Collecting Digital Research Data through Social Media Platforms

– Can 'Scientific Social Media' Disrupt Entrepreneurship Research Methods?

Martin Lackéus

Division of Entrepreneurship and Strategy,
Chalmers University of Technology, Sweden
Contact: martin.lackeus@chalmers.se

Abstract

This article investigates how social media platforms tailored for research can help entrepreneurship researchers in their data collection and analysis efforts. The widespread use in society of social media platforms, accessed through people's smartphones, tablets and computers, represents a new opportunity for social scientists to collect both big and thick digital data. Most social media platforms are however designed for commercial purposes, restricting the research questions that can be meaningfully explored to a minimum. The aim of this article is therefore to explore a novel approach labeled 'scientific social media' (SSM). A case study method is applied where an SSM platform called LoopMe is described in-depth and compared to similar phenomena. Generalizations from this case then lead up to an attempt to answer the question: Can SSM platforms offer disruptive benefits to entrepreneurship researchers, such as radically increased efficiency or new-to-the-world features? Some identified benefits of SSM include ability to combine key strengths of established research methods and ontologies, ability to triangulate in new ways and ability to conduct very cost-efficient longitudinal studies.

Keywords: Social media, Entrepreneurship, Research methods, Computational social science

1 Introduction

Entrepreneurship research entails meticulous and time-consuming data collection in fuzzy and complex social settings. Theorizing from the myriad of quasi-random events in entrepreneurial practice is so challenging that the rigor–relevance gap often found in social science research sorely applies also to entrepreneurship research (Leitch, 2007, Frank and Landström, 2016). To bridge this gap, methodological plurality and development has been called for (Neergaard and Ulhøi, 2007). Entrepreneurship research has however largely remained a mono-method endeavor, relying almost exclusively on surveys and questionnaires (McDonald et al., 2015). Around the turn of the millennium the field saw a minor increase in emphasis on qualitative and ethnographic methods such as interview studies and observation studies, particularly in Europe (Neergaard and Ulhøi, 2007). The pace of change is however slow, and what in other domains is commonly termed 'disruptive innovation' is arguably absent within entrepreneurship research methods. Disruptive innovation has been defined as situations characterized by a 5-10 times improvement in performance, a 30-50% reduction in cost and / or new-to-the-world performance features (Garcia and Calantone, 2002). The current trend in entrepreneurship research methods is rather of an opposite kind, where new qualitative and ethnographic research methods are even more time consuming and expensive to use for entrepreneurship researchers than the more established survey based methods. In a field where research funding is scarce (Rosa, 2013), this is arguably a key challenge.

Social media platforms could offer one possible way out of this conundrum for entrepreneurship researchers. As digital technologies and devices have become ubiquitous in many countries, the human experience is increasingly blended in terms of consisting of both online and offline modes of experience (Conte et al., 2012, Hine, 2015). The online side of such blended experiences includes social media apps (i.e. software applications) accessed through people's smartphones, tablets and computers. This generates both big *and* thick data, representing qualitative traces of the human condition that can be quantified and harvested for many different purposes (Weltevrede, 2016). This new digital research methodology has been labeled 'computational social science' (Lazer et al., 2009, Conte et al., 2012). Its emergence has triggered significant optimism, even labeling it as 'the end of theory' (Anderson, 2008). When you have enough data the numbers allegedly speak for themselves and make biased theoretical assumptions such as models, categories, hypotheses and metaphors somewhat obsolete in science (Madsen, 2015). While the most common application of such a purely inductive research approach so far has been to improve the precision and efficiency of commercial advertising, the application of primary interest here is how social media can help entrepreneurship researchers in their meticulous data collection endeavors.

A fundamental challenge is, however, the commercial purpose behind most established social media platforms (Langlois and Elmer, 2013), limiting the scholarly use to those rare situations when data collected for commercial purposes can help answering a particular research question being pursued. In order to advance or even disrupt entrepreneurship research through use of social media, there is arguably a need for a different approach that takes into account some fundamental differences between commercial and academic research (Fiske and Hauser, 2014). Therefore, the purpose of this article is to explore a novel approach where a research purpose is allowed to fully inform the design and development of a social media platform being used to collect research data. More specifically, this entails researchers designing and deciding on all those laws and regulations that govern the underlying logic of the user communication taking place online in a social media platform. The case will be made that this new approach opens up for constructing a techno-social online world that is optimized on ability to capture causal mechanisms of interest to social scientists rather than on commercial utility for the toolmaker (cf. Langlois and Elmer, 2013, p.10). Such an approach is here labeled a 'scientific social media' (SSM) approach, defined as social media platforms optimized for social science purposes and used primarily for data collection and analysis.

A case study method is applied in order to fulfil the purpose here by attempting to draw from a recent SSM endeavor and discuss its broader implications for entrepreneurship research. The development process and current functionality of an SSM platform called LoopMe is described. While not the first attempt to build an SSM platform (see for example Garaizar and Reips, 2014), LoopMe is most likely the first SSM platform designed, built and broadly used specifically for entrepreneurship and education research purposes. In early 2014 a research team at Chalmers University of Technology in Sweden founded a spin-out venture in order to hire programmers to build an SSM platform tailored for entrepreneurship research. The purpose of this platform was to empower an ongoing research program investigating if, how, when and why people develop their entrepreneurial competencies in a variety of different settings. This arguably 'paradigmatic' SSM case (cf. Flyvbjerg, 2006, p.232) then leads up to an attempt to answer the key question treated here: Can scientific social media platforms disrupt entrepreneurship research?

The structure of the article is as follows. First a background is given on research methods in general, in entrepreneurship and around social media platforms. Then a detailed account of the case being used here for generalization follows. LoopMe is described through an overview, a brief history, three application areas, some key challenges, some future applications and a comparison with similar kinds of IT systems. An example is also given, showing in considerable detail how LoopMe can be used to conduct a longitudinal study on entrepreneurial behavior. This is followed by an attempt to generalize beyond the LoopMe case towards more general characteristics of research employing SSM platforms. Finally some key implications, limitations and conclusions are given.

2 Background on research methods

2.1 Mono-method and mixed-method research

The choice of which research methods to use significantly shapes and limits the resulting theories and perspectives generated (Bergman, 2011). Such a choice should ideally be made to suit the research question being pursued (Edmondson and McManus, 2007). In reality however, research questions are often opportunistically or ideologically chosen that fit with a single prevailing research paradigm, a preferred method or a conveniently available data set (Onwuegbuzie and Leech, 2005). Such a mono-method emphasis, often focused on either words or numbers, has been stated to represent a significant threat to advancements in social sciences (ibid). The resulting division into quantitative and qualitative research methods has been stated to be a false and dangerous dichotomy between "small versus large samples, inductive versus deductive approaches, or hypothesis generating versus hypothesis testing" (Bergman, 2008, p.16). An emerging alternative is the mixed-methods approach, i.e. a pragmatic combination of quantitative and qualitative data collection and analysis techniques within a single study, despite seemingly incommensurable ontological positions (Bryman, 2006). This approach, at times also labeled 'triangulation', has been claimed to overcome many weaknesses of one method through the complementary strengths of another method (Molina-Azorín et al., 2012). A key question that remains difficult to resolve is how such a combination is to be achieved in practice, in terms of mixing data, findings, theoretical approaches and epistemologies (Bergman, 2008).

