Using aspect-based sentiment analysis as a tool for socio-technical system design.

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Abstract

Automation can enhance performance and reduce human errors, but poorly designed interactive technologies can harm the user experience, leading to suboptimal outcomes for both systems and organisations. Social and technical subsystems are essential and interdependent and must be considered when designing organisational structures. Neglecting these aspects limits the potential for effective change. This paper explores the role of Aspect-Based Sentiment Analysis (ABSA) in improving user experience (UX) by addressing social factors in automated environments. As a subfield of Natural Language Processing (NLP), ABSA extracts insights tied to specific aspects from user feedback, allowing for targeted improvements that enhance both UX and system performance. With the growing reliance on unstructured data from sources like social media, we ask: Can ABSA play a key role in enhancing system design? Can it facilitate data collection and interpretation for the development of automated systems in large organisations? To assess ABSA's effectiveness, we compiled a dataset of 8,060 tweets (2016–2023) related to automation and smart workplaces, using it as a case study. Six pre-trained or fine-tuned ABSA models were applied to analyse the data, focusing on dimensions such as usability, effectiveness, and innovation. Our findings highlight ABSA's potential to guide improvements in socio-technical automated systems, and we propose recommendations for decision-makers, developers and researchers to identify strengths and weaknesses in automated systems using any type of user-generated comments. Finally, we present a lifecycle model using sentiment analysis to refine UX strategies, though further exploration of factors like trust and accessibility is needed. While the study offers valuable insights, further exploration of factors such as trust, accessibility, and ethical considerations is needed.

Keywords

Aspect-Based Sentiment Analysis, Socio-Technical Systems, User Experience

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1. Introduction

In today's fast-paced business environment, large organizations are embracing digital transformation to remain competitive. This involves overhauling back-end systems, customer interactions, and internal processes with emerging technologies such as AI, ML, and IoT. Automation is crucial for refining workflows, decision-making, and user satisfaction. However, integrating new technologies within complex organizations poses significant challenges. A user-centric approach and automation of routine tasks can streamline communication and foster success. Human-machine collaboration will be key, necessitating job redesign for effective synergy. Organizations must bridge the gap between potential and realized value from technology investments, requiring a managerial framework that emphasizes user experience, value proposition, digital evolution, skills, and improvisation. Designing effective social and technical systems requires user insights, but traditional methods like cognitive task analysis and workshops, climate surveys, and participatory design may be impractical in large, diverse organizations. More efficient methods, such as social network analysis and user-generated comment analysis, can provide iterative design insights.

Understanding public sentiment towards products and services is essential in the digital age. Aspect-based Sentiment Analysis (ABSA) is a critical technique within sentiment analysis, offering a detailed examination of opinions expressed in user-generated content. Unlike general sentiment analysis, which assesses overall sentiment [1], ABSA focuses on specific aspects or features of a product or service [2] as shown in figure 1 below. ABSA's effectiveness can be influenced by domain-specific language and short, informal text [3]. This detailed analysis provides actionable insights for targeted improvements [4] and helps companies tailor their offerings and communications to align with user preferences. It also identifies trends and issues, allowing for proactive enhancements in the user experience [5].

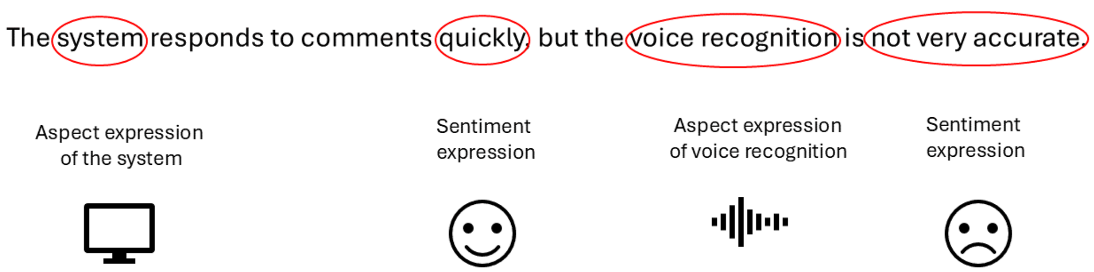


Figure 1: Example of ABSA in a sentence with two aspects.

ABSA is particularly useful in sociotechnical computing, where the interaction between social and technical systems is complex. By incorporating ABSA, researchers can gain nuanced insights into user experiences and expectations, aiding informed design decisions and improving user satisfaction. Recent advancements in NLP and machine learning, such as BERT and Graph Neural Networks, have enhanced ABSA's accuracy and contextual understanding [4, 6, 7]. These advancements enable comprehensive analysis of large text datasets from various sources, enriching sociotechnical studies.

This paper explores ABSA's application as a sociotechnical tool for interpreting data in large organizations and enhancing the user-centered design of autonomous technologies. It discusses ABSA model results, and applications, and concludes with challenges and future directions for this interdisciplinary approach.

2. Literature Review

Aspect-Based Sentiment Analysis (ABSA) and socio-technical approaches both focus on the interaction between technology and human systems, though in different contexts. Socio-technical approaches emphasise the co-evolution of social and technical systems, recognising that technology does not operate in isolation but is deeply embedded within human contexts [8]. This approach highlights the importance of designing systems that consider not only technical performance but also human factors such as culture, workflow, and communication. It is often used in fields such as system design, organisational change, and technology implementation to ensure a harmonious interaction between people and technology [9]. Integrating ABSA within socio-technical frameworks can indeed offer valuable insights into how users perceive specific aspects of technological systems, influencing their broader adoption and integration into society. By breaking down sentiments expressed by users into specific aspects of the system (e.g., usability, reliability, security), ABSA helps in understanding what elements of the user experience contribute positively or negatively to system adoption [5] or if the result is neutral what type of strategies can be taken for improvement?

