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SENTIMENT ANALYSIS OF TEXTS FROM SOCIAL NETWORKS BASED ON MACHINE LEARNING METHODS FOR SENTIMENT MONITORING

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Contents

Introduction

Social networks have become one of the major platforms of communication and sharing information and opinions [1], providing a real-time and rich source of data, including sentiments. However, timely understanding of the sentiment of the population, also defined as *subjective well-being* (SWB), is one of the key goals for intergovernmental organizations and governments [2] because it not only allows increasing the speed of the feedback loop for policymakers [3], but it can also be considered as one of the key guidelines[1] for the development of the state instead of currently utilised indicators such as gross domestic product [4]. Although self-report scales are currently the most popular (and quite accurate [5]) means in psychological and sociological studies to measure SWB [6], they also suffer from a series of disadvantages. For example, reactivity of classical survey research [7], possible exaggeration of self-reported answers [8], possible influence of momentary mood on corespondents' responses to SWB questions [9], respondents' tendency to recall past events that are consonant with their current affect [10], and general impact of a variety of biases (e.g., question order bias [11], demand characteristics [12], and social desirability bias [13])). Self-report surveys cannot provide constant updates on SWB to interested parties, and conducting them is relatively expensive, thereby making it challenging for many countries to estimate well-being frequently [7; 14; 15].

Given the formidable list of limitations, researchers across disciplines have recently discussed several innovative digital data sources, also called *digital traces*, and methods that have the potential to overcome the limitations of traditional survey-based methods [7]—in particular, for measuring SWB [15]. According to the definition by Howison et al. [16], digital trace data are found (rather than produced for research), event-based (rather than summary data), and longitudinal (since events occur over a period of time) data that are both produced through and stored by an information system. As was highlighted by Nemeth et al. [17], the most epistemological advantages of digital trace data is that it provides observed instead

[1]Back in 2011, the UN General Assembly adopted Resolution A/RES/65/309 entitled "Happiness: Towards a Holistic Approach to Development". Recognizing that GDP by nature was not designed to reflect the happiness and well-being of individuals in a country, the UN General Assembly invited Member States to pursue the elaboration of additional measures that can better capture the importance of the pursuit of well-being and happiness in the development with a view to guiding their public policies.

of self-reported behaviour, which is also characterized by real-time observation with continuous follow-ups. Since digital trace data are spread over time, it provides researchers with the opportunity to conduct studies that are otherwise impossible or at least difficult to conduct using traditional survey-based approaches [7]. Thus, digital traces such as social network posts have the potential to be a useful source for obtaining data on SWB. To differentiate approaches based on digital traces from classical survey-based approaches, we will further refer to them as **Observable Subjective Well-Being** (OSWB) [18], which explicitly characterizes the data source as observed (not self-reported) and does not make any assumptions about the *evaluative* or *experienced* nature of the data[2] (both can be presented in different proportions).

A growing body of literature [15; 20—25] has been investigating different variations of OSWB indices calculated based on textual content from social media sites. However, one of the main challenges with existing studies is the lack of representative data (in terms of the data source, general population of Internet users, or general population of the analysed country) and comparing with the survey-based indexes to measure the reliability of the results. At the same time, the research of Russian-language content (e.g., [26—28]) remains quite limited and targets particular social networks, groups of users, or regions, but not the general population of Russia. In general, these studies were focused on the particular group of users or a sample of a social network audience, but they did not project the results with respect to the general population of Russia. Furthermore, a recent poll [29] by the Russia Public Opinion Research Center (VCIOM) showed that the vast majority (85%) of Russians are convinced that public opinion polls are needed, and about 42% of respondents state that polls are absolutely necessary. Almost three-quarters of our respondents (72%) agree that public opinion polls help to determine the opinion of people about the situation in their place of residence so that the authorities can take into account the opinions of the people when solving painful problems. Moreover, according to another recent survey [30] by VCIOM, welfare and well-being were most often cited by respondents as the main goals of Russia in the 21st century. Measures of SWB

[2]Even though debate continues about the classification, so far most psychology research has conceptualized SWB as either a combination of experienced affect (*experienced* well-being measures) or an assessment of life satisfaction or dissatisfaction (*evaluative* well-being measures) [19]. Questions may be raised about the attribution of SWB based on digital traces to either *experienced* or *evaluative* measures, but we argue that so far digital traces cannot be unambiguously attributed to either *evaluative* or *experienced* measures because they may contain both evaluative and experienced characteristics at the same time and/or in different proportions, especially depending on the particular source of digital traces.

are likely to play an increasingly important role in policy evaluation and decisions because not only do both policy-makers and individuals value subjective outcomes, but such outcomes also appear to be affected by major policy interventions [31].

The **goal** of this work is to develop models, methods, and software systems designed to monitor public sentiment by analyzing the sentiment of textual posts from social networks written in the Russian language. The **objectives** of this research are the following.

1. Analyse existing studies on sentiment analysis on Russian-language texts.
2. Analyse modern methods of natural language processing for sentiment analysis and identify the most efficient in terms of classification quality for the Russian language.
3. Develop a model and a method for assessing the impact of classification error of the sentiment classification model on calculated public sentiment indexes.
4. Develop a model and a method for calculating public sentiment indexes based on posts from social networks.
5. Conduct an experimental study of the proposed models, methods, and software systems on data from social networks.
   (a) Collect data from social networks.
   (b) Train sentiment classification model.
   (c) Apply the proposed models, methods, and software systems on collected data to calculate public sentiment indexes.
   (d) Verify the reliability of the results.

Key aspects/ideas to be defended.

1. A mathematical model for social indicators research based on digital traces.
2. A simulation method for assessing the impact of misclassification bias of the particular classification algorithm on the calculated indicator formula.
3. A mathematical model for constructing an index of public sentiment from textual posts published on social networks.
4. A method for constructing an index of public sentiment from textual posts published on social networks taking into account user demographic characteristics.

Theoretical and practical significance. The proposed models and methods pave the way for further advancements in public sentiment monitoring based on social media content. These models and methods can allow interested parties (e.g., intergovernmental organizations and governments) to measure public sentiment not only automatically, but also for the past periods of time and reduce costs associated with constructing such studies, which is especially crucial during the time of a global pandemic. For sentiment analysis, we identified the most efficient approaches in terms of classification quality for Russian-language texts. For dealing with non–error free nature of classification algorithms, estimating the impact of classification algorithm errors on the calculated public sentiment indices, we proposed a new simulation model and a mathematical method for estimating the impact of misclassification errors of a particular classification algorithm on the calculated social indicators. For public sentiment indices calculation, we proposed a new mathematical model and a method for calculating public sentiment indicators based on digital traces, which takes into account sociodemographic characteristics of users and is designed to make the given user sample representative of general audiences in terms of the selected sociodemographic characteristics. Finally, we applied the proposed models and methods to the data from the social network Odnoklassniki and calculated the public sentiment index based on expressed sentiment. The obtained index demonstrated a high correlation with the traditional survey-based Happiness Index reported by VCIOM, confirming the reliability of the proposed models and methods.

Approbation of the work. The main results on the topic of the dissertation were presented and discussed at the following scientific conferences and workshops.

1. XX April International Academic Conference on Economic and Social Development, April 9–12, 2019. “Development of a Classifier for Analyzing the Sentiment of Russian-language Products Reviews from Online Stores”.
2. IEEE 21st Conference on Business Informatics (CBI), July 15–17, 2019. Topic: “Sentiment Analysis of Product Reviews in Russian using Convolutional Neural Networks”.
3. International Conference on Computational Linguistics and Intellectual Technologies “Dialogue 2020”, June 17–20, 2020. Topic: ”Toxic Comments Detection in Russian”.
4. IEEE 23rd Conference on Business Informatics (CBI), September 1–3, 2021. Topic: “Share of Toxic Comments among Different Topics: The Case of Russian Social Networks”.

5. 6th International Research Workshop on Big Data at 2021 International Conference on Information Systems (ICIS), December 12, 2021. Topic: “Public Mood Monitoring Based on Social Media Content”.

Personal contribution. The first work was conducted solely by the thesis' author. In the second and third works, the author proposed the key scientific ideas, implemented models and methods, collected data, conducted all experiments, analysed and interpreted results, and wrote the text; the second author supervised the research and helped with domain expertise. The fourth work was conducted solely by the thesis' author.

Publications. The main results on the topic of the dissertation were presented in 4 articles published in first-tier academic journals.

1. **Smetanin S.** The Applications of Sentiment Analysis for Russian Language Texts: Current Challenges and Future Perspectives // IEEE Access. 2020. Vol. 8. P. 110693–110719.
2. **Smetanin S.**, *Komarov M.* Deep transfer learning baselines for sentiment analysis in Russian // Information Processing and Management. 2021. Vol. 58. No. 3. Article 102484.
3. **Smetanin S.**, *Komarov M.* Misclassification Bias in Computational Social Science: A Simulation Approach for Assessing the Impact of Classification Errors on Social Indicators Research // IEEE Access. 2022. Vol. 10. P. 18886–18898.
4. **Smetanin S.** Pulse of the Nation: Observable Subjective Well-Being in Russia Inferred from Social Network Odnoklassniki // Mathematics. 2022. Vol. 10. No. 15. Article 2947.

Volume and structure of the work. The thesis contains an introduction, contents of publications, and a conclusion. The full volume of the thesis is 56 pages with 4 figures, 3 tables, and 144 references.

