From Comments to Campaigns: Turning Tenant Signals on Social Media into Sustainability Campaigns with WoonPraat Lezer

Housing associations need tenants on board for sustainability measures, and tenants respond to these plans on social media. However, their responses do not always inform campaign design, as there are too many comments to read and like counts say little about tenants' intended meanings. We present WoonPraat Lezer, an AI-powered platform that classifies Facebook comments by communicative intent, sentiment, and semantic relatedness to posts. Developed through a research-by-design approach and validated with a housing provider, the platform turns tenant discourse into actionable input for sustainability campaigns.

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1. Introduction

Housing associations want to make homes more sustainable: better insulated, powered by clean energy, and surrounded by greener gardens. None of this works without tenants. They must agree to renovations, change how they heat and ventilate their homes, or decide to swap paving tiles for plants. But where should a housing association start? To design a campaign that tenants respond to, it first needs to know what they think, what they ask, and what holds them back.

Much of this is already out in the open. Tenants share their views on social media, in the comments under their housing association's posts. They ask practical questions, voice frustrations and sometimes express appreciation. These comments are valuable signals for the next campaign. But a single housing association can receive hundreds of them, and reading and interpreting each one by hand is hardly feasible. As a result, these signals rarely make it into campaign design.

Listening to tenants is not optional. For Dutch public housing providers (housing associations, or HAs), communication is how they win tenants' cooperation. By law, housing associations must secure approval from at least 70% of tenants before implementing major sustainability retrofits [Ossokina et al., 2021]. Voluntary measures, such as saving energy or greening a garden, depend entirely on tenants' willingness to take part. A growing body of research shows that the content and quality of online communication influence both citizen participation [Zollo et al., 2026, Nisar and Prabhakar, 2018] and the effectiveness of organisational initiatives [Nguyen et al., 2024, Liu et al., 2023]. Campaigns that start from what tenants actually say are therefore more likely to succeed.

However, the tools housing associations have today do not tell them what tenants say. Current practice relies heavily on aggregate engagement metrics, counting likes, comments, and shares, which capture participation volume but obscure its qualitative nature [Leppert et al., 2022, Stone and Can, 2020, Han and Baird, 2024, Liu et al., 2023]. A post with 50 comments looks equally successful whether those comments are questions, praise or complaints. When only using interaction counts, distinct forms of engagement in user comments, such as criticism, inquiry, or passive redistribution (forwarding a message by tagging others), are treated as equivalent, despite their different implications for legitimacy, trust,

and policy implementation [Contri et al., 2025, Grimmelikhuijsen et al., 2013].

We therefore formulate the following design problem:

How can housing associations systematically translate tenant signals on social media into better-informed sustainability campaigns?

To answer this question, we develop *WoonPraat Lezer*, an AI-powered platform that reads tenant comments the way a communication advisor would, but at scale. For every comment, it answers three questions: Is the comment about the post or about something else (*relatedness*)? Is it positive, negative, or neutral (*sentiment*)? And what is the tenant trying to do: ask a question, criticise, express appreciation, make a statement, or tag others (*intent*)? An interactive dashboard is then developed to allow communication, sustainability and liveability teams to filter these labels by topic, keyword and period, see how reactions change over time, and read the comments behind every number.

We evaluate WoonPraat Lezer in a workshop with nine professionals from Woonbedrijf, a Dutch housing association. The workshop examines whether the dashboard helps them, first, to understand how tenants respond to a sustainability topic and, second, to turn those responses into ideas for new campaigns.

This paper makes two contributions. First, it presents a multidimensional framework for analysing tenant discourse, operationalised through validated classification models. Second, it presents a design artefact, the WoonPraat Lezer dashboard, tested with practitioners at a housing association, and shows how its output can be translated into concrete campaign designs. The scientific analysis of the underlying discourse is reported in our companion paper [Juneja et al., 2026].

The rest of this paper is organized as follows. In Section 2, we introduce the institutional background, discussing how HAs communicate with their tenants. In Section 3, the design and development requirements for the tool are introduced. The functionalities and performance of WoonPraat Lezer are discussed in Section 4. Section 5 presents evaluation results, based on a workshop run at Woonbedrijf. Section 6 discusses implications for practice. Section 7 concludes.