For example, identifying aspects such as "ease of use" or "accessibility" in user feedback allows system designers to address critical pain points, thus improving the seamlessness of the user journey [10]. The socio-technical approaches, which emphasise the interplay between human users and technological systems, benefit from this insight, as it ensures that both technical and human factors are aligned to enhance user satisfaction and system efficiency[9].

By focusing on specific user experience factors as aspects, ABSA, ABSA provides actionable insights to system developers, ensuring that technology evolves not only with technical innovation but also in alignment with user needs and expectations, leading to broader and more successful adoption of technological solutions [11].

2.1. Sociotechnical Approaches for Competitive Advantage in Large Organisations

Research emphasises user-centred design as pivotal in developing Sociotechnical systems. Findings by [12] underscore that leading companies embracing digital transformation (which has some element of automation) experience significant revenue growth compared to laggards. Failure to adapt may result in substantial revenue loss. Therefore, achieving digital value creation through such systems is crucial for market competitiveness [13].

In designing future systems, the initial step involves comprehensive problem diagnosis using tools like systems thinking, future inquiries, and human-centred research [12, 14–17]. Effective diagnosis, however, does not guarantee successful strategy formulation. Organisations must grasp system dynamics to establish design principles and intervention models. This iterative process demands experimentation and evaluation to drive impactful change. Engaging the end user's insights and experience in the design systems is a must to increase the acceptance of the systems and increase user satisfaction. Following a sociotechnical systems theory which underscores the interdependence of social and technical components within complex organisational systems is a key to success. Neglecting either aspect impedes effective organisational change and improvement, necessitating input from all stakeholders.

Future-oriented design requires creativity and collaboration, leveraging tools such as design thinking, design fiction, prototyping, work domain analysis, collaborative modelling [18, 19], and computer-based simulation.

In addition, it is proven that human-centric approaches are gaining traction for their efficiency and user engagement benefits [20, 21]. Participatory design, involving stakeholders as co-designers, is increasingly employed in organisational development and system design, though its effectiveness varies across different contexts [22, 23]. However, trials and pilots are common strategies for testing future automated systems in large organisations [24]. Despite being resource-intensive, these methods provide realistic insights, particularly in integrating AI technologies [25, 26].

In conclusion, adopting sociotechnical approaches for the selection or design of new automated systems offers a competitive edge in the digital era by ensuring systems are technologically advanced, socially relevant, and user-centric. Organisations that embrace these principles effectively navigate digital Ergonomic and human factors, which is critical for digital transformation in complex organisations. Various studies present models addressing these factors, enhancing task performance and employee engagement [27–30]. These models are often standardised [31] transformations, driving innovation and sustainable growth.

2.2. Sociotechnical Approach in Complex Organisations

Bostrom and Heinen (1977) described organisational work systems as composed of two interconnected subsystems: social (involving people and structure of the company) and technical (comprising technology and tasks of the organisation) [32]. The authors believed that organisational behaviour issues involving social subsystem components directly impact the technical subsystem's failure and success (Figure 2). It is proposed that an STSD approach will provide a more realistic view of organisations [33].

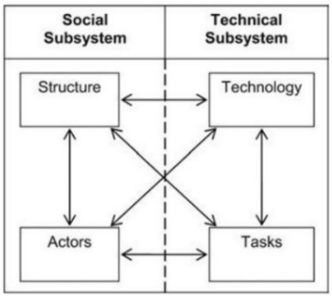


Figure 2: Sociotechnical system [33]

In this approach, organisational variables will also be considered to build vast, complex infrastructures that contain cohesive systems of human relations, technical objects, and cybernetic processes. This application has extended beyond the workplace setting, such as smart homes [8].

Based on STSD, the human and machine interaction should not be considered in isolated scenarios (Figure 3 on the left). Designing effective systems for complex organisations need a pragmatic approach to the engineering of socio-technical systems similar to Figure 3 (on the right) [8].

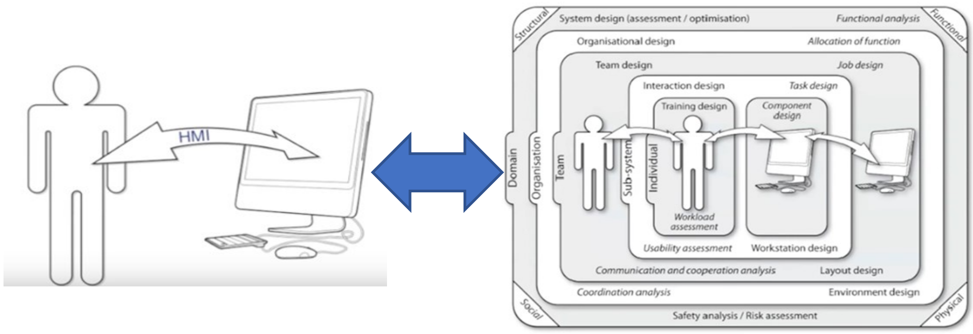


Figure 3: Human-machine interaction in a sociotechnical approach

According to the STSD approach, the ergonomic and human factors must be studied for digital transformation in complex organisations. These factors can assist the employees in their tasks and increase their engagement [27–30]. Some of these models have been transformed into a list of standards by the International Organisation for Standardisation (ISO) [31].

