D6.2: Report about the design of decision-making tool.

WP6 – **EnergyWizard** design and development cycle

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ENCHANT Report

D6.2: This report provides an overview of the development web-tool called **EnergyWizard**. We define the detailed requirements of the tool, provide a high-level architecture and the design process, and steps to develop and test of the recommender system algorithm. Finally, we provide suggestions about sanity checks.

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ABSTRACT

The main objective of the report is to provide a design document guiding the partners and readers through various steps involved in designing the tool. A demo of the tool is provided, and an overview of the analysis steps developed as part of WP6. It also provides an overview of the workflow of the tasks and software life cycle in the development of the code and machine learning algorithms. Finally, it delves into the decisions made with the hyperparameter choices to get the results.

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1. Introduction and Overview

1.1 Purpose and scope of this document

The **EnergyWizard** is the tool that is developed as part of WP6 that processes the data collected from the ENCHANT interventions in three major steps. Each of this step uses a machine learning (ML) algorithm in the background that can be used for identifying the underlying behavioural patterns, correlating the user-behaviour with energy consumption, and answering the validity of the hypothesis put forward by ENCHANT. As these methods use existing trends within the data, it is interesting to explore their relevance when applied to survey data collected under ENCHANT pilots. Given the data from various intervention surveys conducted over a period when contacting people through various communication channels, the aim is to explore hypotheses by ENCHANT from the objective of WP6, which is to:

- O1: Determine the best intervention for a group of people from the survey.
- O2: Identify a suitable channel for reaching out to the end-user.

In this report, we summarize the progress in WP6 to meet the goals mentioned above. The report provides an overview of:

- Summary of the progress in tool development in WP6.
- Process of identifying the group structure within the data.
- Data cleaning, normalization, and sanity checks for learning a uniform representation from the data.
- Recommender systems (RS) role and data used in training.
- Effect of data imputation on the analysis.
    - Results without imputations
    - Results with imputations
- Cluster analysis to identify patterns in behavioural data.
- Projection choices for behavioural groups (BGs) visualization.
- Correlation of learned representation of user data with energy usage
- Intervention stratification within BGs

This document is organized as follows. In Chapter 1 – Section 1.2, is a summary of the progress made in tool development and its contributions towards O1 and O2.

Chapter 2 breaks down the idea behind the recommendation system (RS), its role in ENCHANT, and design choices made to train on the data.

Chapter 3 – Section 3.1 provides a summary of the demo of the deployed web-tool that is up and running. Section 3.2 provides an overview of the exploratory capabilities of the tool under development and not yet deployed online.

The Appendix is showing all the analysis plots in detailed.

1.2 Summary of the tool capabilities and development cycles

As the current report describes the inner working of the tool that is currently under development, we summarize its capabilities here:

***Table 1** Summary of the tool capabilities*

Deployment cycles	Capabilities	Utility
Online	RS trained with the ability to predict from incomplete data	Proof of concept of RS and its ability to learn intermediate representation to data for downstream analysis tasks.
Offline	In addition to incomplete data prediction, this RS can also determine group patterns paving way to realise O1 and O2	1) Determine exact number of possible behavioural groups in data. 2) Correlate the user behaviour data with energy consumption. 3) Identify the intervention strata within the BGs along with incremental energy consumption over successive weeks 4) Determine best suited intervention and communication channel per BG.

The software development cycles followed in along two paths:

- Offline code repository: This is the research branch of the ML algorithms developed in the project. Data collected is parsed and cleaned, followed by sanity checks. The data is then used to train the ML models to run predictions and inferences. As this setup is experimental, once the features are more stable and are working as intended, they are transferred to the online web tool.

- Online web tool: Here the trained ML models are deployed for open access for the user. The features exposed in this tool are in line with the project outcomes from ENCHANT. However, some of the more experimental features developed might not be available. These functions will be made open once their usage is finalized through experiments run on the offline repository.

2. Training recommender system

2.1. Data parsing and cleaning for training

The data from an intervention survey and behaviour measurement (here the data from the ENCHANT intervention platform) can be seen as a matrix in which each user response is represented as a row and each question along as a column. We denote all users as $\{u_1, u_2, \ldots u_n\}$ and all questions as items $\{i_1, i_2, \ldots i_m\}$ this can be seen as a user-item interaction matrix M of size $n \times m$ denoted as $M^{n \times m}$. An example of a typical response to a survey can be visualized as shown below with strong responses to a question (>3) in red, weak response (<3) in green, responses with value 3 in blue and empty responses are denoted as blank nodes.

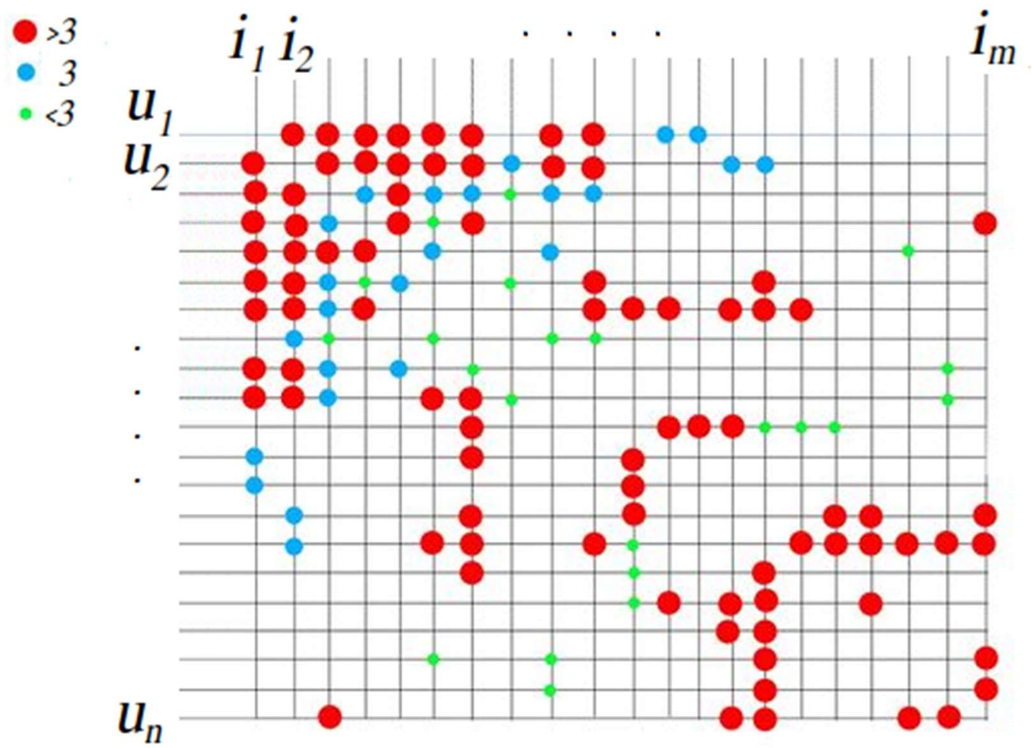


Figure 1: Visualizing user-item interaction matrix with color coded values

Typical challenges encountered with raw intervention data are:

- Handling null responses: Users in the survey have opted not to respond leaving the question unanswered or with an invalid option (out of 1-5 range)

- Pruning data: Data such as demographic, energy consumption[1] etc. though important for answering ENCHANT objectives are beyond the scope of behavioral analysis of users. Hence, these responses were pruned in current analysis.
- Sanity checks: Response rates were also gauged to eliminate entries with very few responses to the questions (typically threshold being > 15% empty responses)
- Normalization of the electricity consumption data: To make data across the countries comparable, the raw electricity use data from the web platform is normalized with regard to the household size and the seasonality in the country from the past data. Also, some the inconsistency in reporting absolute readings versus difference in readings has been fixed.
- Handling binary input: The algorithm considers a response as *strong* (set to +1) if the rating to a question is ≥ 3 else a *weak* response (set to -1)

The dataset from the ENCHANT intervention platform after the sanity checks was used to train a ML recommendation algorithm.

2.2. Training a recommendation system

The missing user-item interactions is interpolated by the recommendation algorithm using:

Content based filtering

Genre (Features/Attributes)							Ratings					
Action	Comedy	Horror	Sci-fi	Fantasy	Mystery	Movies	User1	User2	User3	User4	User5	User6
Yes	No	No	No	No	No	Item1	1		2	2	5	1
No	No	Yes	No	No	No	Item2	3	5	3	3	4	5
Yes	No	No	No	No	No	Item3		2		1	2	3
No	Yes	No	No	No	No	Item4		4	1	2	5	5
No	No	Yes	No	No	No	Item5	4	4	3	4	3	4
No	No	No	No	No	Yes	Item6	2	2		5	1	1
No	No	No	Yes	No	No	Item7	4	1		1	2	3
No	No	No	No	Yes	No	Item8	2		4	4	1	2
No	No	Yes	No	No	No	Item9	??					

- A content-Based recommender system tries to guess the features or behaviour of a user given the item features, he/she reacts positively to.
- Content-based filtering is independent of other users' data when making recommendations to a user.
- Here, using the movies as an example, User1 has a strong liking for the Horror genre so a new movie as Item9 belonging to the Horror genre can be recommended to the user.

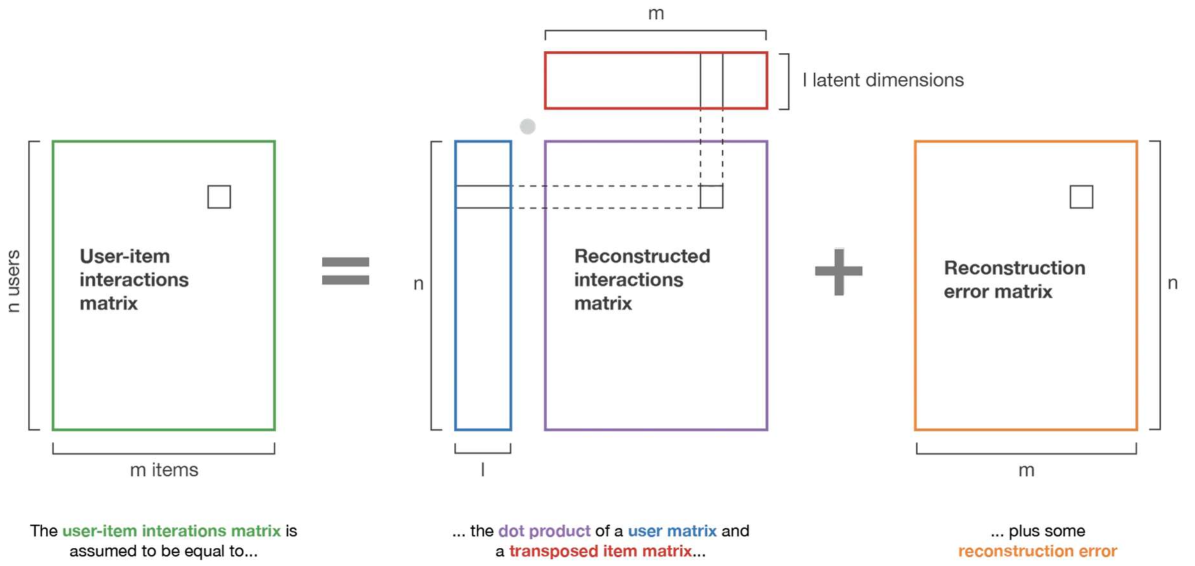
Collaborative filtering

Genre (Features/Attributes)							Ratings					
Action	Comedy	Horror	Sci-fi	Fantasy	Mystery	Movies	User1	User2	User3	User4	User5	User6
Yes	No	No	No	No	No	Item1	1		2	2	5	1
No	No	Yes	No	No	No	Item2	3	5	3	3	4	5
Yes	No	No	No	No	No	Item3		2		1	2	3
No	Yes	No	No	No	No	Item4		4	1	2	5	5
No	No	Yes	No	No	No	Item5	4	4	3	4	3	4
No	No	No	No	No	Yes	Item6	2	2		5	1	1
No	No	No	Yes	No	No	Item7	4	1		1	2	3
No	No	No	No	Yes	No	Item8	2		4	4	1	2

- A collaborative filtering recommender system compares the likes of users to form relative matches. It recommends items based on similarities shared among users.
- Collaborative filtering is independent of the features of the items to be given.
- Using the movie example, the movies not watched by User1, User2, User3 can be recommended to them based on the movies watched by User4, User5, User6 based on similarity of interests.

[1] Energy consumption will in a later step be used for identifying successful interventions, therefore, it cannot at the same time be included as a criterion for forming the BGs.

The algorithm used in training the RS is a *matrix factorization* (MF) algorithm that can be



understood visually as shown in the figure above. The algorithm tries to decompose the

Figure 2: Matrix factorization algorithm

user-item interaction matrix $M^{n \times m}$ into the product of the user latent matrix $U^{n \times l}$ and the item latent matrix $I^{m \times l}$ such that as per matrix multiplication we have:

$$M^{n \times m} = U^{n \times l} \cdot \left(I^{m \times l}\right)^T$$

The algorithm tries to find the values for $U^{n \times l}$ and $I^{m \times l}$ such that the reconstruction error is minimized. The RS model in general tries to exploit user and item-based similarity. This requires a *distance metric* that measures the similarity between any two pairs of users/items. A commonly used distance metric in RS is *cosine similarity* that measures as the cosine of the angle between the two users' vectors. For users u and u', the cosine similarity is:

$$\mathbf{sim}(\mathrm{u}, \mathrm{u}') = \cos(\theta) = \frac{\mathbf{r}_{\mathrm{u}} \cdot \mathbf{r}_{\mathrm{u}'}}{|\mathbf{r}_u||\mathbf{r}_{u'}|} = \sum_{\mathrm{i}} \frac{\mathrm{r}_{\mathrm{ui}} \mathrm{r}_{\mathrm{u'i}}}{\sqrt{\sum_{\mathrm{i}} \mathrm{r}_{\mathrm{ui}}^2} \sqrt{\sum_{\mathrm{i}} \mathrm{r}_{\mathrm{u'i}}^2}}$$

A key observation here is that we require a means to associate vectors to users and items as the metric treats geometrically a given user's (item's) row (column) of the ratings matrix as a vector. This is the reason the RS employs the MF algorithm. Using the matrix factorization approximation by letting a user u and items i take the form of a ***k***-dimensional vector $\mathbf{x}_u, \mathbf{y}_i$ respectively. We approximate the true rating r_{ui} corresponding to the (u, i) pair by $\hat{r}_{ui}$ as:

$$\hat{r}_{ui} = \mathbf{x}_u^{\mathsf{T}} \cdot \mathbf{y}_i$$

The algorithm tries to pick the $\mathbf{x}_u, \mathbf{y}_i$ values to minimize the loss function shown below.

$$L_{exp} = \sum_{u,i \in S} (r_{ui} - \mathbf{x}_u^{\mathsf{T}} \cdot \mathbf{y}_i)^2 + \lambda_x \sum_u \|\mathbf{x}_u\|^2 + \lambda_y \sum_u \|\mathbf{y}_i\|^2$$

3. Tool architecture and design considerations

3.1 Detecting behavioural groups within intervention data

We start with the embedding (intermediate vectors mapped by RS algorithm) for each user from the interventions U^e. We run the k-Means algorithm on the embeddings space to identify the clustering structure. As we do not know the number of clusters or groups in the data to begin with, we employ two methods to determine the total number of groups.

<u>Elbow method:</u> We iterative run k-Means to identify the number of groups from an enumerated list starting from [2, 3, ⋯ n], then create a plot with the number of clusters on the x-axis and the total within sum of squares error among clusters on the y-axis and then identifying where an "elbow" or bend appears in the plot as shown using *<u>all</u>* the intervention data. This approach is useful in identifying the possible number.

<u>Silhouette score</u>: In the range identified we use the silhouette coefficient or silhouette score of k-means as a measure of how similar a data point is within-cluster (cohesion) compared to other clusters (separation). The Silhouette score calculation is run for the identified range in this case [2, 3, ⋯ 10]. The number of clusters with the highest coefficient is selected as the relevant number groups identified in the data. The elbow and silhouette plots for all the counties are available in the Appendix Figure 3: k-Means elbow plots for Norwegian interventions.to Figure 14: k-Means silhouette plots for rest of EU interventions..

<u>Note:</u> *As the clustering structure varies with data imputation the maximum cluster identified in the silhouette plots in majority of the case is taken as the true cluster number. If there is no clear majority, then data without imputation is used for identification.*

A visualization of the clustering structure in all the cases are plotted in Figure 15: t-SNE plots of behavioural clusters in Norway using user embeddings. to Figure 26: PCA plots of behavioural clusters in rest of EU using user embeddings.. Here is an overview of the steps followed by the algorithm:

1. There were 6, 3, and 3 behavioural groups identified using *<u>all</u>* the interventions data collected from Norwegian, Germany and the rest of the interventions in Türkiye, Italy, Austria, and Romania[2] (using *k-Mean clustering*).
2. The cluster centroids of the group clusters are marked with a star of the corresponding group colour with a black star to mark its centre.

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[2] A supplementary data collection is ongoing in Romania in September/October 2023, which will lead to Romania becoming an own group in the final tool.

3. All the data points corresponding to a group are marked with the respective group color.
4. With the group centroids as the center each group region is filled out with a faded color corresponding to the region (using *Voronoi tessellations*)
5. Marking the regions for the group will help identify the behavior changes for each group over the interventions.
6. The latent representations (*user embeddings* in some high dimensional vector space U^e) of each user learned by the RS are then linearly projected (using principal component analysis [*PCA*]) to two dimensions ($[\Pi_1(U^e), \Pi_2 (U^e)]$) and plotted along each axis as shown in the plots
7. A non-linear projection (using t-Distributed Stochastic Neighbour Embedding [*t-SNE*]) was also be used to visualize the group survey patterns.

Note: *Although the t-SNE plots look visually more pleasing compared to PCA plots interpreting the projections used to map* $U^e \rightarrow [\Pi_1, \Pi_2]$ *by t-SNE can be more complicated compared to PCA. Hence, we opt to use both methods in visualizing the results.*

3.2 Establishing correlation with energy consumption

Before we use the embedding vectors for further analyses, a correlation between these vectors and the energy consumption needs to be established. This is done by training a regression model fitting the user embeddings using <u>*all*</u> the intervention weeks electricity consumption data to the energy consumption per person per day in a household. Another regression model was trained fitting the user embeddings from <u>*each*</u> intervention week data to the energy consumption per person per day in a household. The idea here is to show that there exists a strong correlation between the behavioural data and energy use/saving behaviour.

The results for these experiments are available in Figure 27: Prediction of energy consumption from behavioural vectors (NO). to Figure 32: Prediction of energy consumption from behavioural vectors (OT).. The model predicts the energy consumption with a mean absolute percentage error of ~20-30%. The predicted value and the confidence intervals are also available in the plots.

3.3 Effect of data imputation

In the ENCHANT project, data imputation using expectation maximation was used to impute missing data in central variables from the intervention platform (e.g., missing electricity meter readings or survey answers). The models used for the development of the tool tend to perform better with data imputation as the imputation method used is expectation maximization which tends to approximate value around the mean. This allows regression model to predict values around mean better thus reducing the error. The need for using all the intervention data is to establish a common representation of the user that can be used when comparing all the interventions.

Without data imputation, valid survey response drops to ~20% usable. When this data was used to stratify the interventions within the behavioural group, we are left with very few samples to work. Hence, all the stratification analysis was conducted with imputed data.

3.4 Intervention stratification within behavioural groups

The successive difference in energy consumptions over the five weeks was computed for all the users. Within each behavioural group the users were separated into their respective intervention strata. A histogram of the consumption differences against the user-ids are plotted in Figure 33: BG0 interventions 1-7 stratification. to Figure 62: BG2 channel responses stratification.. Every instance with the intervention strata where the user has shown a reduction in energy (negative bars in the histogram) over the past week are considered as a success case for the intervention. The colour outlined on the border of the histograms correspond to the colour code of the behavioural groups in the cluster plots. A similar histogram was constructed to the responses received over the channels per behaviour group. The following table summarizes the results from these experiments:[3]

Table 1: Summary of best intervention for Norwegian behavioural group

Group	Intervention	Coverage %	Success %	Channel
0	Info + SN + collective framing	7	72	VIKEN, FACEBOOK, FOTE
	Info + SN + commitment	4	68	
	Info + feedback	5	66	
1	Info + SN + commitment + feedback + competition + collective framing	8	79	VIKEN, FACEBOOK, FOTE
	Info + commitment	10	79	
	Info + SN + commitment + feedback + competition	11	78	
2	Info + SN + collective framing	4	72	VIKEN, FACEBOOK, FOTE
	Info + SN + commitment + feedback + competition	9	69	
	Info + feedback	7	65	
3	Info + feedback + competition + collective framing	8	79	VIKEN, FACEBOOK, FOTE
	Control 2 (start-end)	10	77	
	Info + SN	4	71	
4	Info + feedback	3	92	VIKEN, FACEBOOK, FOTE
	Info + commitment	5	83	
	Control 1 (weekly)	5	78	
5	Info + feedback + competition	8	79	VIKEN, FACEBOOK, FOTE
	Info + feedback	6	78	
	Control 2 (start-end)	9	77	

[3] For the content of the intervention techniques, please consider Deliverable D2.2; For the channels: VIKEN=recruited by Viken county; FOTE=recruited by Friends of the Earth Norway; FACEBOOK=recruited by Facebook communication (which was used both by Viken and FOTE in their recruitment campaigns). BADENOVA=recruited by badenova; Bills=recruited through a message in the electricity bills; Newsletters=recruited through newsletters. OTHERS/others_kat=recruited through unspecified channels.

Table 2: Summary of best intervention for German behavioural group

Group	Intervention	Coverage %	Success %	Channel
0	Control 2 (start-end)	0	100	BADENOVA, Bills, Newsletters
	Info + SN	7	72	
	Info + feedback + competition + collective framing	6	71	
1	Control 2 (start-end)	14	78	BADENOVA, Bills, Newsletters
	Info + SN + commitment	5	77	
	Info + commitment	6	70	
2	Control 2 (start-end)	1	100	BADENOVA, Bills, Newsletters
	Info + feedback	3	67	
	Info + feedback + competition	5	67	

Table 2: Summary of best intervention for other EU behavioural group

Group	Intervention	Coverage %	Success %	Channel
0	Control 2 (start-end)	7	75	OTHERS, Others_cat, Newsletters
	Info + commitment	19	66	
	Info	10	63	
1	Info + SN + commitment + feedback + competition	18	81	OTHERS, Others_cat, Newsletters
	Info + commitment	12	77	
	Info + collective framing	6	75	
2	Info + SN + commitment + feedback + competition+ collective framing	16	73	OTHERS, Others_cat, Newsletters
	Control 2 (start-end)	22	72	
	Info	8	71	

Note: *The magnitude of energy saved is not considered as bigger household can have bigger gains. Also, the percentage of sample covered by the interventions also need to be considered as a successful intervention with too small sample size cannot be generalized to the population.*

3.5 Future tasks

The URL to the tool is: https://enchant.sinter.ai.[4] The capabilities described below are available in offline mode and will be integrated into webtool.

1. Analysis features integration: The integration of the mentioned features is ongoing and require further testing. All the user partners will be invited to pilot test the tool once the integration is done. As per the current plan the tool should be functional by the end of October 2023.
2. Tutorial covering web-tool usage: All the user partners in the projects will be invited for a tutorial demonstrating the usage of online web-tool so that intended user may interact with it.

[4] Currently (September 2023), this URL stores a proof-of-concept model which is based on other data than the intervention platform.

Appendix

1.1 Determine number of groups in each intervention

1.1.1 Norwegian intervention without data imputation

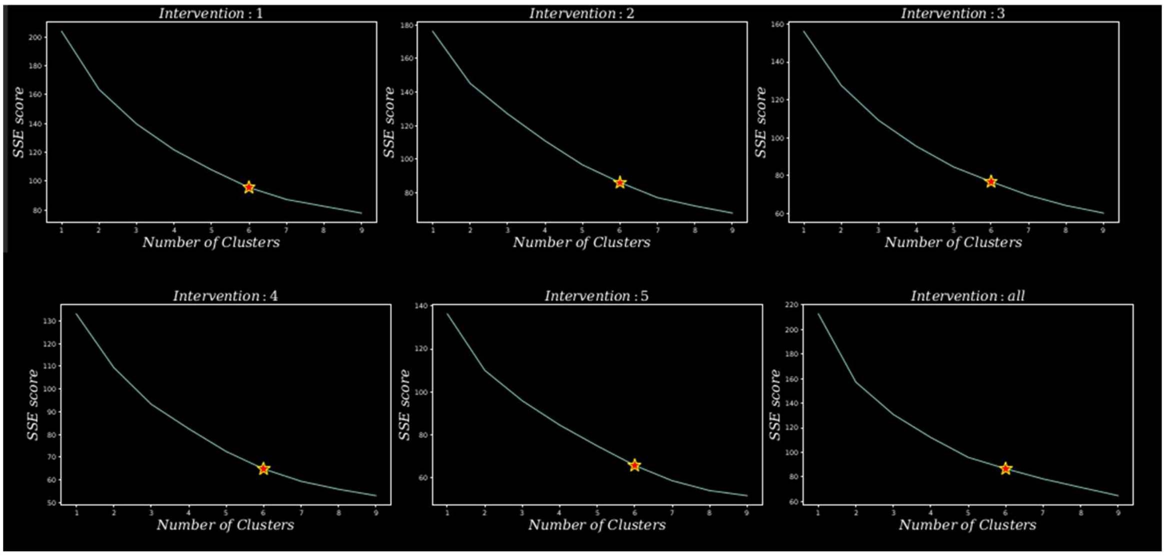


Figure 3: k-Means elbow plots for Norwegian interventions.

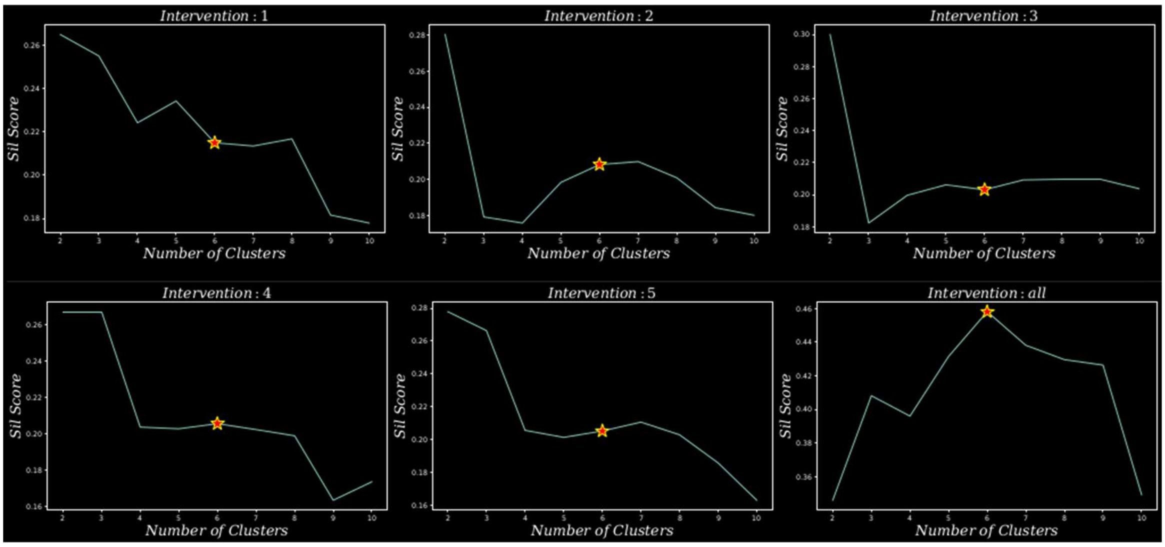


Figure 4: k-Means silhouette plots for Norwegian interventions.