2. Institutional Context and Analytical Requirements

Housing associations in the Netherlands operate in a highly regulated institutional environment and are responsible for managing approximately 30% of the national housing stock. They play a central role in achieving national sustainability targets, including large-scale retrofitting of housing stock through insulation, heat pumps, and solar panels. A defining institutional feature is the requirement to obtain approval from at least 70% of affected inhabitants before implementing major renovations. This transforms communication into a prerequisite for implementation, where inhabitants' responses directly affect policy feasibility.

Beyond this legal requirement, the housing sector increasingly recognises that the tenant's perspective matters. Housing associations are shifting towards a more customer-centric approach, in which efforts to improve the 'soft' side of tenant experience, such as feeling at home or feeling safe in the neighbourhood, are expected to become measurable. Tenant discourse on social media offers a continuous signal of how such efforts are perceived.

In practice, housing associations typically employ three broad communication strategies.[1] The first is *informational communication*, which focuses on providing residents with updates on renovation plans, timelines, and technical details. The second is *branding communication*, aimed at strengthening the organisation's reputation and public image by highlighting its achievements, values, and broader social contributions. The third focuses on *behavioural change*, seeking

to encourage specific actions among residents, such as adopting more sustainable practices in the use of their homes or gardens. Although analytically distinct, these communication strategies are often combined in practice.

As communication increasingly takes place on social media, inhabitants' responses to these communication efforts become observable at scale. However, housing associations lack systematic ways to interpret the content of these responses. Discussions with practitioners revealed two recurring analytical needs:[2]

1. **Topic-specific analysis:** How do inhabitants respond to specific topics or initiatives, such as sustainability measures including solar panels, insulation projects, or heat pumps?
2. **Communication analytics:** What patterns in inhabitants' responses (e.g., recurring concerns, questions, criticism, or appreciation) can inform the framing, timing, and content of future communication strategies?

Addressing these needs requires moving beyond aggregate engagement metrics towards more fine-grained analyses of online discourse. This challenge motivates the development of tools capable of systematically monitoring and interpreting tenant discussions on social media.

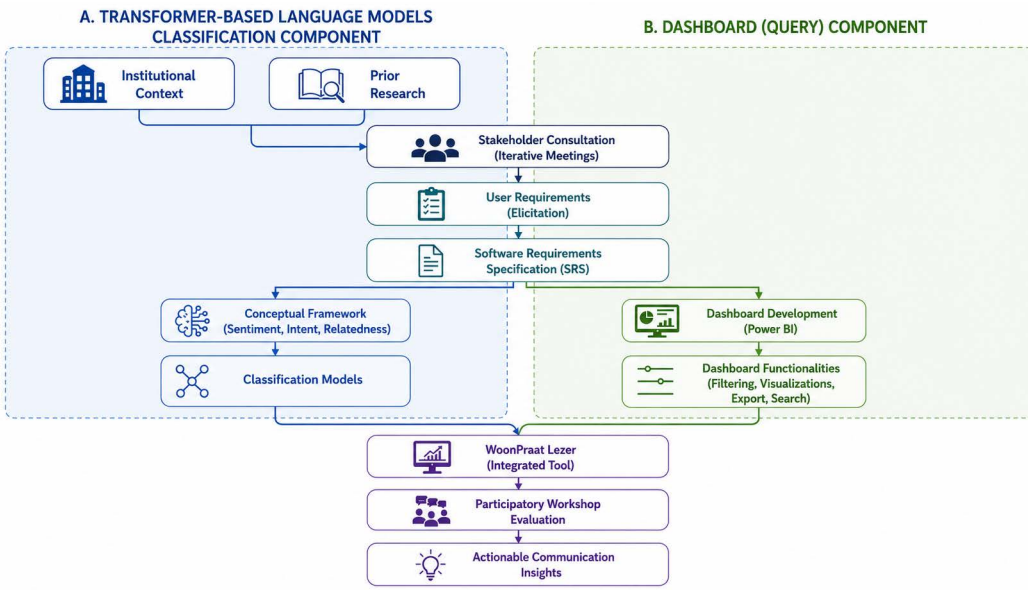
3. Design and Development of WoonPraat Lezer

Figure 1 summarises the development process of WoonPraat Lezer, an AI-powered platform combining a fine-tuned transformer-based language model and a Power BI dashboard with a user interface. Stakeholder requirements and prior research informed the design of the AI-based classification framework, which categorises inhabitants' social media discourse across multiple dimensions. The resulting framework was integrated into a dashboard and subsequently evaluated through a participatory workshop.

