts. This iterative process not only facilitated the achievement of the study's objectives but also provided valuable insights into managing large-scale research projects effectively. The details are outlined in the subsections.

3.1. Results of Phase 1 - product identification phase

A total of 232 responses were obtained for the cross-sectional questionnaire shared on the Google local guides community by the end of two weeks of the sprint timeline. Table 1 summarises the findings of the cross-sectional survey. Based on the survey the key specifications listed for the team were:
- Google Maps is the most important source of reference to participants thus the final tool should be integrated within Google Maps.
- Star ratings play a vital role in decision-making; thus, the analysis should summarise in terms of star ratings for ease of communication with the consumer.
- The aspects deemed to be important for consumers were summarised as quality of food, service from staff, hygiene, cost, waiting time and serving time, food variety and parking space.

The in-depth interviews with the 10 restaurant owners yielded the following findings.

Table 1. Findings of the cross-sectional survey

Parameters	Ranking of factors based on frequency
Mean Age of respondents	27 (SD ± 5.8)
% of Graduates and above in study respondents	78%
Bengaluru as the city of residence	65%
Reason for using the internet for searching restaurants.	1. Explore in detail about the restaurant (80%)
	2. Trust the Internet for providing accurate information (65%)
(listed highest to lowest preferences based on responses)	3. Unfamiliar with the area (63%)
	4. Doesn't know local language (25%)
Common sources used to search for restaurants.	1. Google Maps (97%)
	2. Swiggy (84%)
(listed highest to lowest preferences based on responses)	3. Zomato (81%)
	4. Bing Maps (<1%)
Information used for decision-making.	1. Star Rating (96%)
	2. Proximity of the restaurant (80%)
	3. Pictures of the restaurant (78%)
	4. Pictures of the food (67%)
	5. Pricing (50%)
(listed highest to lowest preferences based on responses)	6. Detailed reviews (38%)
Consumer interpretation of star rating5	
5-star rating	Will definitely go! (94%)
4-to-4.5-star rating	Decisions based on reviews and price (90%)
3-star rating	Read reviews, and check photos and alternatives before making a decision (84%)
2-star rating or less	Avoid going (95%)
(Sorted as top responses for each option)	
Factors important from a consumer point for decision making.	1. Quality of Food (88%)
	2. Behavior of Staff (82%)
	3. Cleanliness of Premises (76%)
	4. Pest Control (75%)
	5. Absence of external Objects in food like hair, stone (73%)
	6. Pocket friendliness (72%)
	7. Waiting time (60%)
	8. Quantity of Food (48%)
(listed highest to lowest preferences based on responses)	9. Parking Space (45%)
	10. Child Friendliness (26%)
How consumers want to access the new tool on sentiment analysis	1. Integrate within the reviews page of the restaurant over Google Maps (74%)
	2. Stand-alone website (61%)
	3. Browser Extension (50%)
	4. Stand-alone application (28%)

Type of restaurants, 4 (40%) were casual dining (restaurants engaged in preparation and service of breakfast, lunch and dinner with proper sitting arrangement and dining hall), 2 (20%) were quick service restaurants (serving either breakfast or lunch or dinner, with standing arrangement or takeaways) 2 (20%) were Pop-Ups and food trucks (serving tea coffee and snacks) 1 (10%) buffet and 1 (10%) fine dining. All the respondents were maintaining an online business presence and accepted that reviews are a very important tool to maintain customer flow and attract new customers.

The 80% of respondents mentioned that they take serious cognizance of negative reviews and read every review left by the customers. The 80% of respondents mentioned they try to contact customers who leave less than 3-star ratings and try to understand the concern and even provide offers or cashback to retain the customer. The 80% of respondents accepted the need for tools to present the overview of reviews and help them better manage customer concerns. Key requirements listed by the restaurant owners were:

- The tool should be available to them discreetly (either app or email)
- The tool should be able to highlight key concerns for them to make decisions
- The key areas listed by the restaurant owners were a) Service, b) Hygiene, c) food quality, and d) Ambience.

Restaurant owners were ready to pay a small subscription fee equivalent to USD 2 (INR 150) per quarter for the subscription to the sentiment analysis tool. Based on the surveys and interviews the team decided to have a single tool with two outputs, an output specific to consumer needs and another output specific to restaurant owner needs. Also, the aspects were standardized into ten a) ambiance, b) external objects, c) pest control, d) behaviour of staff, e) waiting time, f) quality of food, g) quantity of food, h) child friendliness, i) pocket friendliness, and j) parking space. The product specification document was presented to the team and the team had to decide on the feasibility of developing the specifications the final scope was thus defined as presented in Table 2. The project specification list was thus used for the development of the product in phase 2.

The ABSA model underwent substantial refinement and validation to tailor its performance to the nuances of Indian consumer expressions. In the baseline estimation, the model displayed varying effectiveness across aspects, with the Price aspect exhibiting superior accuracy and F Square values compared to others like food and staff. recognizing the need for improvement, extensive efforts were directed toward expanding the keyword dictionaries for each aspect, ensuring relevance to the rich and diverse expressions used by Indian consumers.

New aspects, including hygiene, variety, time, and accessibility, were introduced to comprehensively capture consumer sentiments. The sensitivity and specificity analysis, guided by a cut-off of 0.70, revealed varied values, signalling the necessity for further refinement. In response, additional keywords were strategically incorporated, addressing specific shortcomings in aspects like Food and Variety. Verb forms were introduced to existing keywords for ambiance and hygiene, contributing to enhanced specificity.

The updated model underwent a rigorous reassessment of its performance metrics, resulting in improved precision, recall, F square, and accuracy values across all aspects. Notably, the model's validation process extended beyond its training ground in Bengaluru, encompassing a dataset from diverse cities- Dehradun, Pune, and Bhubaneshwar. The results demonstrated consistent and robust performance across different geographic locations, affirming the model's adaptability and generalizability. The average F Square for all eight aspects reached an impressive 0.86, aligning well with established benchmarks for ABSA model validation. The detailed methodology and results of the development of the algorithm are published elsewhere [17].

3.2. Internal testing, user experience testing

The output was presented during the focussed group discussion and the comments were asked during the focussed group discussion the first iteration of the radar map (Figure 6) of the visualisation tool was described to be complex by both the consumer and restaurant owners. The second iteration of the bar plot with red colour indicating negative sentiment and green indicating positive sentiment (Figure 7) was accepted by both the stakeholders during the discussion. In terms of the names of the aspects the standardised list agreed upon by 84% of the focused group discussion participants was a) overall sentiment, b) waiting time and serving time, c) parking, d) food variety, e) hygiene, f) price, g) ambiance, h) food quality, and i) service.