The environmental factors and their impact on organisations should also be considered for digital transformations. For example, [30] study on automated gates on borders listed several human factors (such as motivation, trust, skills, situation awareness and workload) as well as environmental factors in the socio-cultural, legal, organisational and operational contexts. The reality is replacing AI methods such as ABSA can provide fine-grained feedback analysis and help socio-technical systems become more responsive and adaptive. This is particularly valuable in socio-technical contexts, where both human and technical elements need to evolve together to meet user expectations efficiently. For example, studies have shown that combining ABSA with deep learning and multi-task models can automate the detection of user issues in real-time, enabling faster adjustments to systems (such as in customer service or incident response systems) based on identified trends in feedback about usability, performance, or reliability [34]. In another study, ABSA has been proposed as a key tool for cybersecurity incident response systems, where understanding sentiments about security tools can help adjust processes and communications between users and technical teams [35].

2.3. User Engagement and User Experience Goals

User engagement with technology is a crucial aspect of user experience design, as it determines the success and adoption of interactive systems. Engagement is a complex construct characterised by cognitive, affective, and behavioural components, such as attention, motivation, and emotional investment [36]. One key definition of user engagement is "a quality of user experience characterized by attributes of challenge, positive affect, endurability, aesthetic and sensory appeal, attention, feedback, variety/novelty, interactivity, and perceived user control" [37]. Although user engagement can be assessed before full-scale implementation of any new system (via usability testing or pilot implementation), it should be performed in a real environment for all types of users (e.g., customers and employees). This is particularly important for automating systems that will replace daily human tasks, as they can positively and negatively affect human performance [38]. Human reactions depend on the impact of new systems on the work process and environment [30]. Early studies have shown how employees would be influenced by the feedback they receive from machines, and the perceived reliability and accuracy of automated systems [39]. Automation influences many human factors including performance, situational awareness, workload, motivation, stress and trust [28, 30, 40].

Research shows that human-centred design approaches (e.g., HWID) that engage the end-users before going to the implementation phase result in the development of more effective solutions for problems that need new technologies. Involving the human perspective and emotion in all steps of the new system development helps understand the machine and human interaction on a bigger scale. All these can impact the user experience to have a seamless journey when using the implemented system. In addition, a better understanding of the work domain, customers (users) and employees' needs can be shaped into a shared vocabulary of technical and social requirements between the developers and decision-makers. Involving users in the design process can also increase user empowerment (e.g., via employee engagement).

UX is beyond the material, good industrial design, multi-touch, or fancy interfaces [41] and has a direct relation to user engagement. Positive user experience can be evoked if the technology, system, or product satisfies a generalised set of users experience goals and can happen or improve over time. These goals are targeted experiences that end users should have when collaborating or interacting with a particular technology [42]. They are two main concepts in understanding UX and its constituting factors. The first concept [43] believes that experience is evoked from the interplay of humans and technology. Thus, experiences are dynamic, unique, situated, and never the same. They also believed in objectifying experience into distinct fields of study (i.e., a holistic approach to experience). The next concept is by Hassenzahl and his colleagues. [44] This study proposes categorising experiences based on psychological needs and linking them to affect and product perception. It presents a need to generalise user experience to use human-computer interaction (HCI) applications effectively.

When users use the system to carry out their tasks in both concepts, the UX designer wants them to have a specific experience. Designers collaborate with users to understand the technology's needs, such as emotional and system qualities. These needs determine the UX goals and are crucial in directing system design. This can ensure that the planned attributes are met and result in a better experience [45].

Context relevance is crucial in user experience (UX) research, as it helps in understanding the user's environment, motivations, and behaviours. Providing detailed descriptions is essential for uncovering different facets of user experience and constructing meaningful interactions. While it may be challenging to outline a definitive list of UX goals due to the complexity and uniqueness of each project, several common objectives guide UX design. These include enhancing usability, improving accessibility, ensuring user satisfaction, fostering engagement, and creating seamless, intuitive interactions. Achieving these goals requires a deep understanding of the user's context, making thorough research and attention to detail indispensable.

2.4. Exploring Sentiment Analysis in Social Media Approaches

ABSA allows for extracting sentiments related to specific product or service aspects from user-generated content. By focusing on particular features, ABSA provides a nuanced understanding of user opinions.

In the last decade, opinion mining and sentiment analysis have been the subject of fascinating interdisciplinary research. With the ever-increasing number of social media messages posted daily, millions of users express opinions on various subjects, including the characteristics of products and services they have already bought or intend to buy in the near future. In this regard, [46] introduces a method using Semantic Web technologies, natural language processing, and machine learning for in-depth sentiment analysis of Twitter product opinions. However, scalability challenges may arise due to the reliance on Semantic Web technologies, and the suggested exploration of advanced deep learning algorithms could introduce complexities and increased computational resource needs. [47] states and presents a CNN-based method for aspect term extraction and sentiment analysis in user reviews, offering high accuracy and efficiency. However, the reliance on pre-defined aspect categories may limit accuracy, suggesting potential improvements with Word2Vec and other techniques. The application to restaurant reviews via web scraping could pose challenges in maintaining accuracy for large-scale analysis. On the other hand, [48] introduces ABSA-PER, achieving notable accuracy in sentiment analysis of customer reviews, yet acknowledges limitations in handling diverse information. The study suggests potential enhancements, including multi-word clustering and objectivity feature exploration, to improve performance and accuracy in aspect identification [49].

ABSA is a powerful tool for clear consumer sentiment recommendations, overcoming subjective judgment limitations. The proposed method employs a BERT-based supervised classifier for fine-grained tweets, enhancing ABSA accuracy. Despite its benefits, limitations include the ongoing challenge of improving overall sentiment analysis robustness and accuracy.