The two most common methods for collecting primary data in entrepreneurship research are surveys and interviews (McDonald et al., 2015). Some key strengths of surveys include ease in distribution, also on a wide geography, possibility to have many and anonymous respondents, ease in statistical analysis such as generalization from a representative sample and suitability for hypothesis testing (Kelley et al., 2003, Selwyn and Robson, 1998, Phellas et al., 2011). Some key weaknesses of surveys include a limitation to short and simple questions, difficulties in treating more complex issues, time consuming to develop good quality survey items, a lack of detail in collected data, challenging to achieve high response rates and poor fit when the aim is to generate new ideas and constructs (ibid). Some key strengths of interviews include possibility to explore complex questions, to ask for clarifications, to get an in-depth understanding, to identify patterns and to take context into account (ibid). Some key weaknesses of interviews include time consumption for interviews and transcriptions, risk for interviewer bias and for socially desired responses, difficulties in conducting objective and rigorous data analysis and challenges in generalizing from collected data (ibid). Whereas surveys are good for hypothesis testing of mature theory, interviews are instead good for generating new theory (Edmondson and McManus, 2007). In an emerging field one would thus expect interviews with small populations to first be used for generating new theories, followed by an increasing use of surveys as the field matures, testing the developed theories on larger populations. Entrepreneurship research is, however, characterized by the opposite, representing a "paradoxical situation where explanatory methods have been most popular when the field was most emergent" (McDonald et al., 2015, p.303).

2.2 Entrepreneurship research as a mono-method scholarly endeavor

Entrepreneurship research has been claimed to suffer from a significant and problematic mono-method emphasis (Cope, 2005, Suddaby et al., 2015, Bygrave, 2007, Coviello and Jones, 2004). Structured literature reviews have shown that on a macro level across studies, surveys and questionnaires based on a positivist approach dominate top entrepreneurship journals (McDonald et al., 2015) and conferences (Neergaard and Ulhøi, 2007). On a micro level within studies, more than 90% of entrepreneurship studies rely on only one single method (McDonald et al., 2015, Molina-Azorín et al., 2012). This mono-method emphasis has been argued to result in an inability to generate new theories and perspectives (Suddaby et al., 2015). Scholars also risk missing substantive issues and meanings around entrepreneurship related phenomena (Cope, 2005). This has been posited to explain a state of entrepreneurship research consisting of "mostly pedestrian findings that are of little or no interest to practitioners" (Bygrave, 2007, p.24), making entrepreneurship research a journey towards potential "irrelevance and maybe oblivion" (ibid, p.27). This mono-method emphasis in entrepreneurship research is more prevalent in the US than in Europe (Neergaard and Ulhøi, 2007). It could be due to a less articulated publication pressure among European scholars, making them more open to methodological pluralism (Huse and Landström, 1997). There is also a trend towards an increasing appreciation of qualitative methods (Smith and McKeever, 2015), slowly diminishing the mono-method emphasis on a macro level across studies. On a micro level within studies the mono-method emphasis largely prevails. Triangulation was found to be employed in just one of all 883 articles published in three leading entrepreneurship journals from 2000 to 2009 (Molina-Azorín et al., 2012). The case description in section 3 of this article outlining a mixed methods based research tool that collects significant amounts of both numbers and text thus arguably represents a rare exception in the field.

2.3 Emerging social media platform-based research

Recent research outside the field of entrepreneurship indicates that social media platforms could yield numerous opportunities for entrepreneurship researchers. Facebook has been used for sampling purposes, by increasing the reach of questionnaires to millions of respondents (Kosinski et al., 2015), by bringing down the cost of reaching respondents (Batterham, 2014), and by providing access to respondents difficult to find (Baltar and Brunet, 2012). The data residing within the Facebook platform has also been subject to social research endeavors. Applications include studying human behavior in naturalistic settings, studying social networking among people and studying how people shape and communicate their different identities (Wilson et al., 2012). Another social media platform that contains large amounts of data is Twitter. Notable studies taking advantage of real-time data from Twitter include a study evaluating the mood of stock markets (Arvidsson and Peitersen, 2013), an initiative from United Nations monitoring crises in troubled areas of the world (Madsen, 2015) and a study that claims to have predicted the outcome of the German federal election in 2009 (Tumasjan et al., 2010).

Academic research based on social media platforms is, however, in an early and problematic stage. Serious ethical issues remain largely unsolved, such as individual privacy, informed consent, data ownership and opt out policies (Barnes et al., 2015, Shah et al., 2015, Wilson et al., 2012). In 2018, this was manifested through the Facebook – Cambridge Analytica data scandal, where personal data from 87 million Facebook users were collected and analyzed with the purpose of interfering in national elections. A fundamental challenge is also the commercial purpose behind most established social media platforms. These platforms are usually optimized on economic value creation, leading to a commercial logic being imposed on users' social acts of online communication by social media corporations. This is done by means of various purposively designed laws and regulations built into the technological algorithmic core of social media platforms (Langlois and Elmer, 2013, Skeggs and Yuill, 2016). Collected data can then not be assumed to be objective or 'raw', but is rather generated or 'cooked' for the commercial purpose (Weltevrede, 2016). Since the economic value of the data being collected is so high in today's informational capitalism based society (Fuchs, 2014, Arvidsson and Colleoni, 2012, Shumar and Madison, 2013), it is challenging or even impossible for academics to influence the fundamental design of laws and regulations governing the logic of established social media platforms (Kennedy et al., 2015). Significant ethical challenges around big data research have also scared many owners of dominant social media platforms, increasingly leading to restricted data access for outsiders and for purposes external to the commercial agenda (Kennedy et al., 2015, Schroeder, 2014). Academics thus need to make do with repurposing of a shrinking pool of old recycled data, shaped and collected for commercial purposes that are alien to the research questions pursued by most social scientists (Weltevrede, 2016).

Having given a brief background on some relevant possibilities and limitations around selected established and emerging research methods, the article now will give a detailed account of the LoopMe case in order to allow for a discussion around the question of whether SSM could potentially disrupt entrepreneurship research.

3 A paradigmatic case: The 'Scientific Social Media' platform LoopMe

According to Flyvbjerg (2006), a 'paradigmatic' case is a case that highlights more general characteristics of a new phenomenon that potentially sets a new standard. The choice of describing LoopMe in such a detail here is because it is considered to represent such a paradigmatic case. The author has so far not heard of any other widely used SSM platform that simultaneously combines practitioner and researcher purposes and utility in a similar way as LoopMe does, thus meriting the detailed account. Consider the many users of LoopMe (more than 10 000 unique registered users in 8 countries) in combination with LoopMe-based research having been published in high-ranked journals such as Small Business Economics and Journal of Small Business Management (Lackéus and Sävetun, 2019, Mansoori and Lackéus, in press).

An overview of the information technology (IT) platform LoopMe is first given. Then a historical background is given aiming to illustrate how LoopMe is an example of a social media platform that all along the development journey has been optimized for research purposes, rather than the usual commercial purpose so common for social media platforms. The third section outlines some key application areas for research and practice that have been tested so far, followed by two sections outlining challenges so far and possible future applications. This leads up to a sixth section explaining in detail how to set up a study on entrepreneurial behavior with LoopMe, exemplified through a research question around entrepreneurial methods. The last section compares LoopMe to other similar IT systems.

3.1 Overview of LoopMe

LoopMe is a social media platform originally developed for scientific purposes at Chalmers University of Technology in Sweden. Users access the platform through an app on their smartphone or tablet, or through the web. The first version of the platform was used on entrepreneurship students at Chalmers in 2012. In 2014 the platform was spun out as a research based social enterprise within education technology, and placed in the regional technology business incubator Chalmers Innovation. Seven different research studies have been conducted so far, using LoopMe as a data collection and analysis tool, investigating the impact of different kinds of entrepreneurial education on students of all ages, from primary education to higher education and adult education (for a summary, see Lackéus, 2017). LoopMe has so far been used by around 12.000 registered users in Sweden, Norway, Denmark, France, Italy, Ireland, the UK and Turkey. The LoopMe platform is currently available for sign-up to the public at the website www.loopme.io, managed by the social enterprise Me Analytics AB, currently employing six people. The platform has a wide user base in Sweden and an emerging user base around Europe. The build-up of the LoopMe platform was financed primarily through customers in need for scientific evaluation of their educational practices, but also through a small public loan and a minor social business angel investment. The development cost has so far amounted to around 1.5 million USD spread out over five years.