The pest control and external objects in food were recommended to be merged under the header of Hygiene. Instead of quantity of food the participants across both the stakeholders suggest variety of food as a better aspect. For the pocket friendliness aspect, all the participants recommended changing it to price as heading. Child child-friendly aspect was deemed unnecessary by 75% of the FGD participants and thus was removed. The FGD participants also recommended adding key takeaways to support the visualisation. The final output with branding is presented in Figure 8.

Table 2. Project specification table with action points discussed by the team

Specs listed by consumers and restaurant owners	Feasibility	Remarks
	Consumer-Centric Features	
Google Maps Integration: The tool will be seamlessly integrated within Google Maps, catering to participants who highly rely on this platform for restaurant searches.	Feasible	Need to create Google account with branding and other components to post the results as .JPEG image to be updated once a year for each restaurant. The consumer component should be free for access
Star rating summarization: The sentiment analysis will prominently summarize results in terms of star ratings, recognizing the critical role star ratings play in consumer decision-making.	Feasible with minor alterations	Instead of repeating the star rating a overall sentiment can be added to summarise overall sentiments
Key consumer aspects: The analysis will focus on crucial aspects identified by consumers: quality of food, service from staff, hygiene, cost, waiting time, food variety, and parking space.	Feasible	Standardize the aspects in-line with findings of restaurant owners and consumers requests
	Restaurant Owner-Centric Features	
Discreet Accessibility: The tool will be accessible discreetly, either through a dedicated app or email, ensuring convenience for restaurant owners to stay informed.	Feasible	Integrate auto emailer component in data pipeline. With features of scheduling and choosing the frequency
Highlighting key concerns: The tool will intelligently highlight key concerns, enabling restaurant owners to make informed decisions promptly.	Feasible	Highlight the commonly repeating keywords for presenting as key concerns
Key areas of focus: The analysis will specifically emphasize areas identified by restaurant owners: – Service – Hygiene – Food Quality – Ambience	Feasible	Standardize the aspects in-line with findings of restaurant owners and consumers requests
Subscription Model: A subscription model, with a small fee of USD 2 (INR 150) per quarter, has been established, aligning with the willingness of restaurant owners to invest in the tool for enhanced customer management.	Deferred	To be explored separately after final product development
	General Features	
User-friendly interface: An intuitive and user-friendly interface for both consumers and restaurant owners.	Feasible	User centric designing of the visualisation through FGDs and IDIs
Real-time updates: Real-time updates for consumers to access the latest sentiment analysis results.	Rejected	The algorithm and pipeline require batch processing of minimum 100 reviews to present valid results
Communication channel: A built-in communication channel for restaurant owners to engage with customers, especially those leaving less than 3-star ratings.	Rejected	This will require separate development and integration mechanism and create issues on data privacy and ownership with Google Maps
Adaptive design: Adaptive design to ensure compatibility with various devices and operating systems.	Rejected	Current plan is to integrate with google maps and email. This doesn't necessitate extra investment on compatibility

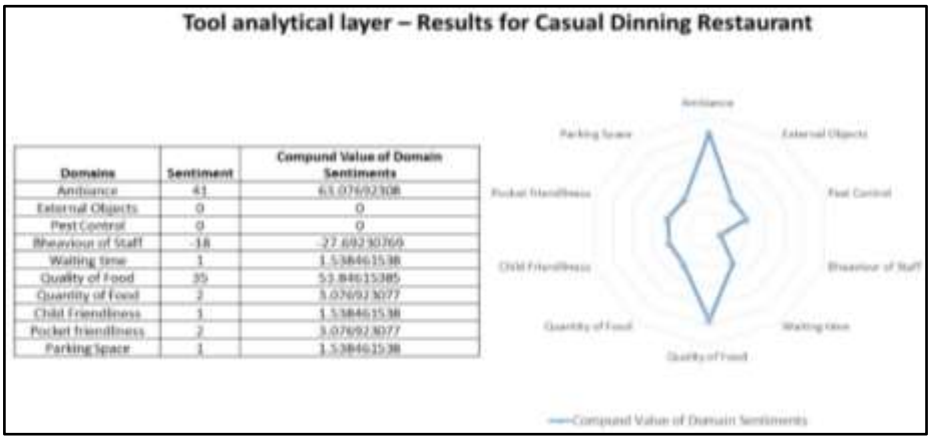

Figure 6. Radar Map presentation of the sentiment analysis tool output

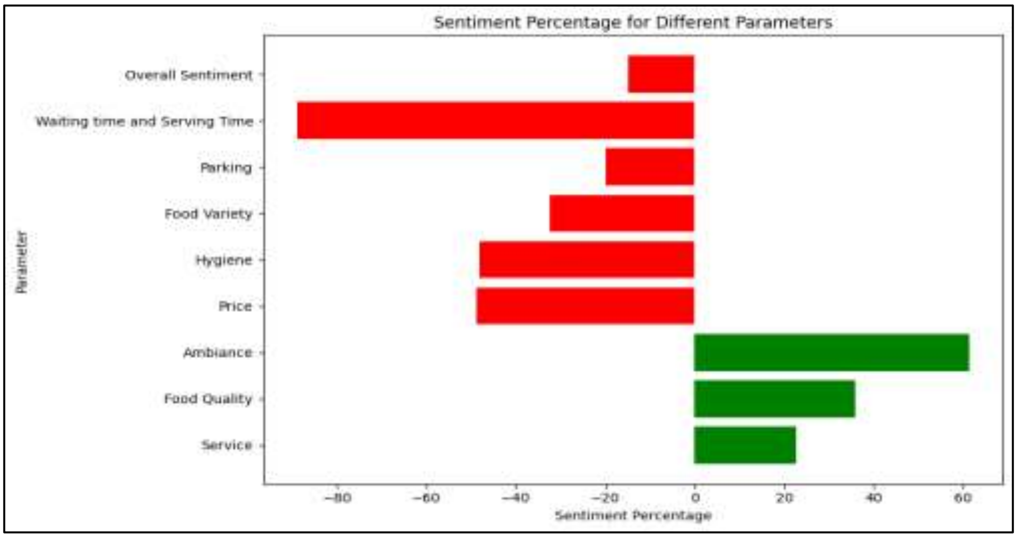

Figure 7. Bar Plot presentation of the sentiment analysis with overall sentiment as one of the aspects at the top

3.3. Data pipeline development and validation

The detailed methodology is discussed in the methodology section, and the results of testing of the pipeline are presented with an example of a casual dining restaurant in electronic city Phase 1 of Bangalore city. For, casual dining restaurant in electronic city, the analysis was conducted by retrospectively collecting data for reviews from the first two quarters of 2023, specifically for the periods January to March 2023 and April to June 2023 (retrospective data), as well as concurrently for July to September 2023 (concurrent analysis). A bar plot was generated to visualize the collective sentiment expressed by individuals across the eight aspects considered in the ABSA model. After the pipeline output was functional a meeting was sought with the Manager of the restaurant to discuss his views on the output and how it could aid in decision-making. The results of each quarter are presented along with comments from the manager as follows (Figures 9 and 10). The manager stated the negative sentiment associated with parking "earlier our customers were parking on the road, however the BBMP guys were putting jacks on the bikes, we had this problem … four wheelers couldn't park only".