3.1 Conceptual Framework

To address the analytical requirements identified in the previous section, a framework was needed that captures not only what inhabitants discussed, but also how they responded and whether their responses related to the original communication. Topic-specific analysis required

FIGURE 1 ▸ RESEARCH-BY-DESIGN PROCESS USED TO DEVELOP AND EVALUATE WOONPRAAT LEZER



distinguishing comments that are substantively related to a communication initiative from those that are not, while communication design required understanding both the tone of responses and the communicative functions they served. We therefore conceptualised audience response through three complementary dimensions: semantic relatedness, sentiment, and communicative intent.

1. **Semantic Relatedness** – the topical dimension, capturing the extent to which a response substantively engages with the content of the original communication (e.g., on-topic or off-topic), measured as the cosine similarity in meaning between a comment and the post it responds to.
2. **Sentiment** – the affective dimension, capturing the evaluative orientation of a response (e.g., positive, negative, or neutral).
3. **Communicative Intent** – the behavioural dimension, capturing the functional purpose of a response (e.g., inquiry, criticism, statement, appreciation, or forwarding behaviour).

These dimensions were analytically distinct but jointly characterised audience discourse. Rather than evaluating responses independently, the framework conceptualised comments as recurring combinations of these dimensions, supporting systematic comparison across communication contexts.

We fine-tuned pre-trained transformer models to classify the discourse for intent detection and used pre-trained models for relatedness and sentiment detection [Juneja et al., 2026].

3.2 User interface requirements

To access and query the trained models, a dashboard was developed based on a structured Software Requirements Specification (SRS). Requirements were elicited iteratively through regular consultations with stakeholders from the participating housing association, who helped identify analytical needs, evaluated prototypes, and refined functionality. These requirements were then translated into actionable and testable system specifications to guide dashboard development (see Table 1).

The primary objective was to enable domain experts, specifically communication and sustainability teams, to explore the qualitative nature of tenant responses. To this end, the platform was required to support flexible filtering, temporal analysis, and content exploration. Users must be able to filter discourse by keyword, sentiment, communicative intent, relatedness, and time range; examine how these distributions evolve; identify frequently occurring keywords; and access individual comments for contextual interpretation. Additionally, the system provides export functionality to support reporting and decision-making processes.

The dashboard was developed through an iterative design process, with functionality evolving in response to user needs. The first iteration introduced core monitoring features,

TABLE 1 ▸ USER REQUIREMENTS FOR THE INTERACTIVE DASHBOARD

Functionality	User Requirement
Data Filtering & Navigation	I want to filter and explore comments by keyword, as well as sentiment, intent, relatedness and date range so that I can navigate the dataset along multiple dimensions and identify patterns in how these dimensions interact and change over time.
Distribution & Pattern Analysis	I want to view the distribution of sentiment and intent categories and identify the most frequent keywords associated with each so that I can understand the overall composition of discourse at a glance.
Data Export	I want to export filtered results to an Excel file so that I can conduct further analysis outside the dashboard.

including sentiment and intent filtering, predefined time windows, visualisations, word clouds, and comment search. The second iteration added more flexible exploration tools, such as post- and comment-level keyword search, seasonal filtering, and custom date ranges. The third iteration incorporated advanced analytical capabilities, most notably a semantic relatedness filter that enabled users to distinguish between comments that are substantively aligned with a post and those that are not. In addition, users were given control over the display of word clouds, allowing them to tailor the interface to specific analytical tasks.

Together, these iterations transformed the dashboard from a descriptive monitoring tool into a more sophisticated analytical platform. By combining automated classification with interactive visualisation, WoonPraat Lezer operationalises the multidimensional discourse framework in a scalable and practical form.

4. Functionalities & Performance of the Platform

4.1 Data

WoonPraat Lezer is built on publicly available data from the Facebook pages of 92 Dutch housing associations, collected over the period 2018–2023. These are the associations' own public pages, not closed resident groups. The corpus contains 792 sustainability-related posts published by the housing associations and 3,197 comments on these posts. Replies to comments are not included. Emojis were kept in the comment text. The full corpus is loaded into the dashboard and forms the basis of both use cases in Section 5.