Content of the Work

1 Applications of Sentiment Analysis for Russian Language Texts

Sentiment analysis is an area of natural language processing whose objective is to identify the sentiment expressed in a specific type of user-generated content, most commonly textual content. Analysis of sentiment expressed in text collections allows scholars and practitioners to solve a wide range of problems, such as predicting the stock market (e.g., [32]) and election results (e.g., [33]), measuring reactions to particular events or news (e.g., [34]), and identifying attitudes to specific subgroups of the population (e.g., [35]).

Although sentiment analysis applications were widely studied for the English language content [36—38], non-English content, and especially Russian, has so far received much less attention. To the best of our knowledge, at this writing, only one survey by Viksna and Jekabsons [39] directly explores the sentiment analysis of the Russian-language content[3], and several others studies [45—48] mentioned sentiment analysis of Russian in the contexts of overall comparison with globally existing approaches. However, these studies were mostly focused on sentiment analysis approaches and their classification quality rather than their applications and applied data analysis. Thus, confirming the knowledge gap, we comprehensively reviewed the applications of sentiment analysis of the Russian language content and identified the major current challenges and key future research directions. We performed a literature search in scientific databases (see full methodology in our article [49]) that covered leading computer science journals and conferences using the following search query: *(("SENTIMENT "OR "POLARITY") AND ("ANALYSIS"OR "DETECTION"OR "CLASSIFICATION"OR "OPINION MINING"OR "TOPIC MODELING") AND ("RUSSIAN"or "RUSSIA")).* After obtaining 4,041 potentially relevant publications, we analysed the title, keywords, and abstracts of publications to further narrow down the literature sample, which yielded 32 publications that described at least one applied sentiment analysis approach for Russian-language content.

[3]Some other studies were dedicated to different aspects of sentiment analysis of content in Russian (e.g., [40—44]), but these did not survey sentiment analysis in general.

We comprehensively reviewed the selected studies and categorized them by the utilised data source[4] into five categories: *User-Generated Content from Social Network Sites*, *Product and Service Reviews*, *News from Mass Media*, *Books*, and *Mixed Data Sources*. *User-Generated Content from Social Network Sites* (hereinafter referred to as UGC_{SN}) was the most common data source, which was primarily used for studies in three directions: attitudes abouts different topics [35; 50—64], public sentiment indices [26; 27], and user behaviour [65; 66]. The attitude about different topics was studied from different angles such as measuring the level of social tension (e.g., [60]), identifying attitudes towards migrants and ethnic groups (e.g., [35]), exploring expressed sentiment during the Ukrainian Crisis (e.g., [58]), and focusing on other significant topics (e.g., [61]). Studies on UGC_{SN} commonly applied a combination of sentiment analysis and topic modelling to extract topics of interest and corresponding sentiments. Whereas UGC_{SN} tends to contain subjective texts, the situation changes in the case of analysis of *News from Mass Media*. In general, journalists try to avoid making judgments or overt partiality because objectivity (or at least widely acceptable neutrality) is their philosophical basis [67]. Consequently, news articles are less likely to contain affective vocabulary and more often describe the content in a matter-of-fact way. *News from Mass Media* became the second most common data source, which was studied in two directions: constructing economic and business forecasts based on the sentiment of the news (e.g., [68]) and the analysis of sentiments expressed in news articles (e.g., [69]). In contrast with the analysis of UGC_{SN}, there were no challenges regarding the access to the historical data since mass media platforms commonly impose no restrictions on access to all published data. *Product and Service Reviews* was the next most common data source, which was analysed in terms of characteristics of reviewers (e.g., [66]), characteristics of products and services (e.g., [70]), and characteristics of merchants (e.g., [71]). Similar to studies on news, studies on reviews posed no challenges regarding access to historical data. Also, in these studies, it was possible to construct training datasets automatically using a rating of reviews as class labels. *Books* as a data source appeared only in 2019 and have so far received less attention from academics than previously mentioned data sources. These studies were focused on the influence of the sentiment of textbooks on the educational process (e.g., [72]) and the comparison of the sentiment expressed in different textbooks (e.g., [73]). One of the major

[4]Depending on the data source used, studies commonly share similar research goals, challenges, and limitations.

challenges for this group of studies lies in the absence of the sentiment lexicons and training datasets within the target domain of educational textbooks. Moreover, considering that texts in books are much longer than texts in $\mathrm{UGC}_{\mathrm{SN}}$, authors may express different emotions in reviews, and news, and throughout the texts; thus, it was challenging to identify the dominant sentiment. In order to cover a broader range of opinions, some studies utilised *Mixed Data Sources*, where the most common use cases were to identify attitudes towards different topics (e.g., [74; 75]). Since these studies utilised a mixture of previously mentioned data sources, this type of data can be used in all mentioned research directions. However, as the reverse side of the coin, authors also received all source-specific challenges and limitations.

The overview of sentiment analysis applications on Russian-language content can be found in Table 1. As can be seen from the year-wise distribution, studies on Russian-language content proliferated during the 2014–2016 years and reached a maximum number in 2017. The percentage of rule-based (40.63%) and machine learning–based approaches (37.5%) is almost equal, with a slight predominance of the former. Additionally, 15.6% of identified studies used third-party cloud services for sentiment analysis (e.g., Medialogia, IQBuzz, and Crimson Hexagon), so we were unable to identify the specific sentiment analysis models used. Among rule-based approaches, custom rule–based models and SentiStrength [80] were the most common choice. Among machine learning–based approaches, Support Vector Machine, Logistic Regression, and Naive Bayes were the most frequently used options. Whereas most attention was given to basic machine learning approaches, neural networks were applied only in 16.7% of all machine learning-based approaches. Prior to 2018, the share of rule-based approaches was higher or at the same level as the share of machine learning–based approaches, but since 2019, the proportion of machine learning based–approaches is significantly greater than the rule-based approaches.

Based on the analysis of selected studies, we identified the following major challenges.

1. **Access to the representative historical data**. Although historical data such as posts or tweets collected via API or basic parsing is the most common data source, usually API providers only grant partial access to all publicly available data, which can be not representative to the full audience of the analysed platform.

Table 1 — Overview of sentiment analysis applications on Russian-language content.

Category	Subject	Goal	Study	SA Approach	SA Level
UGC	Attitudes to topics	Identifying attitudes towards ethnic groups and migrants	[50]	ML (Logit)	DL
			[51]	ML (Logit)	DL
			[53]	ML (Logit)	DL
			[54]	RB (SentiStrength)	DL
			[35]	ML (SVM)	DL
		Identifying attitudes during the Ukrainian Crisis	[52]	RB (custom)	DL
			[55]	RB (POLYARNIK)	DL
			[56]	RB (SentiMental)	DL
			[57]	UNK (IQBuzz)	DL
			[58]	RB (custom)	DL
		Measuring a level of social tension	[59]	ML (SVM)	DL
			[60]	RB (SentiStrength)	DL
		Examining reaction to the meteor explosion in Chelyabinsk	[61]	n/s	DL
		Measuring reaction to Sochi 2014 Olympics	[62]	RB (SentiStrength)	DL
		Examining mass protests in Russia between 2011 and 2012	[63]	RB (SentiStrength)	DL
		Distribution of emotions in Saint Petersburg	[64]	ML (NBC)	DL
	Public Sentiment Index	Constructing the Index of Subjective Well-Being	[26]	RB (custom)	WL, DL
			[27]	ML (GBM)	DL
	User Behaviour	Measuring of the impact of sentiment on the mechanisms of feedback from the audience.	[65]	ML (BiGRU)	DL
Reviews	Characteristics of Reviewers	Identifying reasons why employees leave Russian companies	[66]	n/s	DL
	Characteristics of Products and Services	Evaluating road pavement assessment of the Northwestern Federal District of Russia	[70]	ML (NB, SGD)	DL
	Characteristics of Merchants	Identifying sellers' product quality	[71]	ML (RNTN)	DL
News	Content of News	Identifying hot topics and polarity of media coverage of news	[76]	RB (custom)	DL
			[77]	RB (custom)	DL
		Examining sentiment coverage of technologies and innovations mentioned in the mass media	[78]	RB (custom)	DL
		Comparing the networked issue agendas of Vladimir Putin and Alexey Navalny	[69]	UNK (Medialogia)	DL
	Economic and Business Forecasts	Constructing a high-frequency indicator of economic activity in Russia	[68]	ML (SVM)	DL
Books	Content of books	Comparing the sentiment expressed in Russian textbooks on Social Studies and History	[73]	RB (custom)	WL
	Educational process	Measuring the correlation between the sentiment of educational texts, a subjective assessment by the international students, and the real success of educational process.	[72]	ML (n/s)	DL
Mixed	Attitudes to topics	Identifying attitudes during the Ukrainian Crisis	[79]	UNK (Crimson Hexagon)	DL
			[74]	UNK (Crimson Hexagon)	DL
		Analysing the intensity and sentiment of the media coverage of Alexei Navalny	[75]	UNK (Medialogia)	DL

RB	–	rule-based approaches	n/s	–	not specified	SGB	–	Stochastic Gradient Descent	Logit	–	Logistic Regression
ML	–	machine learning-based approaches	NB	–	Naive Bayes	RNTN	–	Recursive Neural Tensor Network	DC	–	document-level
UNK	–	unknown approaches	MNB	–	Bidirectional Gated Recurrent Units	SVM	–	Support Vector Machine	WC	–	word-level