1.1.2 Norwegian intervention with data imputation

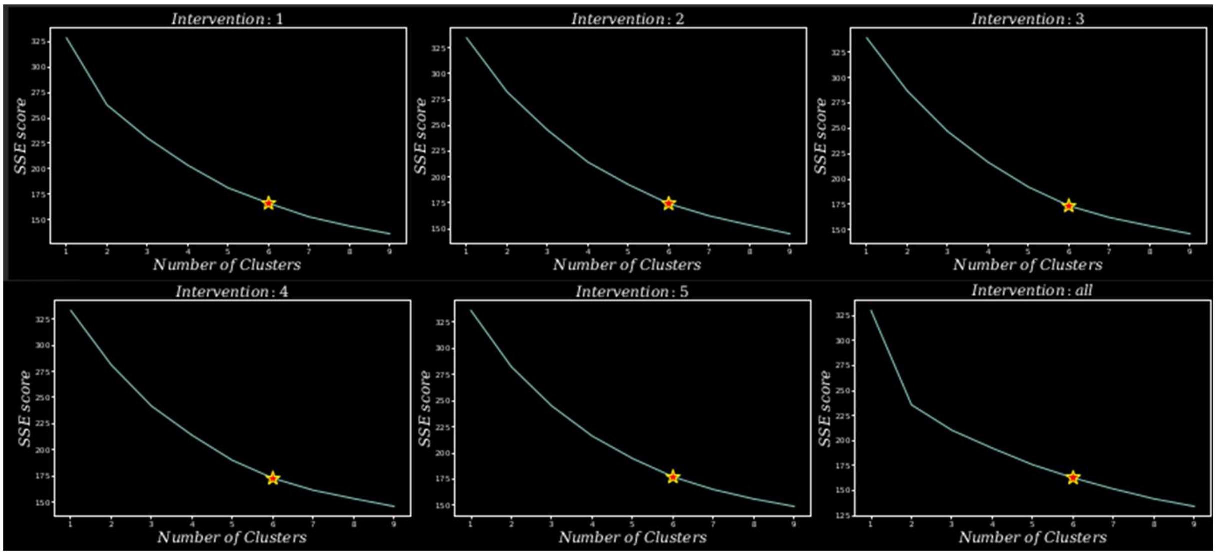


Figure 6: k-Means elbow plots for Norwegian interventions.

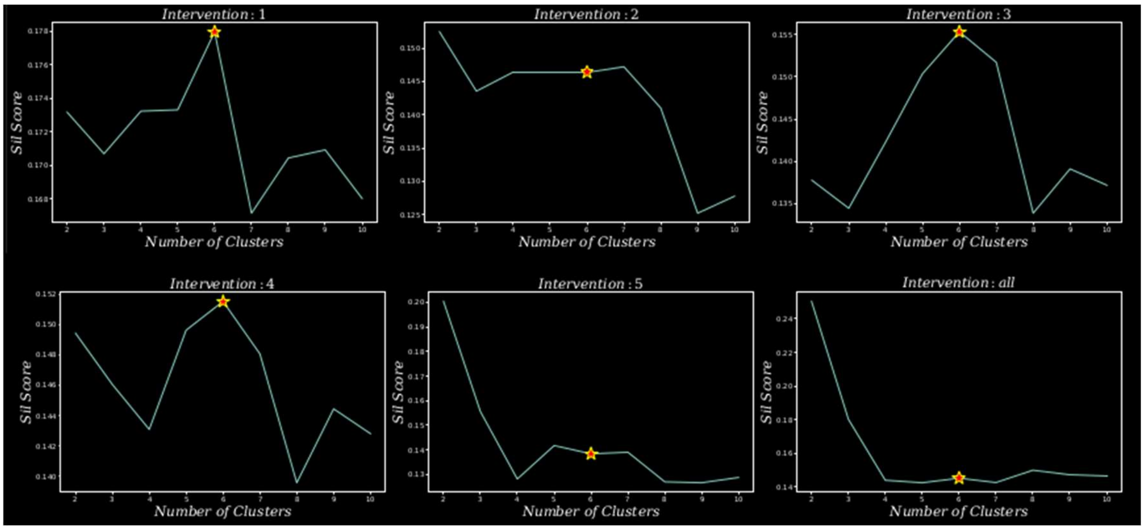


Figure 5: k-Means silhouette plots for Norwegian interventions.

1.1.3 German intervention without data imputation

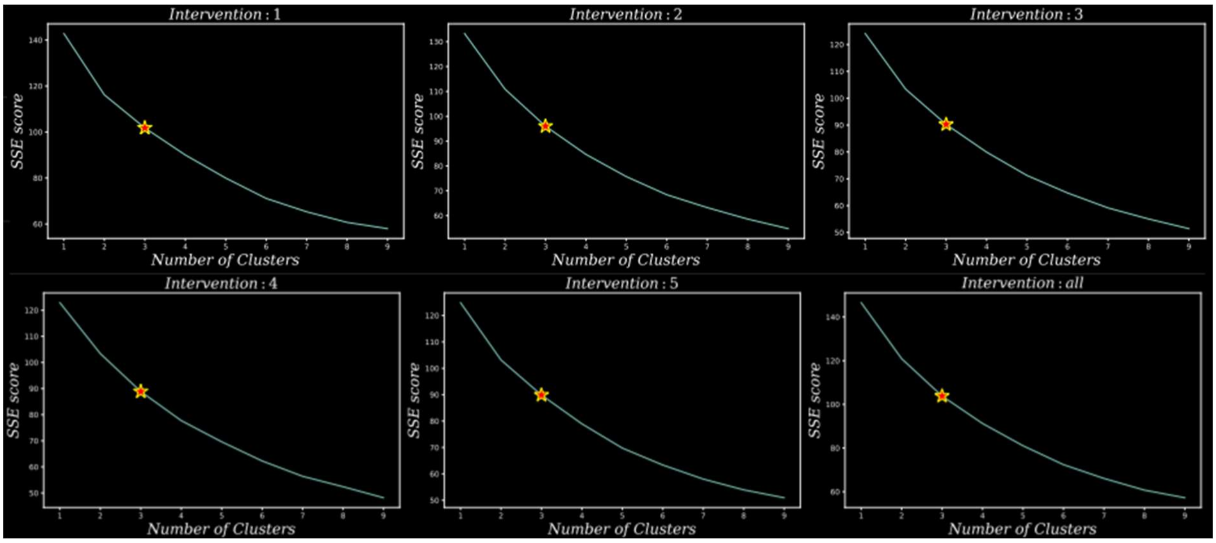


Figure 7: k-Means elbow plots for German interventions.

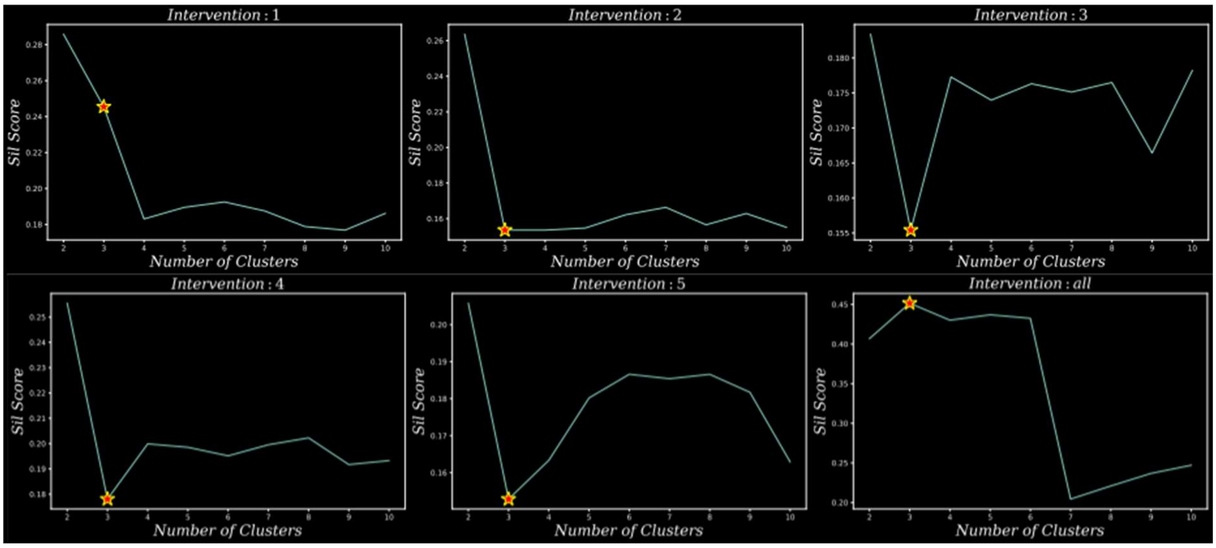


Figure 8: k-Means silhouette plots for German intervention

1.1.4 German intervention with data imputation

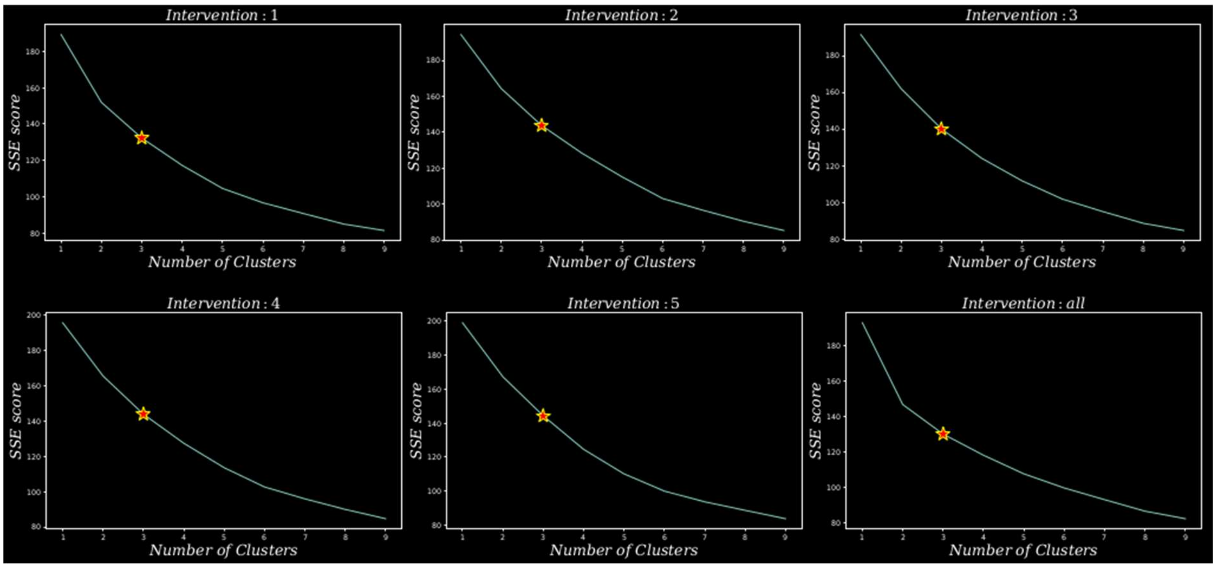


Figure 10: k-Means elbow plots for German interventions

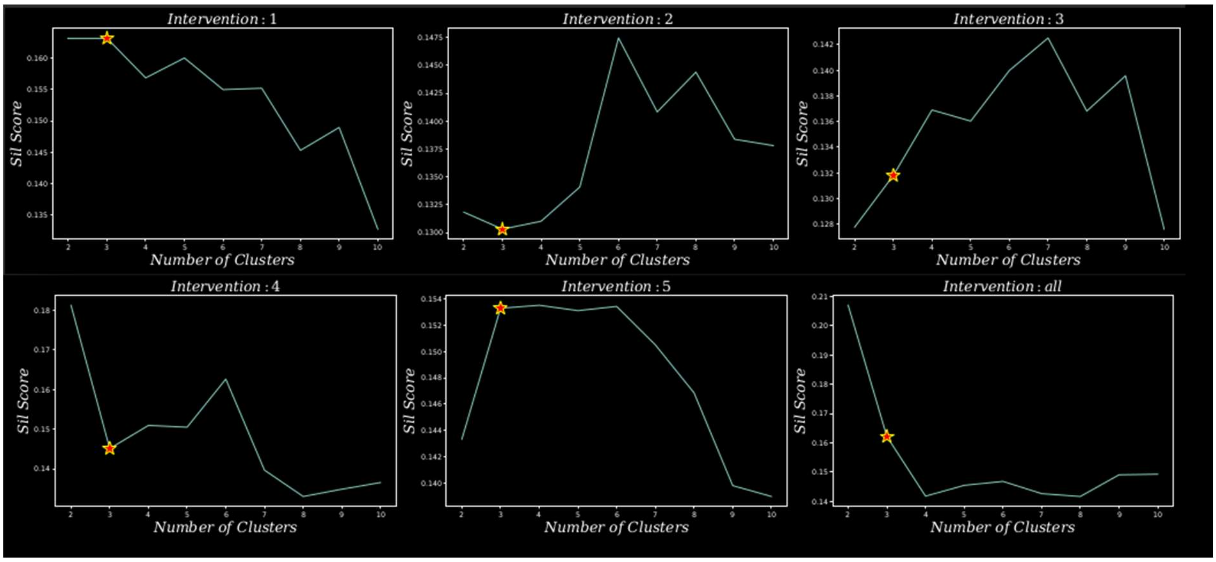


Figure 9: k-Means silhouette plots for German interventions

1.1.5 Other EU interventions without data imputation

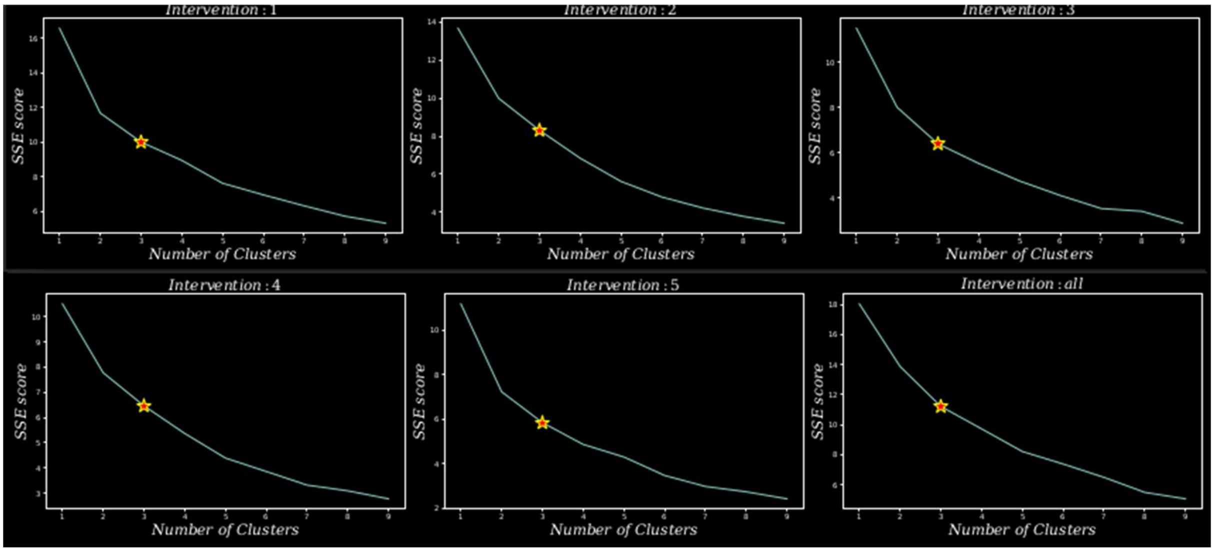


Figure 11: k-Means elbow plots for rest of EU interventions.

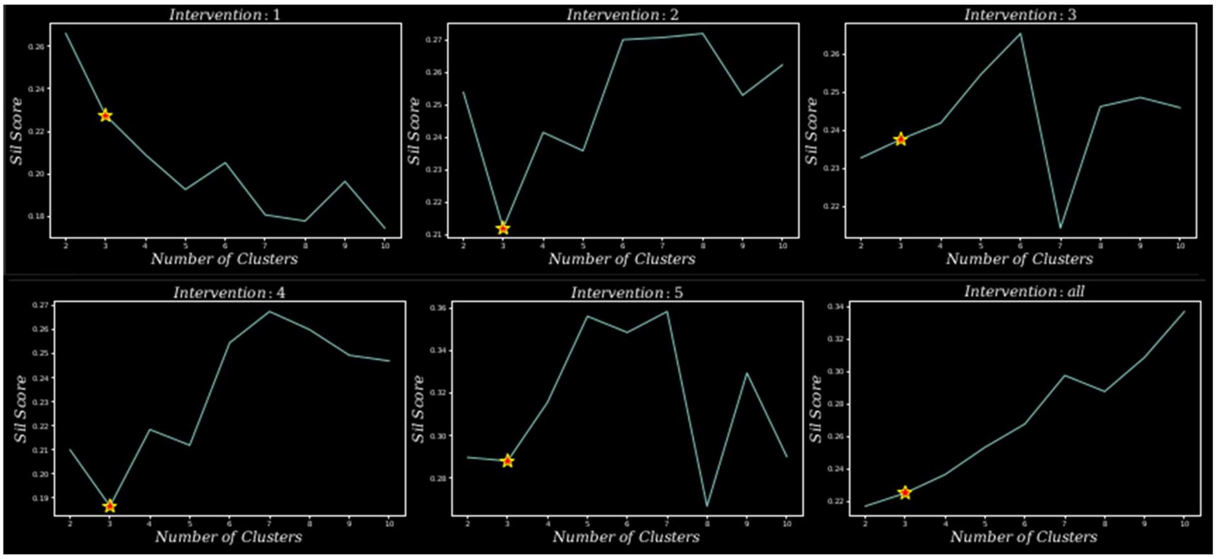


Figure 12: k-Means silhouette plots for rest of EU interventions.

1.1.6 Other EU interventions with data imputation

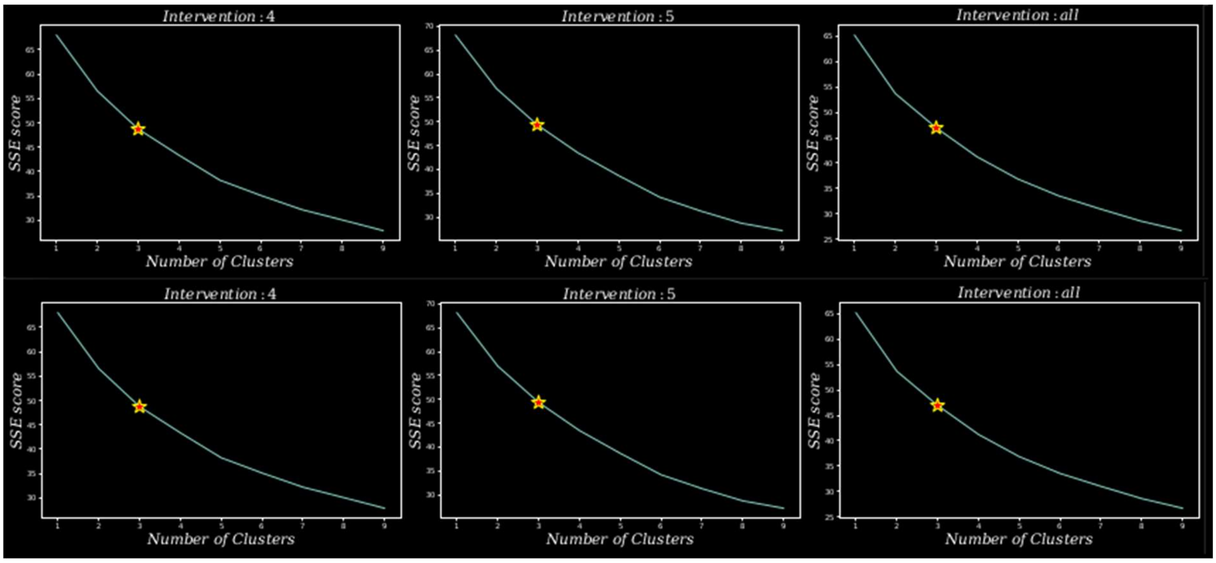


Figure 13: k-Means elbow plots for rest of EU interventions.

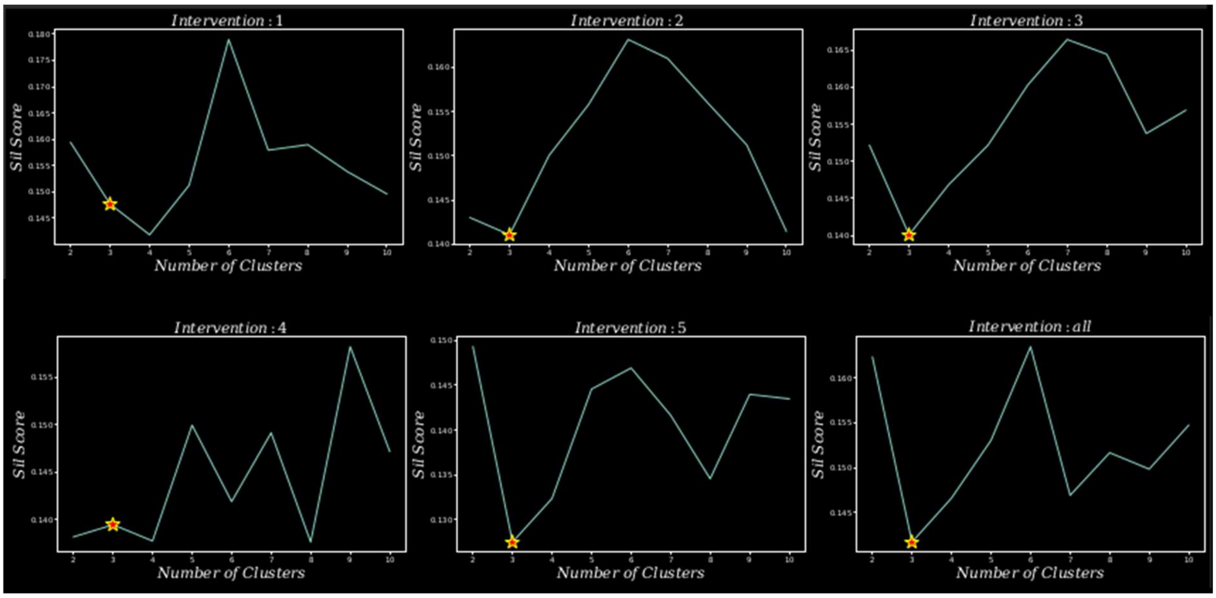


Figure 14: k-Means silhouette plots for rest of EU interventions.

1.2 Cluster detection for each country

1.2.1 Norwegian intervention without data imputation

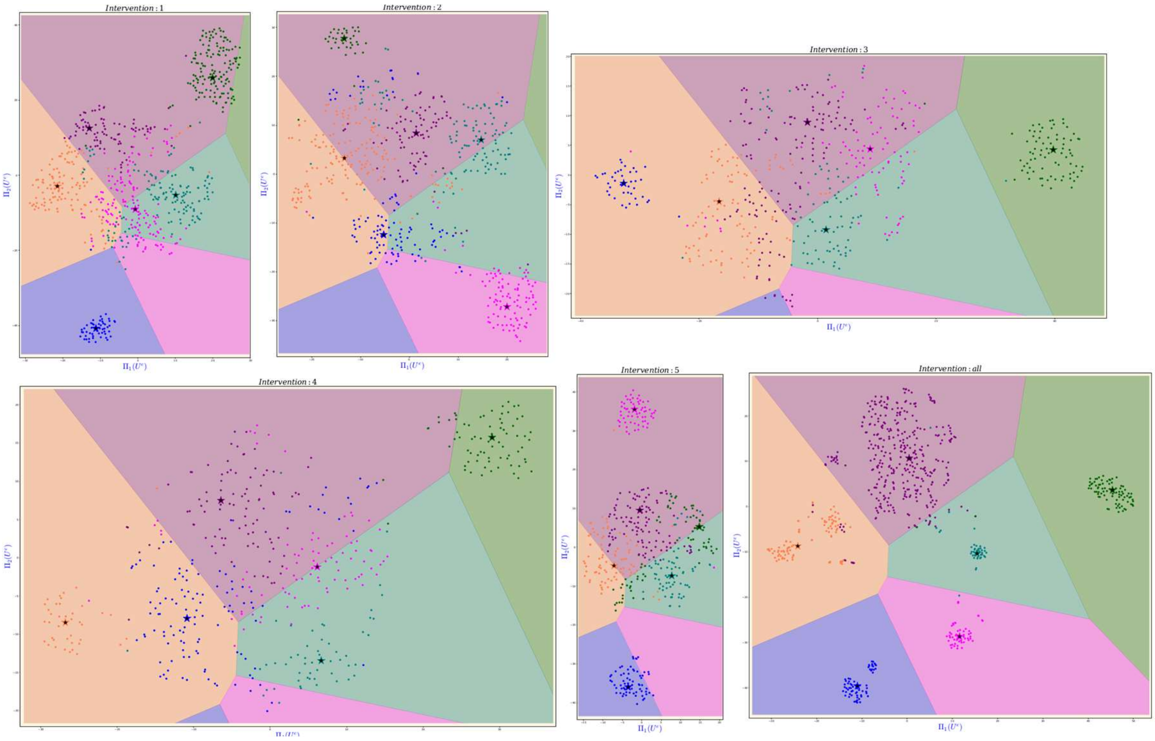


Figure 15: t-SNE plots of behavioural clusters in Norway using user embeddings.

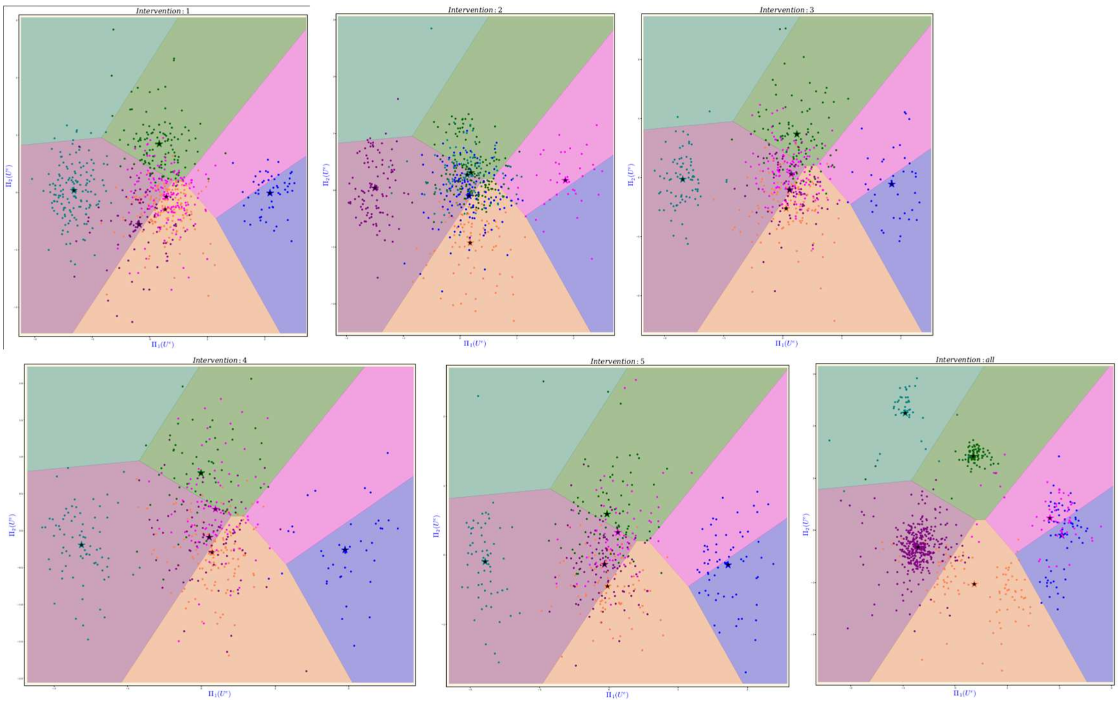


Figure 16: PCA plots of behavioural clusters in Norway using user embeddings.