For model development, 246 comments were hand-labelled. A separate held-out set of 262 hand-labelled comments was used only for testing. Details on data collection and annotation are given in our companion paper [Juneja et al., 2026].

4.2 Transformer-based Language Models

The analytical capabilities of WoonPraat Lezer rely on automated classification of audience responses across the proposed discourse dimensions. For both sentiment and intent, several Dutch and multilingual models were tested, and the three best-performing models were combined into an ensemble.

Sentiment classification was implemented using an ensemble of three pre-trained classifiers.[3,4,5] The model performed a three-way classification of comments into *positive*, *negative*, and *neutral* sentiment categories, achieving an accuracy of 0.72 on a held-out test set of N = 262 comments.

Communicative intent classification was implemented using an ensemble of three fine-tuned BERT-based classification models.[6,7,8] BERT is a language model pre-trained on large amounts of text to understand words in their context; we fine-tuned such models on hand-labelled tenant comments to recognise communicative intent. The model categorised comments into five intent classes: *criticism, appreciation, statement, inquiry*, and *forwarding behaviour*, and achieved an accuracy of 0.85 using the same held-out evaluation procedure.

A relatedness score was computed for each comment–post pair using cosine similarity between their respective text embeddings.[9] Higher scores indicated stronger semantic alignment between the content of a comment and the corresponding post. Comments scoring above 0.35, the average score in the dataset, are treated as on-topic; comments below this threshold are treated as off-topic. All comments are classified and kept in the dashboard: relatedness serves as a filter, not as an exclusion criterion. Table 2 shows examples.

These results indicated that the models provide sufficiently reliable classifications to support exploratory analysis and communication-oriented decision-making within the platform. Detailed methodological descriptions, model

TABLE 2 ▸ EXAMPLES OF ON-TOPIC AND OFF-TOPIC COMMENTS (ANONYMISED AND TRANSLATED FROM DUTCH).

Post (summary)	Comment	Label
Do you, as a tenant, ever wonder where your rent goes? Below we've listed what we spent our 2022 rental income on. This is based on the average rent at [ORG] in 2022: €541.	But the landlord levy was abolished as of 1 January 2023.	On-topic
	Been waiting months for a reply to my several ignored emails from [PERSON]. Too bad.	Off-topic
Want to know about the annual rent increase? How to apply for rent subsidy? Or file an objection? Read it in the Rent Newsletter 2022.	So the rent subsidy goes up right along with it! Oh wait, no, that only happens next year, and you can't even file an objection, because then you'd pay double for a while, even with a rent freeze.	On-topic
	[ORG] Someone was supposed to come by to help with insulation, and had products for it, but never showed up.	Off-topic

architectures, and evaluation procedures are presented in our companion research paper [Juneja et al., 2026]. Within the present study, the output of these models forms the structured data layer that underpins the dashboard.

4.3 Dashboard

The dashboard was implemented in Power BI and served as a front-end interface connected to a database of pre-classified comments. It supported exploratory analysis through a range of interactive components. Users can define the scope of analysis using filters for sentiment, intent, relatedness, season, time period, date range, and keywords.

The dashboard combines quantitative and qualitative insights. Summary cards provides an