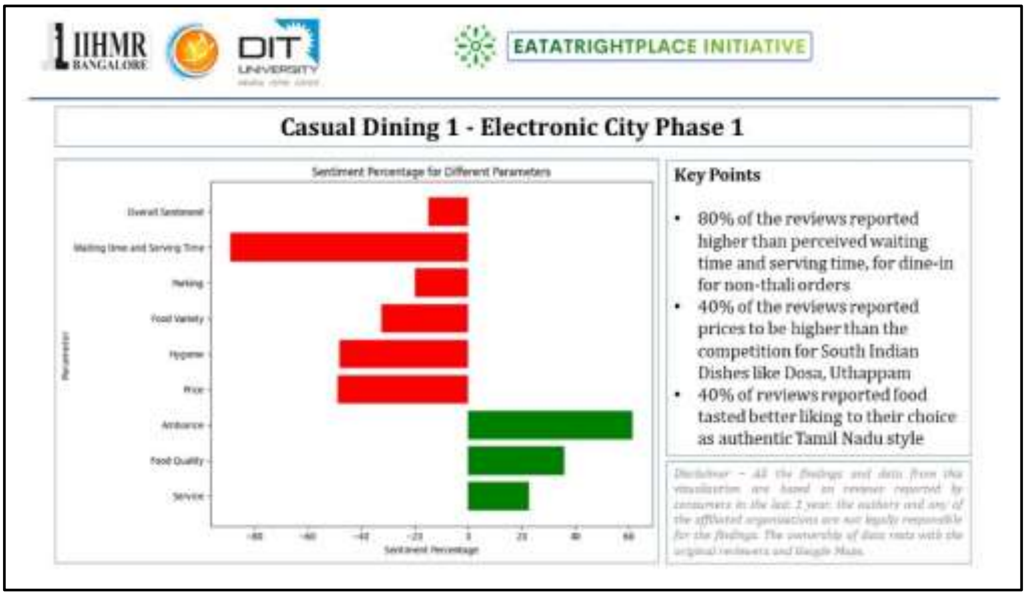

Figure 8. Final output designed after approval of FGD participants from consumer and restaurant owner groups

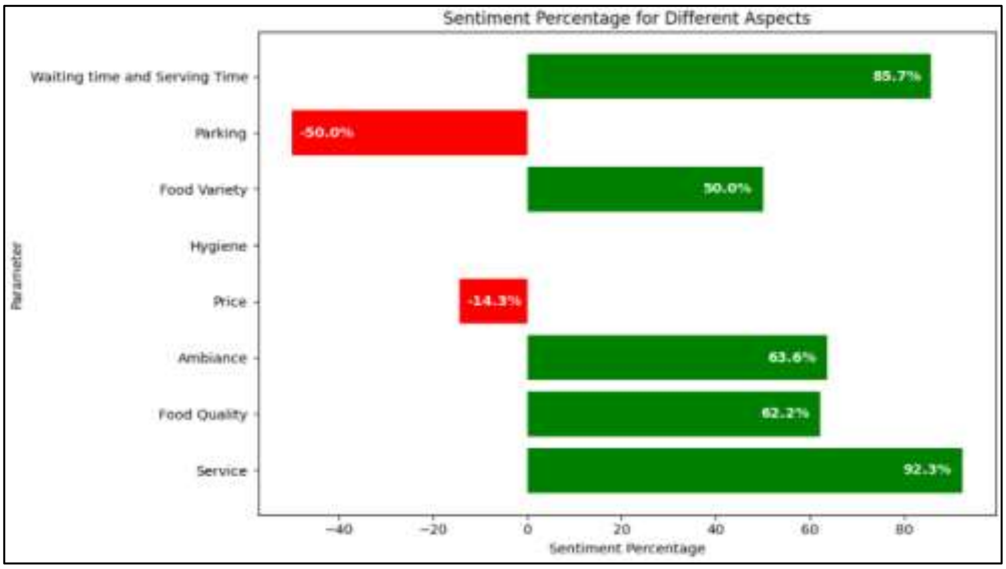

Figure 9. ABSA sentiment analysis for quarter 1 from January to March 2023

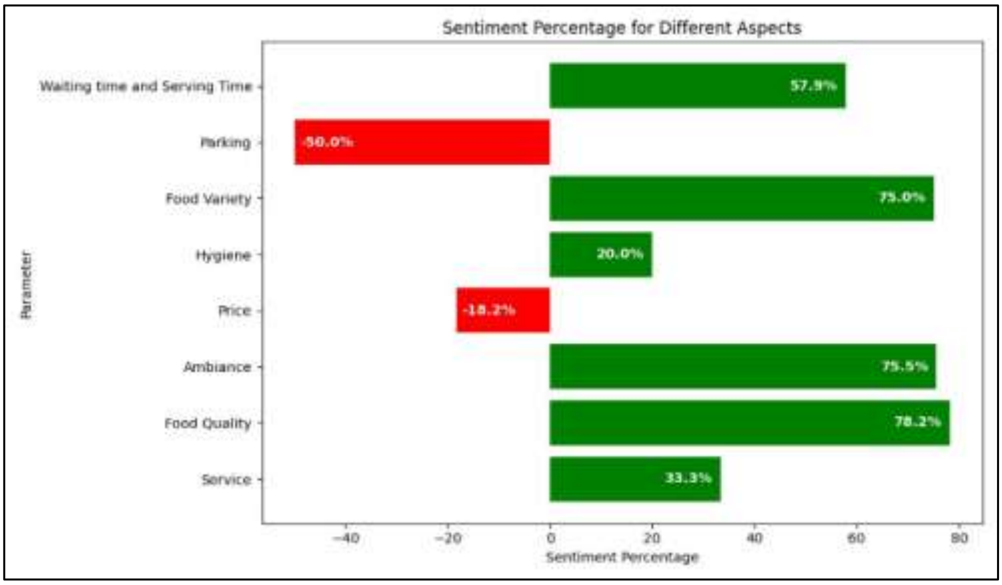

Figure 10. ABSA sentiment analysis for quarter 2 from April to June 2023

Another point he mentioned service positive sentiments on service and waiting and service time "Last year only we added more staff and renovated the restaurant, I am glad to see people as positive of the change. The manager was not able to exactly explain why service sentiment has dropped as nothing changed in terms of management between quarter 1 and quarter 2. For the third quarter (Figure 11), the manager agreed the parking issue was resolved as the road expansion work was undertaken allowing pay and parking for bikes and cars on the roadside. Again, the explanation for fluctuations in service and waiting and service time was not explained by the manager. On price sentiment, the manager explained "We had to increase our prices since the cost for gas, oil, manpower and all other substance had increased, and we have also received many complaints from our regular customers… we couldn't do much."