1.2.2 Norwegian intervention with data imputation

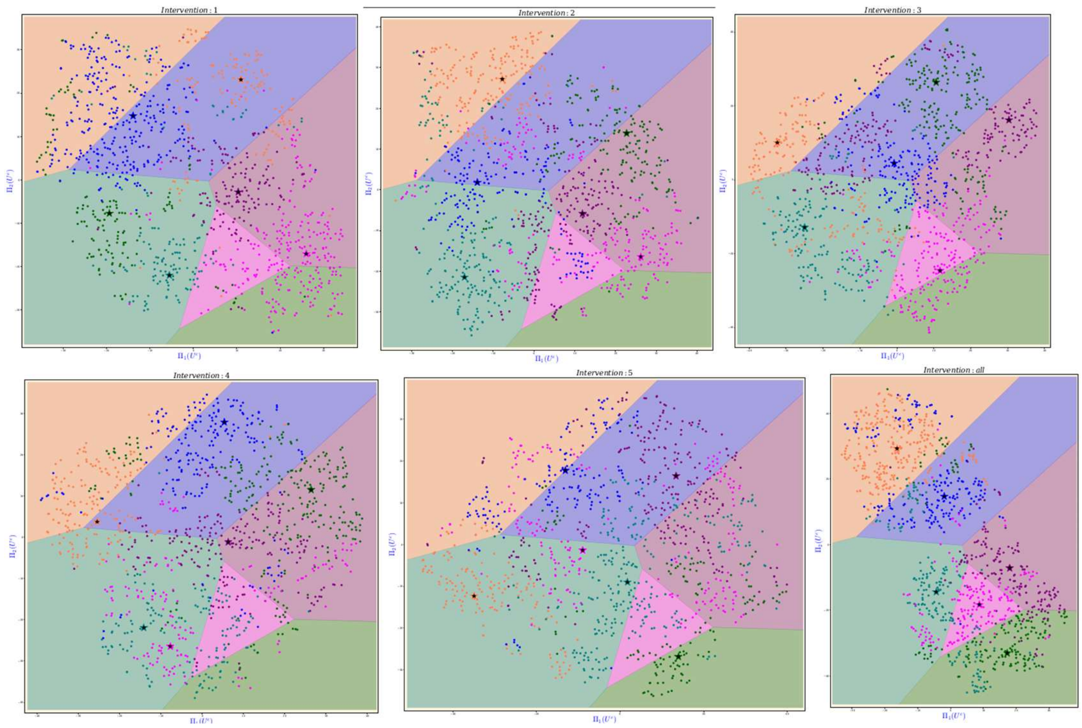


Figure 17: t-SNE plots of behavioural clusters in Norway using user embeddings.

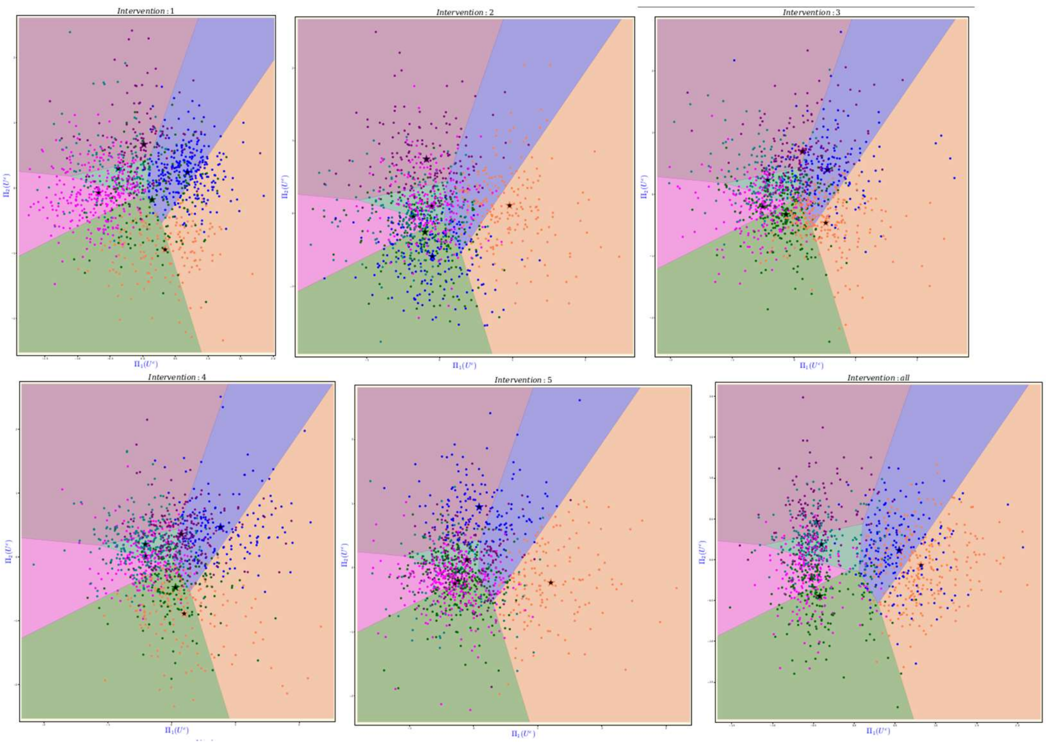


Figure 18: PCA plots of behavioural clusters in Norway using user embeddings.

1.2.3 German intervention without data imputation

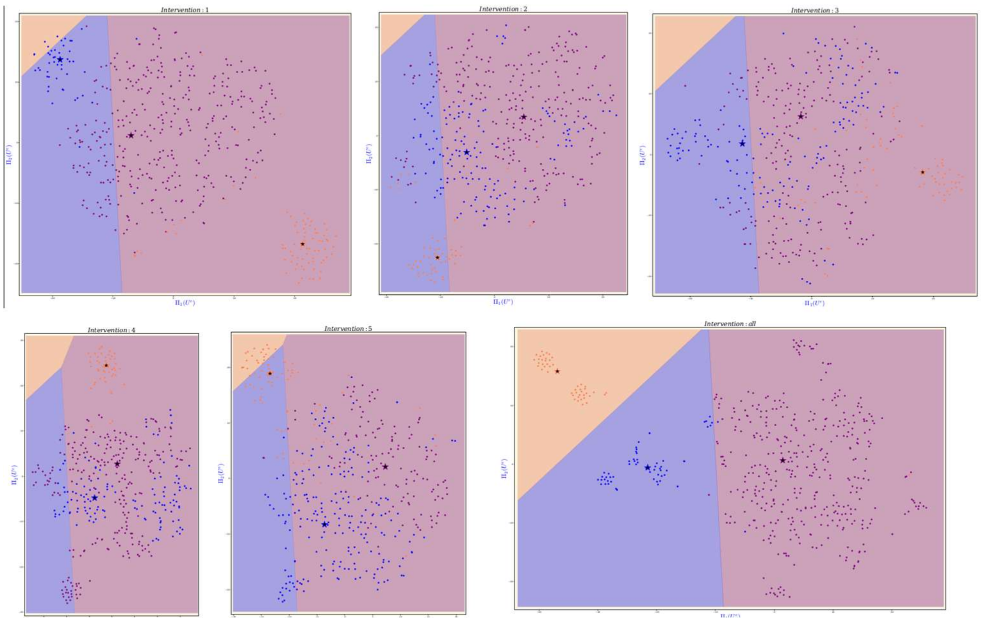


Figure 19: t-SNE plots of behavioural clusters in Germany using user embeddings.

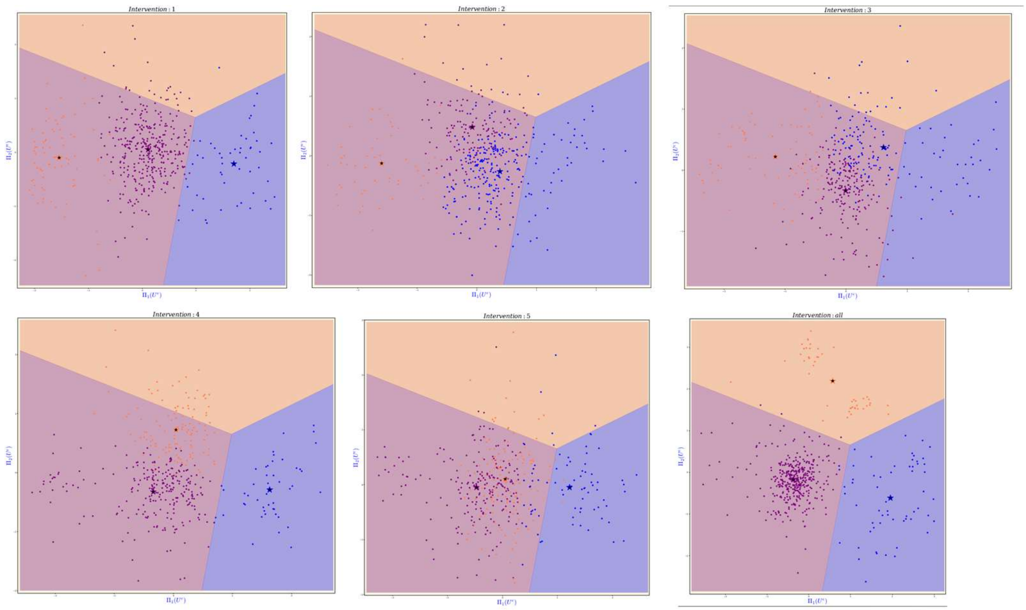


Figure 20: PCA plots of behavioural clusters in Germany using user embeddings.

1.2.4 German intervention with data imputation

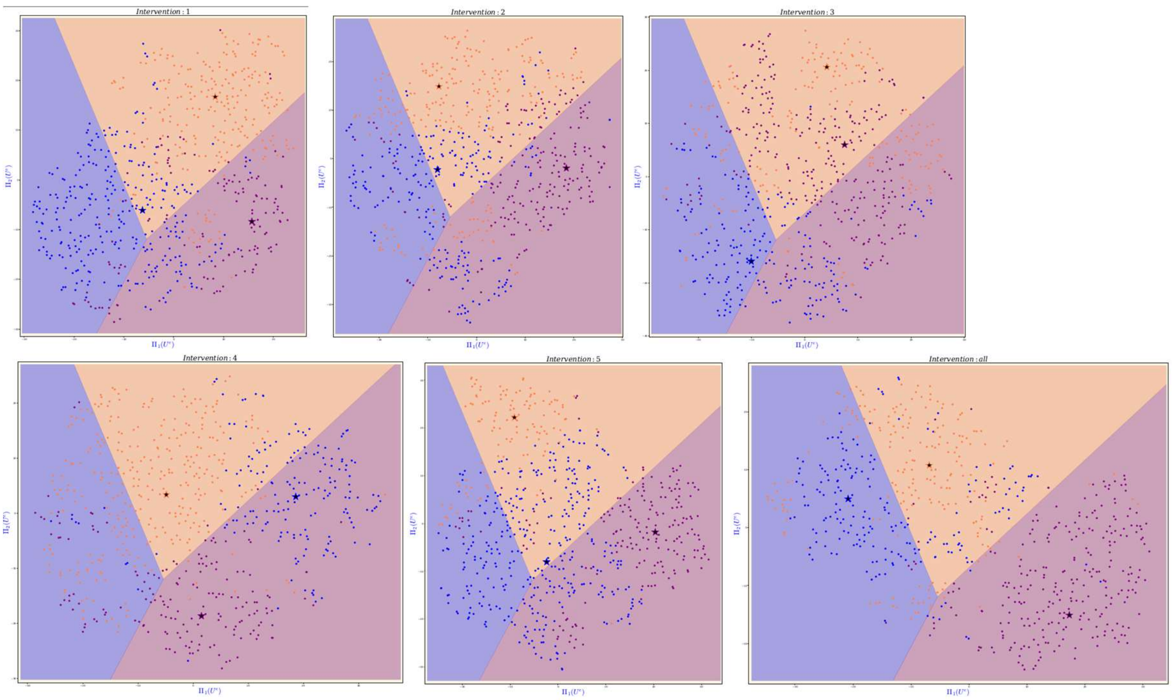


Figure 21: t-SNE plots of behavioural clusters in Germany using user embeddings.

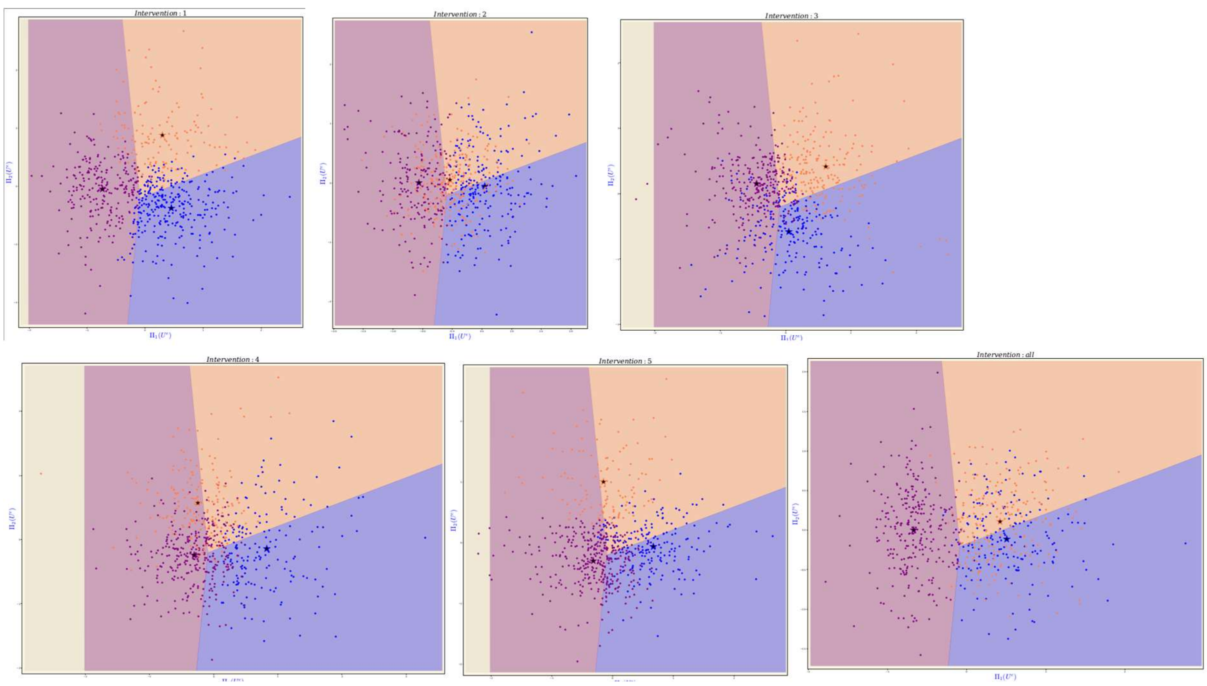


Figure 22: PCA plots of behavioural clusters in Germany using user embeddings.

1.2.5 Other EU interventions without data imputation

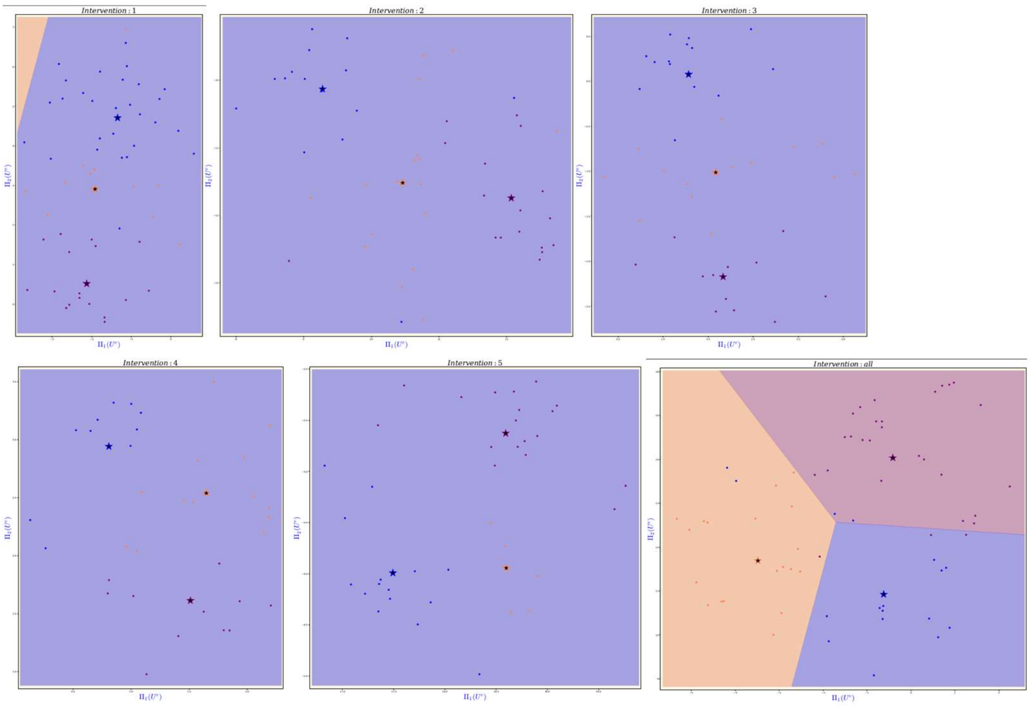


Figure 23: t-SNE plots of behavioural clusters in rest of EU using user embeddings.

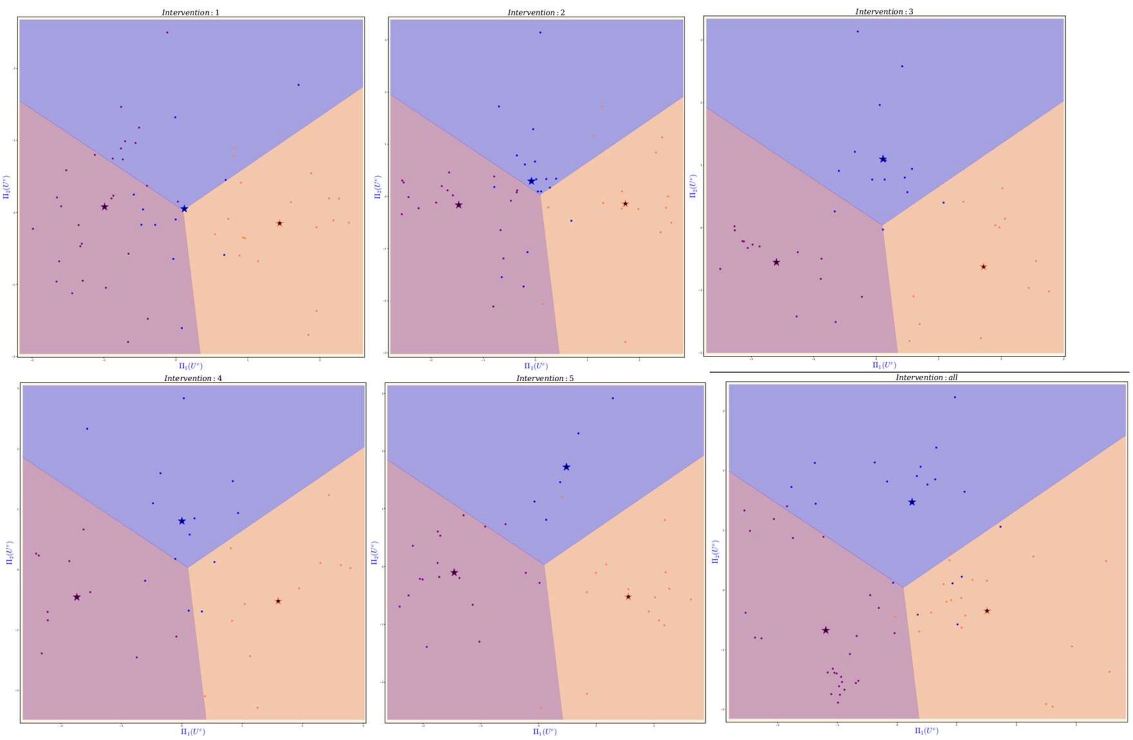


Figure 24: PCA plots of behavioural clusters in rest of EU using user embeddings.

1.2.6 Other EU interventions with data imputation

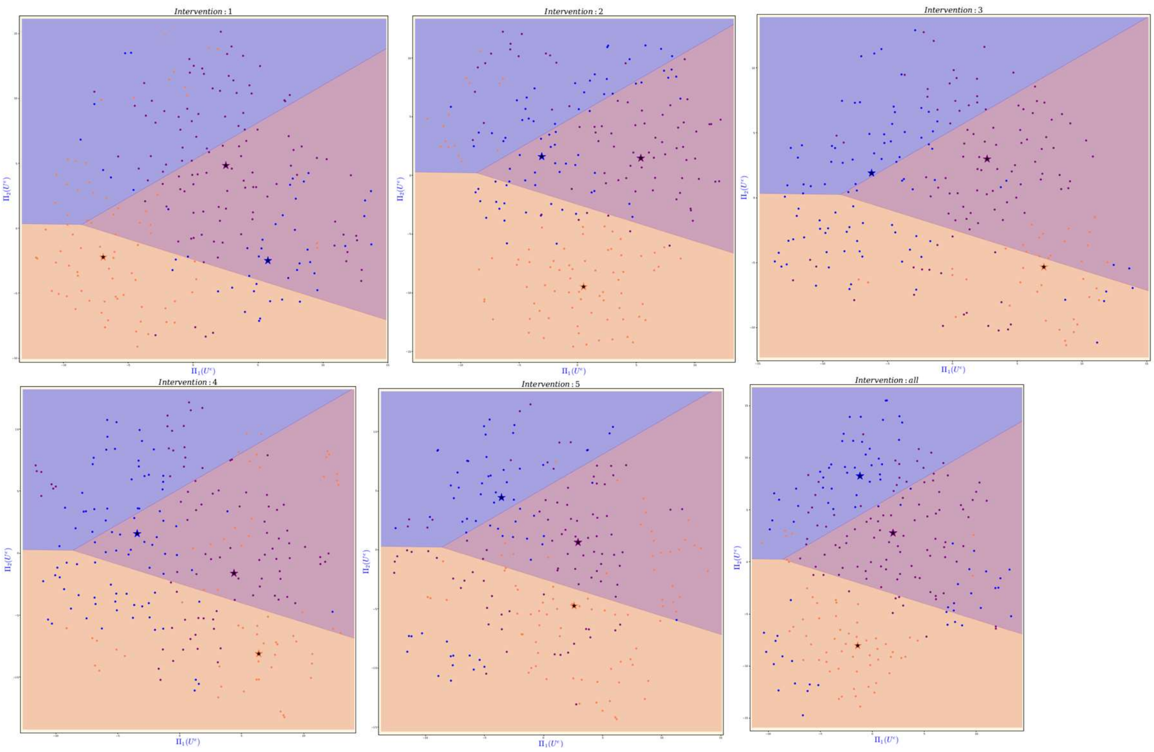


Figure 25: t-SNE plots of behavioural clusters in rest of EU using user embeddings.

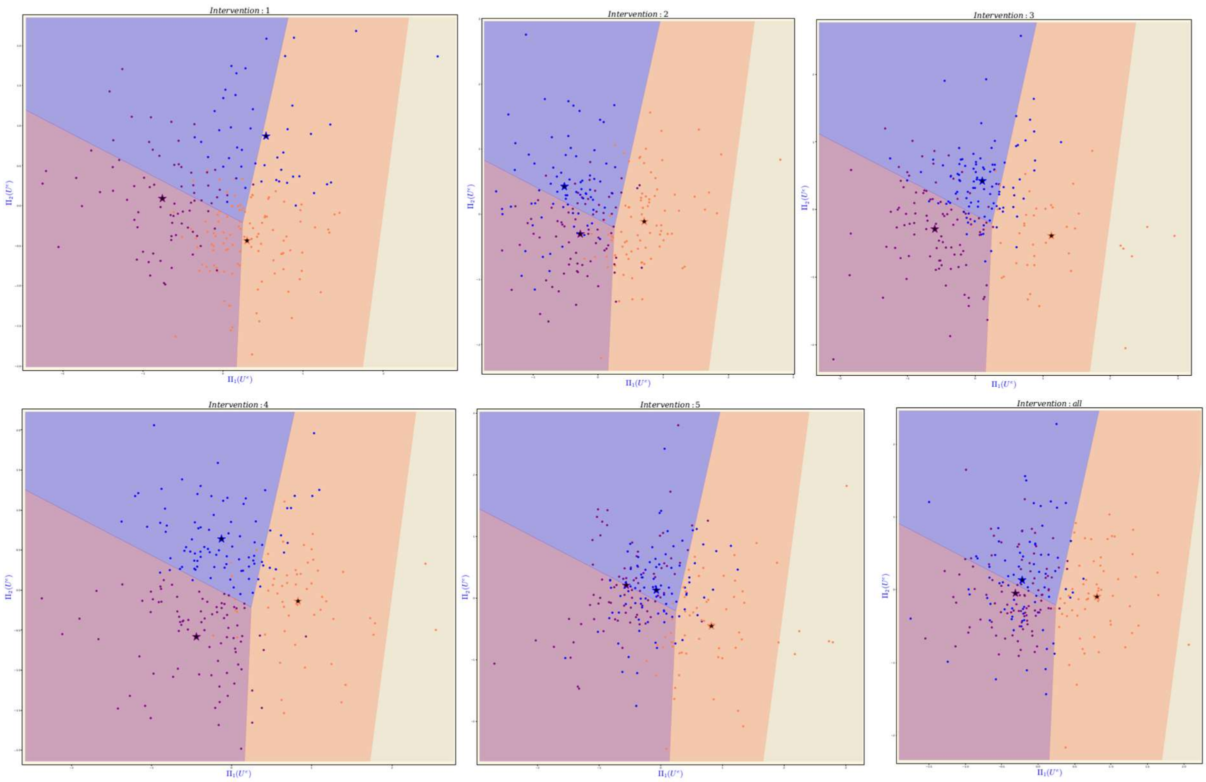


Figure 26: PCA plots of behavioural clusters in rest of EU using user embeddings.