FIGURE 2a ▸ OVERVIEW PANEL SHOWING SENTIMENT AND INTENT DISTRIBUTIONS TOGETHER WITH TEMPORAL TRENDS

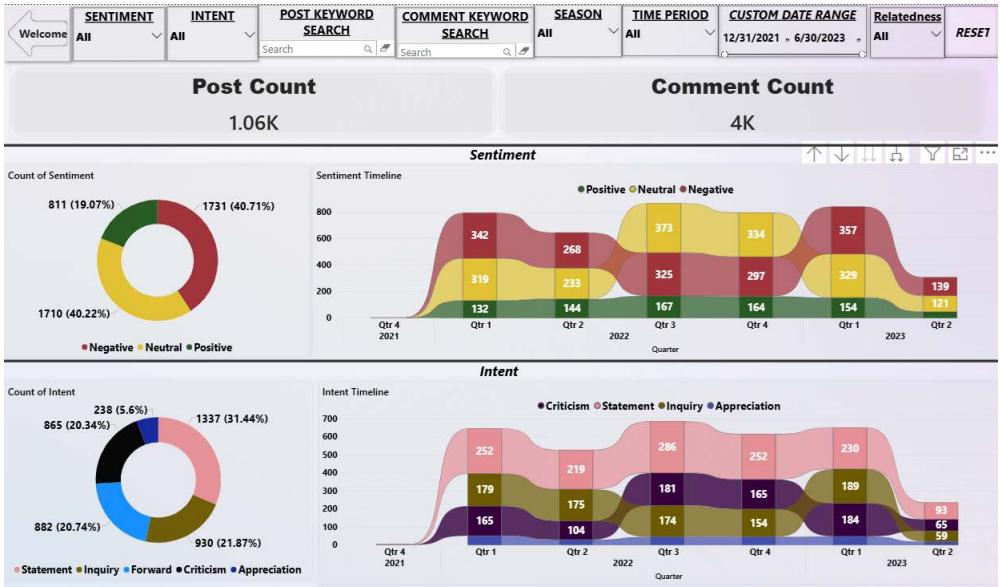


FIGURE 2b ▸ EXPLORATION PANEL SHOWING WORD CLOUDS AND THE CORRESPONDING POSTS AND COMMENTS

overview of sentiment and intent distributions, while ribbon charts shows how these patterns evolve. Word clouds highlights prominent keywords within selected subsets of data, and a post/comment view allow users to examine individual entries in their original context. Figures 2a and 2b illustrate the two main dashboard panels of WoonPraat Lezer: the filter panel and the dashboard's main visualisation components. Users can switch between an overview panel for monitoring discourse patterns and an exploration panel for inspecting keywords and individual comments

By combining aggregated metrics with drill-down functionality, the dashboard supports both high-level monitoring and detailed interpretation.

5. Evaluation of WoonPraat Lezer

5.1 Setup of the Evaluation

To evaluate whether WoonPraat Lezer provides practical value for communication-related analysis and decision-making, we conducted a participatory workshop (focus group) with nine employees from Woonbedrijf. The workshop size was considered sufficient for identifying usability issues, given evidence that the number of newly discovered usability problems decreases substantially beyond five users [Nielsen and Landauer, 1993]. Participants represented diverse professional backgrounds and organisational roles, including renovation managers, sustainability advisors, communication advisors, and IT specialists.

The workshop was structured around the two analytical use cases related to the analytical needs identified earlier in the paper:

1. Topic-specific analysis;
2. Communication analytics - Designing future communication.

5.2 Use Case 1: Topic-Specific Analysis

Task definition To evaluate the dashboard's exploratory capabilities, participants were asked to use WoonPraat Lezer to investigate discourse surrounding solar panels (*zonnepanelen*). Participants explored the data using filtering and keyword search functionality, frequently navigating comments containing terms such as energy (*energie*), renovation (*renovatie*), and solar panels (*zonnepanelen*).

Feedback received Through this analysis, participants observed that discussions often diverged from the original communication topic. Rather than responding directly to posts about solar panels, tenants frequently redirected conversations toward broader frustrations and criticism concerning housing conditions and renovation experiences.

Participants particularly valued the relatedness metric, as it enabled them to distinguish comments that substantively engaged with the original post from those expressing more general dissatisfaction. This provided contextual insight that would not have been captured by conventional engagement metrics alone. Off-topic comments are therefore not irrelevant: they signal broader concerns, such as housing conditions and renovation experiences, that housing associations should also hear.

These findings suggest that qualitative analysis of discussion supports a more nuanced interpretation of tenants' responses and helps communication teams distinguish issue-specific reactions from broader concerns.

5.3 Use Case 2: Designing Future Communication

Task definition To evaluate whether the dashboard could support communication design, participants were presented with discourse insights related to biodiversity communication, focusing on discussions surrounding the topic of garden ('tuin' in Dutch). The underlying dataset consisted of comments sampled from the full corpus of housing association Facebook pages, specifically comments in which inhabitants discussed gardens and garden-related topics. These comments were analysed and visualised through the dashboard to provide an evidence base for communication planning.

Participants were divided into groups and tasked with developing a communication campaign from one of three professional perspectives: *sustainability advisor, liveability advisor*, or *communication advisor*. As supporting material, they were given dashboard query outcomes printed on paper, including comments by intent and associated word clouds, temporal trends, and distributions of communicative intent and sentiment (Figures 3a-d, Examples of dashboard outputs provided to participants during the communication campaign design exercise).