The team undertook internal evaluation for a. complete acquisition of data from reviews, b. appropriate data lemmatisation and processing, c. confirmation of correct aspect identification and confirming polarity of the sentiment algorithm. 10 reviews were randomly selected from the data set subjected to the data pipeline, the same is exhibited in Table 3. The internal assessment provided clear results on the three areas of testing; the data acquisition was able to fetch completed reviews irrespective of the word count. The data processing algorithm was able to convert the data into lowercase, remove punctuations and smiley and identify stop words. The aspect identification was accurate for all the 10 reviews tested internally along with sentiment polarity. Overall, the pipeline was able to capture and present time pertinent sentiments that resonate with the business needs of the restaurant owners.

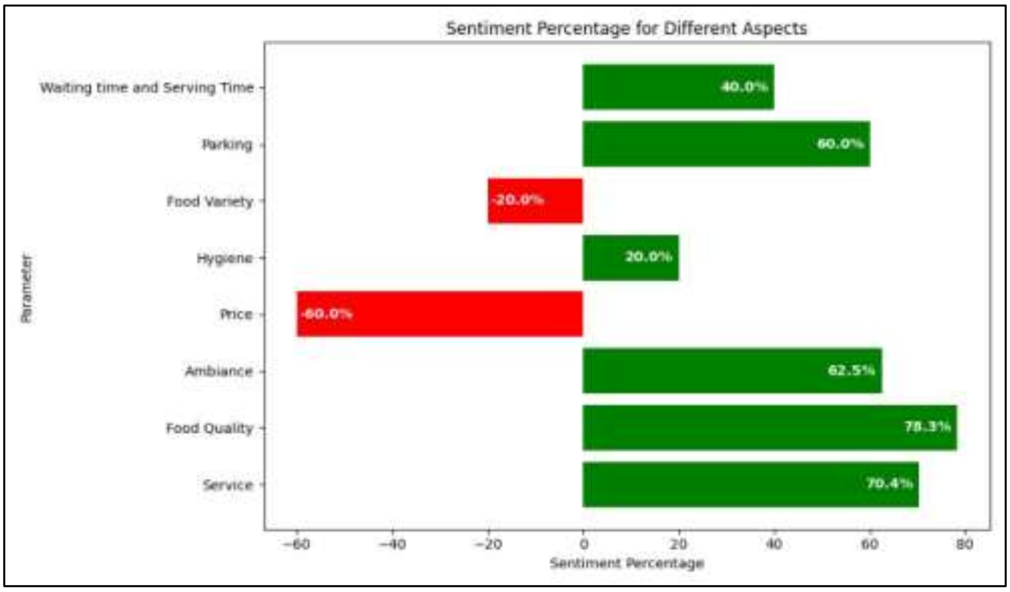

Figure 11. ABSA sentiment analysis for quarter 3 from July to September 2023

Table 3. Exhibits from the internal testing and validation

Author	Original review Reviews	Restaurant Name
Anonymised reviewer 1	Food was not much tasty (5 words)	Casual Dining Restaurant in Electronic City
Anonymised reviewer 2	Best place for having a family lunch ... Their meals is excellent (11 words)	Casual Dining Restaurant in Electronic City
Anonymised reviewer 3	Service was a bit slow, and the food tasted awesome. Very hygienic place and hotel in Avenue road. (18 words)	Casual Dining Restaurant in Electronic City
Data Preprocessing, Aspect Confirmation and Sentiment Polarity determination Exhibit for the aspect confirmation and sentiment polarity determination “Service was a bit slow, and the food tasted awesome very hygienic place and hotel in avenue road”. – Aspect food quality – positive sentiment (0.99) – Aspect service – negative sentiment (0.41) – Aspect hygiene – positive sentiment (0.79)		

3.4. Results of phase 3 – beta testing

Out of the six restaurants selected for beta testing through semi-structured interviews, only four owners provided consent for participation. In electronic city Phase 1, two casual restaurants were covered, each having both a consumer volunteer and a restaurant manager respond to the semi-structured questionnaire. The fine dining restaurant had a consumer volunteer and a manager participating. In the case of the QSR, two volunteers responded, but the manager declined, citing corporate policy. Similarly, for the Buffet restaurant, one volunteer responded, but the manager chose not to participate in the questionnaire. Moving to Dehradun, the food truck and Dhaba type of restaurant had two volunteers respond, and the owner also provided input for the interview. In total, eight volunteers were interviewed, capturing insights from a diverse set of restaurants, although the participation of restaurant owners varied based on their consent. Figure 8 and 12 presents the final output for both the casual dining restaurants. The responses from the semi-structured interviews with volunteers and restaurant owners/managers is summarised following the figure.

The consumer volunteer for casual dining restaurant 1 provided key observations regarding the sentiment analysis tool. Overall, they acknowledged that the tool effectively captured and presented consumer sentiments. However, the consumer highlighted a specific issue related to waiting and serving times, particularly during peak hours in the self-service area. Interestingly, the AC service area, where the consumer had dined, did not encounter such problems. This observation underscores the importance of distinguishing between different dining areas within the restaurant. Furthermore, the consumer emphasized that the tool did not adequately capture the differences between the two dining areas self-service and AC service. This finding points to a limitation in the tool's ability to discern nuances related to specific sections of the restaurant. During the interview with manager concerns regarding waiting times and service delays during peak hours were raised. Despite the recent addition of new staff, the feedback indicated that further training might be required to enhance their efficiency. The respondents expressed optimism about observing improvements in these aspects over the next six months, indicating a willingness to address the issues proactively.

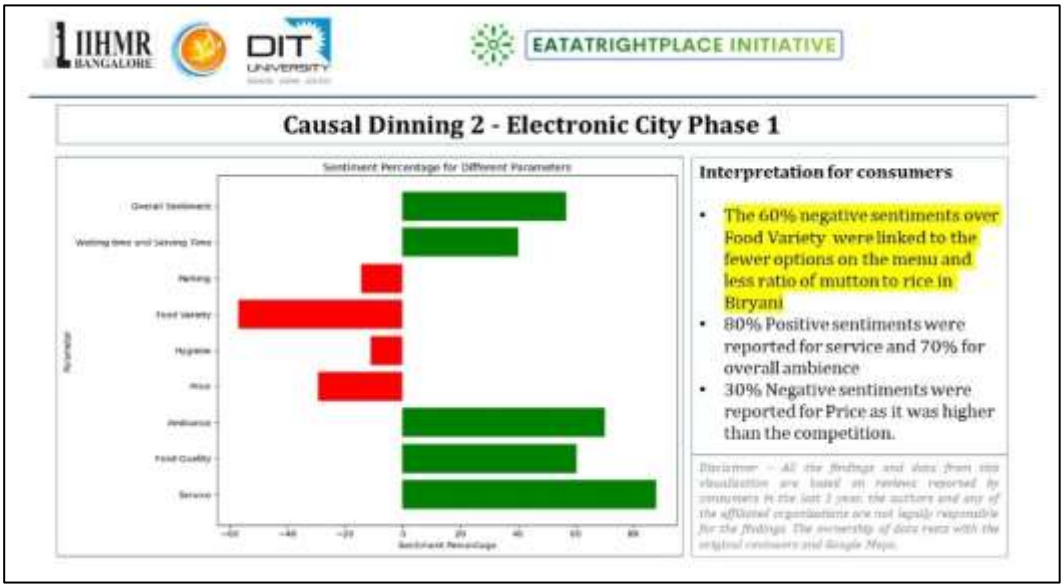

Figure 12. Outcome of the ERPI analysis for the second casual dining restaurant presented to the beta testing volunteers and managers of the restaurants