1.3 Correlation of survey patterns with energy consumption

1.3.1 Norwegian intervention without data imputation

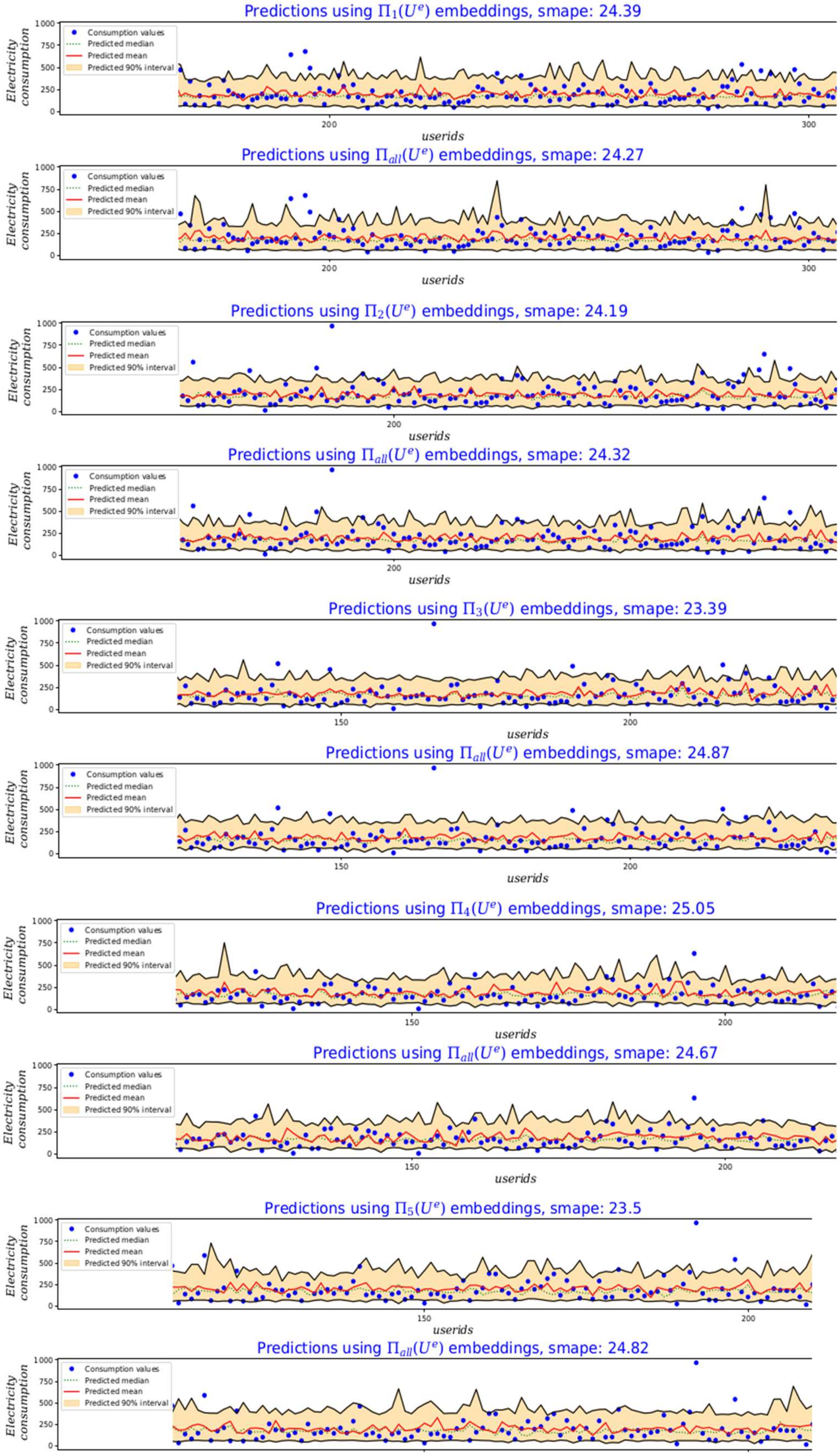


Figure 27: Prediction of energy consumption from behavioural vectors (NO).

1.3.2 Norwegian intervention with data imputation

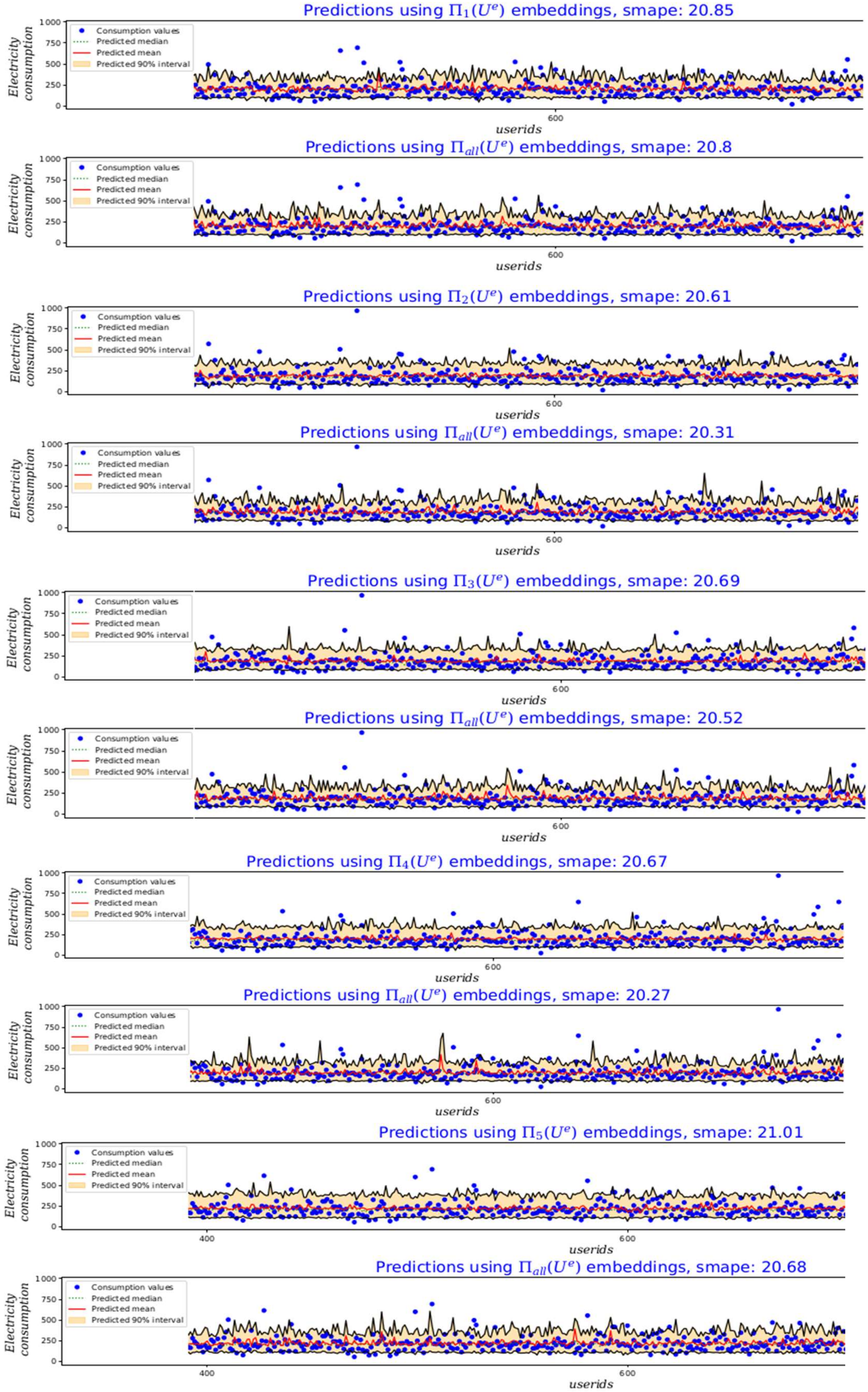


Figure 28: Prediction of energy consumption from behavioural vectors (NO).

1.3.3 German intervention without data imputation

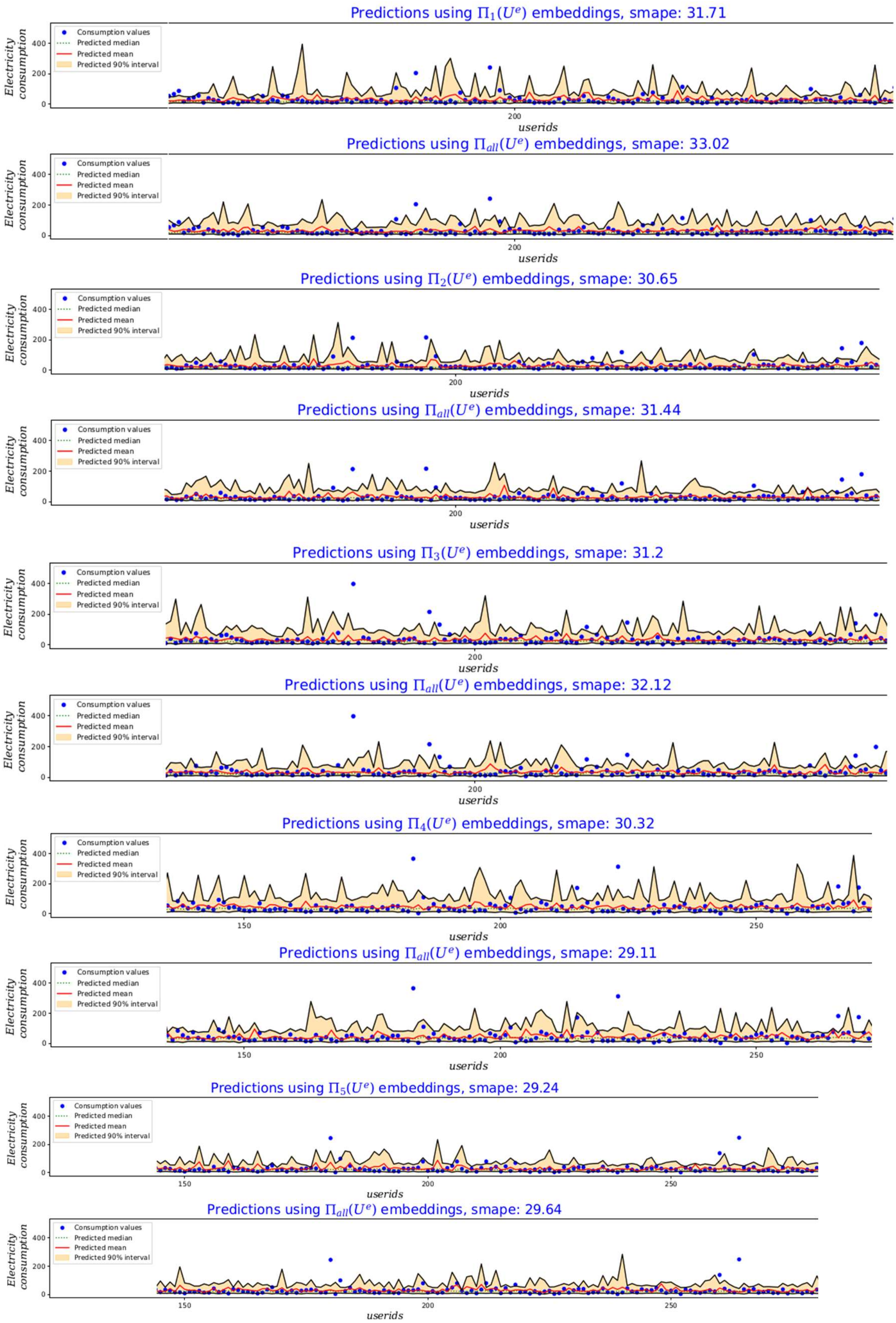


Figure 29: Prediction of energy consumption from behavioural vectors (DE).

1.3.4 German intervention with data imputation

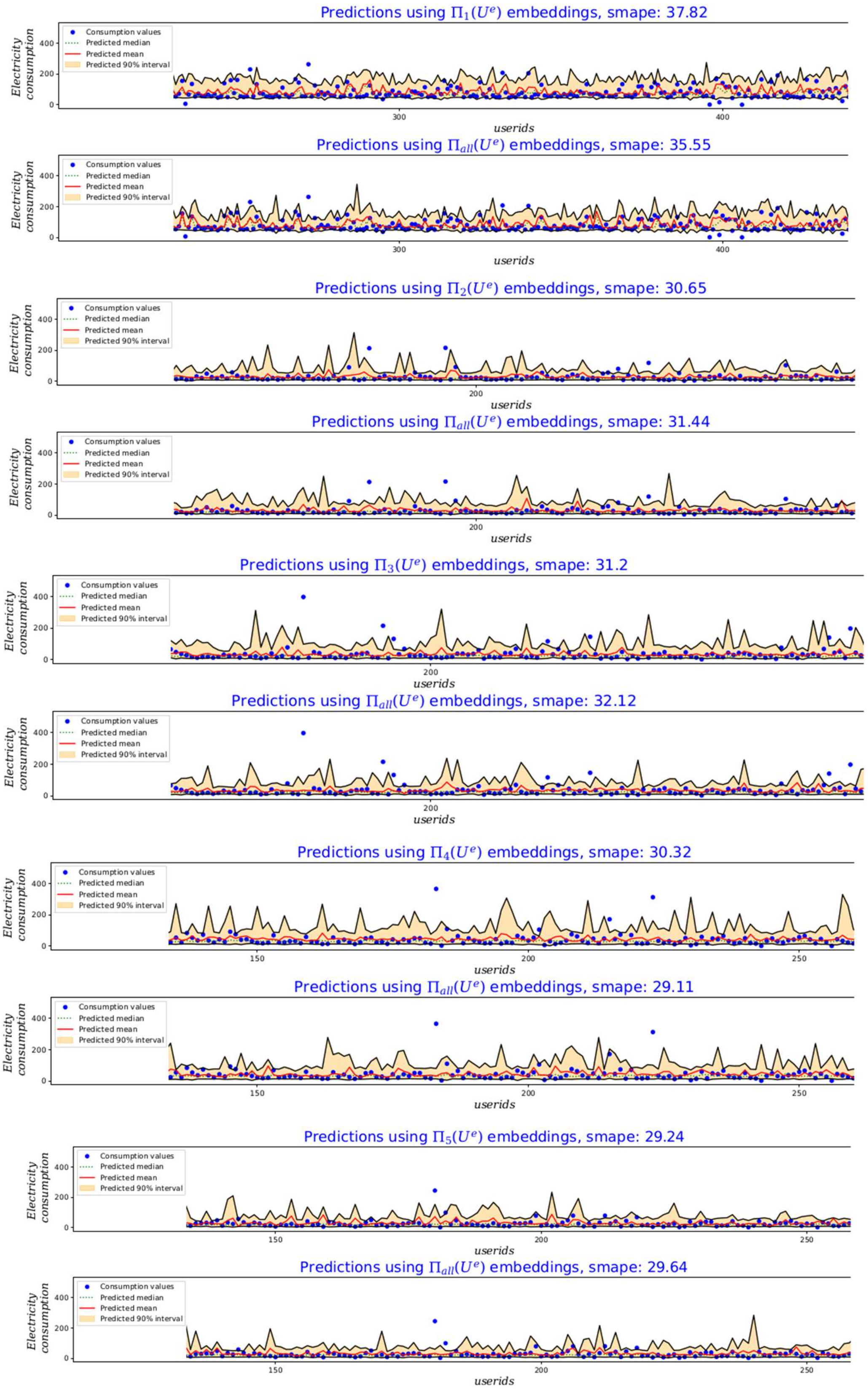


Figure 30: Prediction of energy consumption from behavioural vectors (DE).

1.3.5 Other EU interventions without data imputation

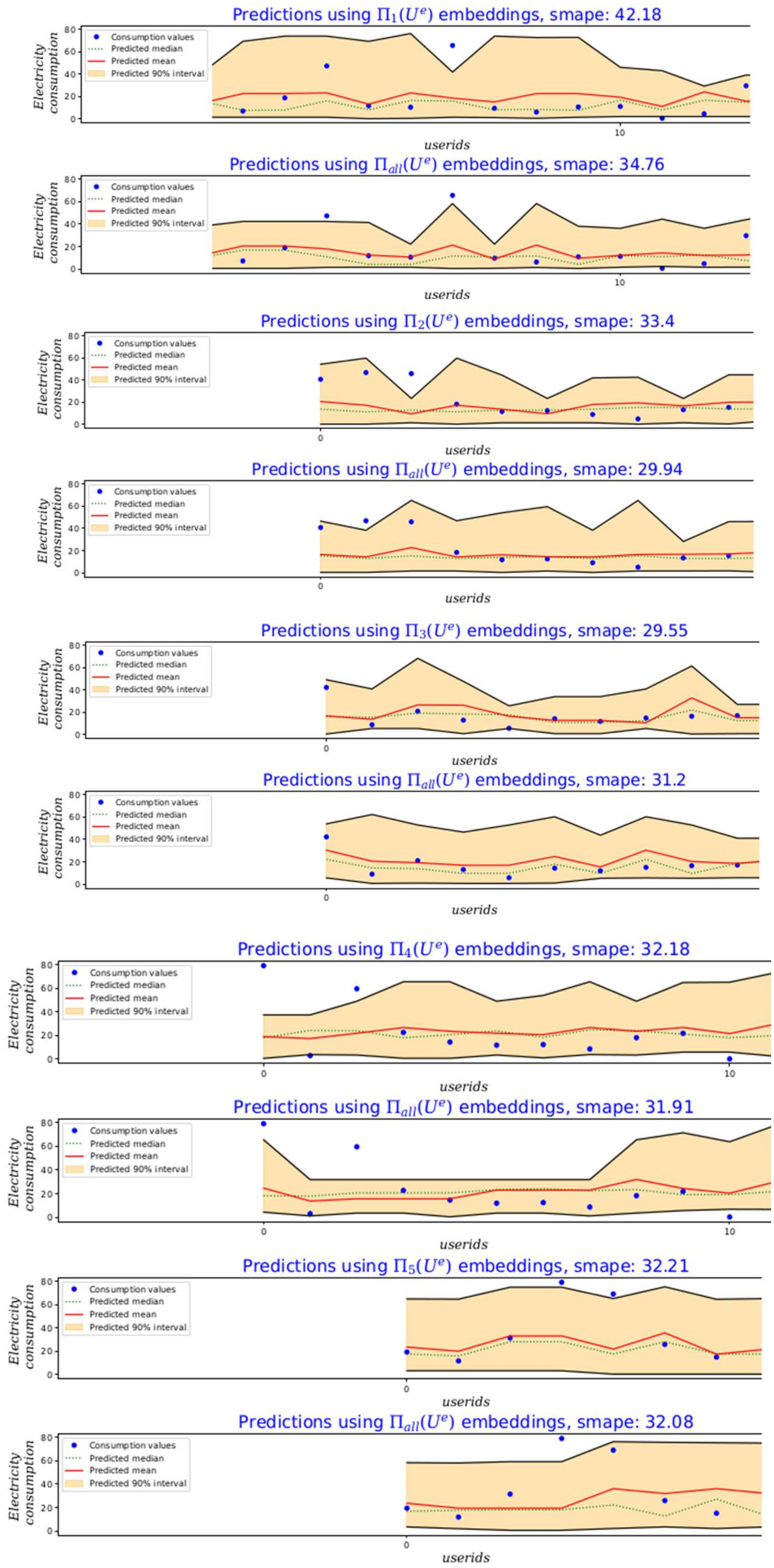


Figure 31: Prediction of energy consumption from behavioural vectors (OT).

1.3.6 Other EU interventions with data imputation

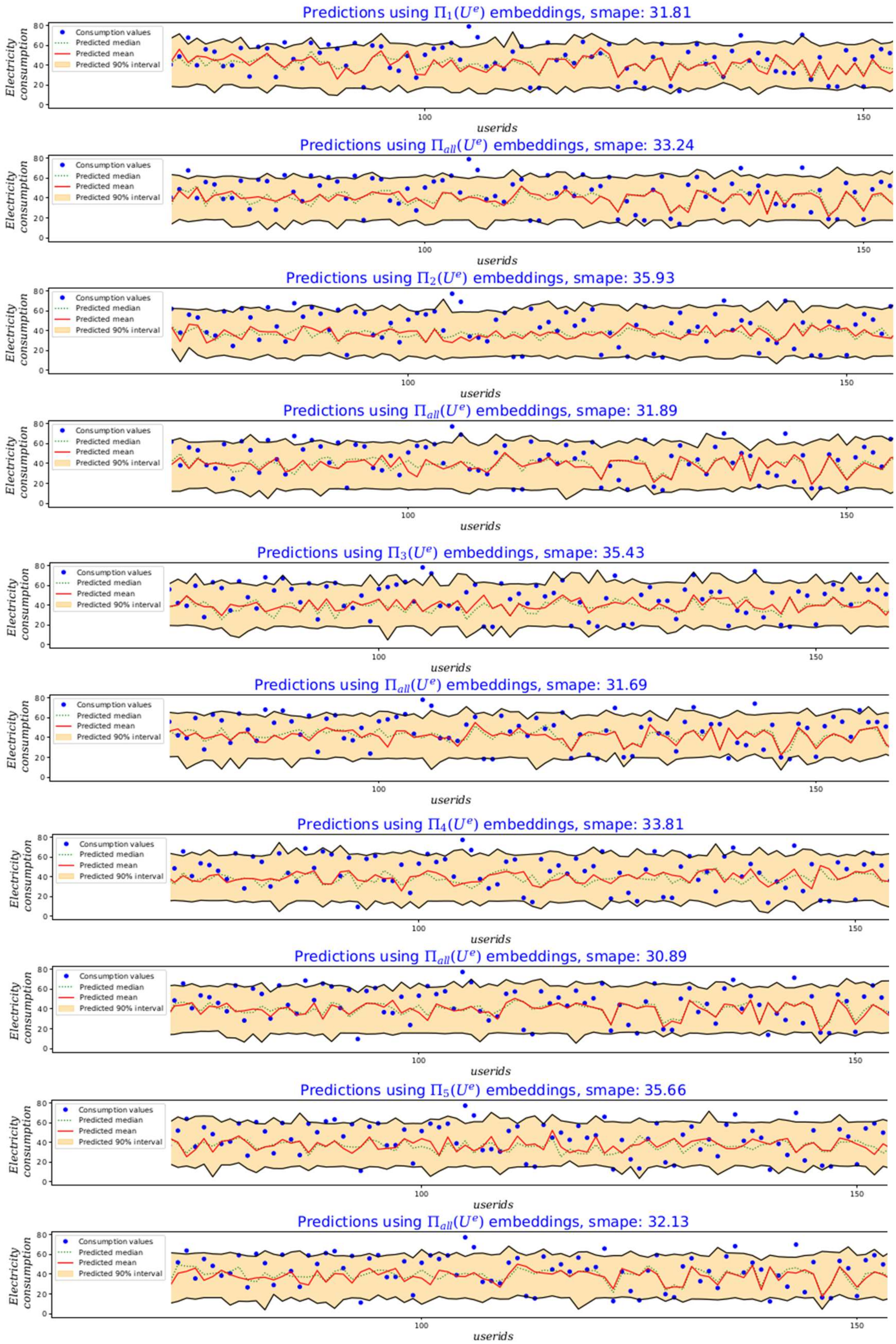


Figure 32: Prediction of energy consumption from behavioural vectors (OT).

1.4 Stratification of interventions per behaviour group

1.4.1 Norwegian intervention with data imputation

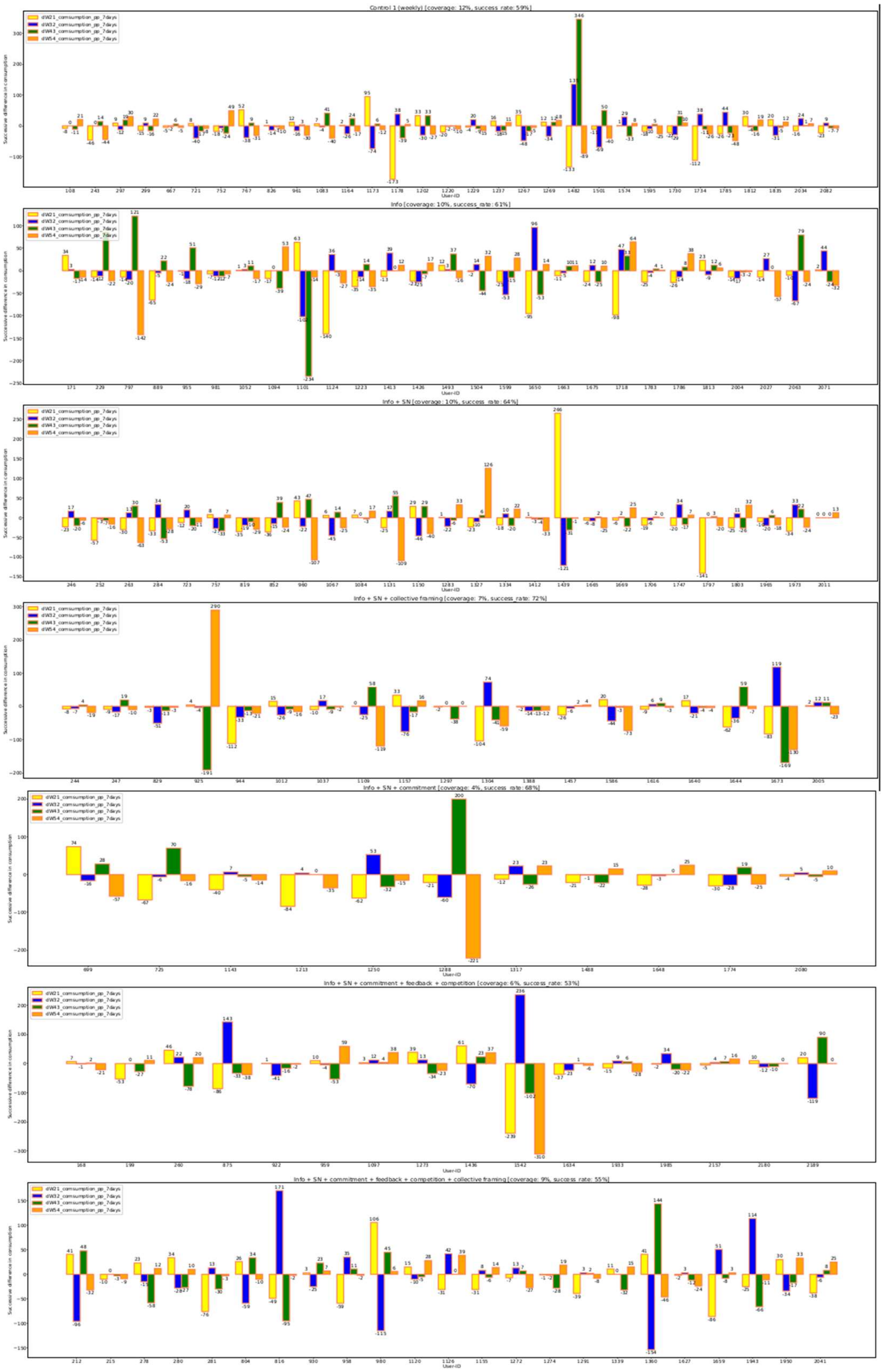


Figure 33: BG0 interventions 1-7 stratification.