3.1.1 LoopMe as a system

LoopMe works like a system consisting of input, process and output (cf. Von Bertalanffy, 1950), see Figure 1. The *input* consists of a leader designing a few predefined behavioral tasks that are intended to trigger personal and organizational development among users, and a few associated "tags", i.e. meta-information text labels predefined by the researcher, signifying desired (or undesired) outcomes. The leader could be a teacher, a manager, a coach, a therapist, a parent or literally any other kind of leader or facilitator. The users could be students, employees, entrepreneurs, clients or literally any other kind of user.

The *process* entails a group of users doing those behavioral tasks having been assigned to them by their leader through an app accessed on their smartphone, tablet or computer. The tasks are done offline, i.e. in the social setting where the user is embedded. Whenever a task has been completed, the user reflects upon the experience with free text, and selects one or more tags to further describe the experience. A mandatory emotionality rating of the experience is also collected. This reflection is then submitted to the leader, who is presented with a social flow of reflections. The leader can comment in real-time, just like on regular social media, and also approve the completion of each task.

The *output* consists of digitally documented personal learning and / or organizational development. All the data that is generated by users and their leaders can be analyzed afterwards on the web, or extracted to Excel for in-depth analysis. Leaders are encouraged to share insights they get from analyzing the data with their users. Usage of LoopMe thus contains three phases – (1) a leader defined input, (2) users completing, reflecting upon, rating and tagging a few behavioral tasks, followed by leaders approving and commenting, and (3) all people involved benefiting from and analyzing the output.

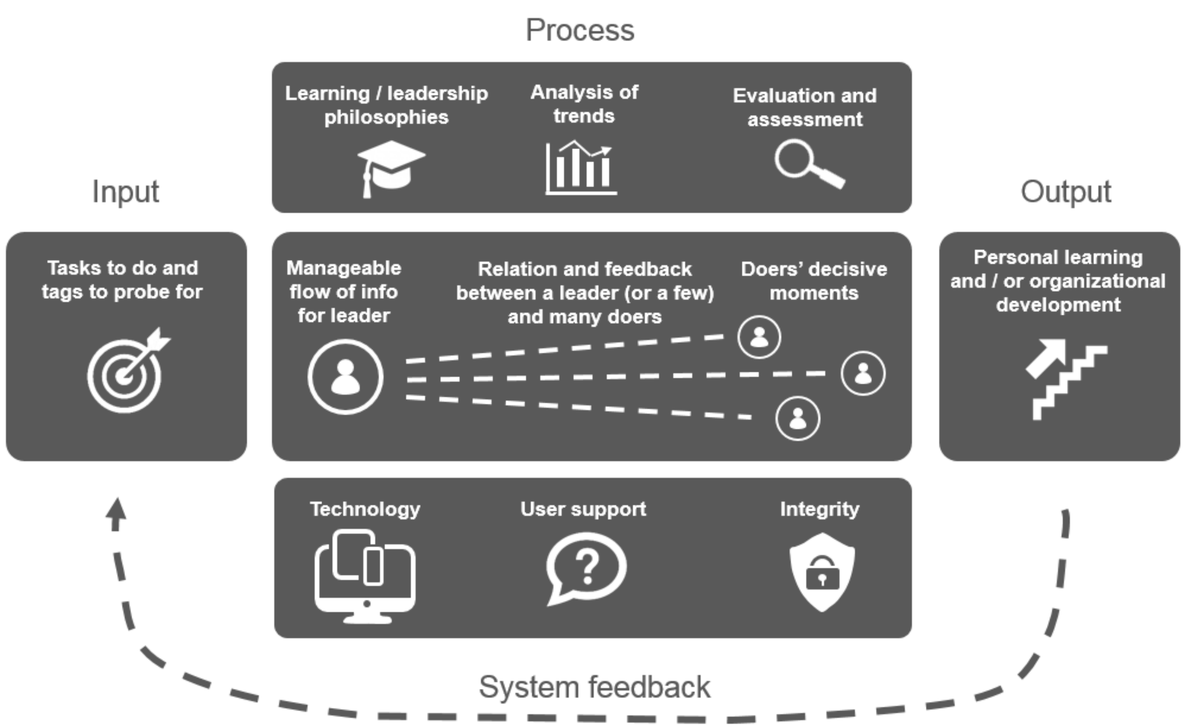


Figure 1. LoopMe as a system of input, process and output.

Each iteration through the model in Figure 1 represents a full lap through Kolb's (1984) famous experiential learning cycle model, encompassing all four steps in the model. Step one in Kolb's model is abstract conceptualization (a user sense-making and planning how to do the behavioral task given to him/her by a leader of some kind), followed by active experimentation (a user doing the actual behavior stipulated by the task), concrete experience (the resulting experience that the behavior triggers for a user) and reflective observation (a user reflecting on the experience with text, tags and emotional rating).

3.1.2 Introduction to research utility of LoopMe

When LoopMe is deployed on a broad number of users who complete tasks and reflect to their leader, this generates large amounts of very detailed data. Such data can be harvested for a broad variety of different research purposes. The LoopMe platform collects data in real-time about actual human behavior and its associated cognitive and emotive characteristics. Since users reflect on a behavioral task and attach emotional rating and predefined tags to it, the data is both qualitative and quantitative. The main quantification benefit of LoopMe for researchers is the causality that can be established by studying which completed tasks that lead to which tags being chosen by users. The independent variable is then the predefined task, and the dependent variable is the tags that users choose to attach to their experience. By design, LoopMe thus allows for multiple independent and dependent variables. Causality can also be established qualitatively by investigating and interpreting the free text reflections and chat dialogs that each task generates from many users. In a typical LoopMe study it would be expected to include a couple of hundred up to a thousand users, each completing between 3-20 tasks and associating 1-10 tags to each completed task by choosing among 10-30 eligible tags for each completed task. As an example, a recent study in 19 primary schools where LoopMe was used to collect data for 9 months included 481 students who completed a task 5895 times, reflecting upon this to their 35 teachers through LoopMe (Lackéus and Sävetun, 2017). The students associated 17 188 tags to their 5895 completed tasks and produced 96 688 words of free reflections. The 1994 subsequent chat dialogs between students and teachers that these 5895 loops triggered represented another 33 160 words produced. This study thus shows how SSM can produce both big and thick data that is both qualitatively and quantitatively interesting for social science scholars (cf. Weltevrede, 2016, Langlois and Elmer, 2013).

3.2 **Development history of LoopMe**

In order to explain how SSM can be used for research, it is deemed necessary to give a brief historical background of LoopMe. The development of LoopMe has passed through four distinct phases over seven years from 2012 to 2018, each phase resulting in a new major version of the platform. Example graphical designs taken from each version are shown in Figure 2. The phases will now be briefly outlined.

3.2.1 LoopMe version 1 launched in 2012

The first version of LoopMe was a simple web survey deployed as a link shortcut visible on the "desktop" screen in the personal smartphones of 13 students in entrepreneurship at Chalmers University of Technology. The participants were instructed to complete the web survey whenever they experienced an emotional event related to their education. The survey was completed 556 times by the 13 participants over a period of 18 months. The research purpose was to study links between education induced emotional events and developed entrepreneurial competencies in an action-based entrepreneurship education program (Lackéus, 2014). Here, LoopMe served primarily to increase the quality of the interviews. The first version of LoopMe was also used in a study in 2013, following seven students in two lower secondary schools in Sweden working with entrepreneurial projects (Lackéus and Sävetun, 2014).