Another common issue highlighted was parking challenges in the area. Respondents emphasized that the problem is pervasive and attributed it to the absence of underground parking facilities in the building. This constraint seemed to pose a significant challenge for the restaurants, reflecting a sense of helplessness in addressing the parking issues. The interviews captured these nuanced insights, revealing the complex interplay of staffing, training, and structural limitations in influencing the overall customer experience. Key observations from the consumer volunteer at casual restaurant 2 include the acknowledgement that the sentiment analysis tool effectively captured the overall sentiment. However, the consumer expressed concern about the perceived overcharging for the quantity of food provided during their visit. This feedback emphasizes the tool's success in reflecting the sentiment related to pricing issues. On the managerial side, the response indicates a doubt regarding the negative sentiments around hygiene. The manager asserts that the restaurant maintains high standards of hygiene and ensures that the staff is well-groomed. Additionally, the manager acknowledges the parking issue and provides insight into addressing it by placing a board indicating the direction to a free parking spot in the next lane. However, the manager recognizes the need to enhance the visibility of this information to further alleviate parking concerns.

In the case of the fine dining restaurant, both the consumer and the manager expressed unanimous agreement with the results of the ERPI analysis. The consumer characterized the place as "awesome" and commended the well-behaved staff, ample parking facilities, and overall maintenance. These positive sentiments align with the ERPI findings, indicating a positive and satisfactory experience for the consumer.

Similarly, the manager of the fine dining restaurant concurred with the ERPI analysis. Specifically, the manager emphasized that the pricing aligns with market standards for fine dining establishments. This agreement between the consumer and the managerial perspective underscores the tool's accuracy in capturing positive sentiments and the restaurant's alignment with consumer expectations in crucial aspects like pricing, service quality, and overall ambiance. Figure 13 presents the ERPI analysis for fine dining restaurant.

In the case of the quick service restaurant (QSR), the feedback from two consumer volunteers highlighted concerns not about the variety of food offered but rather the availability of options on the menu.

They reported consistent issues, particularly with items like ice cream and combos, often finding them unavailable despite being listed on the menu. This discrepancy between the menu offerings and actual availability was identified as a significant concern by the consumers. Figure 14 presents the ERPI tool outcome for QSR category.

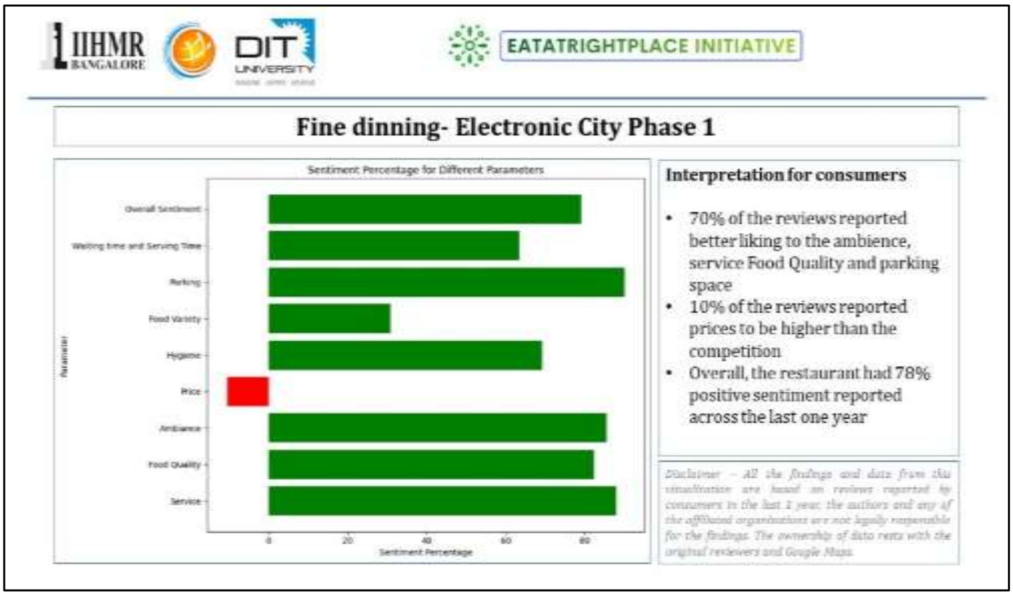

Figure 13. Outcome of the ERPI analysis for the fine dining restaurant presented to the beta testing volunteer and managers of the restaurant

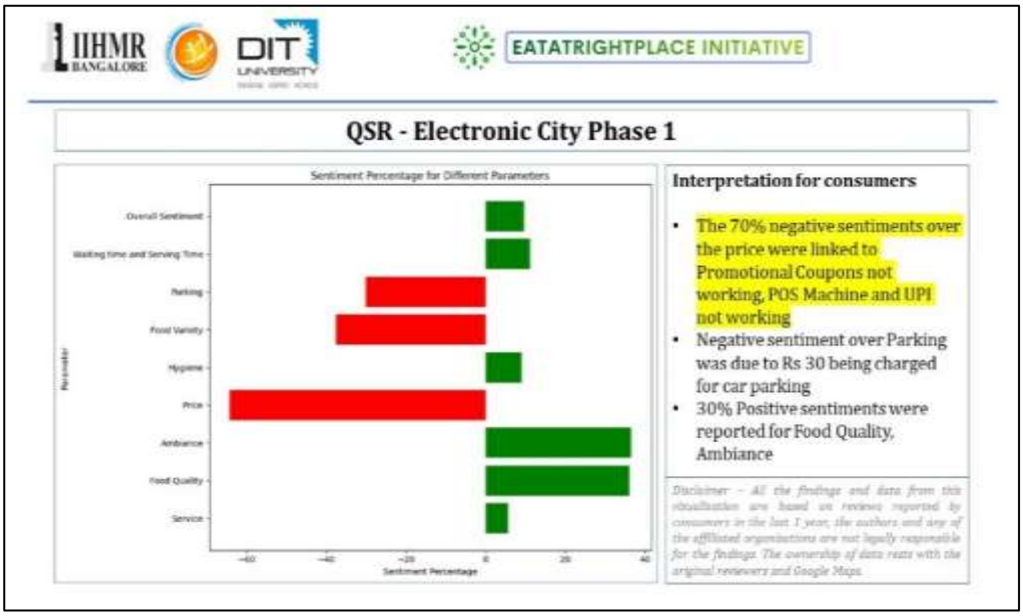

Figure 14. Outcome of the ERPI analysis for the QSR restaurant presented to the beta testing volunteers