In conclusion, integrating ABSA within socio-technical frameworks offers valuable insights into how users perceive specific technological aspects, influencing adoption and engagement. By addressing both technical and human factors, ABSA enhances system design by identifying key user experience elements, such as usability, accessibility, and effectiveness. This alignment ensures that technology evolves in harmony with user needs and expectations, fostering broader and more successful adoption. Additionally, sociotechnical approaches, which consider the co-evolution of social and technical systems, provide a competitive edge, especially in large organizations undergoing digital transformation.

3. Methodology

We utilized Twitter Scraper to collect tweets, a powerful tool that enables efficient data extraction from the Twitter platform. Twitter Scraper is a Python library that simplifies retrieving tweets based on specific search criteria, allowing researchers to gather relevant data for analysis. Web scraping has become a source of data collection for aspect-based sentiment analysis and has recently been used for different purposes. From young people's attitudes in the climate change debate [50] to predict the trend of cryptocurrencies [51], identifying user interest from social data [52] and even child tracking and predicting the violence on children in social media [53]. Figure 4 summarises the steps taken for the methodology.

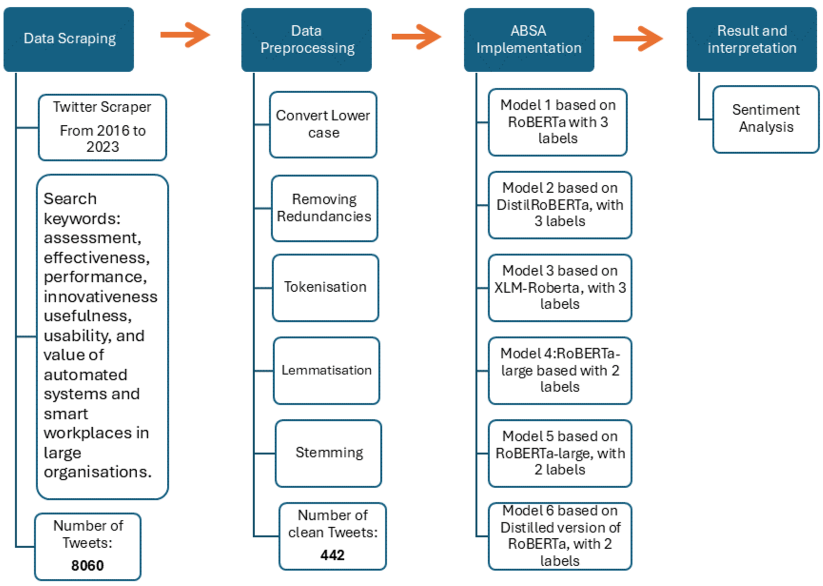


Figure 4: Data Pre-Processing

3.1. Data collection and Pre-Processing

The study collected relevant tweets using keywords related to the assessment, effectiveness, performance, innovativeness, usefulness, usability, and value of automated systems and smart workplaces in large organisations. These keywords were carefully derived from the literature review and case studies to ensure the relevance and depth of the data. The tweets were downloaded, extracted, and processed from the Twitter platform (now known as X), adhering to the ethical and legal guidelines of both the platform and associated universities. Data collection spanned from 2016 to the first quarter of 2023, a period marked by significant advancements in automation and Industry 4.0 technologies, including the widespread adoption of IoT and AI [54–56]. The collection ended in early 2023 when X implemented a paywall restricting automated access to tweets, impacting thirdparty tools' ability to access the platform's data [57].

We used 8060 Tweets for our experiment. Pre-processing is essential for sentiment classification, especially with unstructured data, to address inaccuracies, redundancies, missing values, and inconsistencies. The pre-processing stage, illustrated in Figure 5, involves:

- Data cleaning
- Handling missing values
- Removing redundancies
- Transforming data formats
- Extracting relevant features

This process ensures the dataset is clean and consistent, leading to more accurate and reliable classification results and ultimately enhancing the models' performance and the analysis's validity.

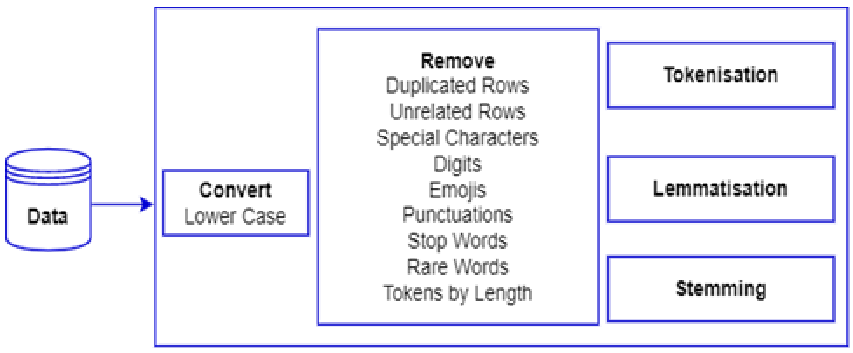


Figure 5: Data Pre-Processing

3.2. ABSA Models Utilised for Analysis

For this study, all selected models are primarily focused on and pre-trained for English language tasks. They are either based on RoBERTa or its distilled version, DistilRoBERTa, which was initially trained on large English-centric datasets. Both Models do not inherently include multilingual capabilities as part of their original design or pre-training; their architecture is language-agnostic, but the choice of training data focuses them on English. Theoretically, the models can be adapted to other languages by fine-tuning non-English data. However, for further use in non-English data, it is better to use models that have been explicitly designed or fine-tuned for those languages or multilingual models such as mBERT (Multilingual BERT) and XLM-RoBERTa, which are trained on text from multiple languages and are capable of understanding and processing text in those languages. Table 1 lists the models used for this paper and explains their architecture, application and labels.

