OpinionSim: modelling and simulating stakeholders' feedback to product-service systems

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Abstract — **This paper describes the OpinionSim simulator developed in the scope of project DIVERSITY. DIVERSITY is related with the design of product-service systems (PSS) using real time feedback loops from internal and external stakeholders. For that purpose, the DIVERSITY platform includes Sentiment Analysis components that process posts retrieved from social media networks. Nonetheless, the test of Sentiment Analysis components requires a dataset, i.e. a set of posts, which exploit the full range of possible opinions in a controlled way. Additionally, to test the market segmentation functionalities we need to control the characteristics of the population generating the posts. The *OpinionSim* simulator here described meets the requirements to support the testing process.**

Keywords — *Simulation, social media, product-service systems*

I. Introduction

This paper describes the *OpinionSim* simulator developed in the scope of project DIVERSITY - *Cloud Manufacturing and Social Software Based Context Sensitive Product-Service Engineering Environment for Globally Distributed Enterprise* [1].

Project DIVERSITY is related with the design of product-service systems (PSS) using real time feedback loops from internal and external stakeholders. DIVERSITY aims at providing a collaborative environment for product-service design supporting companies from the context sensitive capturing and searching of knowledge to the transformation of these data into product-service functionalities.

The feedback from external stakeholders is provided via social media networking services (e.g. Facebook or Twitter) used by the final consumers of the developed PSS (or products manufactured by the developed PSS). The feedback is collected in the format of posts (i.e. plain text) and processed to extract the corresponding sentiment [2]. For that purpose, the DIVERSITY platform includes a Sentiment Analysis component that continuously receives posts that reflect some type of opinion about a specific product (or PSS) and uses natural language processing to quantify the degree of satisfaction, i.e. the sentiment, towards a product or a particular feature of it. That knowledge is latter on used to support decisions in the design process of future products and services.

The development and initial test of the Sentiment Analysis component requires large amounts of data, i.e. posts. These post could be easily get from any social media tool but the validation process would require to analyze the used posts (and the profile of the users generating them) almost one-by-one to check if the tool was providing the correct results. Using simulation we can generate this large dataset in a controlled way so that the sentiment processing algorithms can be verified and validated before starting to use real (uncontrolled) data.

Another important aspect being exploited in DIVERSITY is the contextualization of the collected data. In particular, it has been identified that the segmentation of the consumers providing the feedback is a key aspect to support the redesign of products targeting specific market segments. Basic market segmentation variables include gender, age grouping and geographical location, among other possible ones. Thus, the simulation generates, not only the posts, but the users generating them with a controlled relation between their segmentation characteristics and their opinions.

II. Posts and opinions

The objective of the work here described is the automatic generation of a massive number of messages simulating the normal activity of popular social media where consumers express their opinion about… everything.

First of all, what is social media?

Social media are web-based computer technologies that enable the creation and sharing of information among a set of users aggregated in a virtual community. The informational content is user-generated in the format of text posts or comments, images or videos. Additionally, users can usually have a way to recommend other users' content by clicking on a button, such as e.g. the Facebook like button. Social media enables the development of social networks by connecting users with other individuals or groups, sharing the same interests or ideas.

Social media users start by adhering to a particular network and establishing their profile. Basic elements are the name by which they will be recognized and an avatar image. People that center their online social activity with other people that they also have contact outside the online world tend to be

978-1-5386-0774-9/17/$31.00 ©2017 IEEE

truer about the profiling characteristics, using their true name and face image. Nonetheless, other people prefer to establish a somehow anonymous participation on social networks. In the majority of the social media offers it is not possible to verify the true identity of a user, but then, other people are free to accept or reject the connections with them. Other profiling elements usually asked during registration in the networks are: gender, birth date (i.e. age), city (if not automatically shared by the location service in our devices). All this additional metadata is very valuable as it allows to contextualize the opinions of users.

The text post has been the most common way for people to express their opinions about specific topics. The topics could be many different things like: a thought; a citation of a public figure; a past, present or future event; or an opinion about something active on the market. Of interest to the current work, it is an opinion about a product, a service or a product-service system.

The text post can be created by a user from scratch, shared from a post generated by other users, or comments to an already published post. Let us designate **original-post** as the first post that starts a particular thread on a subject, latter commented by other users.