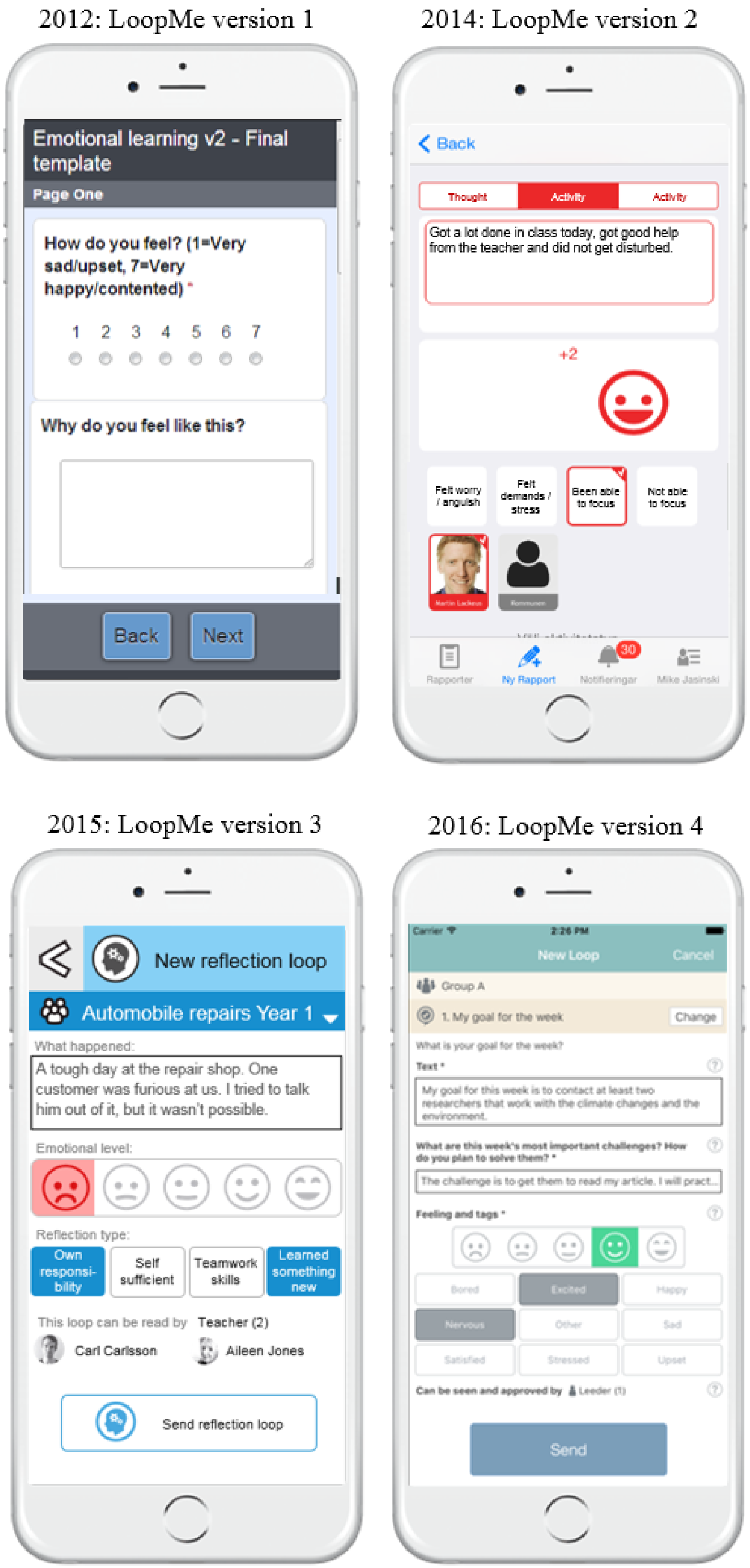


Figure 2. Historical overview showing graphical design of four different versions of LoopMe. For more detailed screenshots, see images and videos at the website www.loopme.io.

3.2.2 LoopMe version 2 launched in 2014

The second version of LoopMe was built by a team of professional programmers employed at the social venture Me Analytics AB, founded in early 2014. The aim of building LoopMe was here to use it in a study commissioned by Swedish National Agency of Education (SNAE) on entrepreneurial primary schools. This version of LoopMe was the first to include social functions, such as presenting a social flow of "loops" (i.e. survey responses) to participating teachers, allowing users to "tag" their experience and letting teachers initiate a chat with students around specific loops. "Tags" were predefined text labels with meta-information that users can select from to more quickly describe their experience, see Figure 2. The second version of LoopMe was completed in early September 2014, and was subsequently launched on 250 participants in two different studies of entrepreneurial education (Lackéus and Sävetun, 2015, Lackéus and Sävetun, 2016, Lackéus and Sävetun, 2019).

3.2.3 LoopMe version 3 launched in 2015

The third version of LoopMe was designed by an external user interface expert getting input from the research team. Based on needs identified in previously conducted studies, several new functions were introduced in this version. Functions added included grouping and filtering of loops, user notifications, invitations to new users, user profile management, mini-surveys from teachers and information loops from teachers. An emotional classification was also made mandatory for all loops. The third version of LoopMe was used in a large assessment study of entrepreneurial education commissioned by SNAE. (Lackéus and Sävetun, 2017).

The first three versions of LoopMe were all based on the idea that users would determine whenever they wanted to report something to their leaders, just like in most established social media platforms. This worked well in research projects where teachers could keep reminding the participants to produce data when something relevant happened. But it was difficult to get more than around 15-30% of a group to participate. It also proved to be impossible to sustain usage of LoopMe after a research project was finished. This kept eroding the user base of LoopMe each time a research project was finished, resulting in large amounts of inactive users. This in turn led to serious financial problems for the social venture building LoopMe during the spring of 2016, since the research agenda alone could not sustain the venture financially. The founding team therefore decided to adjust the focus of LoopMe in line with a more commercially oriented agenda, making mandatory tasks a standard functionality for all users. While most users had not asked specifically for this, it was hypothesized to be a way to increase perceived relevance and engagement among a wider base of potential users.

3.2.4 LoopMe version 4 launched in 2016

The fourth and current version of LoopMe was rebuilt from the ground up with mandatory tasks as a central feature, requiring all users to complete at least one task. This change clarified usage of LoopMe and allowed for more sustainable usage patterns among participants in a group. The resulting difficulty instead became how leaders were to think around the design of mandatory tasks. This triggered the development of 'content packages', constituting ready-made sets of 3-20 tasks and associated tags that any leader could pick up and distribute to a group of users. The fourth version of LoopMe was completed in August 2016.

While the fourth version of LoopMe could be interpreted as a research oriented agenda reluctantly ceding to a more commercially oriented agenda, this was not what ended up happening. The two potentially conflicting purposes instead ended up strengthening each other. The introduction of a mandatory behavioral task oriented structure in LoopMe opened for a more powerful way to collect and analyze data. The mandatory behavioral tasks allowed for a more fine-grained design of participant behavior. The logical link between behavioral tasks, emotional ratings and user-selected tags / user-generated text allowed for an unexpected opportunity to quantify causality between independent variables (i.e. behavioral tasks) and dependent variables (i.e. emotions, tags and written reflections). Since many of the research oriented functions were kept in version 4 of LoopMe, the research team found itself with even more powerful means at hand for data collection and analysis than before. This implies that it can be difficult to fully separate a scholarly agenda from a practitioner oriented agenda when designing social media platforms with dual purposes. It could instead be viewed as a strength of a social media platform to simultaneously cater for both research needs and practitioner needs. Users' willingness to engage with a social media platform is arguably a key factor determining the amount of scholarly useful data the platform can collect.

3.3 Three tested applications of LoopMe – education, organizational development and research

Three practical examples of LoopMe usage will now be given in order to provide an empirical context. LoopMe has so far been used extensively for the three following purposes; (1) as a tool for teachers or coaches to follow and assess learners in a social learning environment, (2) as a tool at the workplace for managers to steer and follow organizational change, learning and development processes, and (3) as a research tool. These three uses of LoopMe are outlined below. They merely represent an early glimpse of the potential SSM could represent, as implied by section 3.5 on future applications of LoopMe.