Table 1
Information on the model used in this study.

Model Name	Base Architecture	Focus/Application	Labels
Model 1 - Cardiffnlp/Twitter-roberta-base-sentiment-latest	RoBERTa	Deep understanding of Twitter Data	Positive, negative and neutral
Model 2 - Mrm8488/distilroberta-finetuned-financial-news-sentiment-analysis	DistilRoBERTa	Analysing of financial text	Positive, negative and neutral
Model 3 - Citizenlab/Twitter-xlm-roberta-base-sentiment-finetunned	Multilingual XLM-Roberta model sequence classifier fine tunned and based on Cardiff N.L.P.	Span on multiple languages and cultural contexts, tweets	Positive, negative and neutral
Model 4- Siebert/sentiment-roberta-large-English	RoBERTa-large	Sentiment analysis in English texts	Positive and negative
Model 5 - Sonny4Sonnix/Twitter-roberta-base-sentimental-analysis-of-covid-tweets	RoBERTa	Sentiment Analysis of COVID-19-related tweets	Positive and negative
Model 6 - Juliensimon/reviews-sentiment-analysis	Distilled version of RoBERTa	To automate the process of understanding customer feedback at scale	Natural and positive

4. Result

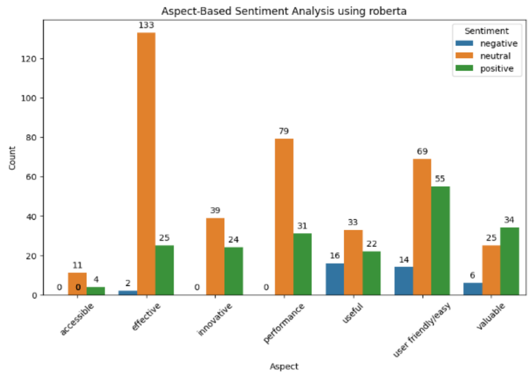
4.1. Identified Aspects and Sentiments

ABSA is a more detailed form of sentiment analysis that identifies whether a text expresses a positive, neutral, or negative sentiment and associates these sentiments with specific aspects or features mentioned in the text. This can provide deeper insights into user opinions on various products, services, or topic attributes.

Our results offer valuable insights into user sentiment on specific product, service, or topic aspects. This can inform targeted improvements, marketing strategies, and user experience design. Related to our main aim, it can provide a better understanding to the development team for improving their UI design and for decision-makers to decide on the selection of the trials quickly.

We used general UX goals from other papers [58] and our previous case studies[59], which we found easy to recognise by the models with no major changes or interpretations. The aspects we used were:

Aspects: ["user friendly", "easy", "valuable", "accessible", "useful", "effective", "performance", "innovative"]



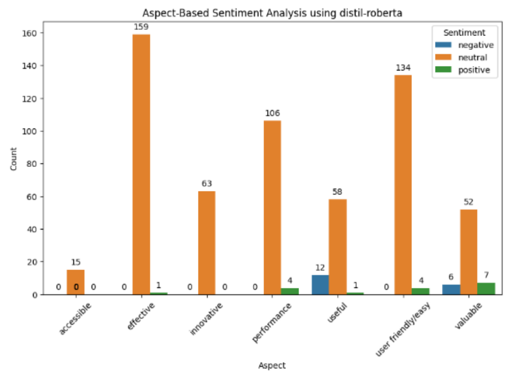


Figure 6: Left: The result of model 1 based on Roberta, and right: The result of model 2 based on distil-Roberta.ata Pre-Processing

The analysis in model 1 shows that most aspects are predominantly viewed neutrally in both models, indicating either a balanced view or a lack of strong opinions. Positive sentiments tend to outweigh negative aspects, suggesting overall positive reception in areas like effectiveness, innovation, performance, user-friendliness, and value (in model 1).

The aspect with the most positive feedback is "User Friendly/Easy," highlighting this as a strength. The "Useful" aspect has the highest number of negative sentiments, suggesting an area that may need improvement or further investigation to understand users' concerns.

When selecting model 2, we acknowledged that the model is trained within the context of financial news or services. Still, we decided to try it on our dataset (which targets automation-related topics) and explore the results. This can produce valuable insights, particularly in areas where financial and economic considerations play a significant role in discussions about automation, such as system performance or economic impacts. It is interesting how changing the model can show different results on specific aspects such as effectiveness and innovation. The rest of the aspects also show different results but with no significance.

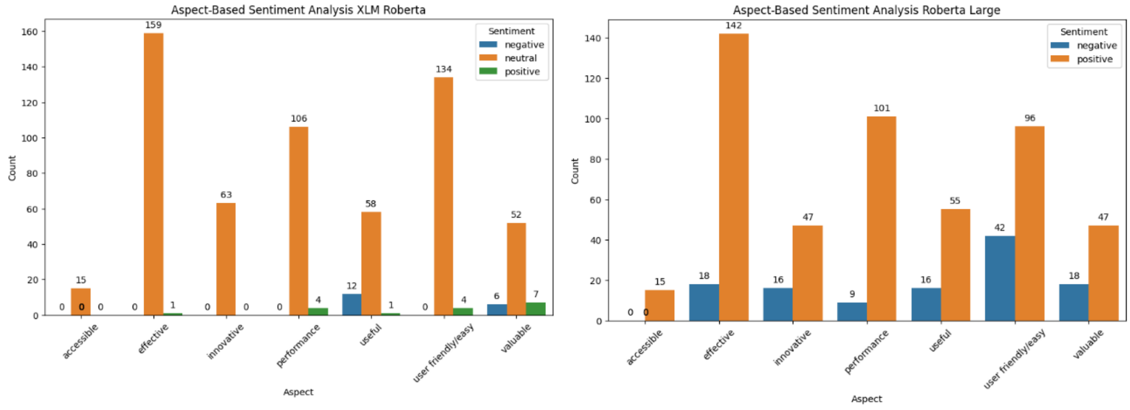


Figure 7: Left: The result of model 3 based on X.L.M. Roberta, and right: The result of model 4 based on Roberta large.