People are many times compelled to share their opinion about the positives and negatives of products or services they're using. This can also be instigated by an original post that triggers the development of a new thread to capture what is the general sentiment towards a brand or its particular product or service.

But not all users of social networks have the same characteristics and relevance: the impact of one's post regarding a subject reflects the perceived authority the author has about the topic and the audience of the post. Top influencers or opinion leaders are social networks users whose posts have the capability of spreading the word-of-mouth and help turn a considerable number of opinions for or against a product or situation [3].

Normally, opinion leaders have the expertise or knowledge about the themes they address, are very active in their online communities and are known as trendsetters in their expertise areas. They are among the first to acquire and comment on new products or events in that area. But opinion leaders are also motivated by their social status in the communities and may be inclined to provide opinions and comments that adequate to their objectives and ambitions inside their networks [4].

In DIVERSITY, a particular emphasis was placed in the modelling of reach and influence. The segregation between reach and influence results from the distinction between a post's and an author's audience. A post may be much participated, but its author may not have a significant audience or vice-versa. The point is that opinions of authors whose posts consistently have a high reach have a greater influence in the overall sentiment towards a product [2].

The reach of a post is measured according to its audience in a particular social network. In the considered networks, reach is the result of views, likes and comments (for Facebook) or views, retweets and comments (for Twitter), computed by

$$\mathrm{reach}(post_i) = w_c \cdot \frac{\#\mathrm{comments}(post_i)}{\phi\mathrm{comments}_{\mathrm{global}}} + w_l \cdot \frac{\#\mathrm{likes}(post_i)}{\phi\mathrm{likes}_{\mathrm{global}}} + w_v \cdot \frac{\#\mathrm{views}(post_i)}{\phi\mathrm{views}_{\mathrm{global}}} \tag{1}$$

The specific weights of each of these variables is defined according to users' preferences, but it was considered that they typically have increasing values for each of the networks, i.e. likes have a bigger value than views and comments have a bigger value than likes.

Both reach and influence are relative values, representing the comparison of the post's/author's performance against the average reach or influence, computed by

$$\mathrm{influence}(author_j) = w_c \cdot \frac{\phi\mathrm{comments}(author_j)}{\phi\mathrm{comments}_{\mathrm{global}}} + w_l \cdot \frac{\phi\mathrm{likes}(author_j)}{\phi\mathrm{likes}_{\mathrm{global}}} + w_v \cdot \frac{\phi\mathrm{views}(author_j)}{\phi\mathrm{views}_{\mathrm{global}}} \tag{2}$$

Although both influence and reach are currently global values, a solution to set partial values (according to theme/product/location) is being evaluated, in order to minimise variances introduced by different contexts.

For the purpose of simulating influence in the generation of posts, among the other thousands users, we are simulating an initial universe of 6 special authors who are responsible for triggering conversations (for generating original posts). Each of the authors has an influence level to be defined when generating the posts. This level results in an amount of comments being generated in conversations by the author. The value presented in **Error! Reference source not found.** is an average and comments for each conversation may vary slightly. The mechanism for calculating the number of likes and views of each conversation follows the same description as presented for comments.

Fig. 1. Influence simulation.

For the goals of the DIVERSITY project and this paper, to calculate the values of reach and influence, it is not relevant if the author's post is the trigger of the conversation or just one of the comments included in it: if the user generally participates in exchanges that have higher reach, his/her opinion has a bigger potential impact.

Reach and influence are then used for weighting opinions in the calculation of the general sentiment towards a subject (a product, service, PSS, etc.) in a time interval. Even if part of the conversation extends to periods outside the defined time interval, only those posts and comments that happened inside the defined interval are used to calculate the sentiment.

III. Modelling and simulation approach

The model that supports the *OpinionSim* simulator has the following main collection of objects:

- the set of **PSSs** targeted by the opinions;
- the set of **actors** generating opinions; and
- the set of **posts** expressing the opinions, i.e. the main output of the simulator.

The **PSS** is the anchor point of the overall simulation process. DIVERSITY project is focused on business to business (B2B) demonstration scenarios and the PSSs are composed by products and services that are used to produced other products to the consumer's market. Thus, the feedback from social networks, is not directly targeted to the PSS but to the products produced by the PSS. For instance, one of the companies in the project manufactures and supplies shoe machines together with supporting services to shoe manufacturers. The feedback on the social networks is towards the shoes and some inference has to be made to relate this feedback with specific characteristics of the PSSs.