3.3.1 LoopMe used in education

Teachers have used LoopMe to design action-based learning experiences by breaking the social learning process down into manageable tasks. It could be anything from just a couple of tasks to 20 or more tasks, depending on how the learning process is designed. When each task that students are required to do is specified in LoopMe, it clarifies goals and prompts students to take action and reflect upon each action. Tasks can be constructed by employing constructive alignment principles (Biggs, 1996), i.e. by thinking about what students need to *do* in order to *learn* what the teacher wants them to learn. The teacher also defines tags that represent expected learning outcomes from a module or program. These tags could be inspired by or aligned with goals in curriculum documents or other documents specifying intended learning outcomes. Once the tasks and tags are distributed to all students and they are instructed to get started doing the tasks, the progress for the entire cohort of students can be followed in real-time. Each time a student completes a task, she is required to reflect upon the event and tag the experience. This reflection is then made exclusively available to the teacher. Unlike in traditional social media, each student thus only sees her own reflections and the feedback from the teacher. Through the detailed real-time feedback that this generates for each completed task, teachers get an overview of how their teaching works in practice, in terms of which tasks that lead to which learning. Individual learners getting stuck can be identified through their negative reflections on tasks or through tasks not being done at all, and given tailored support when necessary. For students, LoopMe has shown to represent an appreciated digital channel for feedback to and from their teachers and for sensitive discussions with their teachers if necessary. LoopMe thus leads to a better relationship between teachers and their students without causing an abundance of information for the teacher. It also gives structure and support to students in the important reflection around learning activities (cf. Schön, 1983, Bond et al., 2011). The types of education where LoopMe has been the most appreciated so far are action-based education, vocational education, apprenticeship education and work-integrated learning. The reason is that LoopMe helps facilitate teachers' attempts to combine theory and practice.

3.3.2 LoopMe used in organizational development

A common challenge in organizational development projects is that the envisioned changes seldom are adopted by the employees (Elmore, 1996, Cuban, 1990, Beer et al., 2016). In this context, LoopMe is an example of how social media can be used to support organizational change in general and school / university development in particular. Managers have used LoopMe to break down a development project into those actionable tasks that employees need to do in order for positive change to occur in practice. It could be anything from just a couple of tasks to 20 or more tasks, depending on how the organizational development process is designed. Each time an employee completes a task, she is required to reflect upon the event and tag the experience. Managers will then be able to follow all employees over time as they complete the tasks, what impact each task makes in relation to desired project outcomes and how the employees reflect around it. When using LoopMe this way, managers define tags that correspond to the desired outcomes of the development project in question. This allows for a quantitative analysis of which tasks that contributed the most to project success. LoopMe can also be used to make it visible who in the organization has taken action, and who has not. Towards the end of a project, the manager checks that all employees have completed and reflected upon all tasks. The data in LoopMe can also be downloaded to an Excel document for more in-depth analysis of the development project.

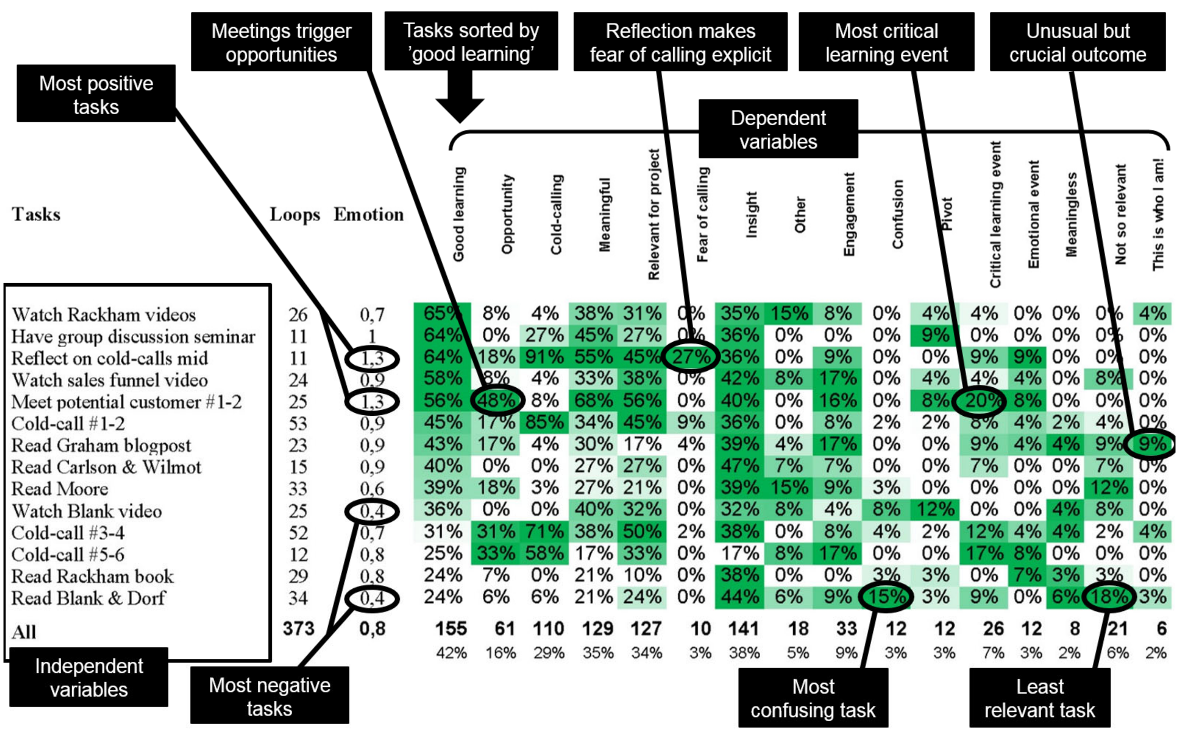
3.3.3 LoopMe used for research

The primary scholarly application of LoopMe has so far been in research on entrepreneurship and enterprise education, since this is the main research focus of the LoopMe founders. The practical benefits of LoopMe for teachers and students have allowed LoopMe to be deployed on large student populations and with a high level of activity among respondents. LoopMe has allowed respondents to share their daily experiences with people they trust, such as teachers, coaches and managers. Through written consent from each respondent and access to excerpts from the central LoopMe database, this information has been made available to the research team, giving a unique access to experiential and highly categorized data on critical learning events, thought patterns and actual entrepreneurial behaviors impacting learning and progress. The many respondents involved have acted as participant observers who notify the research team of any significant events occurring within or outside the classroom. For example, in any given classroom where many students are active users of LoopMe, most events that are relevant for research purposes will likely be reported through LoopMe. Free text reflections and tags help researchers get a clear view of what happens, and what doesn't happen, in the classroom as well as in the minds of the students. Absence of reflections or tags on a certain topic represent evidence of what is not happening. The responses from teachers to students on various critical events also add to the data on what happens and does not happen in the learning environment. LoopMe thus generates both quantitative and qualitative data.

Productive use of LoopMe for research purposes is contingent upon practitioners using it for their own practical purposes. The underpinning principle is to let practitioners use a communication system for their practical needs for behavioral guidance, dialogue, assessment, follow-up, reflection and learning. The resulting data is then mined for research purposes, both in real-time and afterwards. Tasks and tags can be designed so that they fulfil practical purposes while also being relevant for scholarly purposes. Causality can be established quantitatively by studying which tasks that lead to which tags. Causality can also be established qualitatively by investigating and interpreting the free text reflections that each task generates from many respondents. The dialogue that a completed task can spur between people adds to the qualitative analysis. If a particular activity can be articulated as a task in LoopMe, it is possible to get very detailed data on how respondents experience this activity. The researcher can follow the experiential process longitudinally as it unfolds in real-time, allowing for researchers to ask timely questions directly to the relevant respondent. When the data collection process is complete, the researcher can access a data dump file in Excel containing all reflections on all tasks by all respondents, as well as all dialogues that have taken place.

How to analyze the data generated through LoopMe is still an emerging topic, but a number of ways to analyze the data have been developed so far. Since each respondent must categorize every completed task with one or more suitable tags, a correlation matrix between tasks and tags can be produced, see example in Figure 3 from a module on entrepreneurial sales and marketing at Chalmers University of Technology. Such a matrix can be used to study more in detail the plethora of causal mechanisms that mediate between cause and effect, potentially opening up the black box of how, when and why an intervention leads to desired outcomes (cf. Hedström and Ylikoski, 2010). Each cell containing a percentage number in such a matrix can be investigated further by studying numerous qualitative free text reflections associated to it, where many respondents have completed the task in question and tagged it with the corresponding tag. LoopMe has allowed for a web of causal mechanisms to be evidenced empirically and with high ecological validity, such as for example uncovering how, when and why action-based entrepreneurial education can develop entrepreneurial competencies (Lackéus, 2014, 2016, 2017, Lackéus and Sävetun, 2019).