Overall, Model 3's results indicate a general neutrality trend in the perception of various product or service aspects. This suggests that while there are no major areas of failure, there is a significant opportunity to improve the product/service's features, benefits, and overall value proposition to shift these neutral perceptions towards more positive ones. Enhancements, clearer communication, and focus on innovation could be key strategies to improve user perception and sentiment.

Model 4's analysis is more polarised, with only positive and negative sentiment categories, unlike the other three models, which included a neutral category. This approach provides a clearer contrast in user perceptions, highlighting strengths and areas for improvement more distinctly. As this model has no neutral label, it is not a reserved interpretation of sentiments and has a more definitive stance on each aspect.

The absence of a neutral category in this model could imply a more decisive perception from respondents, either favourably or unfavourably, towards the product or service's various aspects. This model offers clearer insights into what aspects are highly valued and which might be problematic or less satisfactory to users. The significant number of negative sentiments in aspects like "user-friendly/easy" underscores specific areas where improvements could substantially impact user satisfaction.

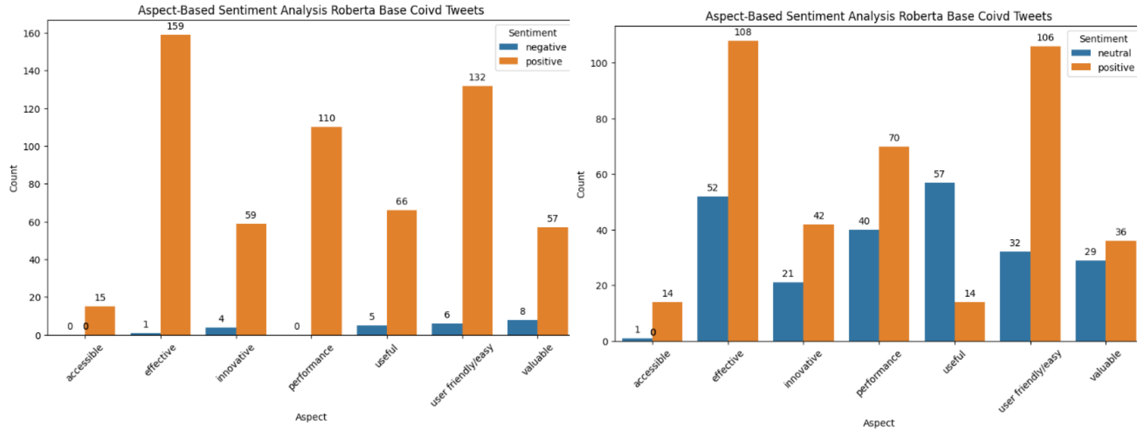


Figure 8: Both models are based on Roberta. Left: The result of model 5 trained on COVID tweets, and right: The result of model 6 trained on Reviews.

Overall, the sentiment analysis in model 5 indicates a predominantly positive reception of various aspects (accessibility, effectiveness, innovation, and user-friendliness) related to the main context of tweets. This positive reception could reflect well on the public's perception of the efforts, information, and innovations shared on Twitter concerning the topic (e.g., Automation). For example, in the context of automation, it suggests that it is seen as a key driver of progress and efficiency. It highlights areas where the response or information dissemination is particularly strong, such as accessibility, effectiveness, and performance. However, the presence of negative sentiments, even in small numbers, suggests room for improvement in making every aspect as effective, innovative, and valuable as possible. The "Juliensimon/reviews-sentiment-analysis" (model 6) analysis shows a generally positive outlook on the evaluated product or service, with strengths in accessibility, user-friendliness, and effectiveness. However, the notable presence of neutral sentiments, especially in effectiveness, performance, and usefulness, signals a critical insight: a considerable group of users or customers is not fully swayed. This neutrality might indicate uncertainty, lack of information, or mismatched expectations, which could be addressed through improved communication, enhancements to the product/service, or more targeted user education.

The significant number of neutral sentiments regarding usefulness poses a particularly interesting challenge, suggesting a need for the product/service to more clearly demonstrate its benefits or adapt to better meet user needs. In contrast, the high positivity in user-friendliness/ease of use highlights a clear advantage, suggesting that efforts to make the product/service accessible and easy to use are paying off.

This nuanced picture painted by the sentiment analysis points towards opportunities to convert neutral perceptions into positive ones, potentially by addressing specific areas of concern highlighted by the study or bolstering communication around the product/service's strengths.

4.2. Factors Influencing ABSA's Performance

During this study, we noticed that several factors influence the role of ABSA in a large organisation's understanding of its users. These factors will influence the ABSA performance and should be strategically planned. For example, the right model and selecting the right aspects adjusted to the organisational environment should be considered. One of this study's first findings is the significance of model selection, training, and fine-tuning in Aspect-Based Sentiment Analysis (ABSA); it is crucial to consider the underlying principles of natural language processing (NLP) and machine learning. The choice of model directly impacts the accuracy, relevance, and depth of insights derived from sentiment analysis. These factors are central to ensuring the analysis is precise and actionable for improving system and product design or enhancing user interaction.