In the simulator, we have a set of PSSs and the lists of products that are manufactured by each PSS. The feedback to be generated is towards the final products.

The **actor** is the source of feedback. Each actor, as an agent, is characterized by a set of characteristics that allows a segmented analysis of the feedback. The list of characteristics can be easily enlarged to support more segmentation of the generated data, but is currently composed by:

- age;
- gender; and
- location.

The simulator allows to establish the distribution of the population through these three vectors. So, if of interest, we can generate a population with specific distribution, more concentrated on a specific location, with the majority of opinions from a specific gender or age segment.

Additionally, the simulator allows to establish how the sentiment towards each product is influenced by each of the characteristics of the actors. The different sentiment inclinations based on each of the characteristics are modelled through and hyperplane. Thus, for example, we can configure that a particular product is more appreciated by women over 40 years, indifferently of their location, or any other combination.

Finally, it is possible to overlap a sentiment variation for a period of 360 days, reflecting the overall baseline sentiment towards a product, independently from other segmentation characteristics.

The post is the vehicle for the feedback to be collected and the only output of the simulator. The application generates a text message reflecting the sentiment towards the product.

The text is generated with two parts:

- a prefix-suffix set randomly taken from a list;
- an adjective taken from a sorted table that best reflects the sentiment value.

The sentiment value is generated based solely from the characteristics of the actor that is generating the post.

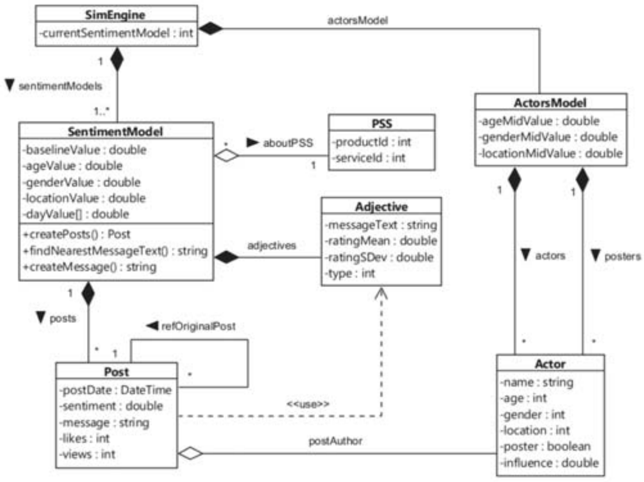

Fig. 2. OpinionSim class model.

Fig. 2 presents the class model used in the simulator to support the implementation of the described model. The object *SentimentModel* models the sentiment hyperplane and the time dependency. The object *ActorModel* models the distribution of the actors' population.

The objects *PSS*, *Actor* and *Post* model the description made above. Finally, the object *Adjective* is mainly a container for the list of adjectives presented in Table I. Adjectives and sentiments. The list of adjectives and corresponding sentiment value have been adapted and compiled based on the previous work presented in [5] and [6].

The simulation algorithm follows the following steps:

1. The *OpinionSim* user sets the characteristics of the Stakeholders, namely the influence of each of the 6 special authors and the distribution of the general population (e.g. an additional one thousand commenters) for age, gender and location.
2. In a second step, the user of the tool can model the evolution of the general sentiment, with ups and downs, for the period of one year.
3. In a third step, for each final product in a list, the user of the simulator establishes if the sentiment is equally distributed accordingly with age, gender and location. If, for example, this product is more appreciated by men, than we push the corresponding slider towards the Male side at the interface.