2. **Access to the labelled data from the target domain**. Only a limited amount of studies made their datasets publicly available, so it is a common challenge to find an appropriate training dataset for a specific domain. In case none of these datasets is appropriate for the target domain of the study, researchers have to perform manually labelling of the training dataset. Given that manual annotation may be resource-intensive and time-consuming, some studies utilised third-party sentiment analysis solutions without testing the classification quality on the target domain, and, as a consequence, it has become challenging to validate the accuracy of their outcomes. We performed additional literature analysis and found 14 sentiment analysis datasets of texts in Russian (see our article [49]).
3. **Topics extraction from texts**. Topic modelling was the most common solution for topic extraction from texts. However, in the case where the share of texts related to target topics is well below 1%, topic modelling is generally unable to deal with topics extraction [81]. Moreover, topic modelling demonstrates poor accuracy in analysis of short texts, especially in the case where texts represent everyday talk [81]. Thus, more accurate and noise-insensitive approaches must be developed.
4. **Reliability of the analysis results**. There is still considerable controversy surrounding the reliability of measuring reactions and opinions through automatic analysis of online content. While some studies [82; 83] considered that social network–based approaches are less accurate than traditional surveys, other studies [84] stated that they demonstrate higher performance in comparison with traditional methods. Thus, it is highly recommended to compare the results of the study with the results received by another methodological approach if it is possible.
5. **Comprehensive description of limitations.**. A significant share of the analysed studies suffers from an non-comprehensive list of limitations. To cover a broad range of study limitations, in addition to the technical and methodological limitations of the utilised approach, it is highly recommended to specify the following limitations: level of internet penetration (certain groups of people may not be considered in the study), representativeness of a data source audience (the audience of a particular social network site may be generally not representative of the general

population), media freedom and internet censorship (restrictive regulation policies on the dissemination of certain information may impact results of the study).

Also, we identified the following further research directions.

1. **Transfer learning of language models for sentiment analysis**. The majority of the analysed papers applied rule-based and basic machine learning approaches, and only several studies [65; 71] utilised neural networks. However, recent studies showed that transfer learning from pre-trained language models has proven to be effective in the sentiment classification task, confidently achieving strong results (e.g., [85—87]). Thus, the usage of fine-tuned language models can potentially significantly increase sentiment classification quality and therefore improve the accuracy of the sentiment monitoring results.
2. **Automatic content analysis as an alternative to traditional polls**. Currently, the analysis of online texts cannot be considered as a full-fledged alternative to the classical approaches for measuring opinions based on mass polls [88]. To overcome this uncertainty, a theoretical basis for generalizing data to more complete groups of the population needed to be done [89]. A traditional mass survey involves associating opinions with sociodemographic groups, whereas in data from social media this reliable demographic information is commonly unavailable. To compare obtained results with the traditional opinion polls, researchers may utilise geolocation information, user profile information, and gender and age prediction systems [90—94].
3. **Monitoring of public sentiment index in Russian**. Though for many languages and countries there have already been attempts to measure public sentiment based on social networks (e.g., [22—24]), the research on Russian-language content remains quite limited [26; 95]. It can be broadened and deepened in terms of analysed data volume, quality of sentiment classification model, and methodology of public sentiment indexes calculation. Moreover, it can be broadened by verifying the reliability of obtained results.
4. **Conversational sentiment analysis**. The context of ongoing dialogue can completely change the sentiment for a user response in comparison

with the sentiment when a response is examined as a standalone statement [96]. As a consequence, in the case of conversational sentiment analysis, such as analysis of comments and responses, it is crucial to capture the context of the conversation in addition to the standalone sentiment of the response.

5. **Likes and other reactions to the content as an indirect way of expressing sentiment**. The majority of analysed studies measured expressed sentiment only via the content of posts. However, likes and other reactions to a post can potentially be considered as an additional source of expressed sentiment by the viewers of the post. Therefore, it may be taken into account in the results of sentiment monitoring.
6. **Analysis of content from lesser explored data sources**. Whereas the majority of studies examine Vkontakte, Twitter, LiveJournal, and YouTube, there are other widespread local social networks that have high potential as data sources—such as Odnoklassniki, My World@Mail.Ru, and RuTube. For example, Odnoklassniki is widespread among the audiences of 35+ years old, so it can be a useful platform for the analysis of the opinions of older generations. Moreover, access to the representative historical data from Odnoklassniki can be requested directly through OK Data Science Lab, an exclusive platform developed by Odnoklassniki for research purposes.

Thus, we surveyed existing applications of sentiment analysis for the Russian-language content. We identified five categories of studies based on the utilised data sources and further synthesised and systematically characterised existing identified studies by their purpose, sentiment analysis approach employed, and primary outcomes and limitations. Finally, we presented a research agenda to improve the quality of the applied sentiment analysis studies and to expand the existing research base in new directions. The full text of the article can be found in our article [49].

2 Deep Transfer Learning Baselines for Sentiment Analysis in Russian

Considering that the quality of sentiment analysis outcomes relates directly to the quality of the sentiment classification methods, the identification of the

Dataset	Classes	Average length	Max length	Train texts	Test texts	Overall texts
SentiRuEval-2016 [42]	3	87.09	172	18,03	5,560	23,595
SentiRuEval-2015 Subtask 2 [41]	3	81.49	172	8,58	7,738	16,318
RuTweetCorp [97]	3	89.17	189	n/s	n/s	334,836
RuSentiment [98]	5	82.02	800	28,218	2,967	31,185
LINIS Crowd [99]	5	n/s	n/s	n/s	n/s	n/s
Kaggle Russian News Dataset [100]	3	3911.85	381.49	n/s	n/s	8,263
RuReviews [101]	3	130.06	1007	n/s	n/s	90,000

Table 2 — Overview of selected datasets.

most high-quality methods is an extremely relevant and important area of research. Transfer learning to a variety of natural language processing tasks has come a long way, ranging from the usage of context-independent word vectors from unsupervised models [102; 103] to the current direct use of pre-trained transformer blocks [86; 104] with an additional output layer stacked for the task-specific fine-tuning. Recent studies showed that transfer learning from pre-trained language models have proven to be effective in the sentiment classification task, confidently achieving strong results [105]. However, so far, only a limited amount of studies [106; 107] have focused on transfer learning from pre-trained language models in the sentiment analysis of Russian texts.

To obtain profound insights into the classification quality of language models on Russian texts, we identified language models that support Russian language and conducted a transfer learning experiment on the Russian-language sentiment analysis dataset. Among available language models, we decided to evaluate the multilingual version of Bidirectional Encoder Representations from Transformers (M-BERT) [86], RuBERT [106] and Multilingual Universal Sentence Encoder (M-USE) [104] in the Russian-language sentiment analysis task. The decision was made based on the following factors. We identified M-BERT, RuBERT, and M-USE as the only recent language models that officially support the Russian language. M-BERT has already been widely recognised by scholars dealing with content analysis in Non-English language, so evaluation of this language model in the context of Russian language sentiment analysis became a necessary priority task. RuBERT is the Russian version of M-BERT, which has already shown good classification results on RuSentiment [98], so we decided to evaluate it on other datasets too. In comparison with the M-BERT model, M-USE has received slightly less attention from scholars. However, based on the classification metrics reported in the original paper, we assumed that this language model also holds significant potential for the sentiment analysis of Russian language content.

Based on the previously identified list of 14 public sentiment datasets of Russian-language texts (see our article [49]), we selected only those datasets to which general methods of sentiment analysis (i.e., not aspect-based analysis) can be applied. Next, through a search in scientometric databases, we counted the number of citations for each dataset considering these values as the proxy measure of research interest and selected for further analysis only those datasets that had received at least one citation. Following this strategy, we selected seven datasets (see Table 2) for further model training.

1. **SentiRuEval-2016** [42] is a dataset of Tweets about telecommunication companies and banks, which was used in the evaluation of Russian sentiment analysis systems in 2016.
2. **SentiRuEval-2015 (Tweets)** [41] is a dataset of Tweets about telecommunication companies and banks, which was used in the evaluation of Russian sentiment analysis systems in 2015.
3. **RuTweetCorp** [97] is a dataset of general-domain Tweets, which were labelled automatically.
4. **RuSentiment** [98] is a dataset of general-domain posts from the largest Russian social network, VKontakte.
5. **LINIS Crowd** [99] is a dataset of social and political blog posts from social media sites.
6. **Kaggle Russian News Dataset** [100] is a public sentiment dataset of news, which was anonymously published at Kaggle.
7. **RuReviews** [101] is a dataset of online reviews from the "Women's Clothes and Accessories" product category on the primary e-commerce site in Russia.

Additionally, for each selected dataset, we identified papers describing current state-of-the-art results in terms of classification quality (see Table 3).