Model Selection: The choice of a sentiment analysis model should align with the specific nature of the data (e.g., tweets, financial news, product reviews) and the analysis goals. For example, models trained on specific data types, such as "Sonny4Sonnix/twitter-roberta-base-sentimental-analysis-of-covid-tweets," may perform better on similar datasets due to their specialised vocabulary and context understanding. This concept is echoed in academic literature. Zhang et al. (2018) discussed how model performance in sentiment analysis could significantly vary depending on the domain-specific data it was trained on, emphasising the importance of model-domain alignment [60].

Training and Fine-tuning: The process of training and fine-tuning a model on domainspecific datasets enhances its ability to interpret the nuances of sentiment within that domain accurately. Ruder et al. (2019) highlight the effectiveness of fine-tuning pre-trained language models on task-specific datasets, noting substantial improvements in model performance across various NLP tasks, including sentiment analysis [61].

In summary, the choice of sentiment analysis model, coupled with strategic training and fine-tuning, plays a pivotal role in extracting meaningful and actionable insights from data. These insights are invaluable for refining product designs and enhancing user interactions, underscoring the intertwined relationship between advanced NLP techniques and practical application in product development and user experience optimisation.

The foundation of strategic approaches can be illustrated in Figure 10.

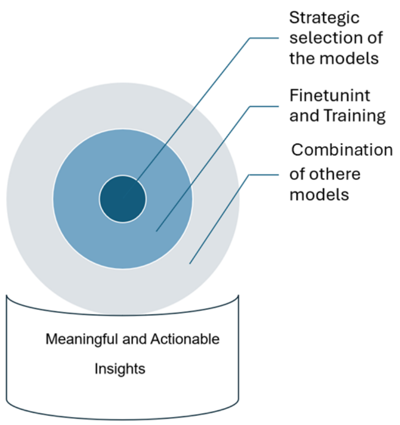


Figure 9: The foundation of strategic approaches for using ABSA for decision-makers.

In addition to the choice of model, training, and fine-tuning, there are several other crucial factors and strategic approaches that companies should consider based on ABSA results to improve product design, user experience (UX), and customer interactions:

1. Combining Multiple Models for a Holistic View

Complementarity: No single model may capture all nuances of sentiment across diverse datasets. Combining insights from multiple models, such as those trained on general social media content and others fine-tuned on domain-specific data, can offer a more comprehensive view of user sentiment. This approach is supported by the ensemble methods in machine learning, where multiple models are used together to improve predictions [62].

2. Actionable Insights for Product and Service Enhancement

Prioritisation: Analyse ABSA results to identify and prioritise areas for improvement. For example, if "user-friendly/easy" receives mixed sentiments, focus on enhancing the UX to be more intuitive.

User-Centric Design: Incorporate user feedback loops, leveraging ABSA to guide the iterative design process. By focusing on aspects that directly impact user satisfaction and engagement, companies can tailor their products more effectively to meet user needs.

3. Strategic Marketing and Communication

Targeted Messaging: Use ABSA insights to craft marketing messages highlighting the most positively received features and addressing common misconceptions or negative perceptions.

Feature Development: Align product development goals with user sentiment trends, investing in features most valued by users, as identified through sentiment analysis.

4. Enhancing User Interaction

Personalisation: Tailor user experiences based on individual or segment-specific feedback. Personalisation can significantly enhance user engagement and satisfaction, as indicated by the positive reception of accessibility and effectiveness.

Feedback Integration: Implement mechanisms for continuous user feedback collection and analysis. This ongoing engagement helps refine the user experience, aligning products with user expectations.

5. Continuous Monitoring and Adaptation

Sentiment Tracking: Regularly monitor user sentiment to capture changing trends, preferences, and pain points. This proactive approach allows for timely adjustments to product features or UX strategies.

Cultural and Contextual Sensitivity: Be aware of the cultural and contextual factors influencing sentiment analysis results. Tailoring products and communications to respect these factors can enhance global user satisfaction and market reach.

In conclusion, while selecting, training, and fine-tuning the right models are foundational for effective ABSA, leveraging these insights requires a strategic, multifaceted approach. By combining insights from multiple models, focusing on actionable improvements, and maintaining a cycle of feedback and adaptation, companies can significantly enhance their products, services, and user experiences.

Life cycle chart illustrating the key stages involved in leveraging insights for effective Aspect-Based Sentiment Analysis (ABSA) in a strategic, multifaceted approach illustrated in Table 2.

Table 2
Key Stages for Strategic, Multifaceted Approach of ABSA as an Organizational Tool

Phase	Stages
1- Selection Phase	Identify relevant data sources and models for ABSA. Choose appropriate machine learning algorithms and techniques. Select relevant aspects and sentiment categories for analysis.
2- Training Phase	Train selected models using annotated data. Fine-tune models to improve accuracy and performance. Validate models using cross-validation techniques.
3- Integration Phase	Integrate multiple models to harness diverse insights. Develop a unified framework for analysis. Ensure compatibility and interoperability between different models.
4- Actionable Insights	Extract actionable insights from the integrated model outputs. Identify areas for improvement based on sentiment analysis results. Translate insights into actionable strategies and decisions.
5- Feedback and Adaptation	Gather feedback from users and stakeholders. Incorporate feedback to refine models and analysis techniques. Continuously adapt the ABSA system to evolving requirements and contexts.
6- Continuous Improvement Loop	Iterate through the life cycle to refine models and processes. Monitor performance metrics and adjust strategies accordingly. Strive for ongoing enhancement of products, services, and user experiences.

Figure 10 below demonstrates the life cycle chart and the iterative and interconnected nature of leveraging insights for effective ABSA based on the phases mentioned in Table 2. Each phase contributes to the overall improvement of the ABSA system, ultimately leading to better products, services, and user experiences.