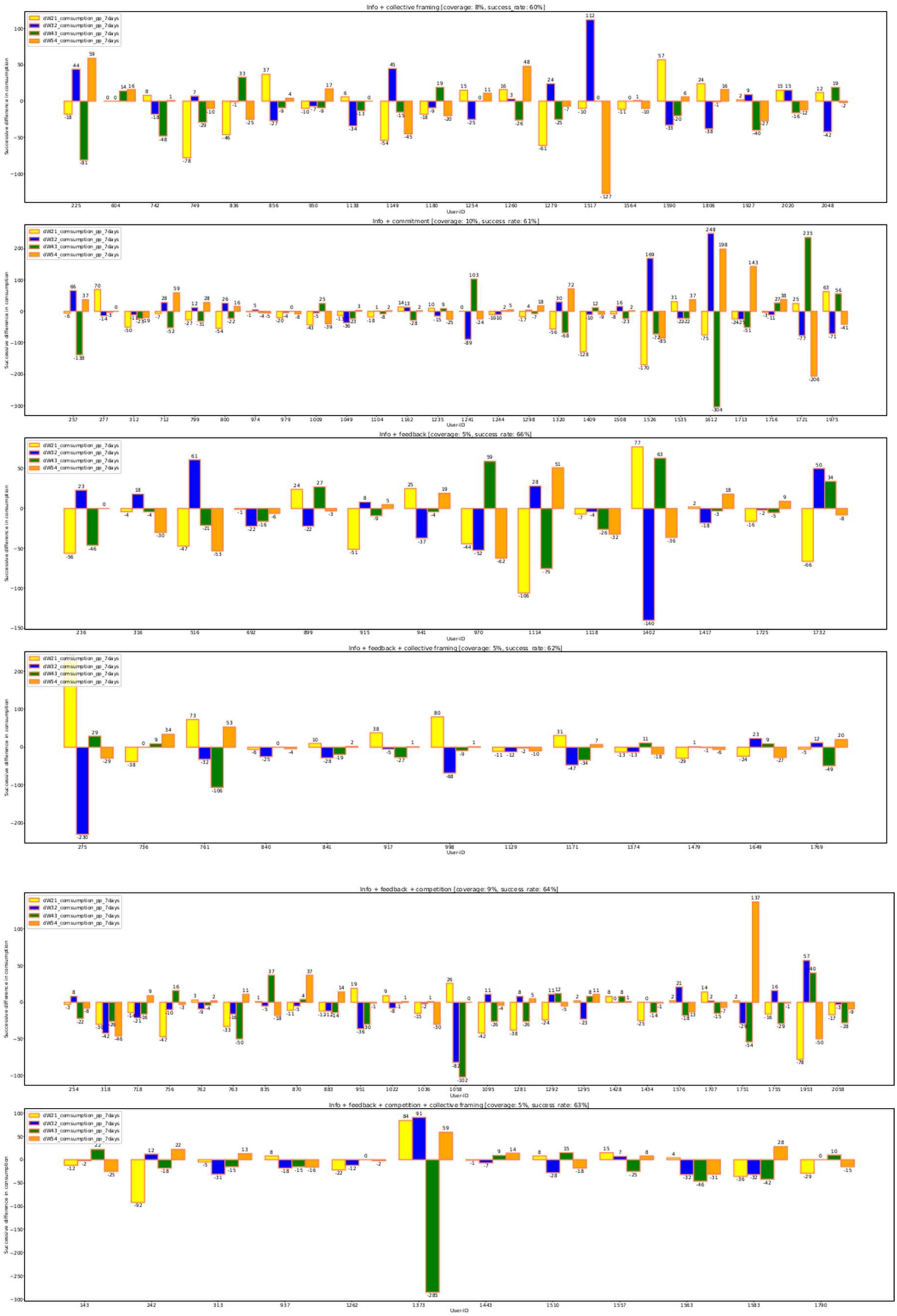


Figure 34: BG0 interventions 8-13 stratification.

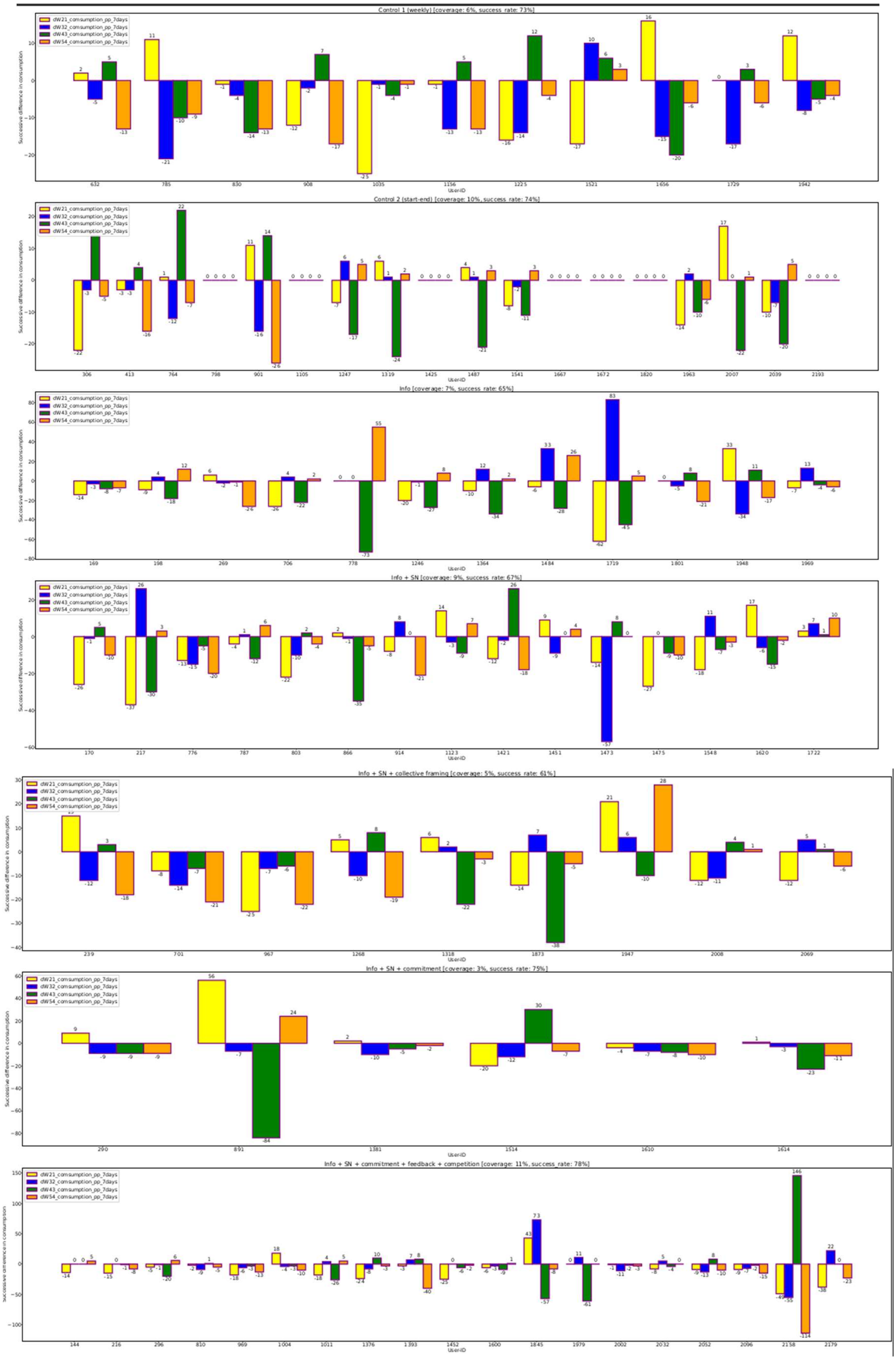


Figure 35: BG1 interventions 1-7 stratification.

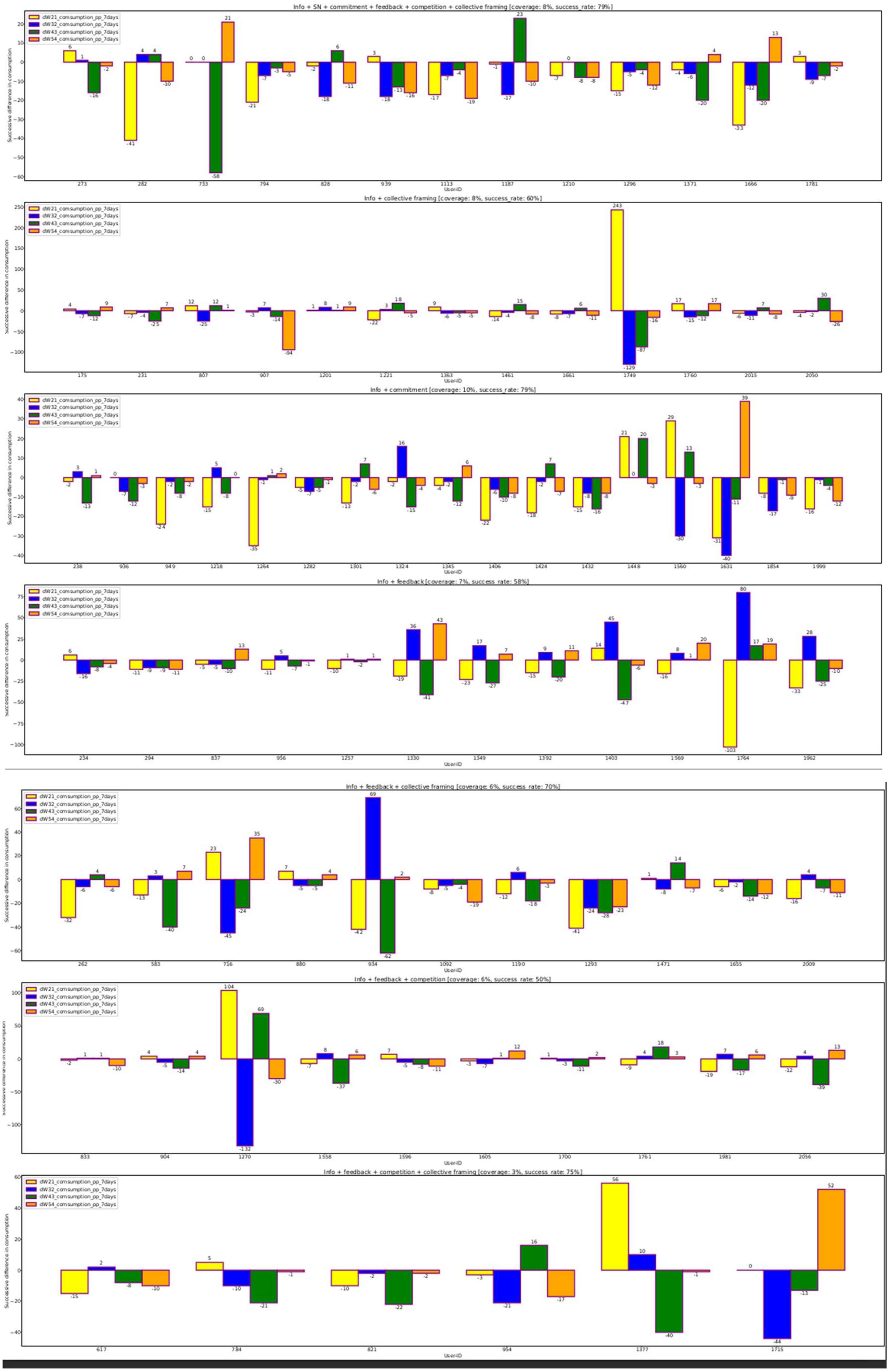


Figure 36: BG1 interventions 8-14 stratification.

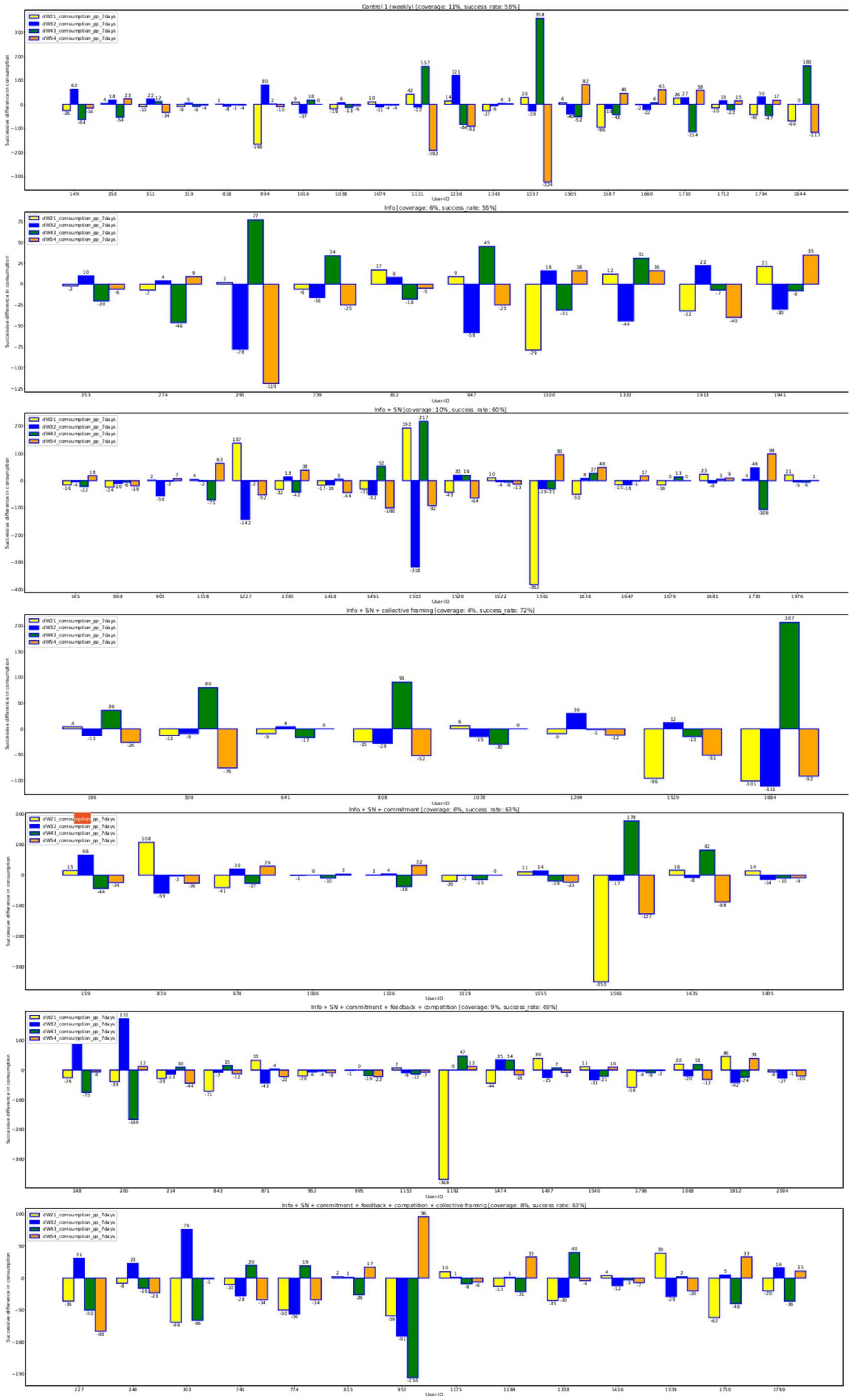


Figure 37: BG2 interventions 1-7 stratification.

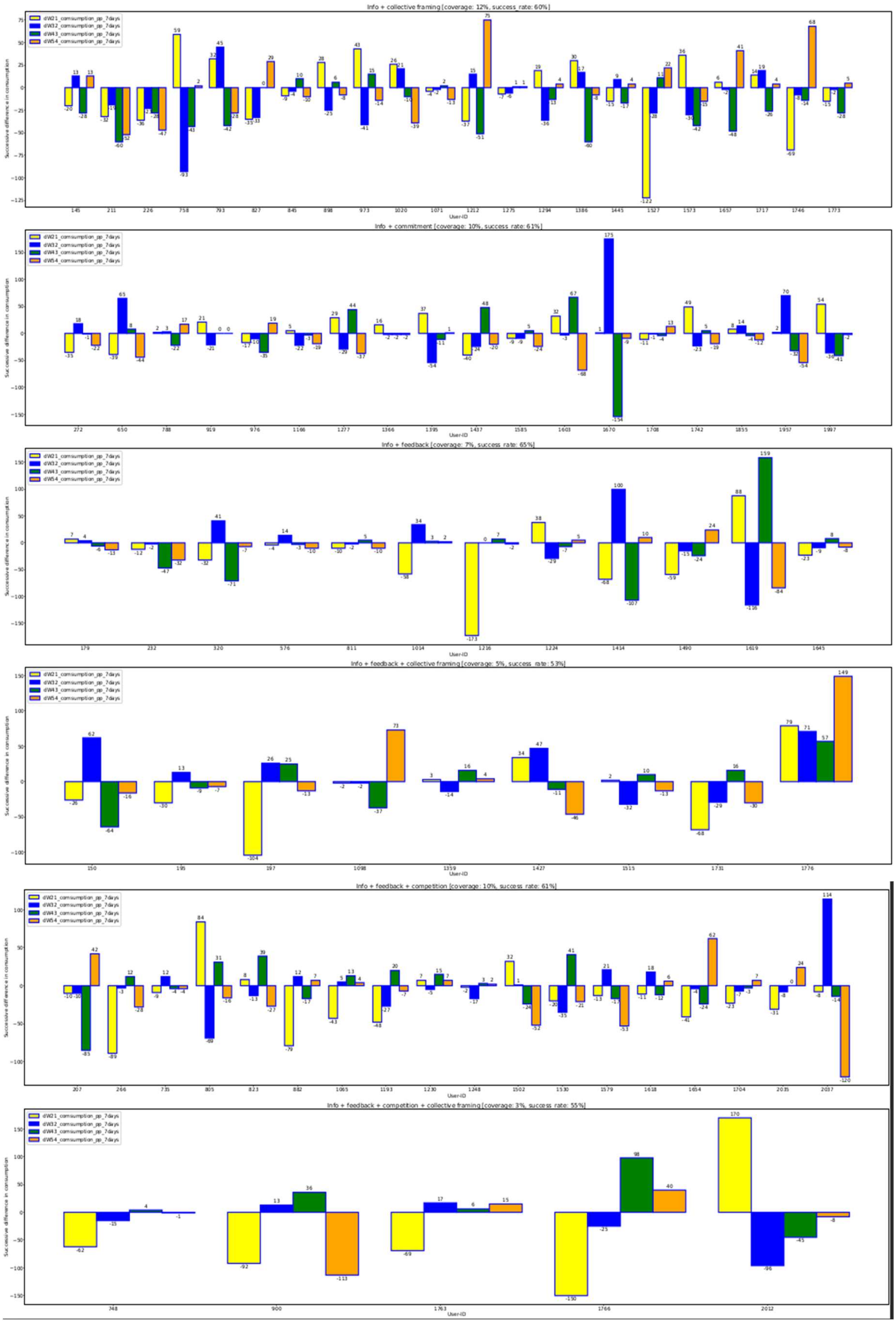


Figure 38: BG2 interventions 8-13 stratification.

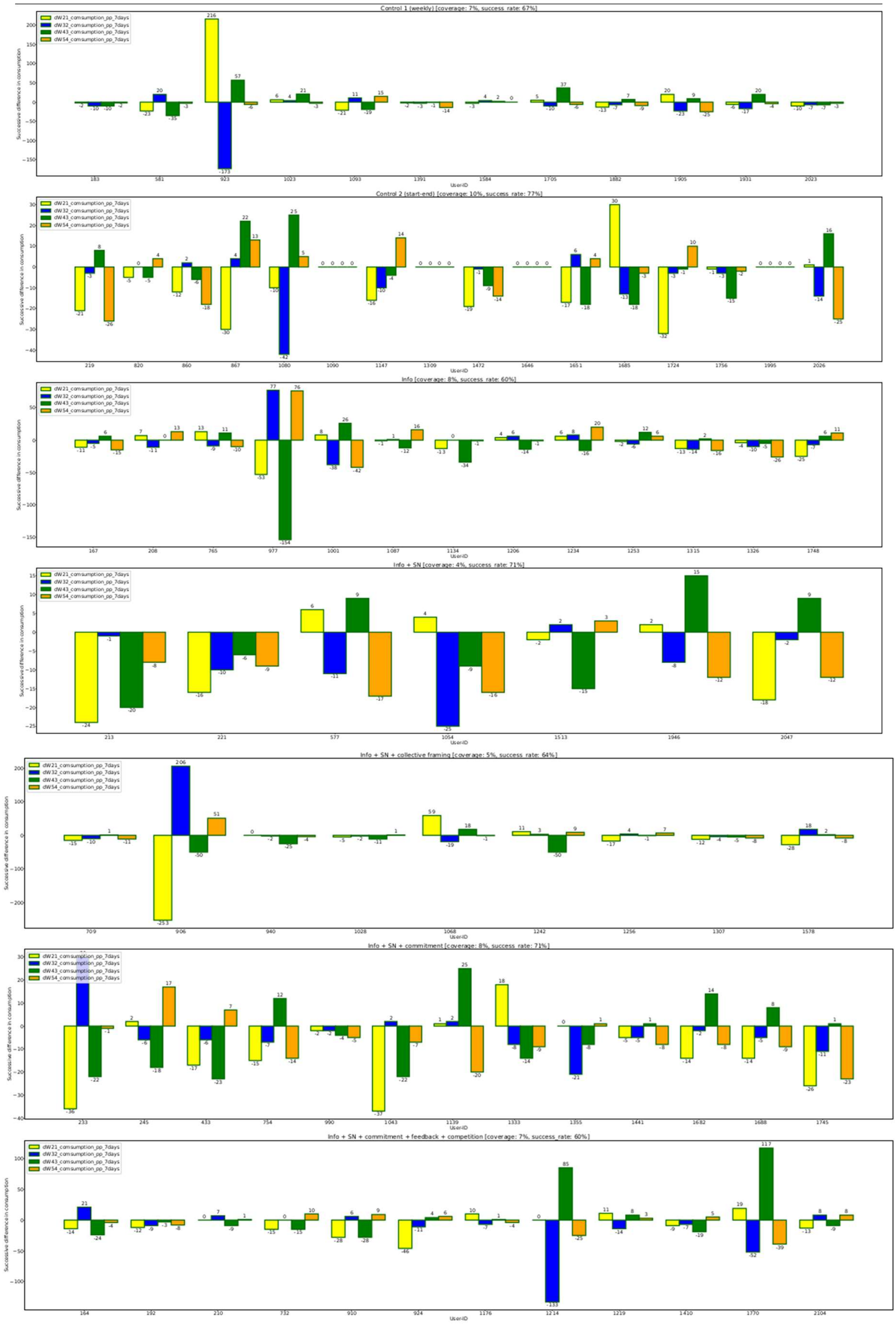


Figure 39: BG3 interventions 1-7 stratification.

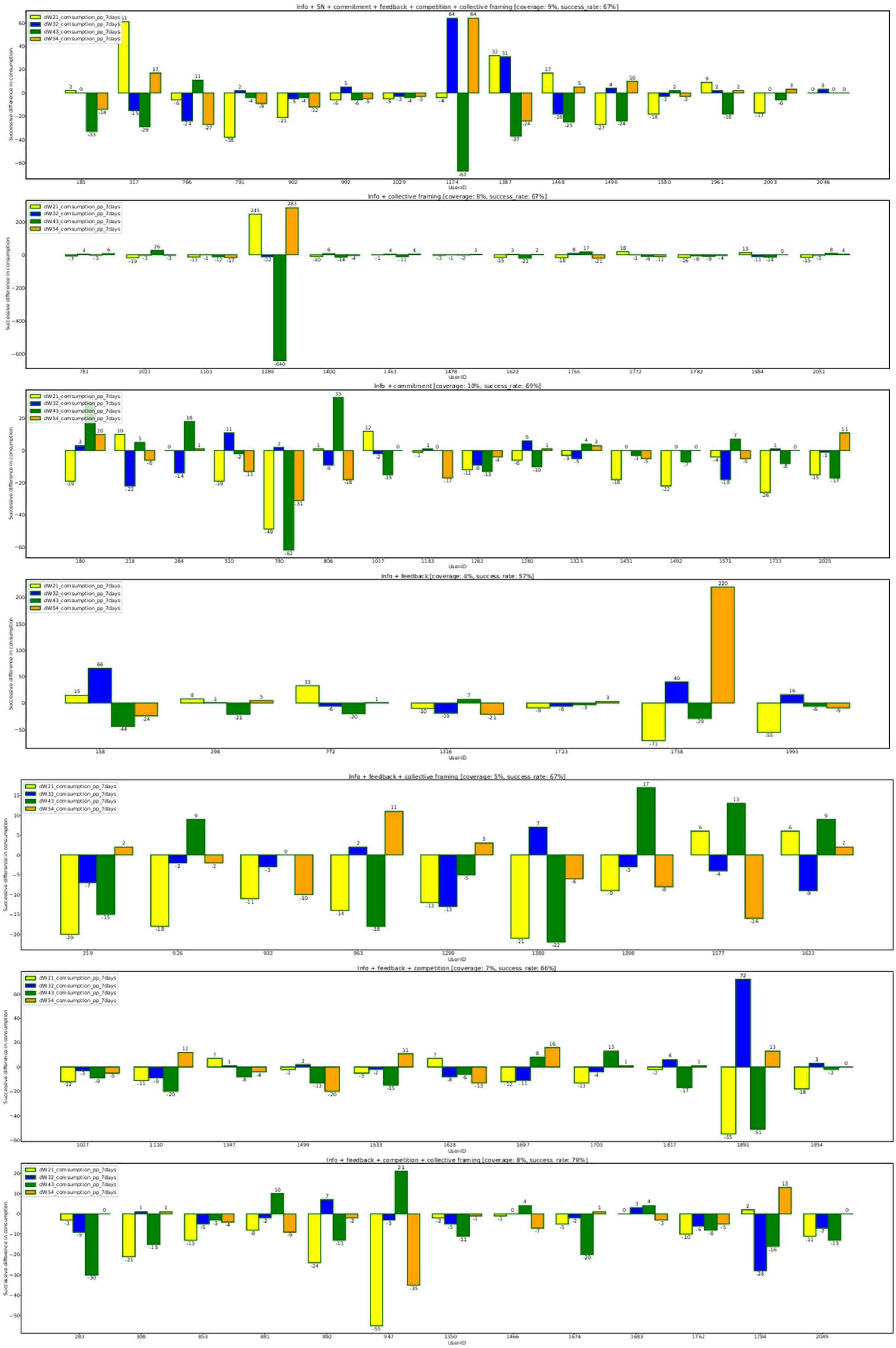


Figure 40: BG3 interventions 8-14 stratification.