During the fine-tuning stage, on top of the pre-trained representations, a simple softmax classifier was employed to predict the final probability of class labels c:

$$p(c|h) = \mathrm{softmax}(Wh), \tag{1}$$

Dataset	Measure	Current SOTA	M-BERT-*	RuBERT-*	M-USE-CNN-*	M-USE-Trans-*
SentiRuEval-2016 TC [42]	**F_1**	68.42	66.29	**70.68**	63.64	68.27
	macro F_1^{PN}	66.07	61.78	**66.40**	58.97	62.77
	micro F_1^{PN}	74.11	72.45	**76.71**	71.31	75.00
SentiRuEval-2016 Banks [42]	**F_1**	**74.06**	65.31	72.83	66.71	72.40
	macro F_1^{PN}	**69.53**	58.00	65.89	58.73	65.04
	micro F_1^{PN}	**71.76**	60.52	68.43	62.41	68.21
SentiRuEval-2015 TC [41]	**F_1**	**68.54**	60.47	64.39	60.57	64.28
	macro F_1^{PN}	**63.47**	53.16	57.76	52.37	57.60
	micro F_1^{PN}	**67.51**	57.03	61.38	57.76	61.18
SentiRuEval-2015 Banks [41]	**F_1**	**79.51**	67.65	70.58	66.32	69.62
	macro F_1^{PN}	**67.44**	56.97	60.95	54.74	59.12
	micro F_1^{PN}	**70.09**	59.32	63.33	57.61	62.17
RuSentiment [98]	**F_1**	n/s	71.37	**72.03**	66.27	68.60
	weighted F_1	**78.50**	75.13	75.71	71.05	73.42
Kaggle Russian News Dataset [100]	**F_1**	70.00	71.36	**73.63**	71.27	72.66
LINIS Crowd [99]	**F_1**	37.29	42.73	**60.51**	56.34	56.95
RuTweetCorp Trinary [97]	**F_1**	75.95	83.04	**83.69**	81.34	83.17
RuTweetCorp Binary [97]	**F_1**	78.1	80.10	**80.79**	78.39	79.69
RuReviews [101]	**F_1**	75.45	77.31	**77.44**	76.63	76.94

Table 3 — Classification quality of fine-tuned models.

where W is the task-specific parameter matrix of the added softmax layer. During the training stage, we fine-tuned both the pre-trained model parameters and W by maximizing the log probability of the correct label (hyperparameters can be found in our article [108]). In the majority of cases, fine-tuned RuBERT demonstrated the best classification quality in comparison with other fine-tuned language models. The closest performance was demonstrated by M-USE$_{\text{Trans}}$, which often showed almost the same results as RuBERT. M-USE$_{\text{Trans}}$ always demonstrated higher scores than M-USE$_{\text{CNN}}$. In several cases, we were unable to exceed the current SOTA results. The first one is the fine-tuned ELMo [107] trained on RuSentiment, which is technically also a language model. The second is the BERT sentence-pair models [109] trained on SentiRuEval-2016 Banks, SentiRuEval-2015 TC, and SentiRuEval-2015 Banks datasets, which are also language models. Thus, considering the obtained results, we can state that in the context of existing approaches, sentiment analysis of Russian-language texts based on language models outperforms rule-based and basic machine learning–based approaches in terms of classification quality.

According to the confusion matrices shown in Figure 1, the most common misclassification errors were classifying neutral texts as negative or positive as well as classifying negative texts as neutral. The examples of such misclassifications can be found in our article [108]. Neutral sentiment is logically located between negative and positive sentiment, so it is expected that it can be classified incorrectly. Moreover, this issue looks like a general challenge to non-binary sentiment classification. For example, Barnes et al. [110] also reported that the most common errors come from the no-sentiment classes (i.e., neutral class in our case). The deep and comprehensive

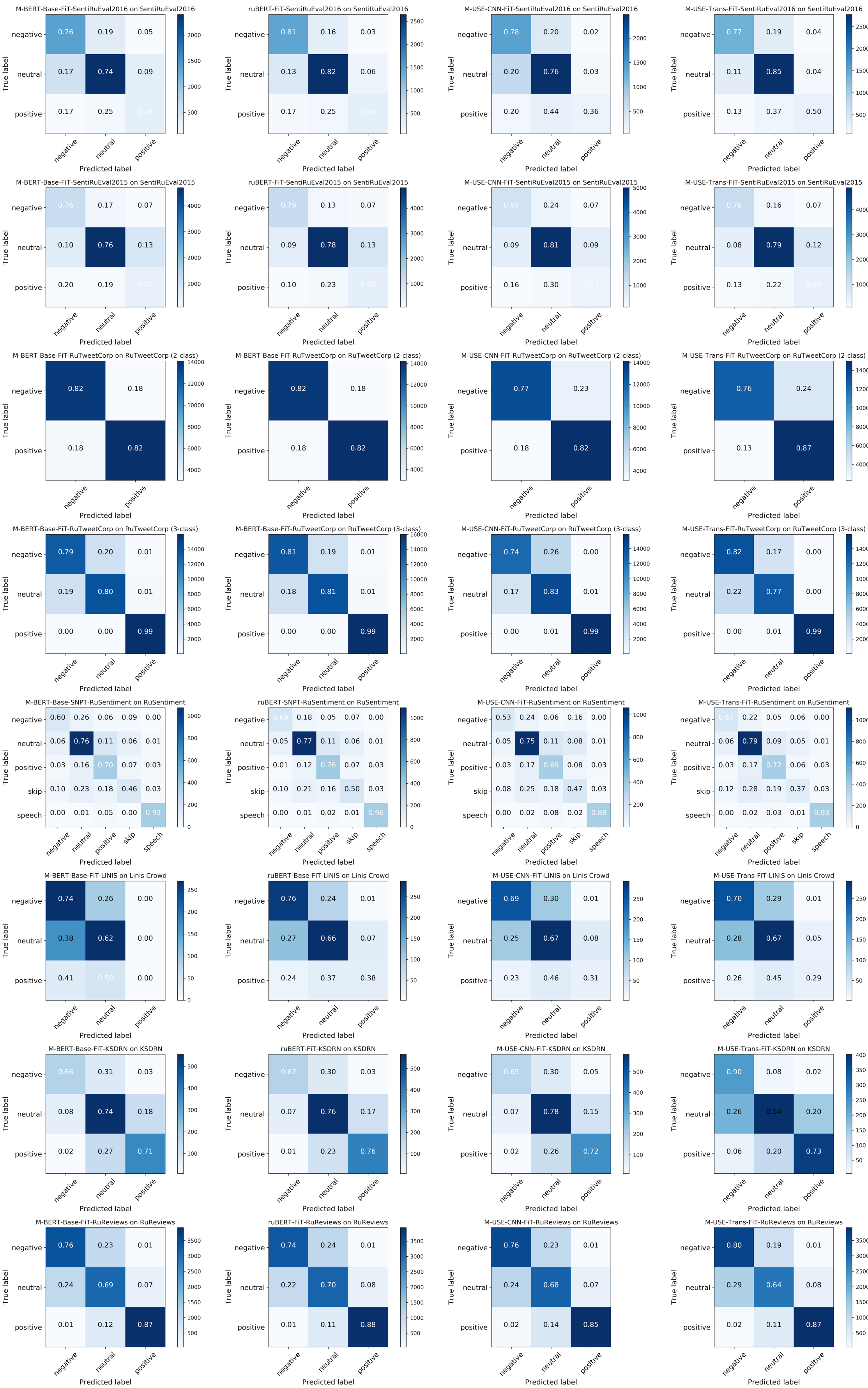

Figure 1 — Confusion matrices.

analysis of these misclassification errors is a great future research direction, which will provide academics with a broader understanding of the root cause of the problem. The framework proposed by Barnes et al. can be considered as a good foundation for this kind of research. The only exception was automatically annotated RuTweetCorp, which utilised Tweets from news accounts as a source of data with a neutral sentiment. In the case of fine-grained classification on RuSentiment, speech acts were clearly separated from other classes. Predictably, the *Skip Class* was one of the most difficult to classify, since it initially contained hardly interpretable posts.

Thus, we conducted a transfer learning experiment on several sentiment analysis datasets of the Russian language and showed that sentiment analysis of Russian-language texts based on the language models shows higher classification results than rule-based and basic machine learning–based approaches in the context of existing approaches.

3 Assessing the Impact of Classification Errors on Social Indicators Research

In the context of measuring public sentiment based on sentiment classification of social network posts, the entire process of sentiment detection is delegated to a certain algorithm, which can also make mistakes. As long as the classification algorithms' predictions are not completely error-free, the estimate of the relative occurrence of a particular class may be affected by misclassification bias [111–113]—thereby affecting the value of the calculated social indicator (e.g., public sentiment index) [114]. The key issue here is that optimal individual digital trace classification can lead to biased estimates of the digital trace class proportions and, subsequently, biased estimation of a social indicator. Generally accepted success criteria for classification—such as accuracy and F-measure on a test dataset [115]—are appropriate for individual-level classification, but they can be seriously misleading when characterizing document populations or dynamics within populations [116]. Although a significant amount of studies have investigated misclassification bias correction techniques (e.g., [113; 116]), they commonly rely on a set of assumptions that are likely to be violated in practice, which calls into question the effectiveness of these methods.

Thus, there is a knowledge gap with respect to the assessment of misclassification bias's impact on a specific social indicator formula without strict reference to the number of classes. Moreover, given the erroneous nature of automatic classification algorithms, the quality of a predicted indicator can be assessed not only using regression quality metrics, as was done in existing literature, but also using correlation metrics. We proposed a simulation approach for assessing the impact of misclassification bias on the calculated social indicators in terms of regression and correlation metrics. The proposed approach focuses on indicators calculated based on the distribution of classes and can process any number of classes. The approach is based on the following assumptions.

Assumption 3.1. The training data for the classification model was labelled manually using high-quality guidelines, and the annotators demonstrated a high inter-rater agreement score.

Assumption 3.2. The classification model was trained on the training data representative of the digital traces available for analysis.

Assumption 3.3. (Mis)classifications are independent across objects, and the (mis)classification probabilities are the same for each object, conditional upon their true class label.

Formally, the problem statement for the estimation of the impact of misclassification bias on the calculated social indicators can be defined in the following way (see Definition 3.1). Given data for analysis X spread over time intervals TI (see Definition 3.2), a trained classification model f_P and its error matrix on a test dataset CM (see Definition 3.3), an indicator calculation formula I, and formulae for the target quality metric qm_i and aggregated target quality metric aqm_i (see Definition 3.4), it is necessary to estimate the classification bias AQ_m.