In the case of the Buffet restaurant, the consumer's feedback indicated a positive alignment with the results from the ERPI tool. The consumer expressed satisfaction with the overall experience, describing the place as great and efficient. There were no reported issues regarding hygiene, although the consumer acknowledged the need for a more thorough inspection, especially concerning skewers, during subsequent visits. It's noteworthy that the consumer had visited the restaurant only twice, suggesting that additional visits might provide a more comprehensive perspective on various aspects, including hygiene. The ERPI tool's ability to capture the positive aspects of the consumer's experience with the Buffet restaurant underscores its effectiveness in reflecting diverse customer sentiments and experiences. Figure 15 presents the ERPI analysis for buffet category.

In the case of the food truck or Dhaba category, the feedback from two volunteers revealed a neutral sentiment regarding parking, highlighting the ambiguity of an empty parking bar-whether it signifies an absence of issues or a lack of mention in reviews. However, hygiene emerged as a significant concern, with reports of flies, cockroaches on the floor, and rats near the compound. Despite these observations, the volunteers noted that the food itself remained clean, and they avoided drinking the water served.

The owner of the food truck or Dhaba shed light on the parking situation, explaining that they lack a dedicated parking space due to financial constraints. The owner acknowledged the hygiene issues raised by customers and expressed plans to address them through a forthcoming renovation of the entire establishment. Figure 16 presents the ERPI analysis for Food Truck or Dhaba category.

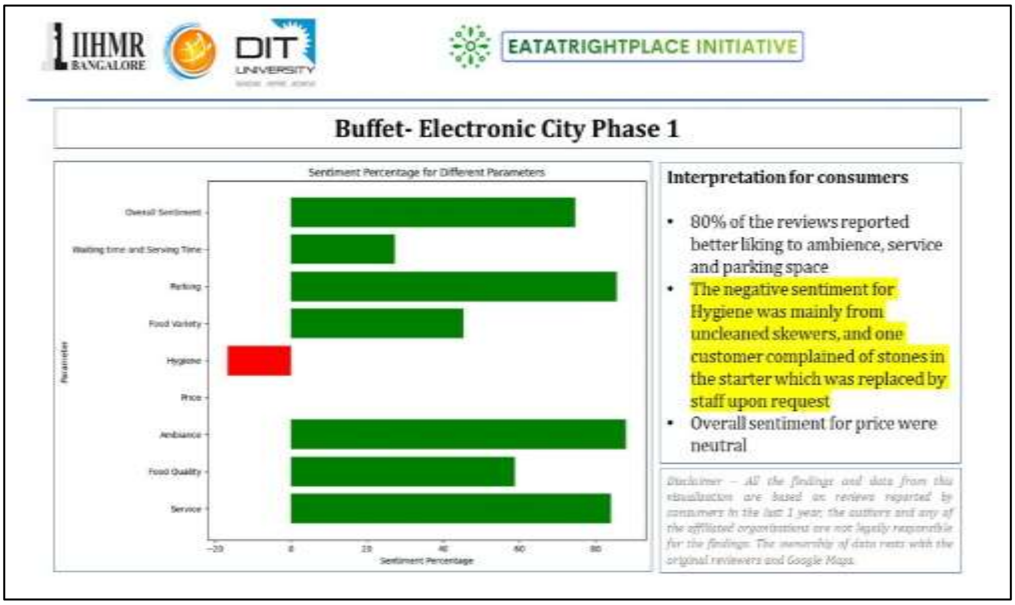

Figure 15. Outcome of the ERPI analysis for the Buffet restaurant presented to the beta testing volunteers

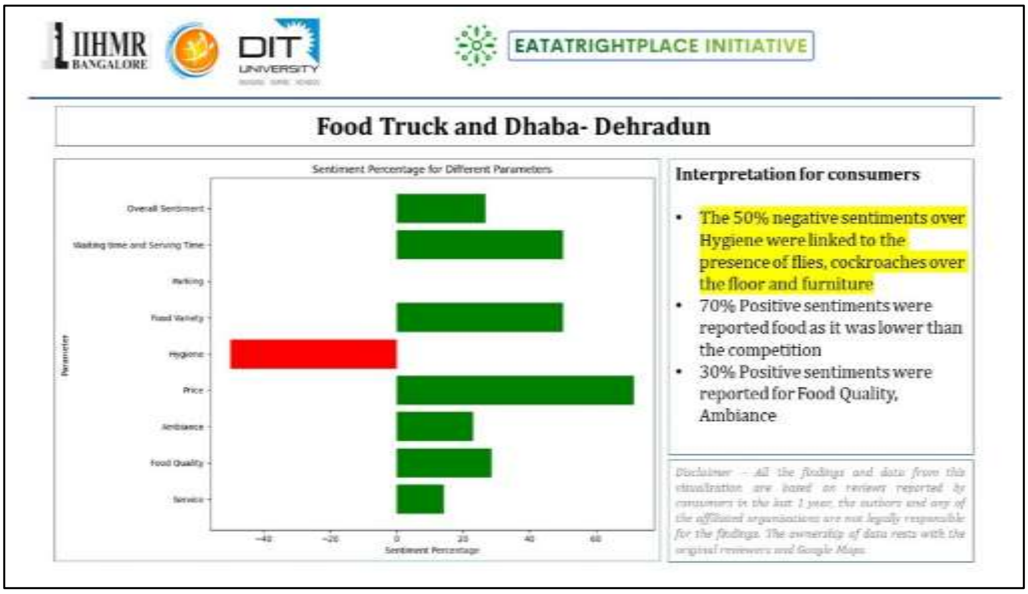

Figure 16. Outcome of the ERPI analysis for the food truck or Dhaba restaurant presented to the beta testing volunteers and owner

The beta testing phase of our project yielded key learnings that informed the final adjustments to the sentiment analysis tool. The team identified specific areas for refinement to enhance the tool's effectiveness and accuracy. Primarily, we recognized the need to address issues related to peak hours, particularly in distinguishing between self-service and other dining areas within restaurants. This led to the development of features aimed at a more nuanced analysis of different dining environments. Additionally, the tool was fine-tuned to better capture customer sentiments regarding the availability of menu options, a crucial aspect of the dining experience. Another significant insight was the importance of hygiene-related feedback in customer reviews. To address this, we incorporated additional keywords and context-specific indicators to strengthen the tool's capability in analyzing hygiene concerns. Lastly, we focused on enhancing the tool's ability to differentiate between various areas within a restaurant, a feature critical for providing comprehensive insights. These enhancements were earmarked for future iterations, while the current version of the tool was deemed ready for final release by the team, marking a significant milestone in our project.