Most of the written reflections provided by respondents are connected to a specific task and are often quite detailed. This gives the researcher a deep insight into which thought and action patterns are triggered by different kinds of activities, and why it happens. Frequent trustful and detailed discussions between respondents and their leaders add to the qualitative understanding of how situations are interpreted by the people involved. If the researcher is an official user in LoopMe visible to the respondents, she can also add to the discussion in real-time by asking questions that are relevant from a research perspective. This allows for getting very detailed answers from those respondents with the most interesting insights, since the sampling of whom to ask a question is done by browsing large amounts of information readily accessible in real-time in the LoopMe platform also for the researcher. Whenever the researcher stumbles upon a respondent with unique insights, strong reflective ability or experiences relevant to the research question pursued, follow-up questions can be asked in real-time.



Tasks	Loops	Emotion	Good learning	Opportunity	Cold-calling	Meaningful	Relevant for project	Fear of calling	Insight	Other	Engagement	Confusion	Pivot	Critical learning event	Emotional event	Meaningless	Not so relevant	This is who I am!
Watch Rackham videos	26	0,7	65%	8%	4%	38%	31%	0%	35%	15%	8%	0%	4%	4%	0%	0%	0%	4%
Have group discussion seminar	11	1	64%	0%	27%	45%	27%	0%	36%	0%	0%	0%	9%	0%	0%	0%	0%	0%
Reflect on cold-calls mid	11	1,3	64%	18%	91%	55%	45%	27%	36%	0%	9%	0%	0%	9%	9%	0%	0%	0%
Watch sales funnel video	24	0,9	58%	8%	4%	33%	38%	0%	42%	8%	17%	0%	4%	4%	4%	0%	8%	0%
Meet potential customer #1-2	25	1,3	56%	48%	8%	68%	56%	0%	40%	0%	16%	0%	8%	20%	8%	0%	0%	0%
Cold-call #1-2	53	0,9	45%	17%	85%	34%	45%	9%	36%	0%	8%	2%	2%	8%	4%	2%	4%	0%
Read Graham blogpost	23	0,9	43%	17%	4%	30%	17%	4%	39%	4%	17%	0%	0%	9%	4%	4%	9%	9%
Read Carlson & Wilmot	15	0,9	40%	0%	0%	27%	27%	0%	47%	7%	7%	0%	0%	7%	0%	0%	7%	0%
Read Moore	33	0,6	39%	18%	3%	27%	21%	0%	39%	15%	9%	3%	0%	0%	0%	0%	12%	0%
Watch Blank video	25	0,4	36%	0%	0%	40%	32%	0%	32%	8%	4%	8%	12%	0%	0%	4%	8%	0%
Cold-call #3-4	52	0,7	31%	31%	71%	38%	50%	2%	38%	0%	8%	4%	2%	12%	4%	4%	2%	4%
Cold-call #5-6	12	0,8	25%	33%	58%	17%	33%	0%	17%	8%	17%	0%	0%	17%	8%	0%	0%	0%
Read Rackham book	29	0,8	24%	7%	0%	21%	10%	0%	38%	0%	0%	3%	3%	0%	7%	3%	3%	0%
Read Blank & Dorf	34	0,4	24%	6%	6%	21%	24%	0%	44%	6%	9%	15%	3%	9%	0%	6%	18%	3%
All	**373**	**0,8**	**155**	**61**	**110**	**129**	**127**	**10**	**141**	**18**	**33**	**12**	**12**	**26**	**12**	**8**	**21**	**6**
			42%	16%	29%	35%	34%	3%	38%	5%	9%	3%	3%	7%	3%	2%	6%	2%

Figure 3. Rich data collected through LoopMe, aggregated into statistics relating authentic tasks to learning outcomes.

The data collected with LoopMe could also be fed into a purely qualitative research phase where respondents to interview as well as topics to discuss are chosen based on LoopMe data collected during a period of months up to years. This could be labeled a social media based sampling strategy as well as a social media induced interview template. These two key methodological steps have been shown to act as amplifiers and increase the signal to noise ratio of the subsequent steps in a research design involving qualitative interviews (Lackéus, 2014, Lackéus and Sävetun, 2019). Choosing interviewees and issues to discuss with them based on such data allows the qualitative research phase to focus on the most relevant aspects of what people are experiencing in the environments studied.

3.4 **Challenges with LoopMe**

While the journey with LoopMe has surfaced many opportunities and unexpected benefits, it has also been a challenging endeavor. As in any attempt to deploy a novel digital system on a large number of people, LoopMe has been subject to much disinterest and attention deficit among prospective users. A number of factors differing from traditional social media significantly reduce the 'stickiness' of LoopMe, i.e. its ability to engage users and sustain their interest and usage long term. While traditional social media typically builds on sharing fun and engaging content widely and receiving mostly positive feedback and endorsement from many friends, LoopMe instead builds on sharing relatively personal reflections around more or less strenuous tasks to a very limited number of people that fulfil a formal role of leader in a job related social setting. This has made LoopMe reliant on leaders (such as teachers, coaches or managers) possessing the authority to make task fulfilment expected or mandatory for many or all members in a group. If such a mandatory prerequisite is not present or utilized, the likely usage ratio of LoopMe is around 15-30% of the members in any group, depending on the nature of the tasks, the design of the sign-up process and the presence of incentives and manual reminders. This might suffice in some cases, but a complete sample is certainly preferable.

Informed consent is another challenge with LoopMe. This is a well-known challenge in social media based research (Fiske and Hauser, 2014), and has recently been the focus of much international media attention due to the Facebook scandal in 2018 where it was revealed that Facebook had inadvertently shared data on millions of its users with election campaign consultants. The process of obtaining informed consent from participants has been rather administrative in the studies conducted with LoopMe so far. Many of the participants have been children and adolescents, thus requiring parents to sign a written consent. This has triggered a few quite lively discussions with parents around questions such as the purpose of the study, how the data will be used and stored, why the identity of participants needs to be known, if participants will have time to use the system, if non-participants will be treated equally in the class and how to treat non-response bias.

Another challenge with LoopMe has been the technical complexity and difficulty of building a stable and attractive social media platform. A broad technological base of expertise often difficult to find in one single computer engineer's skillset is required for building and maintaining a social media platform in accordance with user expectations. This means that access to a complementary team of up to ten engineers for a couple of years is an important requirement when building an SSM platform. The wide diffusion of free and user-friendly global social media platforms built by corporations employing thousands of skilled programmers has also raised the public's expectations around usability, simplicity, design and attractiveness of social media platforms to a very high level. Any research team attempting to build an SSM platform for their own scholarly purposes will thus likely find the challenge quite daunting. This is probably the most important challenge with an SSM approach to entrepreneurship research.

3.5 **Future applications of LoopMe**

While usage of LoopMe has so far been focused on entrepreneurship and enterprise education research and practice, it is possible to envision a much broader application of the technology and methodology. Relating to the purpose of this article, a number of applications could facilitate entrepreneurship research while at the same time offering benefits to practitioners. Incubators and accelerators could use LoopMe to distribute prescriptive advice or even mandatory tasks to their entrepreneurs, and monitor which advice that result in desired outcomes. Scholars could participate in such work and get access to unprecedented sets of longitudinal big and thick data on real-life entrepreneurship as it unfolds from inception day of many start-ups. Investors could use LoopMe to follow and steer their portfolio of investments, allowing for swift responses whenever opportunities or challenges arise. Such a scenario could offer equally rich data access for scholars. Famous entrepreneurship tycoons (and other famous people) could use LoopMe to attract large groups of entrepreneurs that they prescribe entrepreneurial action to and give personal advice to on their journey towards entrepreneurial success. Social entrepreneurs could use LoopMe to distribute socially beneficial behavior on a large number of people, provided that they could come up with a reason other than coercion for such users to complete the tasks in LoopMe. Such endeavors could generate new kinds of data on social entrepreneurship of interest to scholars. Intrapreneurs and change managers could use LoopMe to distribute collective action and learning among large groups of colleagues at an established corporation. This kind of data could be of interest to corporate entrepreneurship and corporate strategy scholars.