Definition 3.1. The *Online Social Data Model for Social Indicators Research* is defined as a tuple $OSDM_{SIR} = (DT, C, I)$, where

- DT is the *Digital Traces* (see Definition 3.2) representing the source digital traces for the analysis,

- C is the *Classification* (see Definition 3.3) representing ML components, allowing mapping of digital traces to corresponding classes of scientific interest, and
- I is the *Indicators* (see Definition 3.4) representing social indicators of interest that should be computed within a particular social indicators research.

Definition 3.2. The *Digital Traces* of the Online Social Data Model for Social Indicators Research is defined as a tuple $DT = (TI, X, \rightarrow_{interval})$, where

- $TI = \{ti_0, ti_1, ..., ti_K\}$ is an ordered set of $K \in \mathbb{N}$ non-overlapping time intervals such as $ti_i < ti_{i+1}$,
- $X = \{x_1, x_2, ..., x_N\}$ is a finite set of $N \in \mathbb{N}$ digital trace objects, and
- $\rightarrow_{interval}$: $TI \rightarrow P_{disj}(X)$ is a partial function mapping time intervals to mutually disjoint non-empty subsets of digital traces created in that time interval.

A subset of digital trace objects created in the time interval ti_i is hereinafter referred to as X_{ti_i}, i.e., $\rightarrow_{interval} (ti_i) = X_{ti_i}$. The number of items in a subset X_{ti_i} is hereinafter referred to as $N_{ti_i} \in \mathbb{N}$.

Definition 3.3. The *Classification* of the Online Social Data Model for Social Indicators Research is defined as a tuple $C = (Y, f_T, f_P, CM)$, where

- $Y = \{y_1, y_2, ..., y_M\}$ is a finite set of $M \in \mathbb{N}$ classes,
- $f_T : X \rightarrow Y$ is a true mapping function,
- $f_P : X \rightarrow Y$ is an algorithm approximating the mapping function f (i.e., classification model), and
- $CM \in \mathbb{N}_{\not{0}}{}^{M \times M}$ is a confusion matrix for the algorithm f_P.

Definition 3.4. The *Indicators* of the Online Social Data Model for Social Indicators Research is defined as a tuple $I = (TSI, QM, AQM)$, where

- $TSI = \{I_{ti_1}, I_{ti_2}, ..., I_{ti_K}\} \in \mathbb{R}^K$ is a vector representing the time series indicator, where $I_{ti_i} : Y^{N_{ti_i}} \rightarrow \mathbb{R}$ is an indicator function mapping a set of $N_{ti_i} \in \mathbb{N}_{\not{0}}$ classified digital traces created in time interval ti_i to an indicator value,
- $QM = \{qm_1, qm_2, ..., qm_U\}$ is a set of U target quality measures, where each item represents a function $qm_i : (\mathbb{R}^K \times \mathbb{R}^K) \rightarrow \mathbb{R}^l$ returning a vector of $K \in \mathbb{N}_{\not{0}}$ real numbers, and

- $AQM = \{aqm_1, aqm_2, ..., aqm_U\}$ is a set of $U \in \mathbb{N}$ aggregated target quality measures, where each i-th item represents an aggregation function suitable for qm_i and is defined as $aqm_i : (\mathbb{R}^L)^V \to \mathbb{R}^H$, where $L \in \mathbb{N}$ is the number calculated target quality measures to be aggregated, and $H \in \mathbb{N}$ is the size of the vector representing the aggregated target quality measure.

TSI, calculated based on mapping function f_T, is hereinafter referred to as TSI_T. TSI, calculated based on the algorithm f_P, is referred to as TSI_P.

Within the given notation, our approach consists of three steps.

1. Simulate the true indicator TSI_T by simulating true mapping function f_T.
2. Approximate the predicted indicator TSI_P by approximating an algorithm f_p based on the true mapping function f_T.
3. Calculate the quality qm_i of the predicted indicator TSI_P for multiple simulations, and then calculate the aggregated quality score aqm_i.

The simulated data for each time interval are a vector with a dimension equal to the number of classes, and it is defined as follows:

$$SCD_{ti_i} = (scd_{ti_i,y_1}, scd_{ti_i,y_2}, ..., scd_{ti_i,y_M}) \in {\mathbb{N}_{\not{0}}}^M, \sum_{j=1}^{M} scd_{ti_i,j} = N_{ti_i}. \tag{2}$$

Also, the simulated data can be presented as a time series

$$STS_{y_i,TI} = (scd_{ti_1,y_i}, scd_{ti_2,y_i}, ..., scd_{ti_K,y_i}) \in {\mathbb{N}_{\not{0}}}^K, \tag{3}$$

where each element scd_{ti_i,y_j} represents the number of digital traces contained in time interval ti_i and labelled as a class y_j. Since the true indicator is unknown, we propose to synthetically generate the number of objects of each class for each analyzed time interval and calculate the true indicator TSI_T based on the generated data. Considering that the distribution in the digital traces available for analysis is equal to class distribution in the training dataset (see Assumption 3.2), we can expect the simulated data to satisfy the following condition:

$$\frac{\sum_{j=1}^{K} scd_{ti_j,y_i}}{\sum_{o=1}^{M}\sum_{j=1}^{K} scd_{ti_j,y_o}} = \frac{\sum_{j=1}^{M} cm_{y_i,y_j}}{\sum_{o=1}^{M}\sum_{j=1}^{M} cm_{y_o,y_j}}, \tag{4}$$

where cm_{y_i,y_j} is the number of objects with true class y_i classified as y_j, as further defined in Eq. (5). However, we do not expect the class distribution for a specified time interval to be equal to the class distribution in the training dataset.

Once the true mapping function is defined and the true indicator is calculated, it is necessary to define an algorithm approximating the true mapping function (i.e., classification model) f_P. First, we need estimates of the algorithm's (mis)classification probabilities. Following [117], we assume that misclassifications are independent across objects and that the (mis)classification probabilities are the same for each object, conditional upon their true class label. The (mis)classification probabilities for each class are estimated via a confusion matrix normalized over true classes, which is calculated based on a confusion matrix CM. Next, we must adjust the true class distribution SCD_{T,ti_i} by (mis)classification probabilities to acquire the approximate predicted class distribution.

The confusion matrix can be presented as follows:

$$CM = \begin{pmatrix} cm_{y_1,y_1} & cm_{y_1,y_2} & \cdots & cm_{y_1,y_M} \\ cm_{y_2,y_1} & cm_{y_2,y_2} & \cdots & cm_{y_2,y_M} \\ \vdots & \vdots & \ddots & \vdots \\ cm_{y_M,y_1} & cm_{y_M,y_2} & \cdots & cm_{y_M,y_M} \end{pmatrix} \in \mathbb{N}_{\not\vdash}{}^{M\times M}, \tag{5}$$

where each row of the matrix represents the instances in an actual class, and each column represents the instances in a predicted class. An asterisk refers to whole rows or columns in a matrix. For example, $cm_{i,*}$ refers to the i-th row of CM, and $cm_{*,j}$ refers to the j-th column of CM.

$$cm_{y_i,y_*} = \begin{pmatrix} cm_{y_i,y_1} & cm_{y_i,y_2} & \cdots & cm_{y_i,y_M} \end{pmatrix}. \tag{6}$$

$$cm_{y_*,y_j} = \begin{pmatrix} cm_{y_1,y_j} & cm_{y_2,y_j} & \cdots & cm_{y_M,y_j} \end{pmatrix}^T. \tag{7}$$

A confusion matrix normalized over true classes can be further calculated as follows:

$$
\begin{aligned}
CM^{ntc} &= \begin{pmatrix} \frac{1}{\sum cm_{y_1,y*}} & 0 & \cdots & 0 \\ 0 & \frac{1}{\sum cm_{y_2,y*}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{1}{\sum cm_{y_M,y*}} \end{pmatrix} \times CM \\
&= \begin{pmatrix} cm^{ntc}_{y_1,y_1} & cm^{ntc}_{y_1,y_2} & \cdots & cm^{ntc}_{y_1,y_M} \\ cm^{ntc}_{y_2,y_1} & cm^{ntc}_{y_2,y_2} & \cdots & cm^{ntc}_{y_2,y_M} \\ \vdots & \vdots & \ddots & \vdots \\ cm^{ntc}_{y_M,y_1} & cm^{ntc}_{y_M,y_2} & \cdots & cm^{ntc}_{y_M,y_M} \end{pmatrix} \in \mathbb{R}^{N\times N}
\end{aligned} \tag{8}
$$

Assuming that a given classification algorithm is unbiased toward a specific type of error and follows a given confusion matrix CM, we can approximate the non-normalized confusion matrix of our model for simulated data as follows:

$$
\begin{aligned}
CM' &= \begin{pmatrix} scd_{T,ti_i,y_1} & 0 & \cdots & 0 \\ 0 & scd_{T,ti_i,y_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & scd_{T,ti_i,y_M} \end{pmatrix} \times CM^{ntc} \\
&= \begin{pmatrix} cm'_{1,1} & cm'_{1,2} & \cdots & cm^{ntc}_{1,M} \\ cm'_{2,1} & cm'_{2,2} & \cdots & cm'_{2,M} \\ \vdots & \vdots & \ddots & \vdots \\ cm'_{M,1} & cm'_{M,2} & \cdots & cm'_{M,M} \end{pmatrix} \in \mathbb{N}_{\not 0}{}^{N\times N}, \\
&\sum_{o=1}^{M} cm'_{y_j,y_o} = scd_{T,ti_i,y_j}
\end{aligned} \tag{9}
$$