FIGURE 3a ▸ SENTIMENT AND INTENT DISTRIBUTIONS

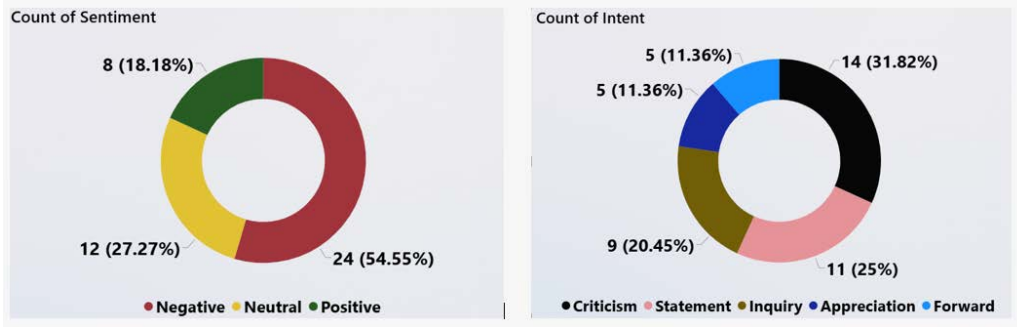
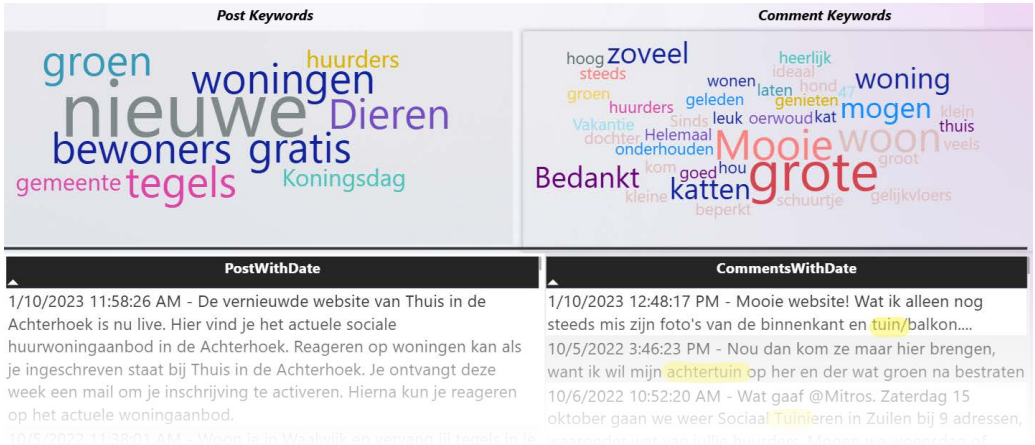


FIGURE 3b ▸ INQUIRY-RELATED COMMENTS AND KEYWORDS

FIGURE 3c ▸ CRITICAL COMMENTS AND KEYWORDS

FIGURE 3d ▸ NON-NEGATIVE COMMENTS AND KEYWORDS



Feedback received The exercise resulted in distinct communication strategies emerging across perspectives (see Table 3).

Participants adopting the *liveability advisor* perspective focused primarily on inquiry-related discourse and proposed campaigns aimed at strengthening neighbourhood cohesion and community engagement. Drawing on questions and discussions about gardens, they suggested creating opportunities for residents to interact with one another, such as a neighbourhood exchange market where inhabitants could give away or swap removed garden tiles. Participants argued that linking garden-related sustainability initiatives to social activities could simultaneously improve neighbourhood liveability and encourage resident participation.

The group working from the *communication advisor* perspective reached a similar conclusion but emphasised shifting communication from an organisational perspective toward an inhabitant-centred narrative. Drawing on observed sentiment patterns over time, they argued that communication grounded in residents' lived experiences and success stories was more likely to generate positive engagement than messages focused solely on organisational goals or policy objectives.

Participants adopting the *sustainability advisor* perspective identified recurring references to unstable or deteriorating garden tiles, as well as discussions about renovation and maintenance practices. Building on these observations, they proposed connecting existing sustainability campaigns to these concerns by encouraging residents to replace unused or problematic tiles with plants and greenery. Participants suggested framing greener gardens as a practical solution to issues already raised by inhabitants and supporting participation through incentives and replacement schemes.

Across all groups, rather than relying solely on intuition or prior experience, participants used observed configurations of sentiment, intent, and timeline to inform campaign design. This suggests that the dashboard supports not only retrospective interpretation of inhabitant discourse but also prospective communication design.