Beyond the fields of entrepreneurship and education there are numerous possible applications of LoopMe that could offer not only practical benefits but also new scholarly opportunities. Areas of use envisioned by the research team so far include health improvement, therapy, personal development, parenting, dieting, mentoring, leadership, sports, sales, personal finance and sustainability.

3.6 How to conduct a research study on entrepreneurial behavior with LoopMe

Conducting a research study on entrepreneurial behavior with LoopMe ideally follows the three steps of input, process and output outlined in Figure 1. Some practical recommendations for each of these three steps will now be given. While these recommendations are based on the author's seven years of experience in conducting studies by using an SSM approach with LoopMe, these are emerging insights. There could be many other ways to use SSM in practice than those outlined here. An example study of entrepreneurial methods will be used to illustrate the recommendations.

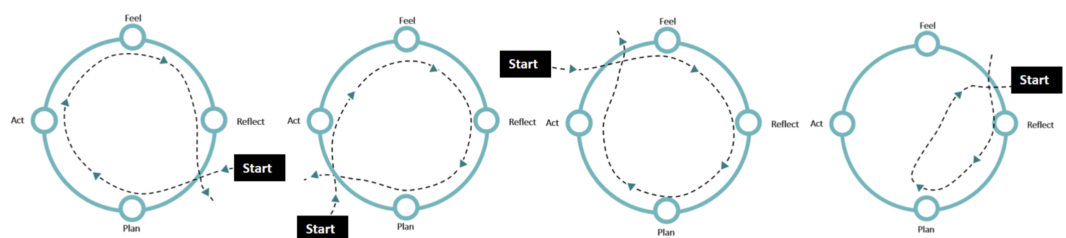
3.6.1 Input: Articulate behaviors and desired outcomes of relevance to the chosen research questions

First, a research question needs to be articulated. Given the action-oriented nature of LoopMe building on Kolb's (1984) experiential learning cycle, it is recommended to choose a research question that requires respondents to balance between theory and practice. An example research question will be used here to illustrate principles and necessary steps. We will assume a research team wanting to explore the use of entrepreneurial methods, such as effectuation, lean startup methodology, design thinking and business planning among practicing entrepreneurs (cf. Mansoori and Lackéus, in press). A possible research question could then be articulated as: "How do recommendations from entrepreneurial methods work in practice for entrepreneurs?". This is an under-researched area that would be challenging to explore further without studying actual entrepreneurs taking action in real-life settings.

Next, a setting where entrepreneurs would be willing to follow prescriptions grounded in entrepreneurial methods needs to be identified. It could be an incubator, an accelerator, an action-based entrepreneurship program or an investor's entire portfolio of start-up investments. While it is also possible to use individual entrepreneurs who are willing to try out entrepreneurial methods as respondents, a structure where leadership of some kind is in place increases the frequency of use of LoopMe, thus generating more data. The coach, teacher or investor in such a setting can then stipulate or even require the entrepreneurs to behave in line with those behaviors that are of interest to study for the research team. If a coercion free setting is required for a study, LoopMe can still be used. Without social pressure or overt coercion related to the studied behavior, around 15-30% of the respondents will still use the system.

When a research question and a suitable setting are in place, LoopMe needs to be properly configured. This entails crafting appropriate tasks and tags. Crafting tasks has shown to be quite challenging in practice. A good task should contain all four steps in Kolb's (1984) experiential learning cycle. A task can start in either of the four steps of Kolb's model, shortened in Figure 4 to 'plan' (abstract conceptualization), 'act' (active experimentation), 'feel' (concrete experience) and 'reflect' (reflective observation). Figure 4 shows that there are four different task types one can use. They will now be further described.

Starting in Kolb's (1984) 'plan' step, a *planned reflective action* begins with the user carefully planning the stipulated behavior, such as for example crafting and testing a venture hypothesis as stipulated by many entrepreneurial methods. Starting in Kolb's 'act' step, an *attitude-changing action* should not require any planning. It should instead describe a behavior that is easy for the user to just do, preferably in less than one minute, such as for example trying to contact a potential customer as stipulated by many entrepreneurial methods. The stronger positive or negative emotions that the stipulated behavior can trigger, the more interesting the generated data will usually be. Starting in Kolb's 'feel' step, an *emotional event based reflection* starts with a feeling triggered by any arbitrary entrepreneurial event, such as any highly emotional event triggered in a venture when applying entrepreneurial methods in practice. It can be positive in terms of good customer feedback, or negative in terms of customers not wanting to buy or even meet. Starting in Kolb's 'reflect' step, a *topic-based reflection* is the least powerful task type, since it does not encompass all steps in the experiential learning cycle. It is nevertheless a task type that can be useful to get users started with LoopMe. Entrepreneurs could for example be asked to reflect upon their use of entrepreneurial methods.



Type	Planned reflective action	Attitude-changing action	Emotional event based reflection	Topic-based reflection
Step 1	Do a carefully planned activity	Do a very simple activity, preferably emotional	Pick a lived emotional event	Think about a given topic
Step 2	Reflect once the activity is done	Reflect once the activity is done	Reflect upon the emotional event	Reflect upon the given topic
Step 3	Deeply probing questions	Deeply probing questions	Deeply probing questions	Deeply probing questions

Figure 4. Four different task types possible to craft in LoopMe. Each type starts in either of the four steps in Kolb's (1984) experiential learning cycle. A task description typically includes three steps as specified in the figure.

Tasks in LoopMe should include a heading encompassing both action and reflection, and a text description outlining the three steps that users are expected to take, see Figure 4. In the case of a planned reflective action, the heading could be something like "Test your venture hypothesis on a potential customer and reflect upon the result". A good task description specifies in step 1 what the user needs to do in order to learn or develop as intended, such as "Meet a customer and test your venture hypothesis". This step ideally represents an answer to a question the leader needs to pose herself: "Learning-by-doing-*what*?", i.e. what the participants need to do in order to learn and develop the way we want them to. Then in step 2 the user needs to be instructed on what to do afterwards, such as "Reflect afterwards here in LoopMe around key insights". A third step is often necessary to get users to reflect more deeply, such as "Reflect by connecting your experience to customer development theory" or "Reflect around what surprised you" or "Analyze if the experience led to changes in any of your deep beliefs around your venture". Such probing reflective questions can be inspired by literature on reflective thinking (Kember, 1999, Hatton and Smith, 1995). The full task, with a heading and a description, then becomes:

> ***Test your venture hypothesis on a potential customer and reflect upon the result***
> *Meet a customer and test your venture hypothesis. Reflect afterwards here in LoopMe around key insights. Reflect by connecting your experience to customer development theory. Reflect also around what surprised you. Analyze if the experience led to changes in any of your deep beliefs around your venture.*

The last step in the input phase of a LoopMe study is to craft tags. Tags in LoopMe are for research purposes used to improve visibility around cause and effect relationships, i.e. to facilitate causality analysis. For practitioners, tags also serve a purpose of allowing for a quick way to describe their experience. Whereas the tasks are designed to be the causes (independent variables) of some interesting phenomenon studied, the tags should be articulated as the hypothesized effects (dependent variables) that such tasks could trigger. Relating to the example used here, some possible tags indicating that an entrepreneurial method works well could then be 'Venture success', 'Venture progress, 'Gained a new customer', 'Improved our business model', 'Felt good', 'Surprised', 'Delighted' or any other word or short text that indicates some kind of entrepreneurial success. The tags should be short enough to allow for very quick selection and relatively unambiguous choice for users. It is advisable to also have a few tags indicating lack of progress or setbacks, for example 'Unhappy customer', 'Got rejected', 'Team issues' or 'Failure', since users otherwise will find the tags to be biased towards success. Such tags can also indicate important negative outcomes interesting to study more in-depth for the research team.