3.5. Discussions

This study provides critical insights into the development and application of sentiment analysis tools in the restaurant industry, emphasizing a user-centric approach and the significance of understanding customer habits. The integration with Google Maps and the focus on diverse aspects like service, hygiene, and ambience demonstrate the need to align with user preferences and behaviors. A key finding is the necessity for continuous refinement of sentiment analysis models, especially to account for geographic variations, which is crucial for ensuring robust and reliable performance.

One of the pivotal contributions of this study is the real-world application and feedback garnered through beta testing. This phase highlighted the importance of flexibility in the tool's design to account for nuanced factors like different dining areas within a restaurant. It underscores the need for sentiment analysis tools to be adaptable and responsive to specific user contexts. Compared to previous studies [18]–[23] that primarily focused on algorithm development and validation, this study extends the utility of sentiment analysis tools by offering actionable insights to both consumers and restaurant owners. This dual-sided approach not only aids consumers in making informed decisions but also assists restaurants in improving their services and business strategies. An essential component of this study involves the incorporation of details regarding the adoption of the Scrum framework for the time-bound and agile development of the ERPI tool. While studies by Sinha *et al.* [24], Koumpouros [25], and Willms *et al.* [26], have presented a user-centric approach for developing consumer-centric tools with a focus on health and well-being, our current study goes further. It not only employs a consumer-centric approach but also elucidates the interconnections between consumer-centricity and development pathways.

The adoption of the Scrum framework for the agile development of the ERPI tool is a significant methodological strength. This approach ensured timely and efficient progress, with iterative development informed by continuous user feedback. The study's comprehensive data collection strategy, encompassing surveys, interviews, and beta testing across different cities, contributed to the development of a well-rounded tool. However, the study's limitations include limited participation in beta testing and potential subjectivity in managerial responses. These factors may impact the generalizability of the findings and introduce biases. Additionally, the tool's current design does not support real-time updates, and its adaptability to different restaurant environments requires further refinement.

In future applications, these insights will be instrumental in guiding the development of more sophisticated, user-friendly sentiment analysis tools. The ramifications of this study suggest a trend towards more consumer-centric approaches in tool development, emphasizing the importance of flexibility, adaptability, and continuous refinement based on real-world feedback. The integration of agile development methodologies like Scrum in the mHealth domain could also become more prevalent, highlighting the need for dynamic and responsive tool development strategies in rapidly evolving industries like hospitality, and healthcare.

4. CONCLUSION

In conclusion, this study presents a robust sentiment analysis tool for the restaurant industry, integrating consumer and owner perspectives. The iterative development process and real-world beta testing contributed to a tool capable of capturing nuanced consumer sentiments. This study lays a foundation for further refinement and research in sentiment analysis tools, aiming to empower both consumers and restaurant owners in the dynamic service industry landscape.

ACKNOWLEDGEMENTS

The authors acknowledge the support received from Ms Apeksha, Ms Meghna, Ms Sakshi, and Mr Sachin for their contribution.

REFERENCES

[1] A. Parikh, C. Behnke, M. Vorvoreanu, B. Almanza, and B. Almanza, "Motives for reading and articulating user-generated restaurant reviews on Yelp.com," *Journal of Hospitality and Tourism Technology*, vol. 5, no. 2, pp. 160–176, 2014, doi: 10.1108/JHTT-04-2013-0011.

[2] G. Askalidis and E. C. Malthouse, "The value of online customer reviews," in *Proceedings of the 10th ACM Conference on Recommender Systems*, New York, NY, USA: ACM, Sep. 2016, pp. 155–158. doi: 10.1145/2959100.2959181.

[3] C. Hutto and E. Gilbert, "VADER: A parsimonious rule-based model for sentiment analysis of social media text," *Proceedings of the International AAAI Conference on Web and Social Media*, vol. 8, no. 1, pp. 216–225, May 2014, doi: 10.1609/icwsm.v8i1.14550.

[4] C. Kaur and A. Sharma, "Twitter sentiment analysis on Coronavirus using Textblob," *EasyChair preprint*, vol. 2974, pp. 1–10, 2020.

[5] IBM, "IBM watson natural language understanding," ibm. Accessed: Nov. 14, 2023. [Online]. Available: https://www.ibm.com/products/natural-language-understanding.

[6] K. Wilson, C. Bell, L. Wilson, and H. Witteman, "Agile research to complement agile development: a proposal for an mHealth research lifecycle," *npj Digital Medicine*, vol. 1, no. 1, p. 46, Sep. 2018, doi: 10.1038/s41746-018-0053-1.

[7] K. Schwaber and J. Sutherland, "2020-Scrum-Guide-US.," scrumguides. Accessed: Nov. 06, 2023. [Online]. Available: https://scrumguides.org/docs/scrumguide/v2020/2020-Scrum-Guide-US.pdf#zoom=100.

[8] Songyouwei, "ABSA-PyTorch," github. Accessed: Jul. 07, 2023. [Online]. Available: https://github.com/songyouwei/ABSA-PyTorch.

[9] L. Yang, "AlexYangLi/ABSA_Keras," github. Accessed: Jul. 07, 2023. [Online]. Available: https://github.com/AlexYangLi/ABSA_Keras.

[10] A. Kushwaha, "Aspect based sentiment analysis," github. Accessed: Jul. 07, 2023. [Online]. Available: https://github.com/yardstick17/AspectBasedSentimentAnalysis.

[11] D. S. Batista, "Aspect-based sentiment analysis," github. Accessed: Jul. 07, 2023. [Online]. Available: https://github.com/davidsbatista/Aspect-Based-Sentiment-Analysis.

[12] S. Thapaliya, "Aspect-based-sentiment-analysis," github. Accessed: Jul. 07, 2023. [Online]. Available: https://github.com/thestrox/Aspect-Based-Sentiment-Analysis.

[13] Ganesh, "ganeshjawahar/mem_absa," github. Accessed: Jul. 07, 2023. [Online]. Available: https://github.com/ganeshjawahar/mem_absa.

[14] Y. Feng, "NNCM," github. Accessed: Jul. 07, 2023. [Online]. Available: https://github.com/jimmyyfeng/TD-LSTM.

[15] B. Do, "SentimentAnalysis," github. Accessed: Jul. 07, 2023. [Online]. Available: https://github.com/peace195/aspect-based-sentiment-analysis.

[16] P. P. Balage, "Semeval aspect based sentiment analysis," github. Accessed: Jul. 07, 2023. [Online]. Available: https://github.com/pedrobalage/SemevalAspectBasedSentimentAnalysis.