The simulated distribution of predicted classes based on simulated true classes distribution SCD_{T,ti_i} for a given time interval ti_i is as follows:

$$
\begin{aligned}
SCD_{P,ti_i} = (\sum_{j=1}^{M} cm'_{y_j,y_1}, \sum_{j=1}^{M} cm'_{y_j,y_2}, ..., \sum_{j=1}^{M} cm'_{y_j,y_M}) \in \mathbb{N}_{\nvdash}{}^{M} \\
\sum_{j=1}^{M} scd_{P,ti_i,y_j} = N_{ti_i}
\end{aligned}
\tag{10}
$$

Finally, we can calculate $Y^{N_{ti_i}}$ (i.e., a set of N_{ti_i} classified objects created in time interval ti_i to an indicator value) based on obtained class distributions SCD_{T,ti_i} and SCD_{P,ti_i} for further calculation of the true indicator and predicted indicator, respectively. Since the order of the items in $Y^{N_{ti_i}}$ is not important, we can define the order of items in any way following our class distributions. After that, we can calculate TSI_T, TSI_P, and qm_i. By repeating the entire procedure multiple times, we can obtain multiple qm_i and calculate aqm_i. However, if for such metrics as mean absolute error (MAE) and mean squared error (MSE) the aggregation methods are well defined (for example, it can be a simple average value), then the correlation aggregation tends to be a more challenging task to accomplish. The algorithm for aggregating correlation scores can be found in our article [118]. Depending on the strength of aggregated correlation scores, we can make the following conclusions.

- If CI_{corr} is perfect, then we can confirm that there is *no impact* of the misclassification bias on the calculation of the indicator, allowing us to achieve the *perfect level* of correlation between predicted and true indicators.
- If CI_{corr} is strong, then we can confirm that there is a *weak impact* of the misclassification bias on the calculation of the indicator, allowing us to achieve a *strong level of correlation* between predicted and true indicators.
- If CI_{corr} is moderate, then we can confirm that there is a *moderate impact* of the misclassification bias on the calculation of the indicator, allowing us to achieve a *moderate level of correlation* between predicted and true indicators.
- If CI_{corr} is weak, then we can confirm that there is a *strong impact* of the misclassification bias on the calculation of the indicator, allowing us to achieve the *weak level of correlation* between predicted and true indicators.

– If CI_{corr} is absent, then we can confirm that there is a *perfect impact* of the misclassification bias on the calculation of the indicator, allowing us to achieve *no correlation* between predicted and true indicators.

Illustrative examples of the misclassification bias estimation ca be found in our article [118].

4 Observable Subjective Well-Being in Russia Inferred from Social Network Odnoklassniki

The *Affective Social Data Model for Socio-Technical Interactions* (see Def. 4.10) consists of two elements: *Actors* and *Interactions*. The *Actors* (see Def. 4.11) represent participants of Socio-Technical Interactions (STI) [119] generating digital traces. The *Interactions* (see Def. 4.12) represent structural aspects of STI and generated digital traces represent Social Sharing of Emotions (SSE) [120]. As a basis for the formal description of the model, we took the *Online Social Data Model for Social Indicators Research* that we previously proposed to analyze the influence of the misclassification bias on the social indicators research. We applied classical set theory to develop our model since recent literature [121; 122] articulated a series of its advantages in the computational social sciences.

Definition 4.1. U_{type} is a finite set of all user types defined as $U_{type} = \{individual, business\}$ where

– *individual* represents a user account that was created for personal use, and
– *business* represents a user account that was created for business use.

It is important to delimit the types of accounts, since the purpose of using a social network—and, as a result, the type of content—can strongly depend on them.

Definition 4.2. AR_{type} is a finite set of all artifact types defined as $AR_{type} = \{post, media, reaction\}$ where

– *post* represents text and (or) media posts or comments,
– *reaction* represents reactions to posted artifacts such as likes or dislikes, and
– *media* represents digital photos, videos, and audio content.

Each artifact type represents a type of user-generated content (UGC). Basically, *post* represents all communications on users' pages that occurs in the social networks, except private messages[5]. Other UGC such as digital photos, videos, and audio published in users' albums but not published on users' pages are represented as *media*. Reactions to *post* and *media* such as likes or dislikes are represented as *reaction*.

Definition 4.3. SX is a finite set of sexes defined as $SX = \{male, female\}$ where

– $male$ represents the male sex, and
– $female$ represents the female sex.

Definition 4.4. BD is a set of birth dates.

Definition 4.5. G is a set of geographical information.

Definition 4.6. MS is a finite set of marital statuses defined as $MS = \{married, single, divorced, widowed\}$, where

– $married$ represents a person who is in culturally recognized union between people called spouses,
– $single$ represents a person who is not in serious committed relationships, or is not part of a civil union,
– $divorced$ represents a person who is no longer married because the marriage has been dissolved, and
– $widowed$ represents a person whose spouse has died.

Definition 4.7. FT is a set of family types (i.e., classification of a person's family unit) defined as $FT = \{nuclear, single - parent, blended, ofchoice\}$, where

– $nuclear$ represents a family which includes only the spouses and unmarried children who are not of age,
– $single - parent$ represents a family of one parent[6] together with their children,
– $blended$ represents a family with mixed parents[7], and
– $ofchoice$ represents a group of people in an individual's life that satisfies the typical role of family as a support system.

[5]Our model does not consider private messages because not only are they extremely problematic to obtain, but their analysis can also raise a series of legal, privacy, and ethical questions.

[6]The parent is either widowed, divorced (and not remarried), or never married.

[7]One or both parents remarried, bringing children of the former family into the new family.

Definition 4.8. $CN \in \mathbb{N}_0$ is the user's numbers of children.

Definition 4.9. $HS \in \mathbb{N}_0$ is the number of people living in the user's household.

The combination of sex SX, birth date BD, marital states MS, family type FT, and number of children CN represents *demographics* of the population and is of interest for conducting SWB studies [123]. This model does not consider other covariates (e.g., material conditions, quality of life, and psychological measures) recommended for collection alongside measures of SWB, since there is virtually no access to them within social networks data.

Definition 4.10. The *Affective Social Data Model for Socio-Technical Interactions* is defined as a tuple $ASDM_{STI} = \{A, I\}$, where

- A is the Actors representing the participants of socio-technical interactions generating UGC as defined further in Def. 4.11, and
- I is the Interactions representing the structural aspects and UGC of $ASDM_{STI}$ as defined further in Def. 4.12.

As provided in the conceptual model and in Def. 4.10, the *Affective Social Data Model for Socio-Technical Interactions* ($ASDM_{STI}$) contains *Actors* (those who are doing and interacting) and *Interactions* (what is being done and interacted with).

Definition 4.11. The *Actors* of $ASDM_{STI}$ is defined as a tuple $A = (U, U_{type}, SX, BD, MS, FT, CN, HS, G, f^U_{U_{type}}, f^U_{S?}, f^U_{BD?}, f^U_{MS?}, f^U_{FT?}, f^U_{CN?}, f^U_{HS?}, f^U_{G?})$, where

- U is a finite set of users ranged over by u,
- U_{type} is a finite set of user types (as defined in Def. 4.1) ranged over by u_{type},
- SX is a finite set of users' sexes (as defined in Def. 4.3) ranged over by sx,
- BD is a set of users' birth dates ranged over by bd,
- MS is a set of users' marital statuses (as defined in Def. 4.6) ranged over by ms,
- FT is a set of users' family types (as defined in Def. 4.7) ranged over by ft,
- CN is the user's numbers of children (as defined in Def. 4.8) ranged over by cn,
- HS is a set of numbers of people living in the users' households (as defined in Def. 4.9) ranged over by hs,

- G is a set of users' geographical information (as defined in Def. 4.5) ranged over by g,
- $f^{U}_{U_{type}} : U \rightarrow U_{type}$ is the user type function mapping each user to the user type,
- $f^{U}_{S?} : U \rightarrow S$ is the sex function mapping each user to the user's sex if defined,
- $f^{U}_{BD?} : U \rightarrow BD$ is the birth date function mapping each user to the user's birth date if defined,
- $f^{U}_{MS?} : U \rightarrow MS$ is the marital status function mapping each user to the user's marital status if defined,
- $f^{U}_{FT?} : U \rightarrow FT$ is the family type function mapping each user to the user's family type if defined,
- $f^{U}_{CN?} : U \rightarrow CN$ is the number of children function mapping each user to the user's number of children if defined,
- $f^{U}_{HS?} : U \rightarrow HS$ is the household size function mapping each user to the user's household size if defined, and
- $f^{U}_{G?} : U \rightarrow G$ is the geographic information function mapping each user to the user's geographic information if defined.

The formal definition of Actors is provided in Def. 4.11. The first two items contain a set of users (U) and a set of user types (U_{type}), respectively. The next six items contain demographic information, including sex (SX), birth date (BD), marital status (MS), family type (FT), the numbers of children (CN), the numbers of people living in the household (HS), and geographical information (G). The rest of the items are mapping functions from a user to the user's type and all mentioned demographic characteristics if defined.