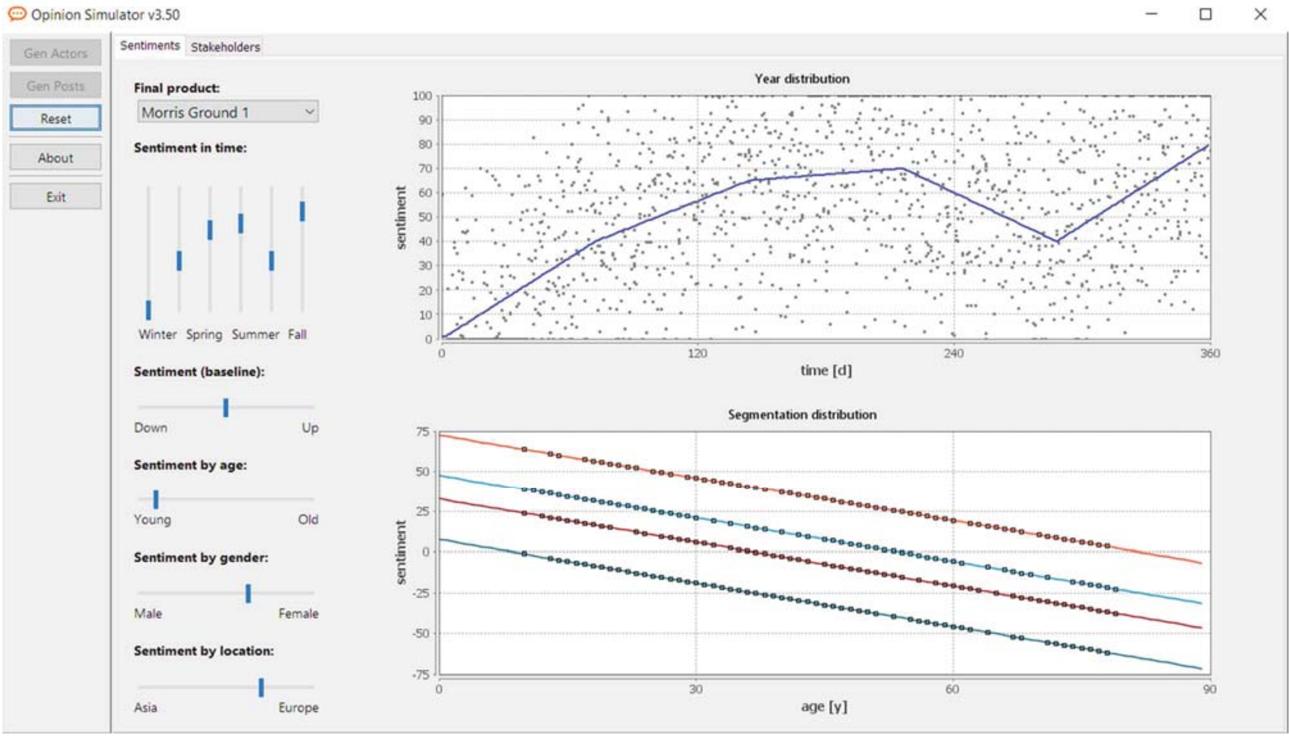

Fig. 3. OpinionSim - Sentiment UI.