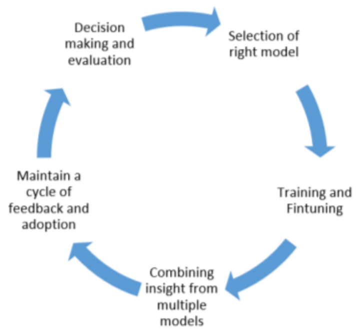


Figure 10: Strategy life cycle of using effective Aspect-based Sentiment Analysis

5. Discussion

We believe the insights gained from ABSA can inform improvements in sociotechnical systems. This can be as small as understanding users' needs, pains, or any gains they want from a system or as a strategic insight for improving the design and functionality of S.T. systems. This section discusses the number of headings, such as model labels, model interpretation, and practical implications of our tweet analysis influencing S.T. systems. The Tweets dataset is used as a use case but can be expanded to any other type of user-generated comments.

Models label positive, negative, neutral and irrelevant.

In the context of sentiment analysis, sentiments are typically categorised into several types, most commonly positive, negative, and neutral. Some models might only distinguish between positive and negative sentiments, effectively forcing every piece of analysed text into one of these two categories. This approach can simplify the analysis but might miss out on capturing sentiments that are not positive or negative but neutral or mixed.

Including a neutral category allows for a more detailed and nuanced understanding of sentiment. Neutral sentiment captures a range of neither explicitly positive nor negative responses. For instance, a review might state, "The product works as expected," without expressing delight (positive) or dissatisfaction (negative). This statement would likely be classified as neutral. Recognising these neutral sentiments is important because they can indicate areas where customers or users are unsure. This can be particularly valuable for understanding aspects of a product, service, or topic where opinions are not strongly polarised but might indicate satisfaction without enthusiasm or a lack of significant complaints.

By acknowledging neutral sentiments, the model provides a more complete picture of how people feel about a subject. It allows analysts to identify what aspects are liked or disliked and what factors might be overlooked, taken for granted, or seen as just satisfactory. This nuanced view is crucial for making informed decisions about improvements or where efforts should be focused to enhance satisfaction, engagement, or perception. Some of the common strategies for addressing aspects with highly neutral sentiments are,

Enhancing communication: as users may not appreciate or fully recognise certain features, better communication about the unique selling points can turn Neutral comments towards more positive ones. For example, they may not understand how effective or useful an automated system is for the organisation. This directly impacts advocating the social side of sociotechnical computing.

User Education: It is worth educating the users while communicating with them and providing more information, tutorials, or demonstrations on effectiveness, ease of use, and performance to help users appreciate these aspects more, potentially converting neutral sentiments into positive ones.

Continuous Improvement: Neutral sentiment often indicates room for improvement. Constant updates, addressing user feedback, and introducing innovative features can gradually enhance user perceptions. It has been proven that using systems helps users understand the system better and improves interaction. Collecting user reviews and feedback and comparing the ASBA in different stages of product/service development can be valuable and help developers and decision-makers.

Segmentation Analysis: If possible, investigate the segments of users who rated these aspects neutrally, which can bring new insights for design or system improvements. Understanding their expectations or comparing their feedback with those who expressed strong positive or negative sentiments might offer actionable insights. For example, in large organisations, segmentation is not possible before the design, but it may be easier to look into it while going through the trials/Pilots.

In summary, while high neutral sentiments suggest satisfactory perceptions, they also highlight opportunities for making the aspects of effectiveness, user-friendliness, and performance stand out more distinctly to users, potentially turning neutrality into advocacy.

6. Conclusion

Our research underscores the pivotal role of Aspect-Based Sentiment Analysis (ABSA) as a tool within sociotechnical approaches in large organisations. By leveraging ABSA, we extracted nuanced insights from user-generated content, particularly tweets, to better understand user sentiments regarding various aspects of automated systems and smart workplaces. These aspects were selected from the UX goals of other studies. We proposed integrating ABSA into the design process combines data-driven insights with humancentred design principles, which is especially valuable in organisations where collecting user feedback is challenging.

Our key findings reveal that ABSA offers a fine-grained understanding of user opinions by linking sentiments to specific aspects or features. This enables researchers, developers, and organisations to more precisely identify system strengths and areas for improvement. We evaluated the efficacy of six different ABSA models based on architectures like RoBERTa and DistilRoBERTa, each demonstrating varying capabilities in capturing and analysing sentiments. This emphasises the need for careful model selection and fine-tuning. The analysis also highlighted the importance of considering contextual factors, such as cultural and situational influences, which affect user sentiments. This consideration is crucial for designing technically sound and socially relevant systems.

These analyses have several implications for sociotechnical systems. Firstly, integrating ABSA into the UX design process allows organisations to develop more user-centric systems that meet specific user needs and preferences, improving overall user satisfaction and engagement. Secondly, ABSA enables decision-makers to base their strategies on concrete data-driven insights, facilitating better-informed decisions regarding system design and functionality. Lastly, continuous monitoring and adaptation based on ABSA findings help organisations keep their systems aligned with user expectations and technological advancements.

Future research should explore additional sociotechnical factors such as trust, accessibility, and ethical considerations to understand user experience in automated environments comprehensively. Further studies are needed to address the challenges of cross-linguistic sentiment analysis, ensuring that models accurately capture sentiments across different languages and cultural contexts. Additionally, combining multiple ABSA models could provide a holistic view of user sentiments, enhancing the accuracy and reliability of sentiment analysis.

In conclusion, integrating ABSA into sociotechnical computing frameworks presents a powerful approach to improving user experience and system effectiveness. By addressing social and technical dimensions, organisations can foster better user interactions and achieve more sustainable digital transformation.

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