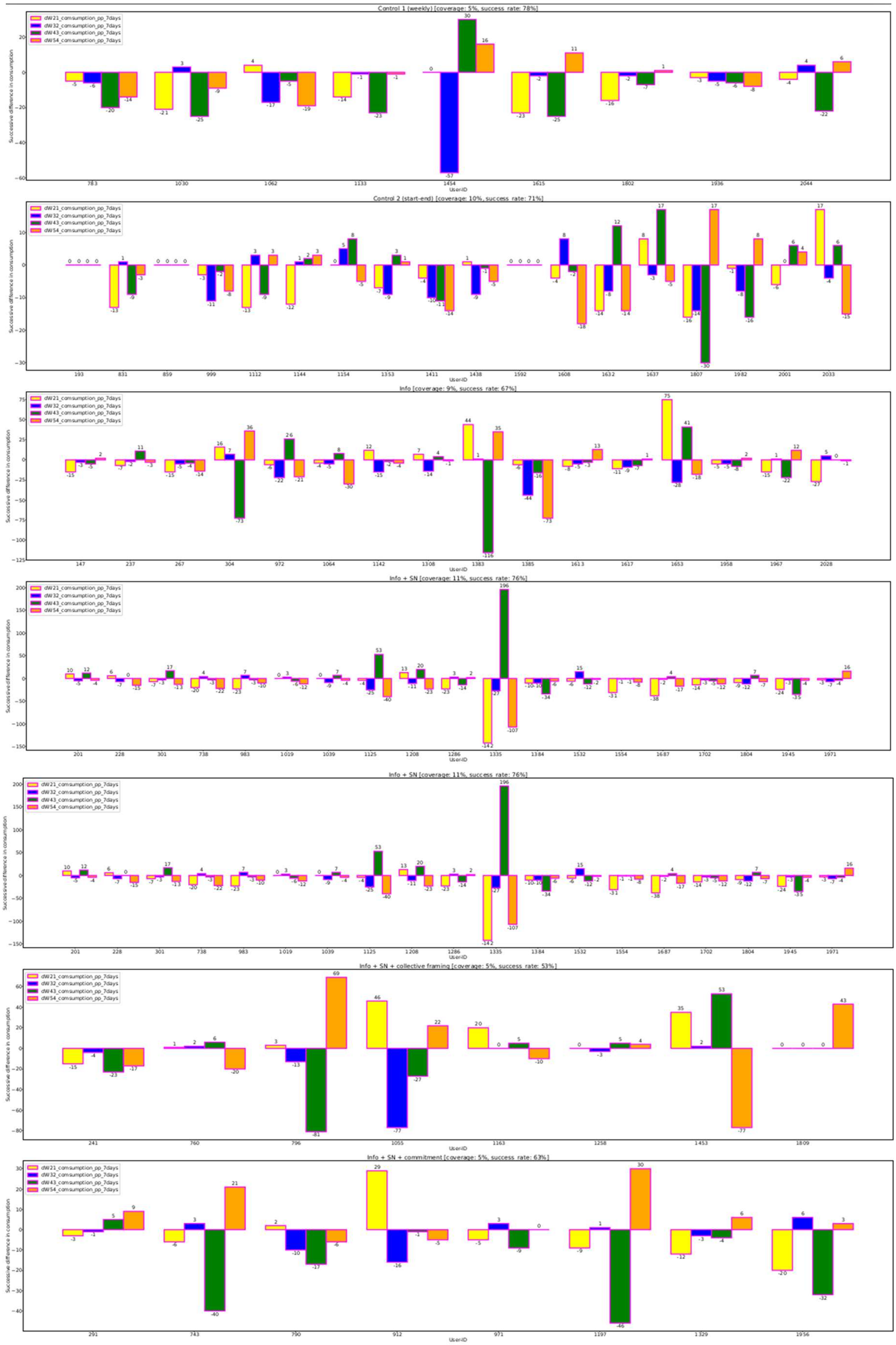


Figure 41: BG4 interventions 1-7 stratification.

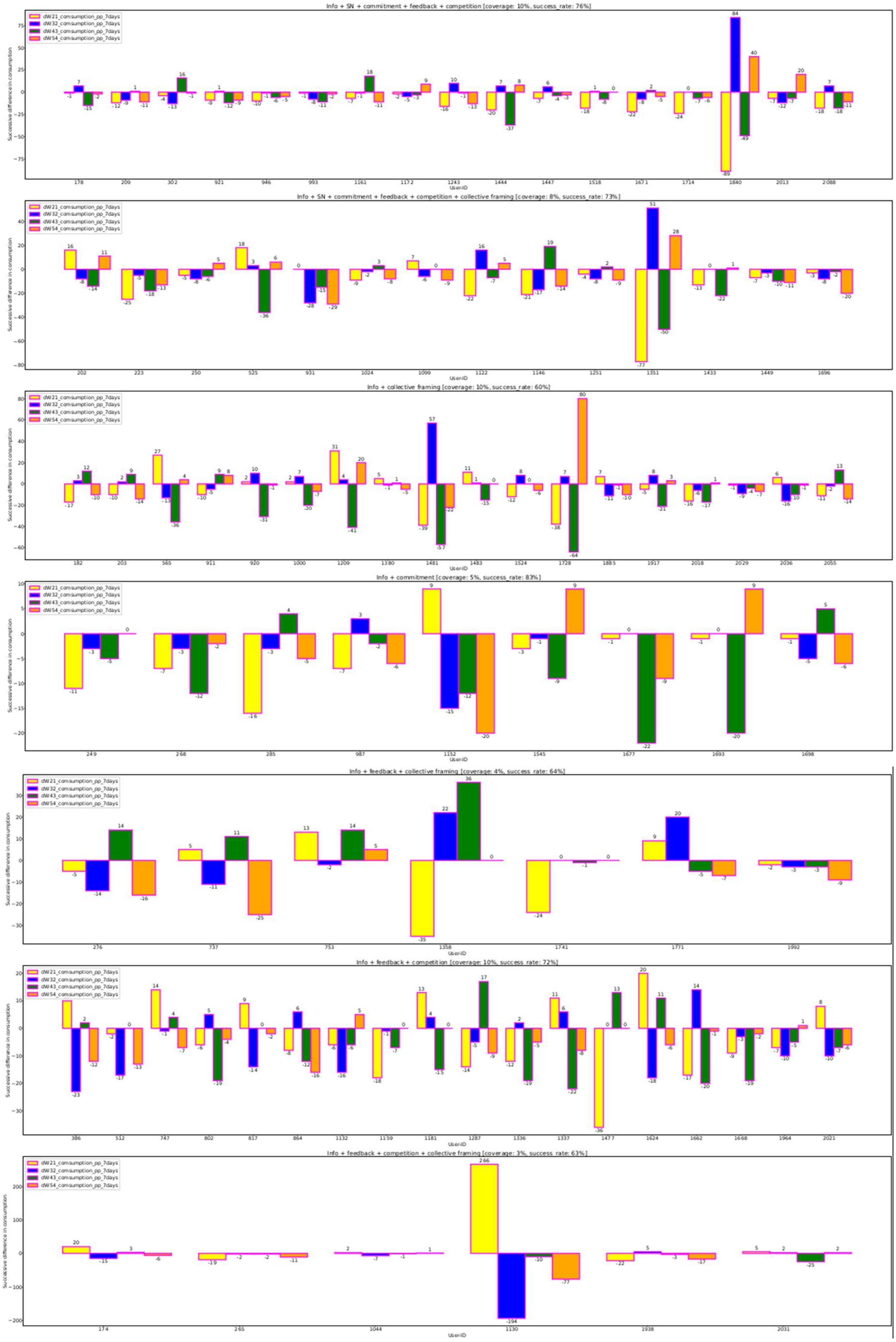


Figure 42: BG4 interventions 8-14 stratification.

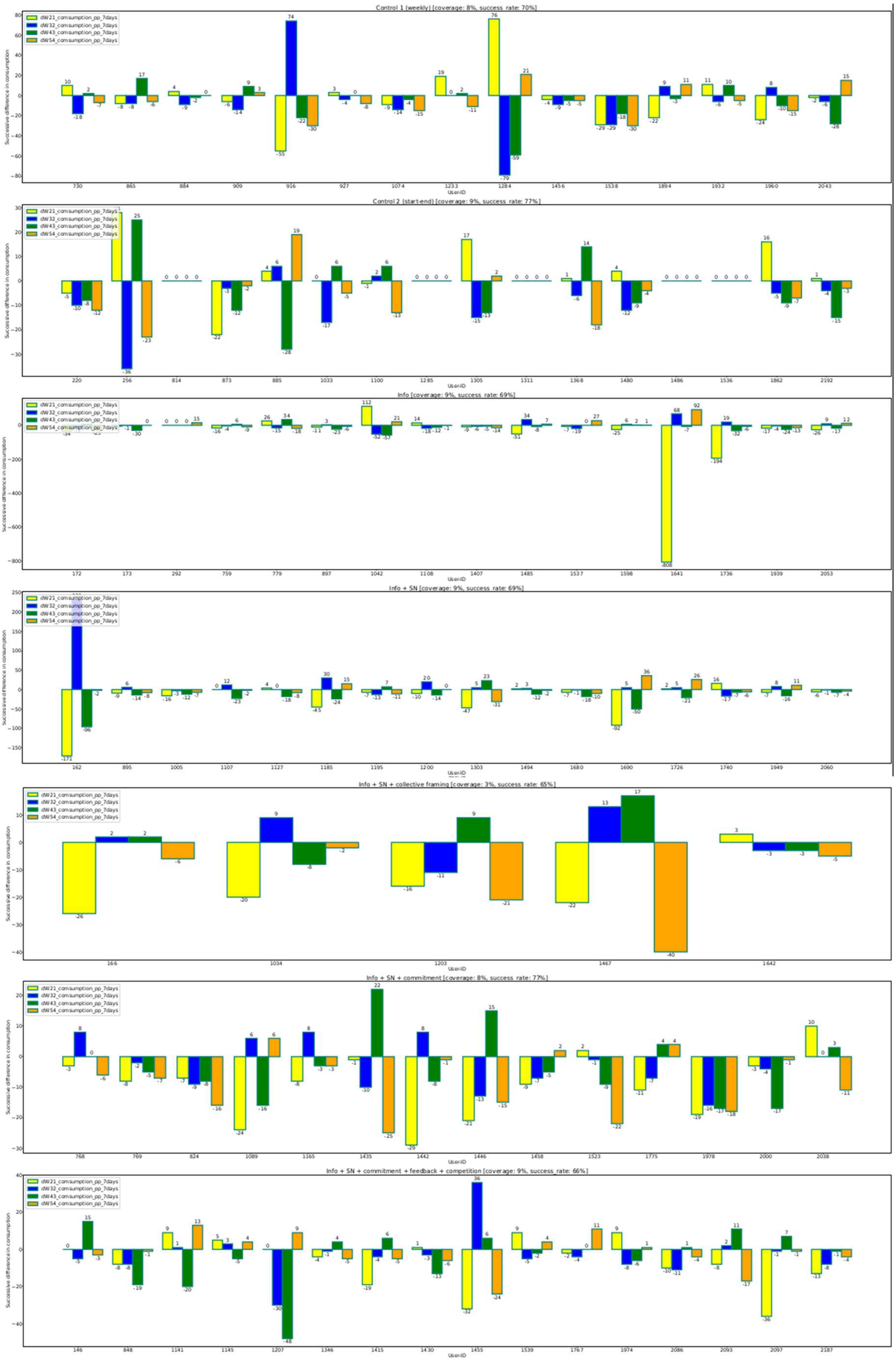


Figure 43: BG5 interventions 1-7 stratification.

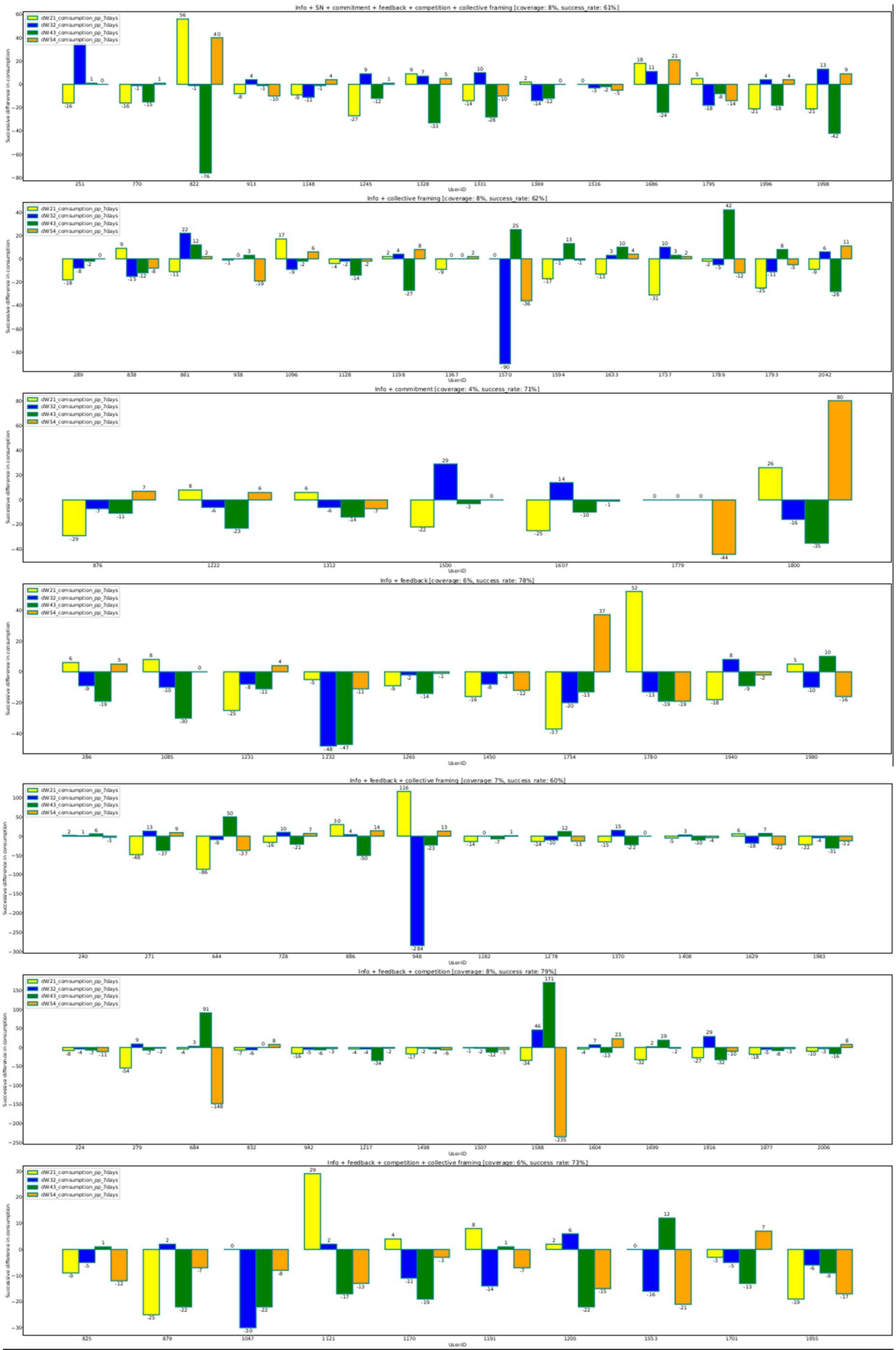


Figure 44: BG5 interventions 8-14 stratification.

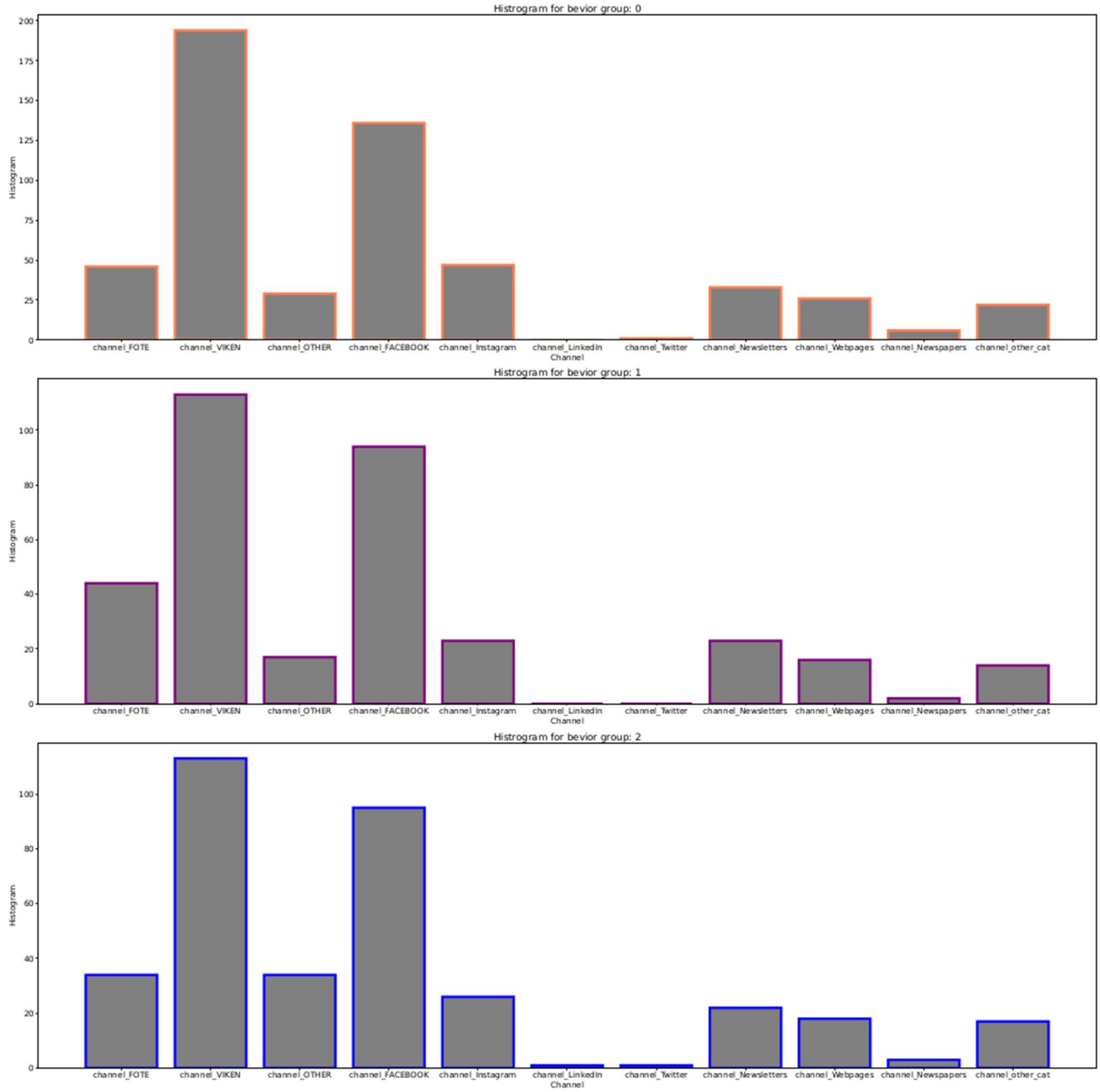


Figure 45: BG0-2 channels responses stratification.

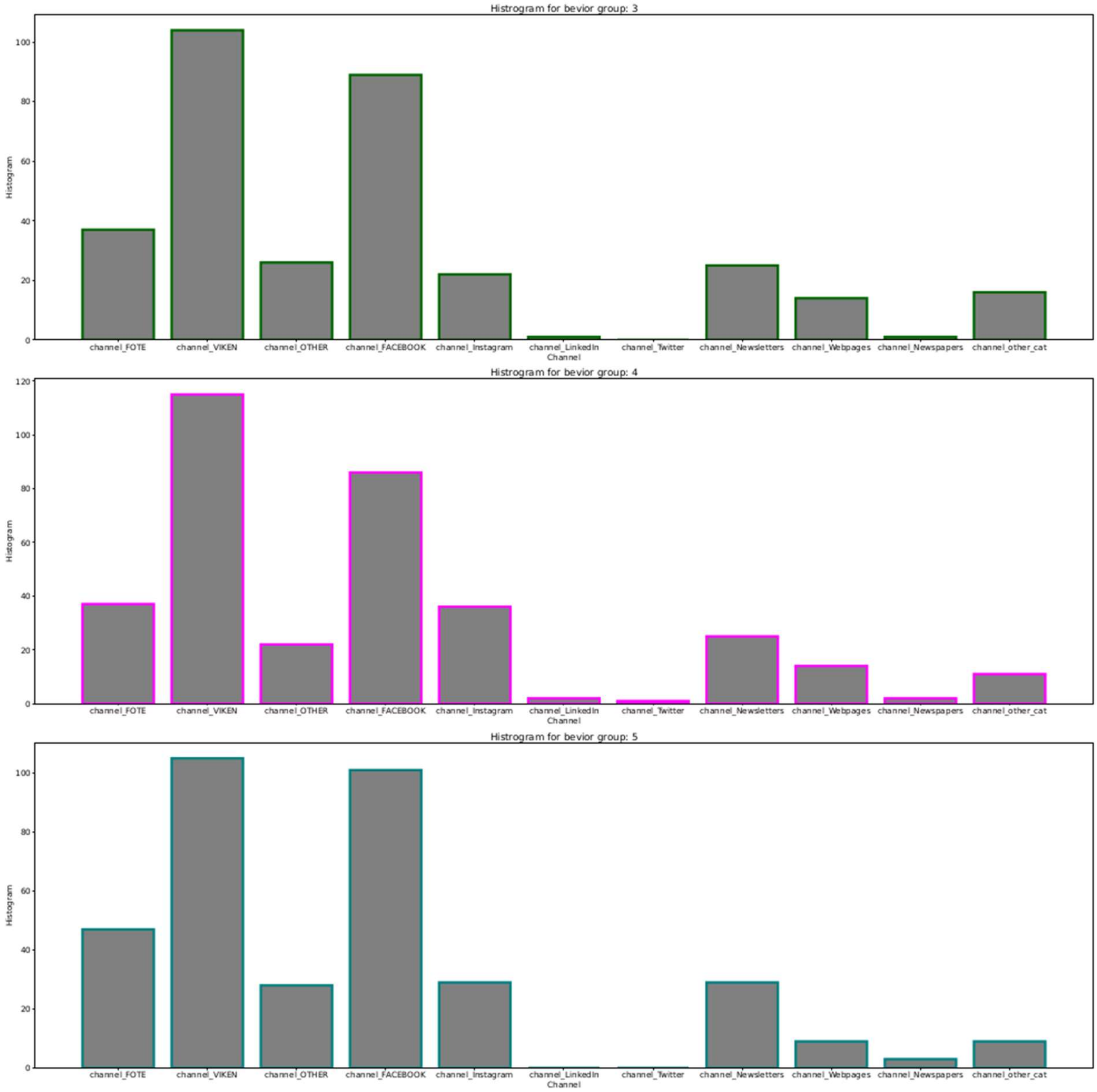


Figure 46: BG3-5 channels responses stratification.

1.4.2 German intervention with data imputation

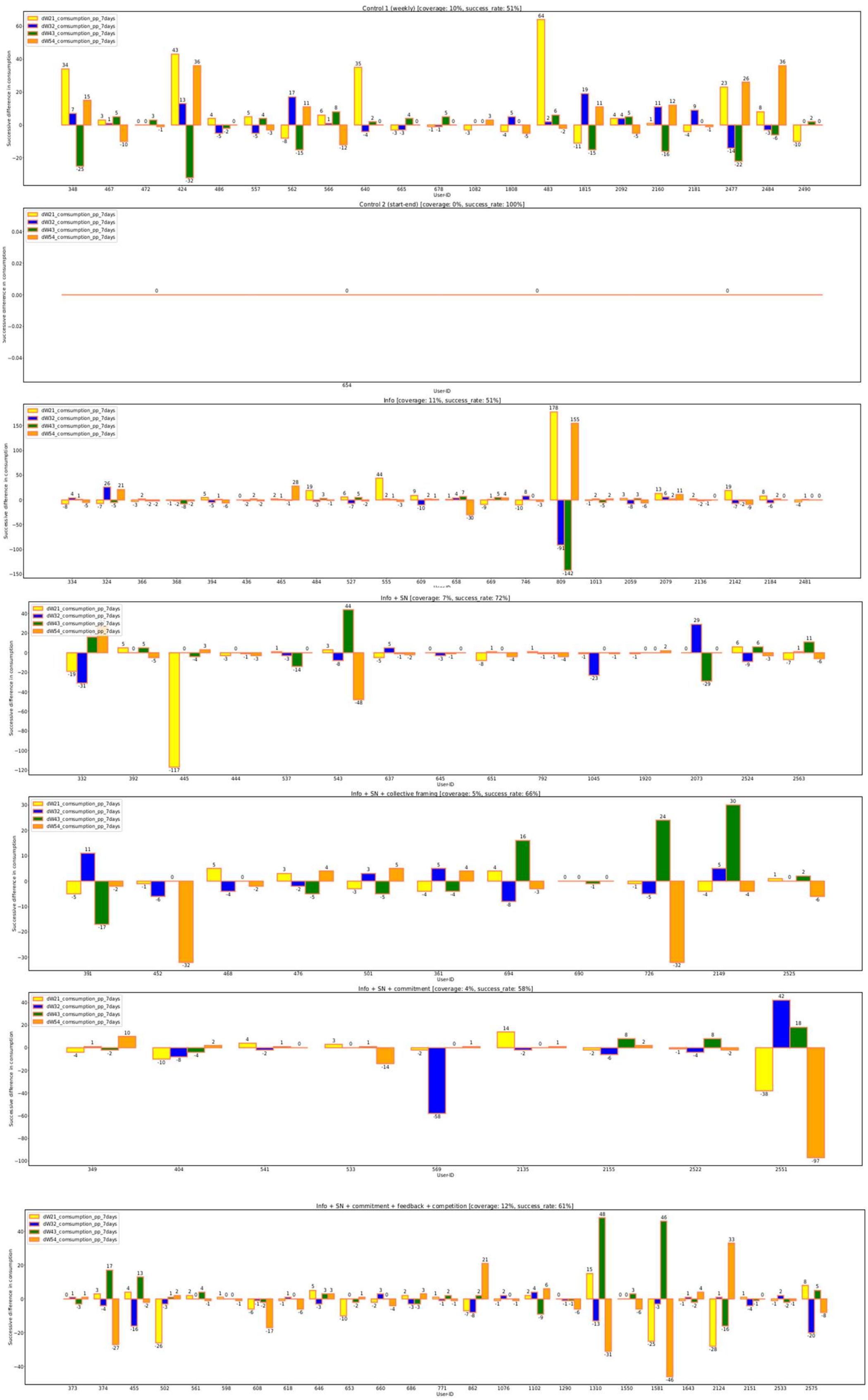


Figure 47: BG0 interventions 1-7 stratification.

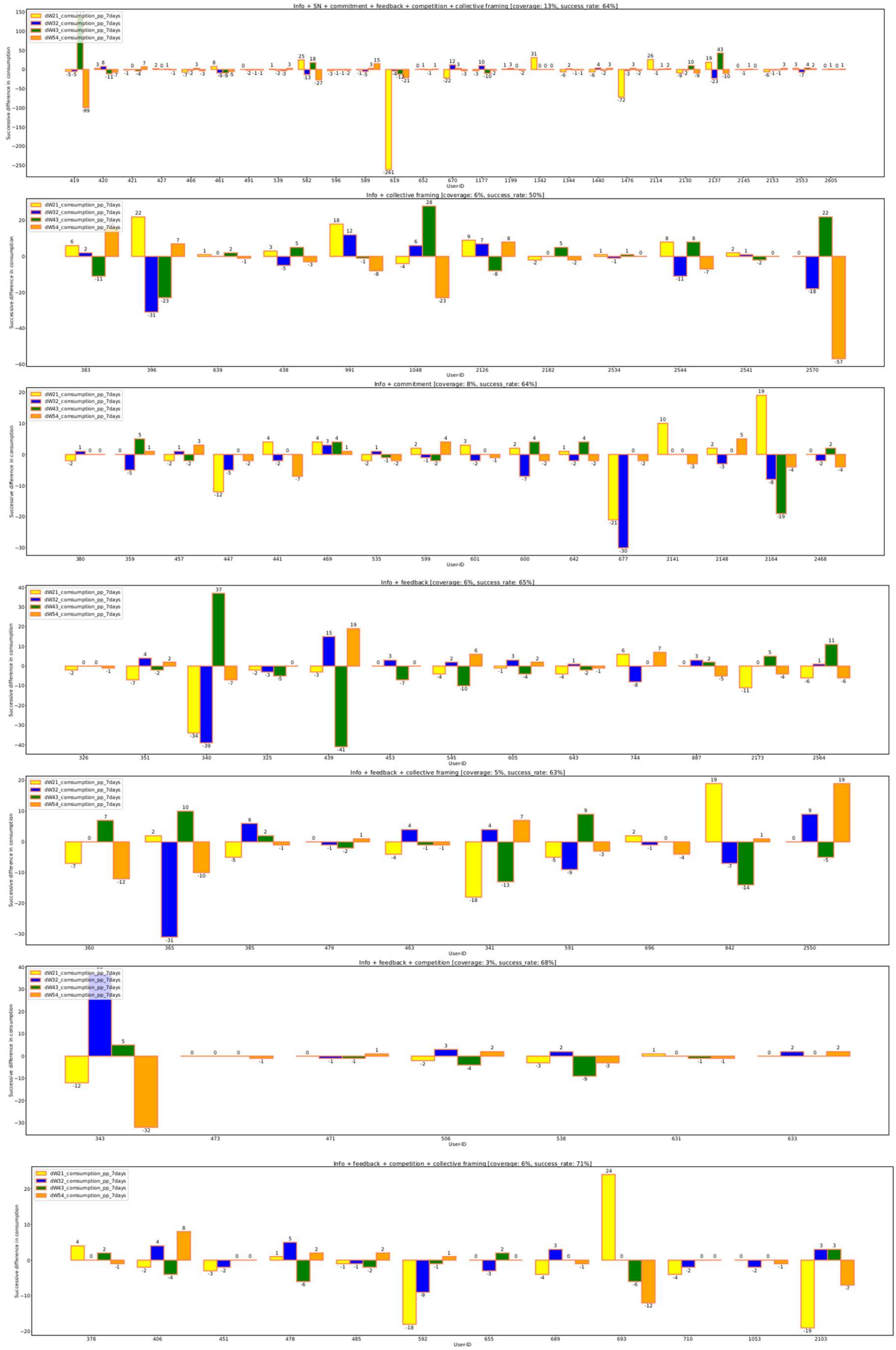


Figure 48: BG0 interventions 8-14 stratification.