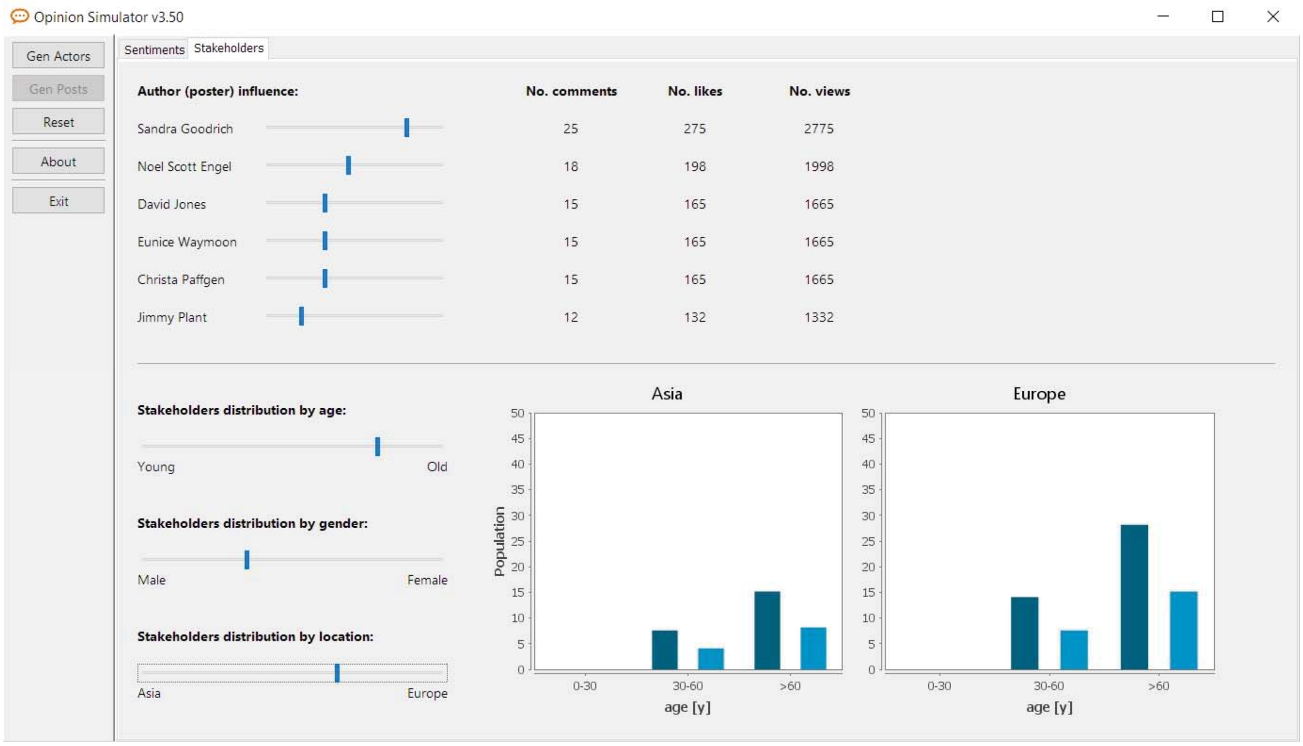

Fig. 4. OpinionSim – Stakeholders UI.

TABLE I. ADJECTIVES AND SENTIMENTS.

adjective	sentiment value [0 - 100]
phenomenal	97.0
world-class	95.0
incredible	92.0
exceptional	90.0
tremendous	88.0
amazing	87.0
terrific	85.0
astonishing	83.0
wonderful	81.0
superior	80.0
fantastic	79.0
excellent	78.0
great	77.0
superb	76.0
fabulous	75.0
splendid	74.0
outstanding	71.0
sensational	70.0
desirable	68.0
good	67.0
decent	66.0
sweet	63.0
fine	61.0
cool	59.0
okay	57.0
fair	55.0
mediocre	46.0
lame	44.0
substandard	40.0
limited	39.0
rotten	38.0
weak	37.0
inferior	36.0
crappy	35.0
deficient	34.0
miserable	33.0
nasty	32.0
bad	31.0
poor	29.0
pitiful	28.0
pathetic	27.0
appalling	26.0
horrible	24.0
dreadful	22.0
terrible	20.0
awful	15.0
abysmal	13.0

4. The simulator generates the population with random characteristics, using the established distributions to calculate the probabilities.
5. The simulator generates a sentiment value, between 0 and 100, for each user towards a product. The sentiment is randomly generated but following the probabilities established by the user preferences.
6. The simulator generates a post text reflecting each of the generated sentiments. Additionally, the simulator plots a dot for each post on top of the time evolution established by the user.
7. The posts are stored to a table in a MySQL database ready to be retrieved by the tool being tested.

IV. RESULTS

The *OpinionSim* was developed with the approach described above with a two panels graphical user interface. The first panel is presented in Fig. 3, for the configuration of the Sentiment model. In Fig. 4, we present the second panel for configuration of the Stakeholders (i.e. population) model.

The output of the simulator is dumped directly to be retrieved by the DIVERSITY platform simulating a direct access to the middleware that stores posts retrieved from social media.

Fig. 5 shows an example of the generated posts when the final product are sneakers. The top post, by one of the six special influencers, identifies the product and already express a sentiment towards it. The following posts are comments from the general population regarding the product.