Definition 4.12. The Interactions of $ASDM_{STI}$ is defined as a tuple $I = (AR, AR_{type}, S, f^{AR}_{U_{feed}}, f^{AR}_{U_{author}}, f^{AR}_{AR_{type}}, f^{AR}_{AR}, f^{AR}_{S}, track^{U,AR}_{T}, age^{U}_{AR} : track^{U,AR}_{T}, \rightarrow_{post}, \rightarrow_{react})$, where

- AR is a finite set of artifacts ranged over by ar,
- AR_{type} is a finite set of artifact types (as defined in Def. 4.2) ranged over by ar_{type},
- S is a finite set of sentiment classes ranged over by s,
- $f^{AR}_{U_{feed}} : AR \rightarrow U$ is a function mapping the artifact and the user on whose feed it was published,

- $f^{AR}_{U_{author}}$: $AR \rightarrow U$ is a function mapping the artifact and the user who created it,
- $f^{AR}_{AR_{type}}$: $AR \rightarrow AR_{type}$ is the artifact type function mapping each artifact to an artifact type,
- f^{AR}_{AR} : $AR \rightarrow AR$ is a parent artifact function, which is a partial function mapping artifacts to their parent artifact if defined,
- f^{AR}_{S} : $AR \rightarrow S$ is a relation defining mapping between artifact and sentiment,
- $track^{U,AR}_{T}$: $(U \times AR) \rightarrow N$ is a time function that keeps tracks of the timestamp of an artifact created by an user,
- age^{U}_{AR} : $track^{U,AR}_{T} \times f^{U}_{BD?} \rightarrow N?$ is a time function that returns the age of the user on the time of the artifact's creation if the user's birthday is defined,
- $\rightarrow_{post}$: $U \rightarrow P_{disj}(AR)$ is a partial function mapping users to mutually disjoint sets of their artifacts, and
- $\rightarrow_{react}$: $U \rightarrow P(AR)$ is a partial function mapping users to the artifacts reacted to by the users.

As can be seen from the $ASDM_{STI}$ definition, S represents a finite set of sentiment classes, and f^{AR}_{S} represents mapping between an artifact and a sentiment. From the sentiment classification perspective, S is a set of classes in a training sentiment dataset, and f^{AR}_{S} is a function that runs the sentiment classification model trained on the sentiment dataset and returns the sentiment of the artifact.

The approach for calculating OSWB indicators consists of three steps.

1. Select content of interest for the analysis; that is, textual posts published by users on their own pages.
2. Make data sample representative of the target population by applying sampling techniques.
3. Calculate selected OSWB measures based on representative data sample.

Definition 4.13. $TI = \{ti_1, ti_2, ..., ti_T\}$ is a finite ordered set of T non-overlapping time intervals such as $ti_i < ti_{i+1}$.

Definition 4.14. $\rightarrow_{interval}$: $(age^{U}_{AR} : track^{U,AR}_{T} \rightarrow N?) \rightarrow TI?$ is a partial mapping a timestamp of an artifact creation to a time interval if the birthday of the user is defined.

Definition 4.15. P is a finite set of PN textual posts published by users on their own pages and defined as follows:

$$\begin{aligned} P = \{ar | f^{AR}_{AR_{type}}(ar) = post | \forall ar \in AR \wedge f^{AR}_{U_{feed}}(ar) = \\ f^{AR}_{U_{author}}(ar) \wedge f_{UBD?} \neq \varnothing \wedge f^{AR}_{AR}(ar) = \varnothing\} \end{aligned} \tag{11}$$

Definition 4.16. P_{ti_i} is a finite set of PN_{ti_i} posts published by authors on their pages during time interval ti and is defined as follows:

$$P_{ti_i} = \{p | \forall p \in P \wedge \rightarrow_{interval} (p) = ti_i\}, \sum_{i=1}^{T} PN_{ti_i} = PN \tag{12}$$

We focus on the user's own posts posted on their pages, as we assume that such posts are more likely to contain the emotional state of the author compared to posts elsewhere. We also believe that the users' pages, in most cases, are not limited to a specific thematic domain, in comparison with the walls of groups and communities; therefore, these posts should contain a larger number of different topics and, on average, be general-domain sources of data.

Definition 4.17. $\dot{U}_{ti_i}$ is a finite set of users who posted textual posts on their own profiles within time interval ti and is defined as follows:

$$\dot{U}_{ti_i} = \{f^{AR}_{U_{author}}(p) | \forall p \in P_{ti_i}\}. \tag{13}$$

After obtaining $\dot{U}_{ti_i}$, it is necessary to validate that the number of users for each time interval ti_i is not less that the minimum sample size n (see our article [18]). In case it is less than n for at least one $ti_i \in TI$, then the calculation of the index with the selected confidence level and margin of error is not possible.

Definition 4.18. $\dot{DF}$ is a finite set of DFN demographics mapping functions with defined values over the given users set and is defined as follows.

$$\begin{aligned} GS = \{f | \forall f \in \{f^U_{S?}, age^U_{AR}, f^U_{MS?}, f^U_{FT?}, f^U_{CN?}, f^U_{HS?}, f^U_{G?}\}, \\ \wedge f(u) \neq \varnothing, \forall u \in U\}. \end{aligned} \tag{14}$$

Since not all of these characteristics can be obtained from social network data, it is recommended to use at least age and gender characteristics for sampling design in accordance with the European Social Survey Sampling Guidelines [124].

Definition 4.19. $\ddot{U_{ti_i}}$ is a finite set of users $\dot{U_{ti_i}}$ representative of the target population by applying stratification[8].

Definition 4.20. $\dot{P_{ti_i}}$ is a finite set of posts created by representative sample of users $\ddot{U_{ti_i}}$ on their own pages during time interval ti and is defined as follows:

$$\dot{P_{ti_i}} = \{p | \forall p \in P_{ti_i} \wedge f^{AR}_{U_{author}}(p) \in \ddot{U_{ti_i}}\} \tag{15}$$

Firstly, it is required to aggregate sentiment for users who posted several times during the considered time intervals.

Definition 4.21. agg_{u,ti_i} is the sentiment aggregation function that aggregates the sentiment of posts published during time interval ti_i by user u and is defined as follows:

$$agg_{u,ti_i} : P \times P \rightarrow S. \tag{16}$$

The aggregation function can be defined in several ways (e.g., major voting).

Definition 4.22. AUS_{ti_i} is the aggregated user sentiment expressed in a post published during ti_i period of time.

$$\begin{aligned} AUS_{ti_i} = \{agg_{u,ti_i}((f^{AR}_S(p^u_0), (f^{AR}_S(p^u_1), (f^{AR}_S(...),\\ (f^{AR}_S(p^u_j)) | \forall p^u \in \dot{P_{ti_i}}, \forall u \in \ddot{U_{ti_i}} \wedge f^{AR}_{U_{author}}(p^u) = u\} \end{aligned} \tag{17}$$

Finally, the OSWB indicator can be calculated.

Definition 4.23. $OSWBI_{ti_i}$ is the OSWB indicator and is defined as follows:

$$OSWBI_{ti_i} = \{indicator(aus) | \forall aus \in A\dot{U}S_{ti_i}\}, \tag{18}$$

where *indicator* is an indicator formula, which can be defined in several ways depending on the study goals (see examples in our article [18]).

As a data source for OSWB measurement, we selected Odnoklassniki, one of the largest social networks in Russia. The distribution of the Odnoklassniki audience

[8]Here, N_tp is the population size, n is the total sample size, k is the number of strata, N_i is the number of sampling units in i-th strata such as $\sum_1^k N_i = N$, n_i is the number of sampling units to be drawn from i-th stratum such as $\sum_1^k n_i = n$. Strata are constructed such that they are non-overlapping and homogeneous with respect to the characteristic under study. For fixed k, the proportional allocation of stratum size can be calculated as $n_i = \frac{n}{N} N_i$, where each n_i is proportional to stratum size N_i

by age is the closest among all social networks to the general distribution of the Internet audience in Russia [125]. Similar information was reported in the study by [126], where the author concluded that Odnoklassniki is the most democratic social network in Russia because it is used by all categories of the population, including "traditional non-users"—that is, the elderly and people with a low level of education. In fact, according to Brodovskaya, the only network used by older Russians is Odnoklassniki, since Russians who have reached the age of sixty do not have accounts on any foreign social networks.

OK Data Science Lab provided us with 7,200,000 randomly selected textual (i.e., $\forall ar \in AR, f^{AR}_{AR_{type}}(ar) = post$) posts published in Russia (i.e., $\forall u \in U, f^{U}_{G?}(u) = Russia$) by individual users (i.e., $\forall u \in U, f^{U}_{U_{type}}(u) = individual$) on their public profiles between April 2020 and May 2021, for a total of 20,000 posts per day. Each post contained anonymized user identifiers (primary identifier of artifacts $ar \in AR$), date of birth if known ($bd \in BD$), sex if known ($sx \in SX$), time of publication (required for $\rightarrow_{interval}$), author's time zone at the moment of publication (required for $\rightarrow_{interval}$), author's country ($f^{U}_{G?}(u) = Russia$ for all posts) at the moment of publication (based on IP and other Odnoklassniki internal heuristics), text (required for sentiment mapping function f^{AR}_{S}), and language used in the post. We then filtered out duplicates, posts of authors without date of birth or gender, and obtained 7,049,907 posts for further analysis. These posts were published by 3,610,891 unique users—1.95 posts per user on average. We checked the number of unique authors of posts for each day and confirmed that it exceeds 1,537 unique authors for each day.

While selecting demographic groups, in addition to general guidelines on measuring SWB mentioned earlier [123; 124; 127; 128], we also relied on recommendations by Russian research agencies to cover country-specific aspects: VCIOM SPUTNIK Methodology [129] and RANEPA Eurobarometer Methodology [130]. Thus, we selected the following demographic variables for post-stratification.