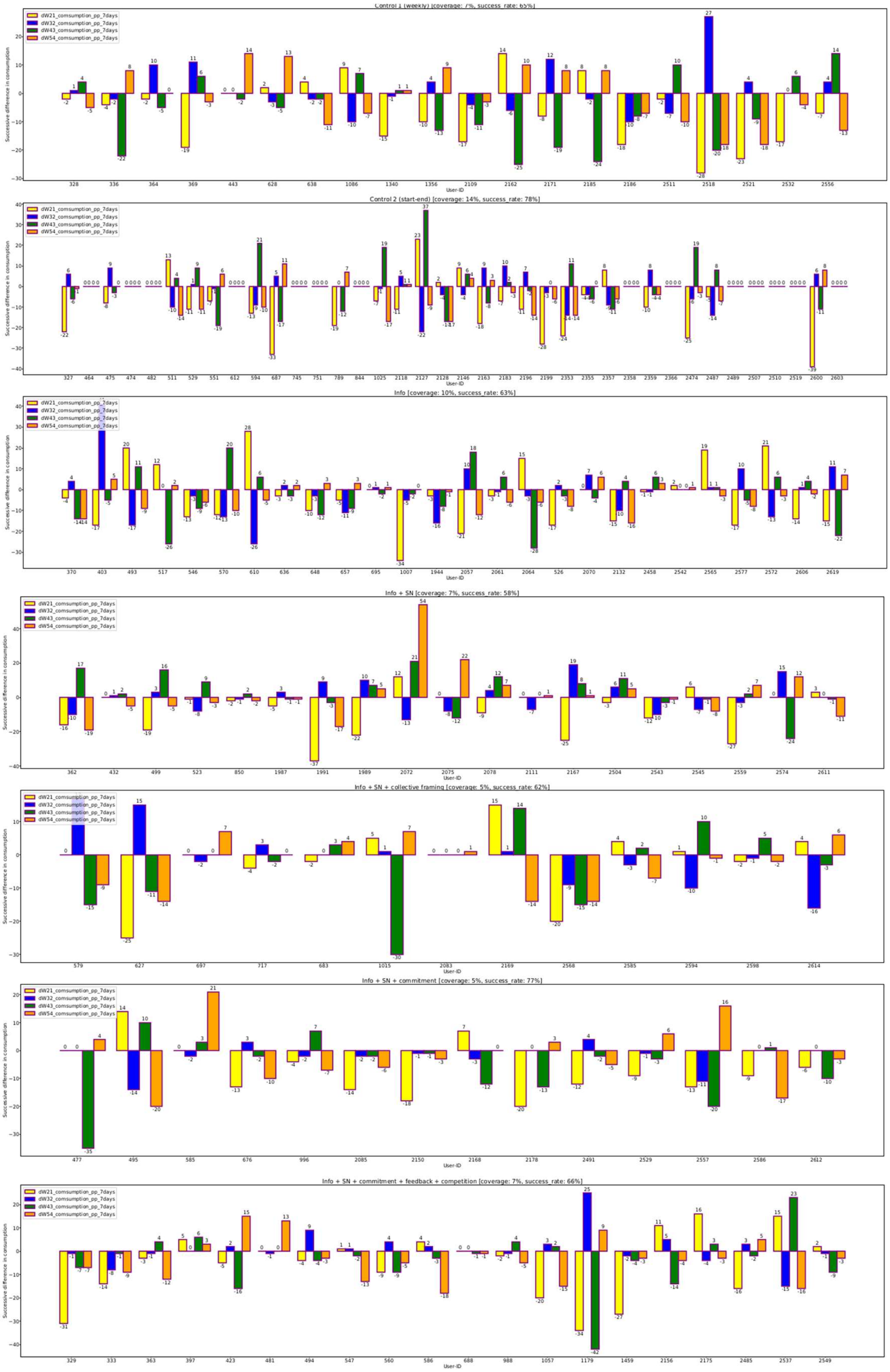


Figure 49: BG1 interventions 1-7 stratification.

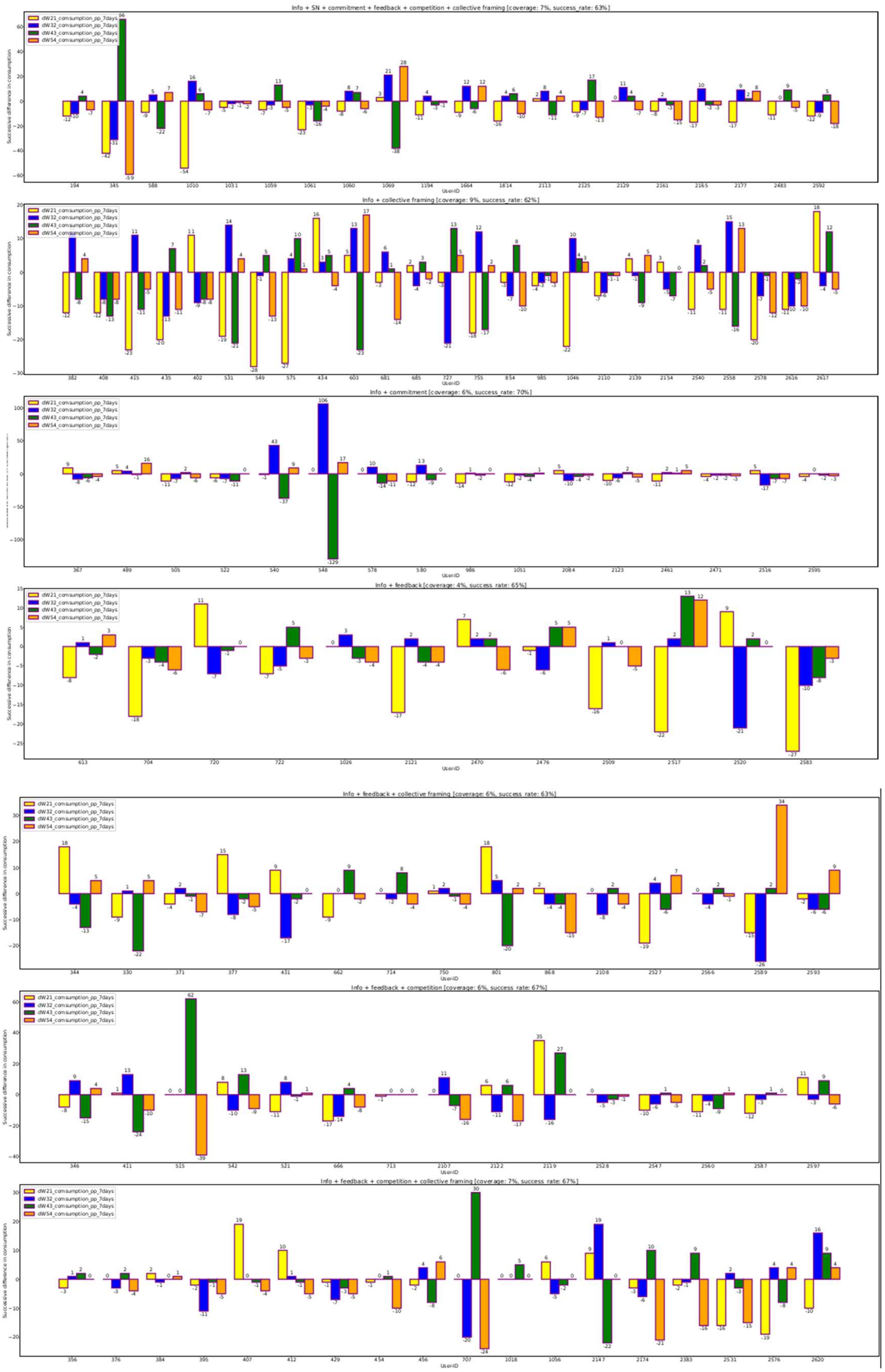


Figure 50: BG1 interventions 8-14 stratification.

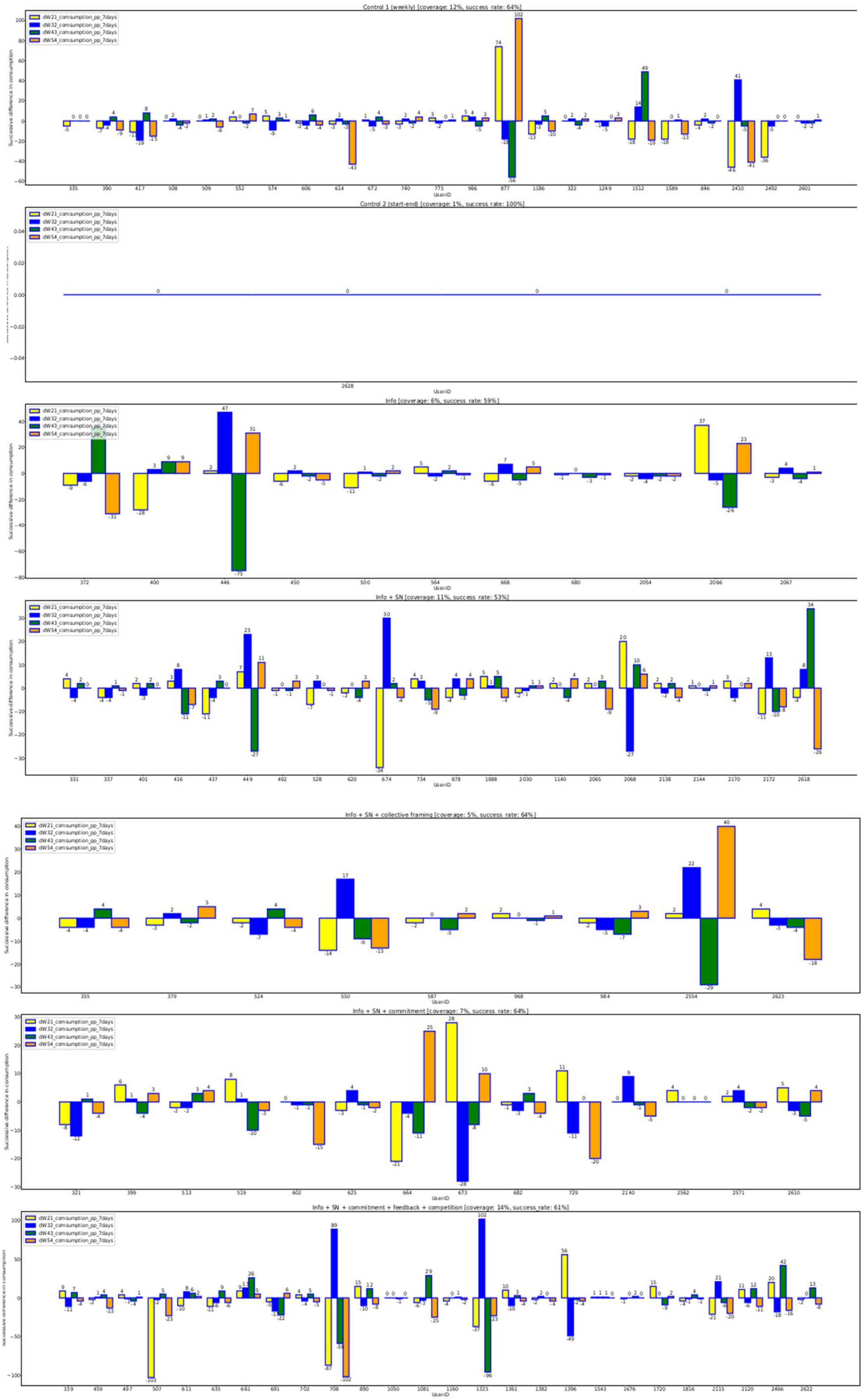


Figure 51: BG2 interventions 1-7 stratification.

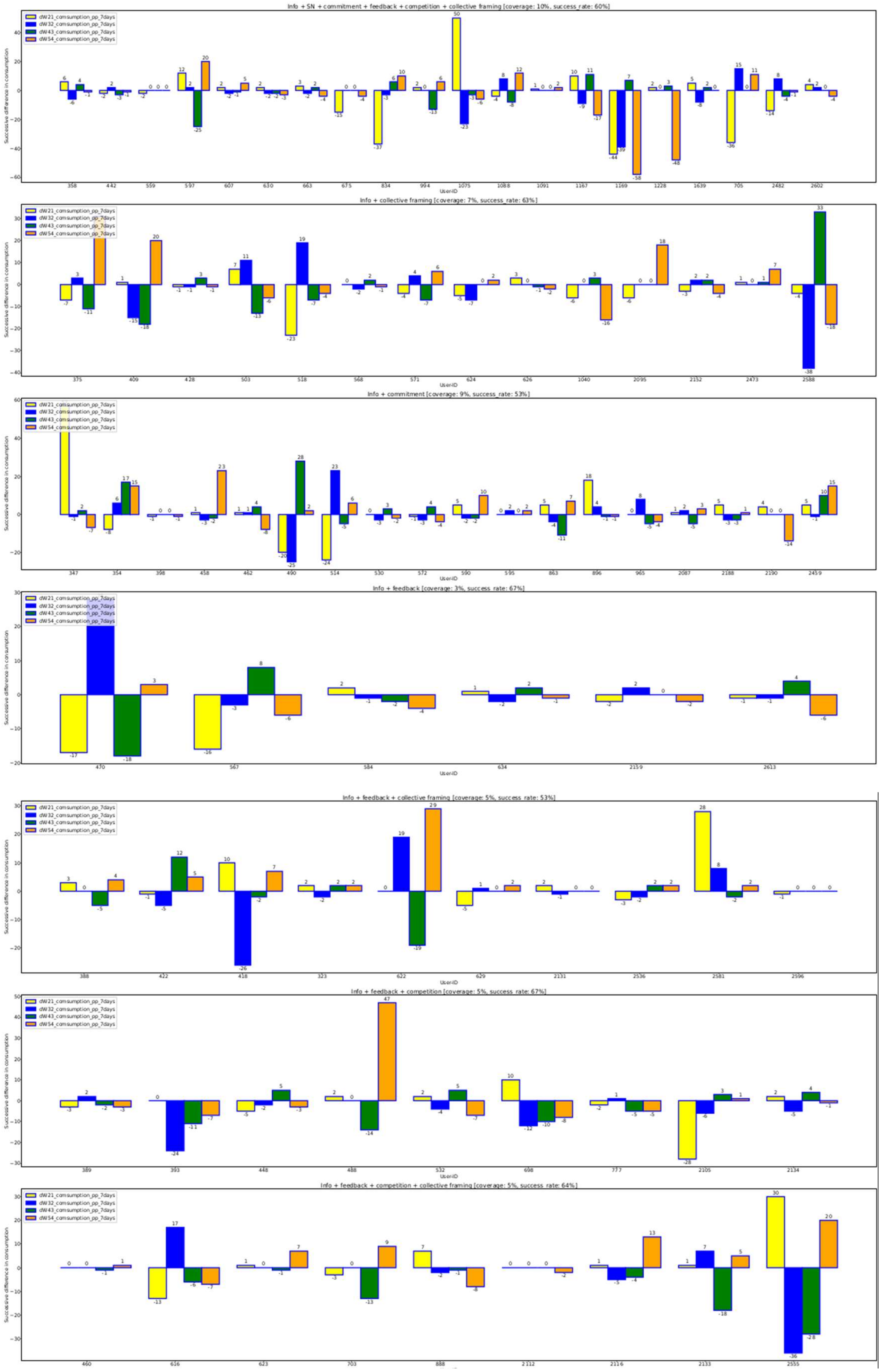


Figure 52: BG2 interventions 8-14 stratification.

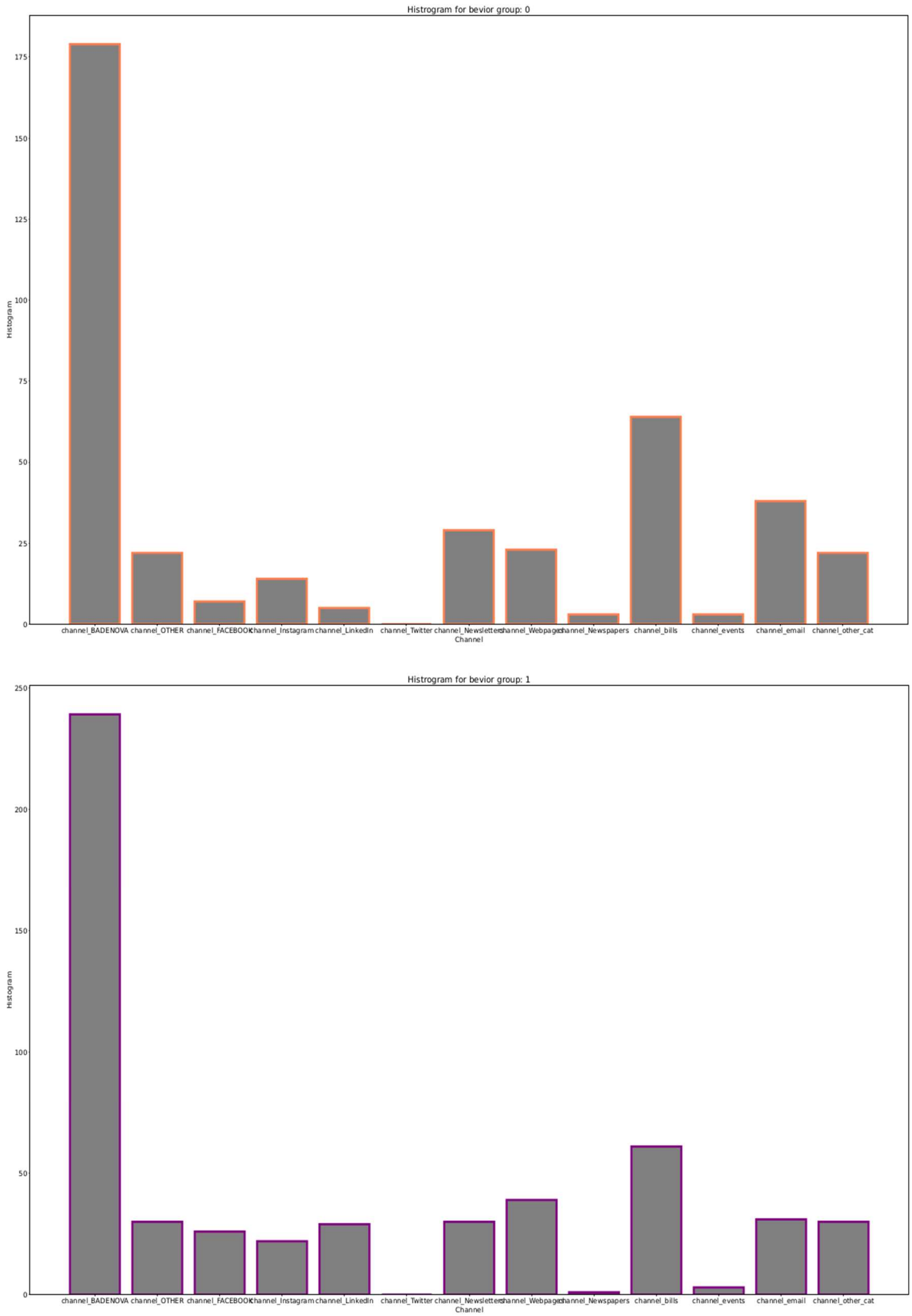


Figure 53: BG0-1 channels responses stratification.

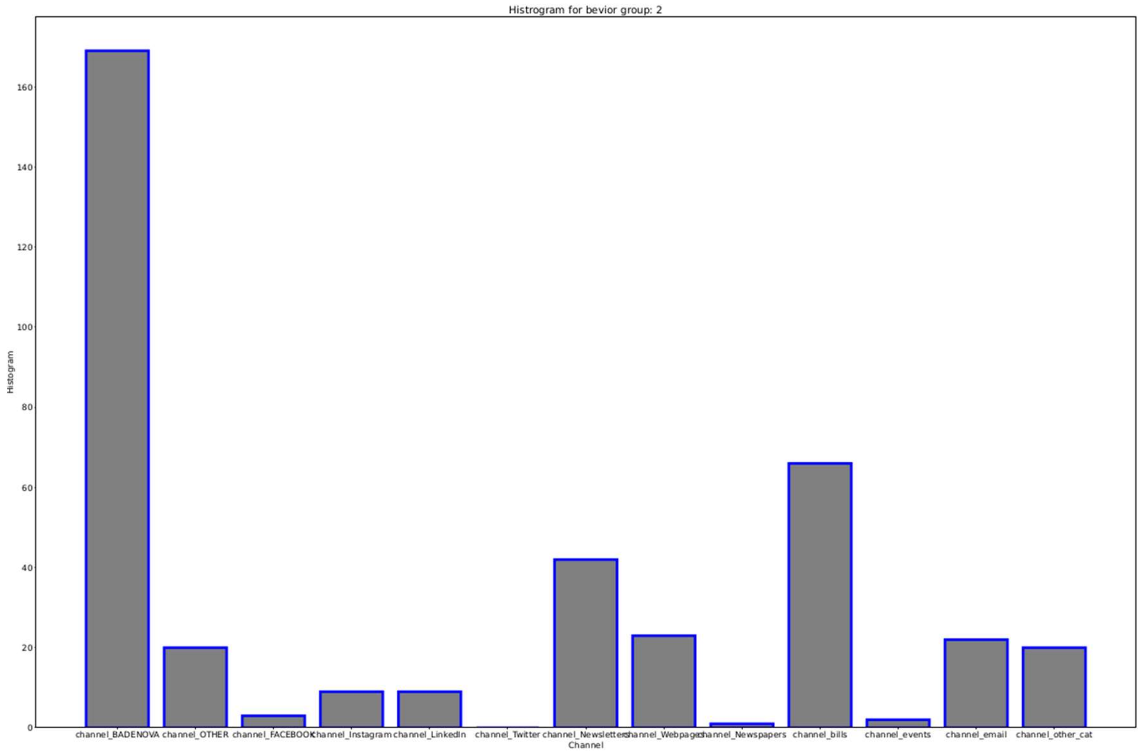


Figure 54: BG2 channel responses stratification.

1.4.3 Other EU interventions with data imputation

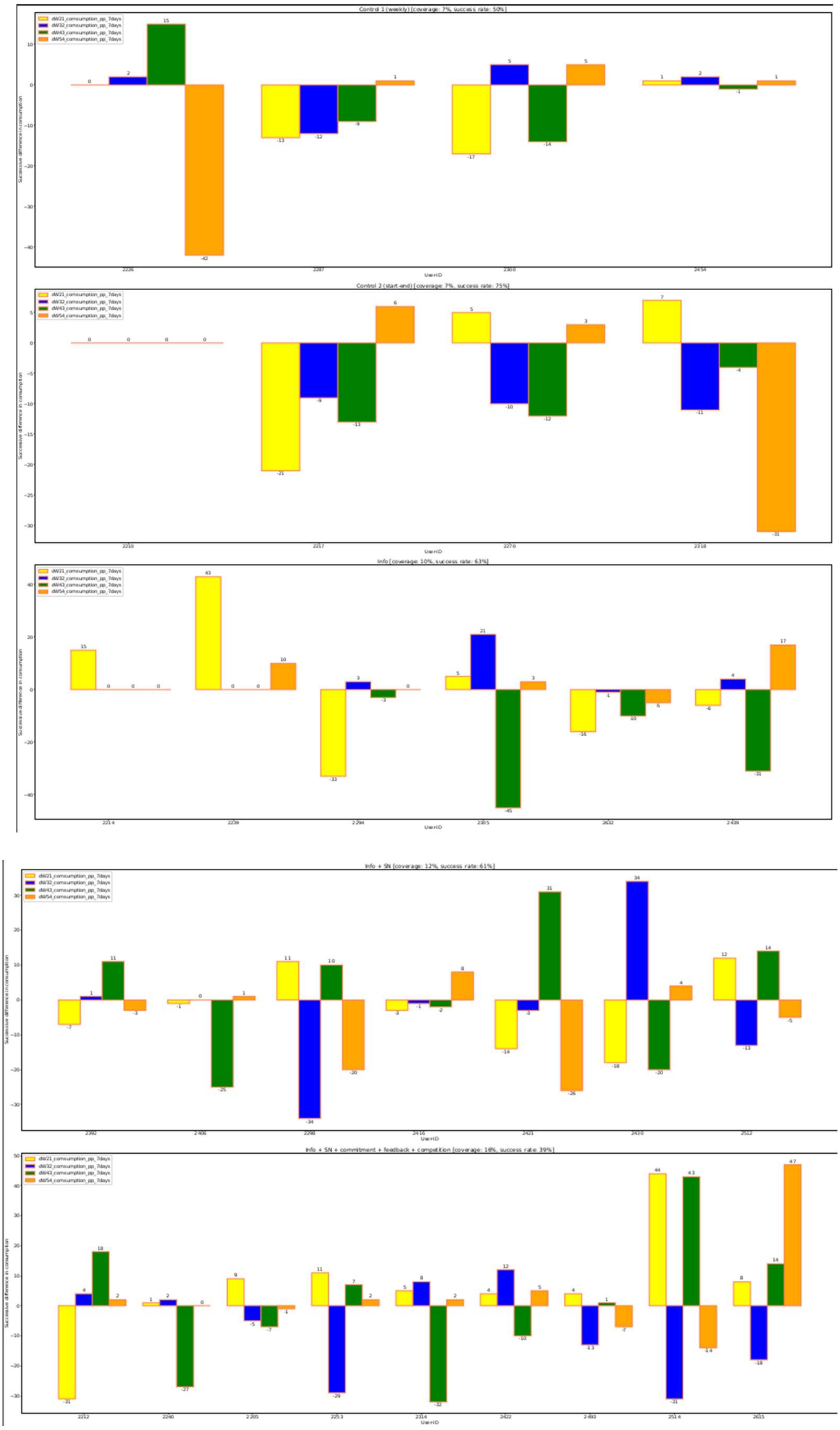


Figure 55: BG0 interventions 1-5 stratification.