timestamp	message
2016-05-10 16:58:43	Check the new Morris Ground 1! In a word: lame!
2016-05-14 07:22:43	Hum, fine!
2016-05-14 16:06:21	These are limited sneakers!
2016-05-15 00:49:59	These sneakers have a very comfy sole!
2016-05-15 09:33:37	I would say: the most comfy sneakers with this sole!
2016-05-15 18:17:15	What a fine sneakers!
2016-05-16 03:00:53	These are fine sneakers!
2016-05-16 11:44:31	I have these sneakers and I think they're sweet!
2016-05-16 20:28:09	The sole of these sneakers is comfy!
2016-05-17 05:11:47	So deficient!
2016-05-17 13:55:25	In a word: average!
2016-05-17 22:39:03	So weak!
2016-05-14 07:22:43	Check the new Morris Ground 1! What a weak sneakers!
2016-05-17 21:46:43	Hum, fair!
2016-05-18 04:38:08	So okay!
2016-05-18 11:29:33	I would say: the most rigid sneak
2016-05-18 18:20:58	The sole of
2016-05-19	

Fig. 5. Output posts on the database.

The visual verification of the generated posts allows to validate the correct operation of the simulator, as a first approach. Additionally, the validation of the simulator was performed using it for what was designed, i.e. testing the component processing the generated dataset.

On the DIVERSITY platform described in [7] there is a set of components dedicated to the Sentiment Analysis. This is the component of the DIVERSITY platform that uses the generated dataset for testing purposes. On the simulator side, the user making the tests configure the parameters of the population distribution and the corresponding sentiment distribution towards each product, before generating a batch of posts for a complete year. On the DIVERSITY platform side, the generated posts are retrieved from the database and processed. The biases introduced on the simulator side and reflected on the generated posts are processed by DIVERSITY components. If the components being tested are performing correctly, the results of the processing should follow the simulation parameters.

V. Conclusions and future work

The test of complex tools requires large datasets that are, simultaneously, realistic and repeatable. Simulation tools allow the generation of these datasets with specific characteristics that allows to exploit the full potential of the other tools being tested. This is true regarding the spatial dimension but also the time dimension. For instance, how can a lifecycle management tool can be evaluated in a time effective way if it is dealing with lifetimes of years or decades? Of course, simulation is the only way to go. Generating the data faster than real life, it is possible to test the some conditions over large periods of time and evaluate all possible scenarios.

For DIVERSITY, the analysis of the stakeholders feedback obtained from social media is a key functionality. We need, nonetheless, to provide confidence that the processing made on top of the collected posts is really extracting the general sentiment of the population and, if possible, characterize it by market segments.

The OpinionSim simulator will be exploited after the end of DIVERSITY to support the further development of DIVERSITY as well as other similar platforms. For that, the segmentation of the market will be further detailed e.g. with more than just two locations, and other segmentation characteristics .e.g. income class. In the generation of the posts, we want to develop the method to consider negative suffixes that reverse the meaning of the users' comments.

Acknowledgment

Project DIVERSITY has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 636692.

The content of this article does not reflect the official opinion of the European Union. Responsibility for the information and views expressed in the therein lies entirely with the authors.

References

[1] R. Neves-Silva, P. Pina, P. Spindler, G. Pezzotta, D. Mourtzis, M. Lazoi, D. Ntalaperas and A. Campos, "Supporting Context Sensitive Lean Product Service Engineering," in *Procedia CIRP*, 2016.

[2] R. Neves-Silva, M. Gamito, P. Pina and A. R. Campos, "Modelling influence and reach in sentiment analysis," in *Procedia CIRP*, 2016.

[3] G. Leal, L. Hor-Meyll and I. Pessoa, "Influence of virtual communities in Purchasing decisions: the participants' perspective," *Journal of Business Research,* vol. 67, no. 5, pp. 882-890, 2014.

[4] P. Y. Chau and K. L. Hui, "Identifying early adopters of new IT products: A case of Windows 95," *Information & management,* vol. 33, no. 5, pp. 225-230, 1998.

[5] F. Hicks, L. Valentine, J. Morrow and I. McDonald, "Choosing Natural Adjective Ladders," 2006. [Online]. Available: http://www.mcdonald.me.uk/storytelling/lichert_article.htm. [Accessed 21 04 2017].

[6] R. Sharma, M. Gupta, A. Agarwal and P. Bhattacharyya, "Adjective intensity and sentiment analysis," in *Proceedings of the Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, p. 2520–2526,* , Lisbon, 2015.

[7] P. Pina, G. Góis, F. Mano, F. Silva and R. Neves-Silva, "A sentiment analysis solution for the re-design of product-service systems," in *ICE 2017*, 2017 (in press).