Overall, the workshop findings indicate that WoonPraat Lezer supports both exploratory understanding of inhabitant discourse and the development of communication strategies informed by qualitative patterns in social media engagement.

6 Implications for Practice

Beyond the two use cases tested in the workshop, WoonPraat Lezer can support housing associations in several practical ways:

- **Preparing renovation approval**: monitoring tenant discourse before and during the 70% approval process to identify concerns early and address them in communication.
- **Evaluating campaigns**: comparing sentiment and intent before and after a campaign to assess how tenants responded.
- **Early warning**: detecting recurring complaints, such as maintenance or housing-condition issues, before they escalate.
- **Input for tenant panels and management reports**: providing evidence on tenant concerns and making soft outcomes, such as tenant satisfaction, measurable over time.
- **Closing the feedback loop**: reporting back to tenants what concerns they raised and how the housing association has handled them.

7 Conclusions and Limitations

This study addressed the question of how housing associations can systematically translate tenant signals on social media into better-informed sustainability campaigns. To address this challenge, we developed *WoonPraat Lezer*, an AI-powered platform that combines sentiment analysis, communicative intent classification, and semantic relatedness analysis to support the

TABLE 3 ▸ CAMPAIGN IDEAS DEVELOPED USING DIFFERENT PROFESSIONAL PERSPECTIVES

Perspective	Dashboard Insights Used	Proposed Solution	How They Reached It
Liveability Advisor	Inquiry comments and word clouds	Tile-exchange market and garden-based community activities	Linked gardening discussions to neigh-bourhood cohesion and resident interaction.
Communication Advisor	Sentiment trends and positive comments	Resident-centred communication ampaign	Observed stronger engagement with inhabitant stories than organisational messaging.
Sustainability Advisor	Critical comments and tile-related keywords	Replace tiles with plants through incentive schemes	Connected recurring complaints about tiles to greening opportunities.

exploration of social media discourse. Developed through a combination of large language modelling and an iterative design process with stakeholders, the platform enables users to dig deeper into the discussions and explore discourse patterns across multiple dimensions.
Evaluation through a participatory workshop demonstrated that WoonPraat Lezer supports both topic-specific analysis and the design of future communication strategies. Participants used the dashboard to identify recurring concerns, interpret audience reactions, and develop communication interventions grounded in observed discourse. These findings suggest that multidimensional discourse analysis can provide housing associations with richer insights into tenant responses. By making tenant responses measurable over time, the platform also supports the sector's broader shift towards a customer-centric approach. In short, WoonPraat Lezer helps housing associations move from comments to campaigns.

Several limitations should be acknowledged. The classification models can further be improved as they, for example, struggle with nuanced language such as sarcasm or implicit meaning. During evaluation, we noticed that the accuracy of both sentiment and intent detection can be further increased, as sarcastic comments were often incorrectly identified. Furthermore, the current implementation is limited to Facebook data, as the models were trained and validated on Facebook comments; applying the approach to other social media would likely require model adaptation. Finally, some dashboard features, such as word-cloud visualisations, are most informative when sufficient volumes of comments are available.

Future work should focus on improving model robustness, extending the approach to additional social media, and exploring methods for evaluating the causal effects of communication interventions. Future research could also examine what drives sentiment and intent, for example whether they are driven by the topic of communication or by other factors. Our next step in platform development is *WoonPraat Schrijver*. This extension uses generative AI to simulate tenant discourse in response to proposed communication messages, supporting the design and testing of communication strategies before deployment.

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FOOTNOTES

1 Insights gained from Woonbedrijf, one of the larger housing associations owning around 30,000 dwellings.
2 Insights gained from Woonbedrijf housing association.
3 https://huggingface.co/nlptown/bert-base-multilingual-uncased-sentiment
4 https://huggingface.co/clips/republic
5 https://huggingface.co/citizenlab/twitter-xlm-roberta-base-sentiment-finetunned
6 https://huggingface.co/GroNLP/bert-base-dutch-cased
7 https://huggingface.co/DTAI-KULeuven/robbert-2023-dutch-large
8 https://huggingface.co/MoritzLaurer/mDeBERTa-v3-base-mnli-xnli
9 https://huggingface.co/sentence-transformers/paraphrase-multilingual-MiniLM-L12-v2

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