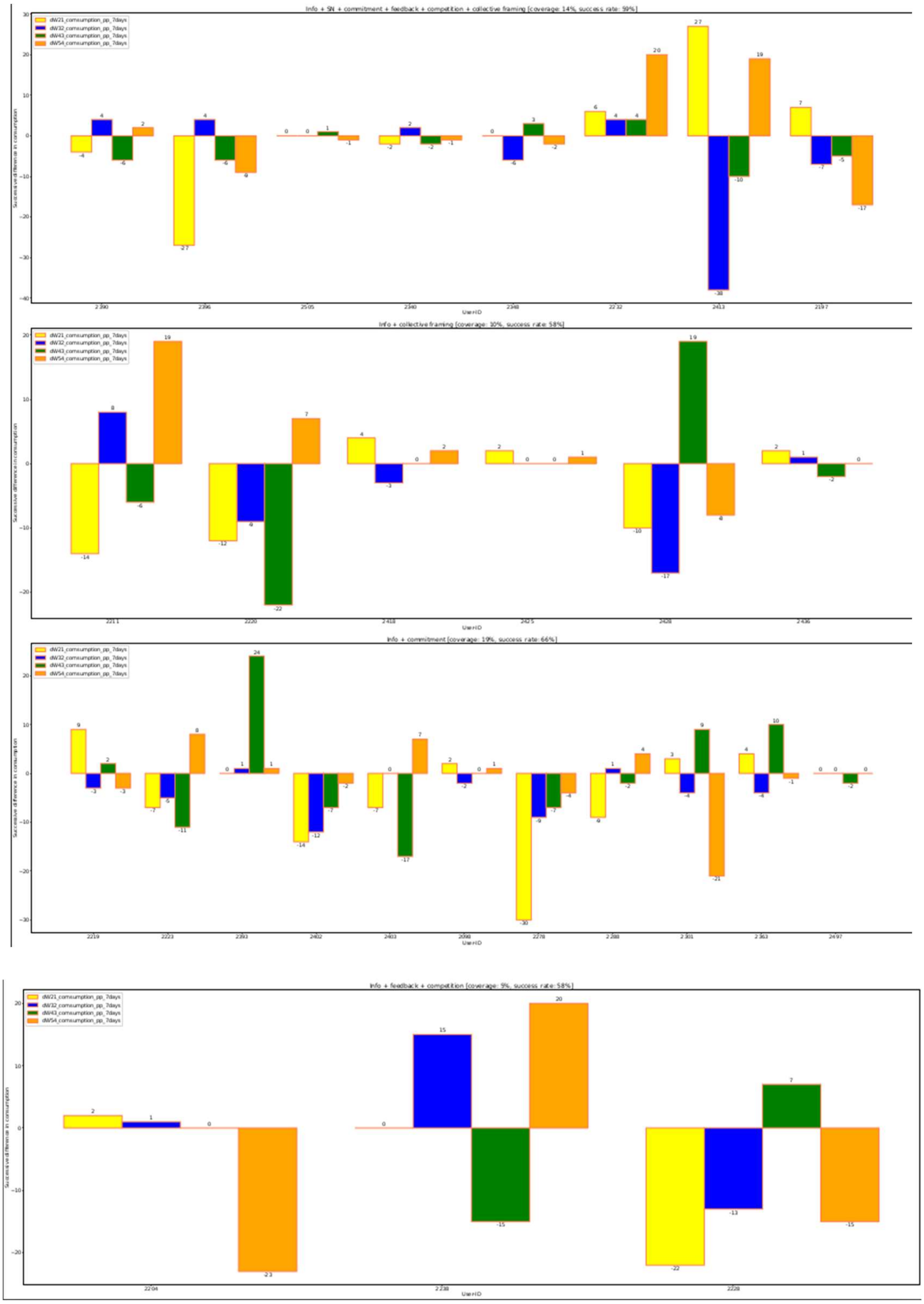


Figure 56: BG0 interventions 6-9 stratification.

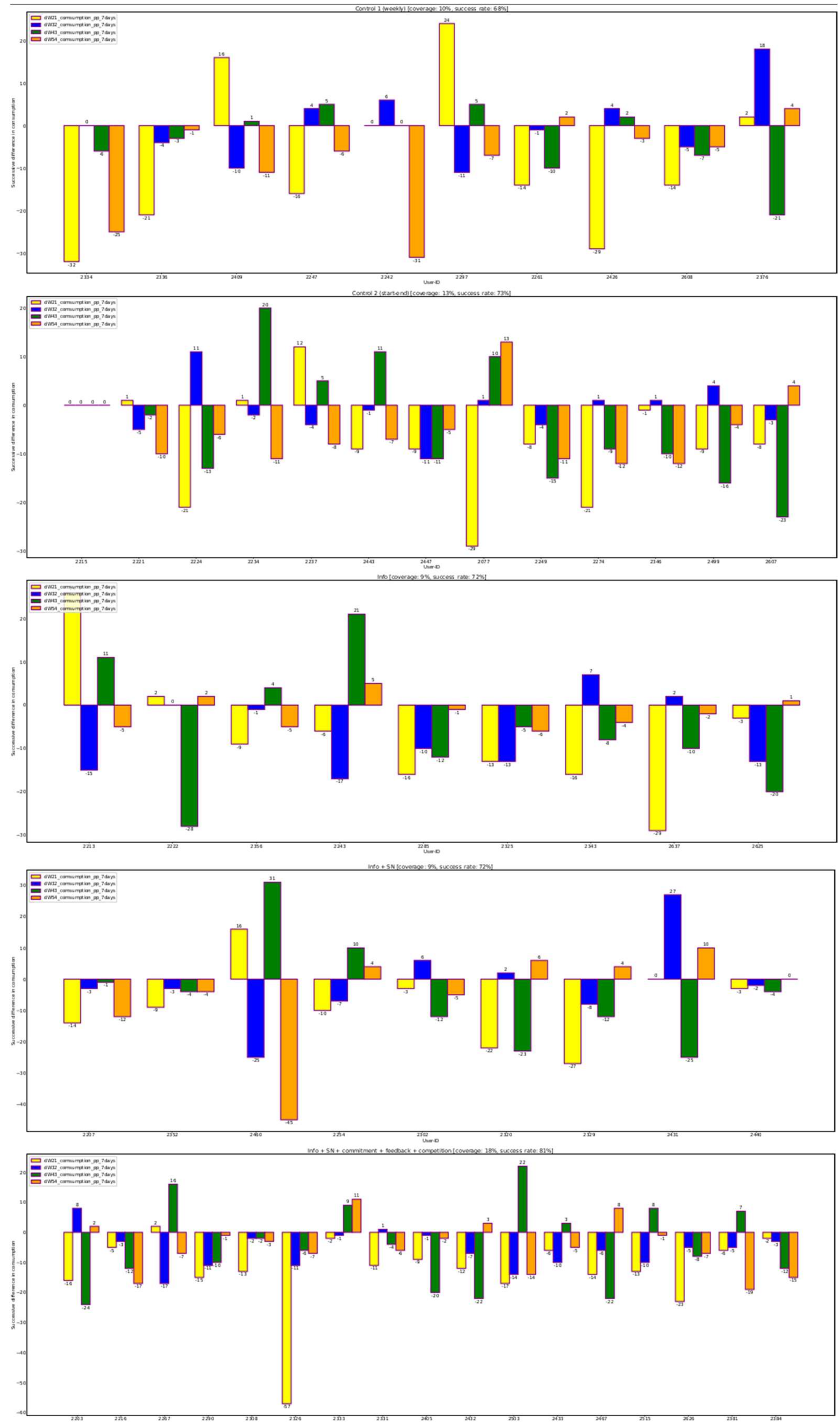


Figure 57: BG1 interventions 1-5 stratification.

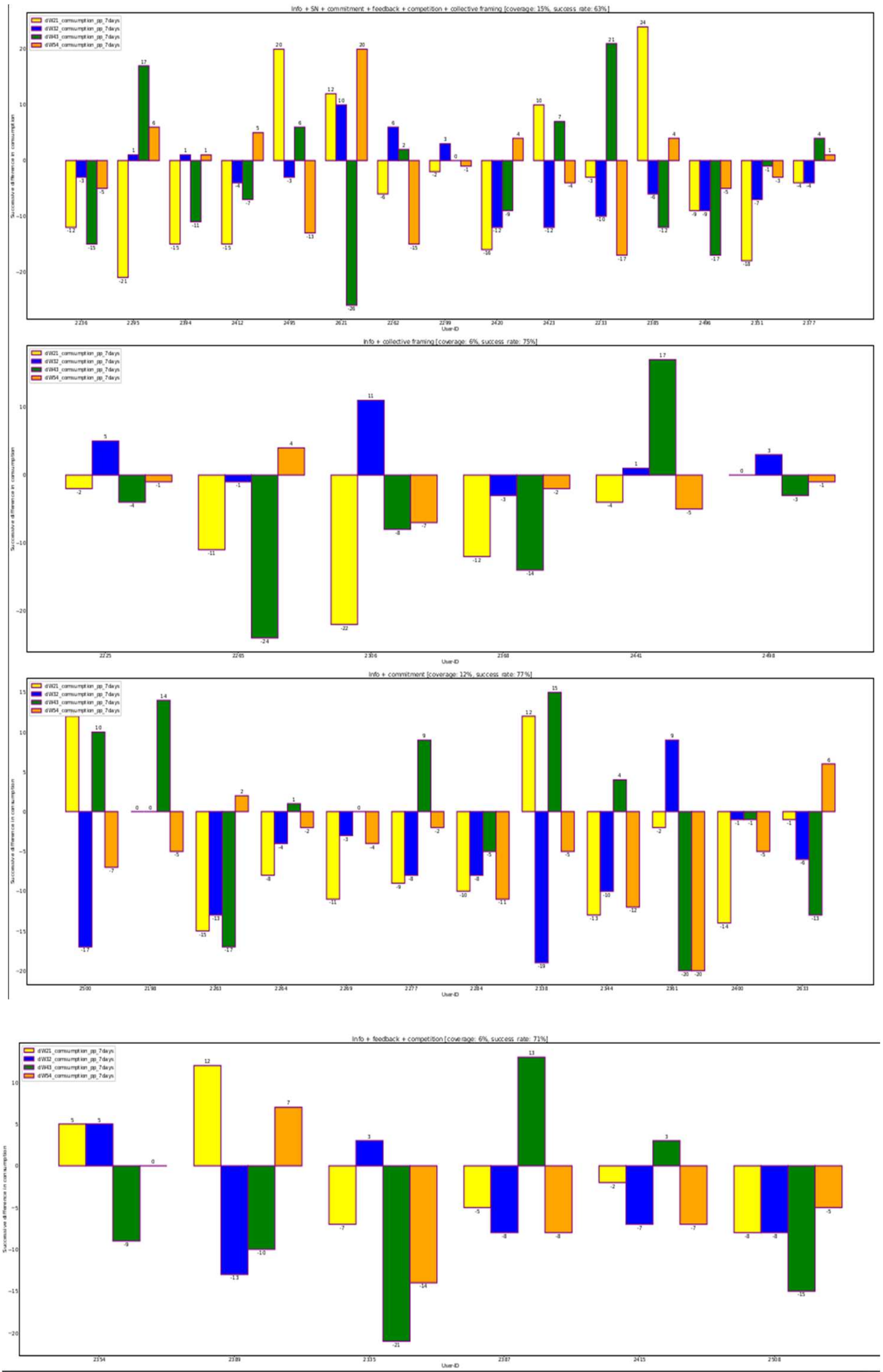


Figure 58: BG1 interventions 6-9 stratification.

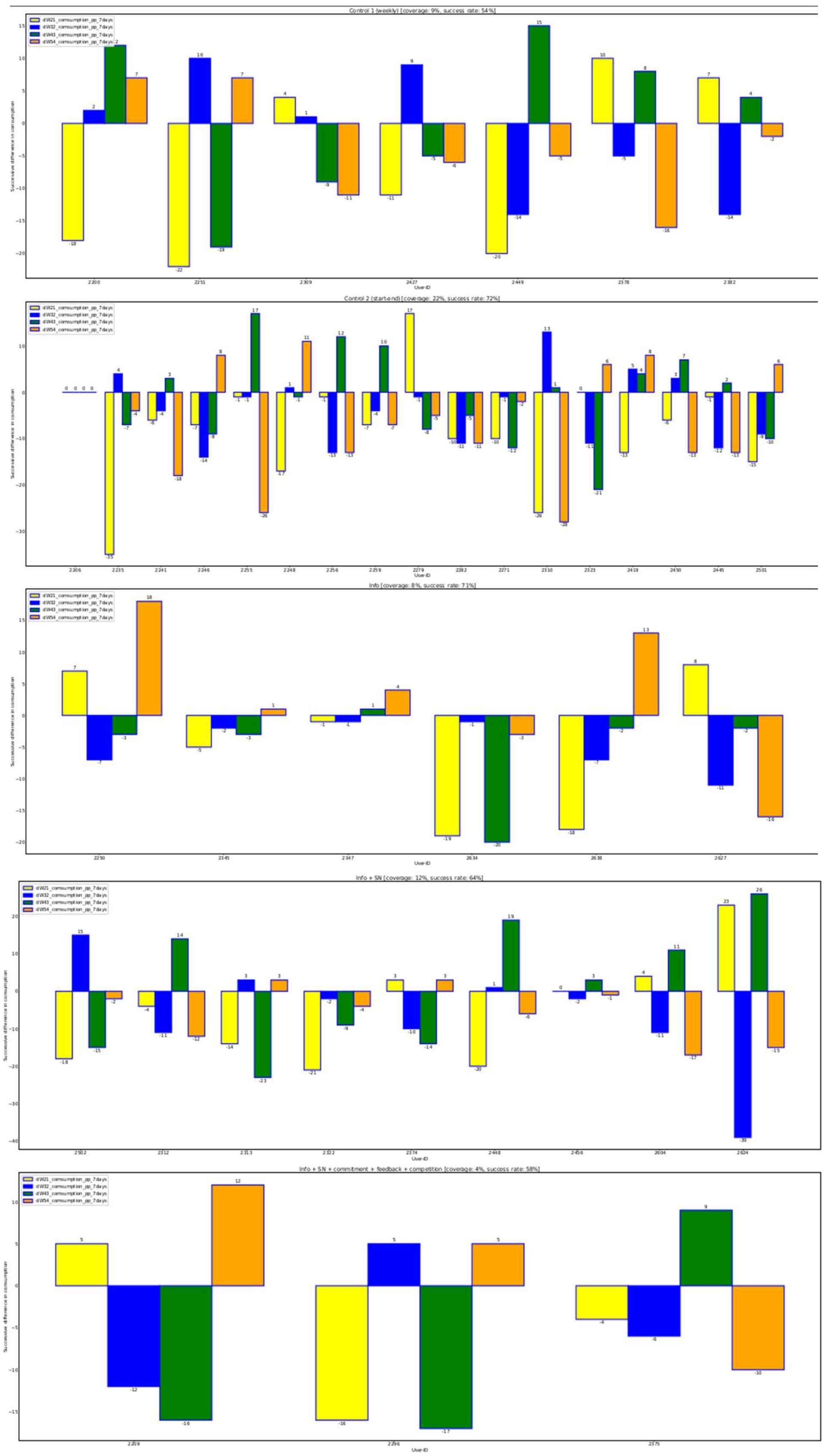


Figure 59: BG2 interventions 1-5 stratification.

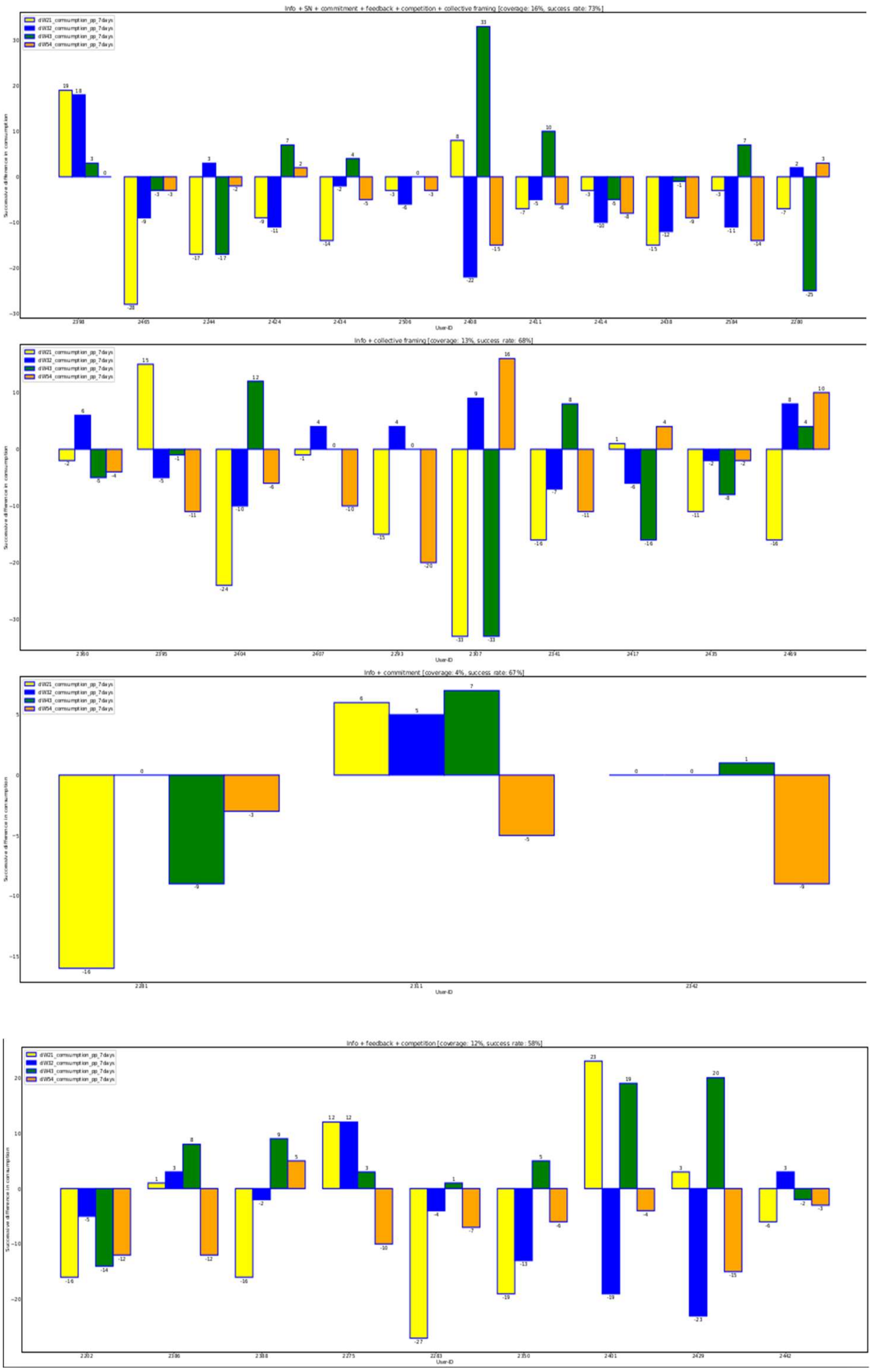
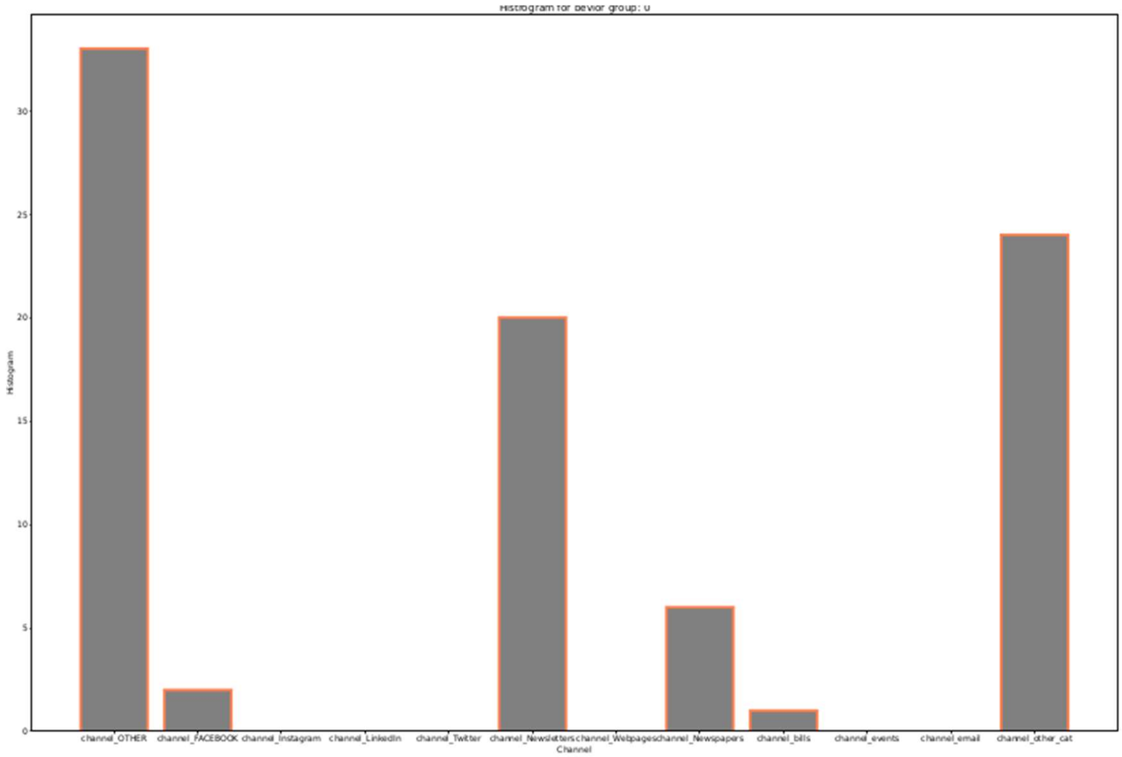


Figure 60: BG2 interventions 6-9 stratification.



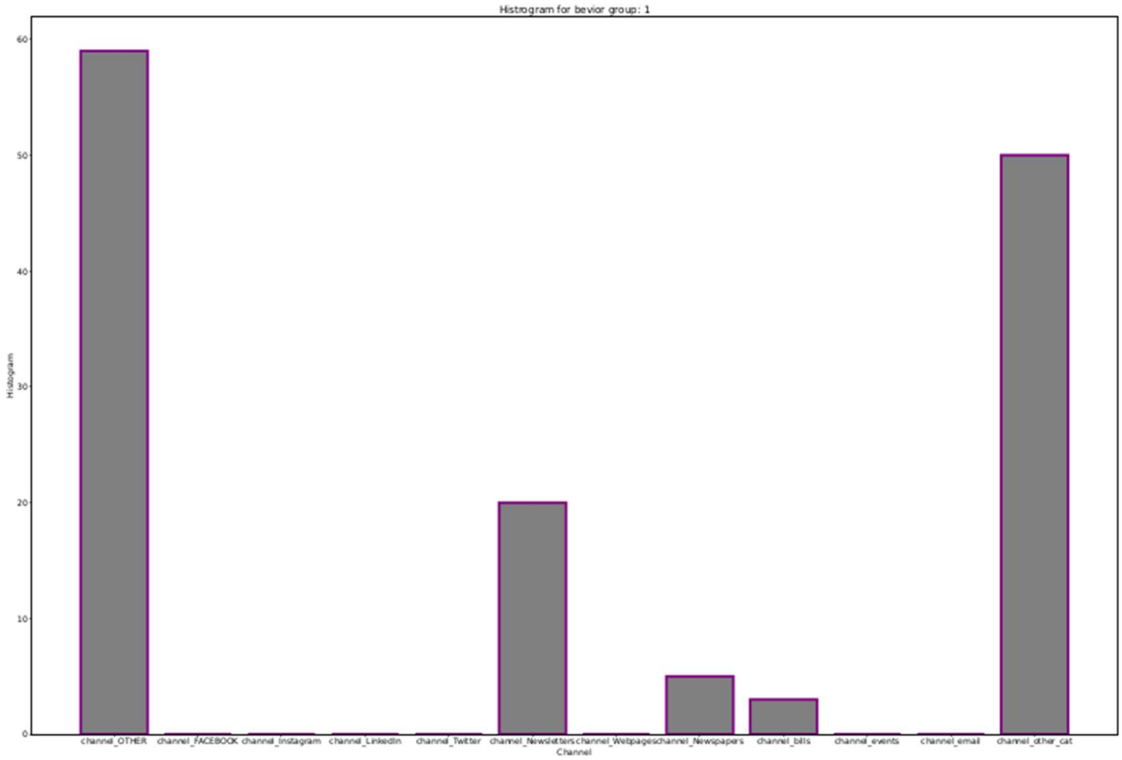


Figure 61: BG0-1 channels responses stratification.

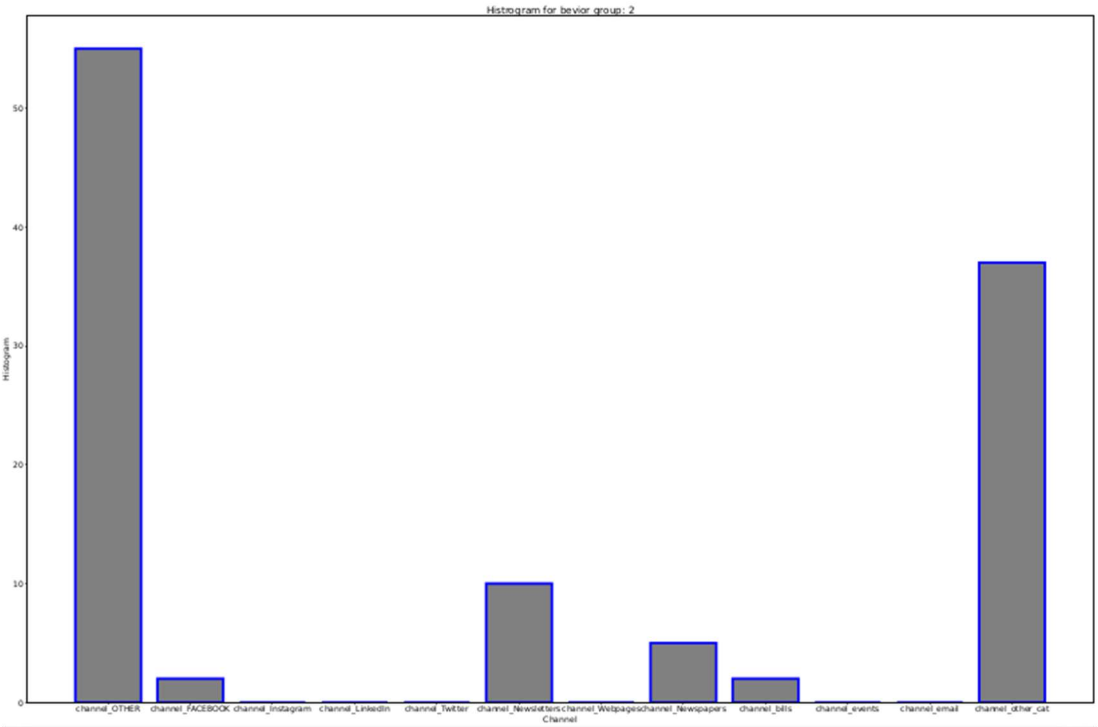


Figure 62: BG2 channel responses stratification.