[17] A. G. Prabhune, V. R. Shri Hari, and N. K. Sethiya, "Adaptation of a BERT model to the india restaurant data using rule-based approach for aspect-based sentiment analysis," in *2023 Second International Conference On Smart Technologies For Smart Nation (SmartTechCon)*, IEEE, Aug. 2023, pp. 457–461. doi: 10.1109/SmartTechCon57526.2023.10391510.

[18] R. A. Laksono, K. R. Sungkono, R. Sarno, and C. S. Wahyuni, "Sentiment analysis of restaurant customer reviews on TripAdvisor using naïve bayes," in *2019 12th International Conference on Information & Communication Technology and System (ICTS)*, IEEE, Jul. 2019, pp. 49–54. doi: 10.1109/ICTS.2019.8850982.

[19] L. Gunawan, M. S. Anggreainy, L. Wihan, Santy, G. Y. Lesmana, and S. Yusuf, "Support vector machine based emotional analysis of restaurant reviews," *Procedia Computer Science*, vol. 216, pp. 479–484, 2023, doi: 10.1016/j.procs.2022.12.160.

[20] P. Rita, C. Vong, F. Pinheiro, and J. Mimoso, "A sentiment analysis of michelin-starred restaurants," *European Journal of Management and Business Economics*, vol. 32, no. 3, pp. 276–295, Jul. 2023, doi: 10.1108/EJMBE-11-2021-0295.

[21] A. Sahay, A. Indamutsa, D. Di Ruscio, and A. Pierantonio, "Supporting the understanding and comparison of low-code development platforms," in *2020 46th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)*, IEEE, Aug. 2020, pp. 171–178. doi: 10.1109/SEAA51224.2020.00036.

[22] EHL Faculty, "Online customer reviews: their impact on restaurants.," hospitalityinsights. Accessed: Nov. 13, 2023. [Online]. Available: https://hospitalityinsights.ehl.edu/online-customer-reviews-restaurants.

[23] A. Agarwal and J. S. Sabharwal, "End-to-End Sentiment Analysis of Twitter Data," in *24th International Conference on Computational Linguistics*, 2012, p. 39. [Online]. Available: http://www.aclweb.org/anthology/W/W12/W12-55.pdf#page=51.

[24] A. P. Sinha, M. Singhal, A. Joshi, B. Kumar, and N. K. Sethiya, "User-centered 'Swayam Diabetes' m-Health application for self-care management of Type 2 diabetes in urban home settings, the usability and utility testing of mobile application and perspectives," *International Journal of Chemical and Biochemical Sciences*, vol. 24, pp. 141–146, 2023.

[25] Y. Koumpouros, "User-centric design methodology for mHealth apps: the PainApp paradigm for chronic pain," *Technologies*, vol. 10, no. 1, p. 25, Jan. 2022, doi: 10.3390/technologies10010025.

[26] A. Willms, R. E. Rhodes, and S. Liu, "The Development of a hypertension prevention and financial-incentive mHealth program using a 'No-Code' Mobile App Builder: Development and Usability Study," *JMIR Formative Research*, vol. 7, 2023, doi: 10.2196/43823.

BIOGRAPHIES OF AUTHORS

Dr Akash Prabhune is a health researcher with 5+ years of experience in health systems strengthening, digital health, and AI/ML applications in healthcare management. He has worked with various state governments, the Indian Council of Medical Research, and several national and international funding agencies to strengthen healthcare delivery using data analytics and build a comprehensive healthcare system. He has conducted training sessions for ASHA workers, nurses, and AYUSH physicians for using digital tools in primary healthcare. He has published 12+ research papers and multiple technical reports, collaborated with researchers across various countries, and worked in multisectoral teams. He can be contacted at email: prabhunesky@gmail.com.

Vinay R Srihari is a data scientist at Institute of Health Management Research (IIHMR) in Bengaluru, focusing on public healthcare, supply chain optimization, machine learning, and data analytics. With a Master's in Machine Learning from Ramaiah University and a BE in Electronics and Communication Engineering from JSSATE, Bengaluru, Vinay has been instrumental in key projects like SDG goals and healthcare personnel optimization in Karnataka. His work includes the computation of indices like MPI, Health Index, and GII, and building models for health infrastructure optimization and drug procurement. Previously at Cognizant, he developed websites using Java Spring and Hibernate. His contributions are marked by a commitment to leveraging data science for social good. He can be contacted at email: vinay.rs@iihrmbangalore.edu.in.

Dr. Neeraj Kumar Sethiya joined Faculty of Pharmacy, DIT University on 2nd July 2019 in the capacity of Senior Assistant Professor and on August 2022 he has been promoted as Associate Professor. He had also worked as Head Department, to establish Centre for Innovation, Incubation, Entrepreneurship and Startup at DIT University. Prior to this, he has worked in the position of Senior Innovation Fellow, at National Innovation Foundation-India (An Autonomous Body of DST-Govt of India), Formulation Scientist, at Regen Biocorps, Vadodara and Teaching Assistant at Pharmacy Department, The MS University of Baroda, Vadodara, Gujarat. He has total 15 year of mixed experience including teaching, research and innovation. He completed his Ph.D. (Pharmacy) in March, 2012 from The MS University of Baroda, Vadodara, Gujarat, M. Pharm from Dr. H. S. Gour Central University Sagar, MP and B. Pharm from RGPV Bhopal. He is recipient of Bharat Gaurav Purushkar, Academic Excellence Award, Excellence in Performance Award, SPER Young Scientist Award, Dr. PD Sethi Best Research Paper and UGC JRF Research Fellowship (for perusing both Post Graduation and Ph.D.). He is also acting as consultant for industrial project and principal investigator for several Govt and private funded project. During his tenure, he achieved H. index-22, and total citation of 2,100 (Google Scholar Score) with 48 peer reviewed paper (with < 100 Impact Factor), 6 book chapter, 7 books and 15 patents. He can be contacted at email: neeraj.sethiya@dituniversity.edu.in.

Dr. Mansi Gauniyal is a distinguished Anthropologist with a Ph.D. from the University of Delhi, specializing in Physical Anthropology. Her expertise lies in molecular genetic research, particularly regarding India's tribal populations. Her notable doctoral work on the Siddi tribe in Karnataka involved comprehensive genetic admixture analysis. She has significantly contributed to Public Health research, focusing on HIV/AIDS and Gestational Diabetes, and has a keen interest in chronic non-communicable diseases, including diabetes and cardio-metabolic conditions. Her proficiency in both qualitative and quantitative methodologies for epidemiological studies sets her apart in her field. At FHTS, she embraces a SMAART approach to evidence-based public health research, contributing to community well-being. Additionally, she mentors Ph.D. scholars, shaping the future of public health professionals. She works exemplifies her dedication to advancing health research and improving diverse population health. She can be contacted at email: mansigauniyal@gmail.com.