- **Gender**. The array reflects the sex structure of the general population: male and female.
- **Age**. The array is divided into four age groups, reflecting the general population: 18–24 years old, 25–39 years old, 40–54 years old, and 55 years old and older.

For sentiment analysis, we fine-tuned RuBERT [106], XLM-RoBERTa-Large [131], RuRoBERTa-Large [132], and M-BART-Large-50 [133] on RuSentiment [98].

RuRoBERTa-Large outperformed all other models and achieved new state-of-the-art results of weighted $F_1 = 76.30$ (4.27 percentage points above existing SOTA) and macro $F_1 = 78.92$ (0.42 percentage points above existing SOTA). The information about characteristics of models, hyperparameters, training procedure, and classification errors analysis is presented in our article [18]. We applied RuRoBERTa-Large to the Odnoklassniki data and classified sentiment for all posts.

For indicators calculation, we used two indicator formulae.

Definition 4.24. $OSWB_{PA}$ is the Positive Affect Indicator (experiencing pleasant emotions and moods) and is defined as follows:

$$OSWB_{PA} = \frac{POS}{POS + NEG + NEU + SA + SKIP}, \tag{19}$$

where POS is the number of positive posts, NEG is the number of negative posts, NEU is the number of neutral posts, SA is the number of posts with greetings and speech acts, and $SKIP$ is the number of ambiguous posts that cannot be unambiguously assigned to one of the other classes.

Definition 4.25. $OSWB_{NA}$ is the Negative Affect Indicator (experiencing unpleasant, distressing emotions and moods) and is defined as follows:

$$OSWB_{NA} = \frac{NEG}{POS + NEG + NEU + SA + SKIP} \tag{20}$$

We calculated the Observable Happiness indicators for each month for a period from April 2020 to March 2021 (12 months) and found moderate to strong (depending on the interpretation guidelines [134]) Pearson's linear correlation ($r = 0.733$, $p = 0.007$) and strong Spearman's monotonic correlation ($r_s = 0.825$, $p = 0.001$) between $OSWB_{PA}$ (further referred to as Observable PA) and VCIOM Happiness indicator. As can be seen in Fig. 2, Observable PA and VCIOM Happiness indicators are quite similar. Both indicators demonstrated growth in the beginning of the analysed period and rapid decline starting from Autumn 2020. Since previous studies reported that the typical reliability of SWB scales is in the range from 0.50 to 0.84 [19; 135—138] (and even between 0.40 and 0.66 for single-item measures like VCIOM Happiness [136]), we can consider obtained correlation as practically close to unity. Interestingly, $OSWB_{NA}$ (further referred to as Observable NA) showed no statistically significant correlation with the VCIOM index.

Figure 2 — Observable Happiness and VCIOM Happiness indicators for a period from April 2020 to March 2021.

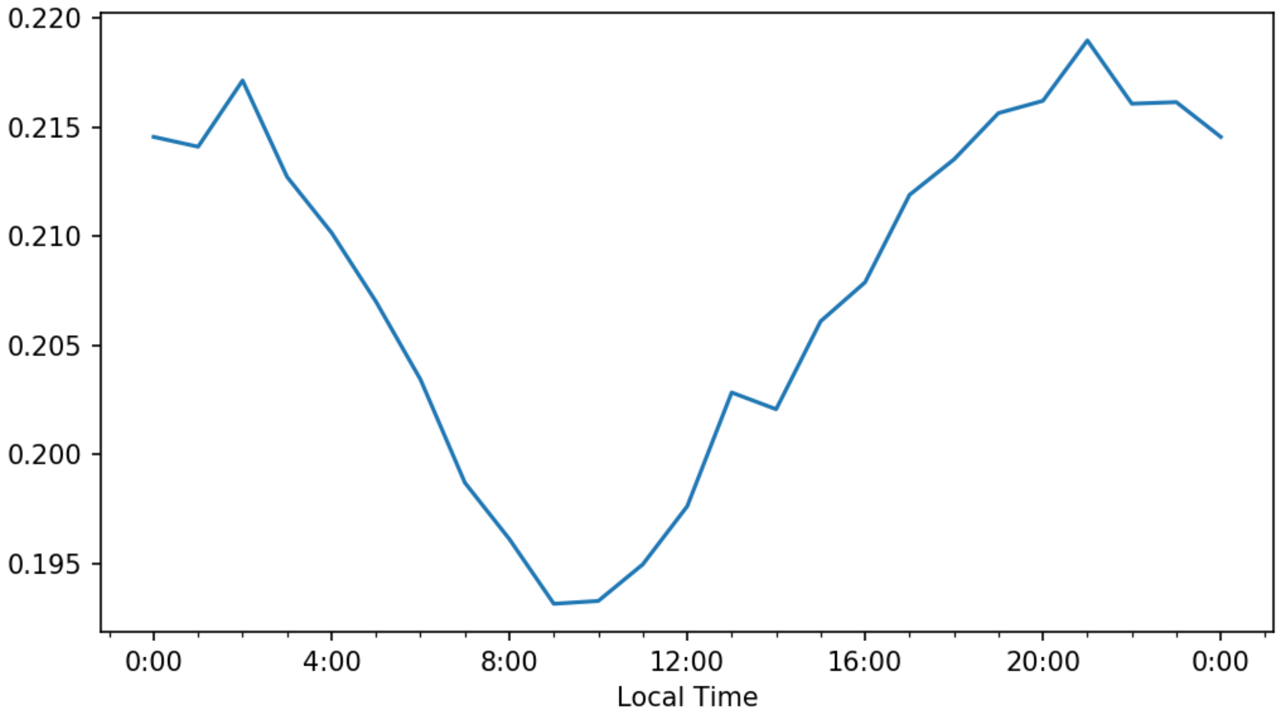

Figure 3 — Daily patterns of Observable PA in local time.

General daily variations can be clearly seen (see Fig. 3), with morning having the lowest level of happiness and late evening having the highest. Obtained general daily patterns differ from the patterns reported in other OSWB studies (e.g., [22; 23]), since in the majority of cases, two spikes were previously reported: one in the early morning and the other in the late evening. In our case, we assume that we did not have an early morning spike due to both methodological and geographical aspects. From the methodological point of view, we deliberately did not consider greetings and speech acts as a manifestation of positive emotions and treated them as a separate class instead. The key reason behind this decision is that greetings and speech acts make use of sentiment (commonly positive) related words while not necessarily denoting the the underlying sentiment of the author [98; 139]. We assume that this is why other studies have reported peaks at the start of the day: this is where the highest number of greeting and speech act posts occur. From the geographical point of view, the presence of different time zones within the same country (for example, Russia has 11 time zones) makes it more difficult to compare patterns between countries and may cause differences in patterns for these countries. In contrast with other studies, we analysed local time of each timezone. The absence of early morning spikes perfectly corresponds to the results of classical survey-based study conducted by Cornelissen et al. [140]. The authors built a Positive Affect indicator, which in shape completely coincides with the graph obtained in our study: the lowest point is reached in the morning, then the graph grows up to 18 hours and begins to fall closer to night. The key difference is that our indicator is shifted by a few hours to the right relative to their indicator (e.g., the lowest point on their indicator is reached at 6am, and on ours at 8am). We suppose that this difference arose due to the discrepancy between the samples under consideration since they surveyed only students, and our study targeted the larger number of demographic groups. A similar pattern can be observed in another study [141], which reported Net Affect and Positive affect measures for Russia. The authors reported that Net Affect and Positive Affect improved as the day passed, with the lowest point around 9am, which corresponds with our results.

Weekly patterns in OSWB can be clearly observed as well (see Fig. 4), with weekends being happier than weekdays. At the level of individual days of the week, we can also observe the previously described daily patterns, which have different amplitudes and extremes depending on a particular day. During the week, the lowest

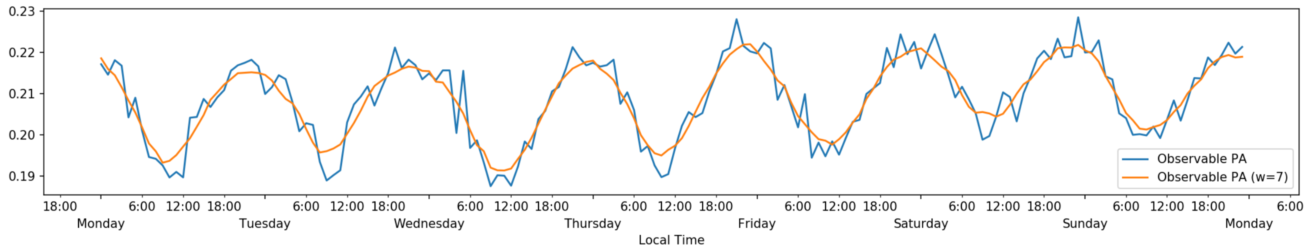

Figure 4 — Weekly patterns in local time.

level of happiness occurs in the first three weekdays, and starting on Thursday it starts to rise and peaks at the weekend. Russians wake up in their best mood on Saturday and reach their highest level of happiness closer to the night. These weekly patterns are intuitively expected, since as was mentioned by Mayor and Bietti [142], weekly patterns are generally associated with cultural traditions and the cultural distinction between weekdays and weekends in modern societies regulating social practices and behaviours. Similar results were reported for other countries both in the framework of traditional sociological research (e.g., [143; 144]) and research based on digital traces (e.g., [23; 139]).

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