When a number of tasks and tags have been crafted, this represents a 'content package', i.e. a combination of tasks and tags that are appropriate for a specific setting. On the website www.loopme.io there are many ready-made content packages to choose from, suitable for many different settings, crafted by both the research team behind LoopMe and by many users of LoopMe sharing their content packages broadly in the online content package library. Instructional videos are also available on the website, showing more in detail how to get started with LoopMe.

3.6.2 Process: Follow respondents' behaviors longitudinally in real-time

Once a content package is crafted or selected in LoopMe, it can be deployed to the users, preferably between 15-50 users or more. An invitation code is generated by the system. This code can be communicated to users in an email, shown to users in a slideshow or written on a whiteboard. It is recommended that it is the leader in the studied setting that introduces the tasks and invites the users into LoopMe, since this increases the chance of the users completing the tasks. The leader also needs to keep talking about the importance of completing the tasks, as well as give feedback to the users in LoopMe as they complete and reflect upon the tasks. What has shown to work particularly well is when there is an incentive structure in place connected to the completion of the tasks, such as university credits, wage increases or next round financing conditions. In terms of wage increase, it often suffices to state that the completion of the tasks will be considered at the next wage discussion.

When submitted reflections start to arrive to the leaders from the users, LoopMe notifies all leaders and the research team so that they can then log in to the LoopMe system and discuss with those who have completed some tasks, either through a smartphone app or on the web. The task completion process for an entire group often takes a few months, but could also go on for a year or longer. A good way to use LoopMe is to introduce tasks at a physical meeting, which then facilitates users taking action until next time they meet their leader in person. If the leader only meets the users once or twice a month or more seldom, LoopMe becomes a way to be virtually present between physical meetings in a way that otherwise would be difficult.

For the researcher, LoopMe allows for asking follow-up questions in real-time to respondents based on interesting events that unfold. While it is not a necessary part of an SSM based study, LoopMe can also be used as an interview sampling tool and an interview template construction tool. Whom to interview and what to discuss can be determined in real-time as respondent experiences unfold, based on the reflections that are submitted by the users through LoopMe. This allows for more effective and relevant qualitative studies, where less time is lost on conducting interviews that turn out to be largely uninteresting. Already before booking an interview, the researcher knows that the respondent has something relevant and interesting to tell.

In the example of studying entrepreneurial methods, the researcher could search for counter-intuitive events, for example if there are situations where entrepreneurs find the widespread and acclaimed lean startup methodology to not be applicable at all. Each time such a situation is identified, the researcher can first ask follow-up questions through the chat functionality in LoopMe, and if the answers to these questions trigger continued interest from a research perspective, an interview can be scheduled with a couple of entrepreneurs who struggle with the method in question. In the next phase, if a certain type of situation is of continued interest, the researcher could add a tag that facilitates identifying it more easily. A tag could for example have the text "Lean startup not working". It then becomes easy to immediately identify every instance when an entrepreneur has tagged her experience with this tag, and see which tasks that triggered this tag, and read the reflections around each event in search for patterns. This thus allows for both inductive and deductive (i.e. abductive) research conducted simultaneously.

3.6.3 Output: Extract the data and search for patterns

When all or most users have completed the tasks assigned to them, analysis can be done on the web with various analysis functions in LoopMe, such as a matrix showing which tasks that led to which tags being chosen by the users. For deeper analysis, the data can be exported to Excel, where further analysis and pattern matching can be made. Analysis can be either qualitative by analyzing the text, or quantitative by analyzing the large number of statistics that is generated, or mixed by first sorting the reflections based on some quantitative measure and then reading the reflections that fulfil the chosen quantitative criteria. A first analysis that often yields interesting data is to look at those reflections that were tagged with the most positive (+2) and the most negative (-2) emotional rating.

Relating to the example of studying entrepreneurial methods, a matrix of tasks and tags could for example show empirically which of all the myths and hopes of entrepreneurial methods that are supported empirically by entrepreneurs using them in action. Does pivoting really compromise passion? (McMullen, 2017) Does lean startup really work for materials ventures? (Harms et al., 2015) And does effectuation lead to dangerous practices among entrepreneurs, such as ignoring planning and neglecting competition? (Arend et al., 2015) Answers to these and many other vexing questions surrounding entrepreneurial methods can now be empirically investigated by distributing prescriptive entrepreneurial advice to entrepreneurs and studying their resulting reflections, emotional ratings and tagging choices made in LoopMe.

3.7 **Comparing LoopMe to learning management systems and to social media platforms**

3.7.1 Semantic comparison of categories of IT systems

The research team has often struggled to explain to practitioners and to other scholars what LoopMe is, and what it is an example of. It is neither a traditional social media platform nor a traditional learning management system, even if these categories are often mentioned by people trying to understand LoopMe. It could rather be viewed as defining a new category. Naming this category has been difficult. Scientific Social Media (SSM) is a term that explains what LoopMe is for scholars. But it does not represent an appropriate term for practitioners who choose to use LoopMe for practical reasons not related to research.

For them, a different term has been used: Social Learning Media (SLM), i.e. social media for social learning. LoopMe has shown to be particularly useful for teachers and employers working with socially situated learning, for example in action-based entrepreneurship education, apprenticeship education, work-integrated learning and organizational learning. SLM is here defined as a digital and mobile communication platform that allows for simple and relevant one-to-one dialogues between a leader and many users, revolving around mandatory action-oriented tasks that a leader defines and that users perform and then reflect upon. This makes SLM a narrower concept than SSM, since social learning is arguably not the only possible purpose one could tailor a scientific social media platform for.

Having two terms for one kind of IT solution could cause confusion. Future will tell if a unified term will emerge that describes IT systems that bridge scholarly and practical uses of social media platforms for learning, education, behavior-based leadership, organizational development and research. Until then, many practitioners will probably prefer to see LoopMe as an SLM tool, especially in areas connected to learning, organizational development and education. Scholars would perhaps rather see it as an SSM tool that becomes particularly powerful due to its SLM based capabilities.

3.7.2 High-level comparison of Canvas, Facebook and LoopMe

Regardless of the terminology, it is here relevant to compare LoopMe to other systems that people perceive as similar. Two IT systems have been chosen for comparison here; Canvas and Facebook. Canvas is the third largest and currently one of the fastest growing learning management systems globally, and has been used in parallel to LoopMe for two years at Luleå Technical University (LTU) in Sweden. The findings from this comparison have been documented in internal reports, kindly shared with the author by professor Mats Westerberg at LTU, and will be discussed briefly here. Facebook is the world's largest social media platform, and has many characteristics similar to those found in LoopMe.

Before engaging in the comparison, two main educational assessment methods first need a brief explanation. Summative assessment is about awarding certificates, diplomas and degrees that can be used for later stages of education and for work-life qualification (Isaacs et al., 2013). Formative assessment is rather about assessment with a purpose of improving the learning process while it is still on-going (Black and Wiliam, 1998). Formative assessment has been claimed to be particularly relevant to experiential learning (Roberts, 2015). It produces various kinds of feedback information that can be used to improve an on-going learning process, either through actions taken by teachers or by learners themselves. Formative assessment can further include both feedback from the teacher to the learner and feedback from the learner to the teacher (Hattie, 2008).

Some key similarities and differences between Canvas, Facebook and LoopMe are shown in Table 1. While the main purpose of Canvas is to administer courses with a pass/fail summative assessment logic, and the main purpose of Facebook is to connect people through a very flat structure where many people see each other's activity, LoopMe is more about facilitating action learning in real-time through a both formative and summative assessment logic. LoopMe thus leans on a one-to-one logic, where leaders assume the role of a trustful mentor engaging in multiple private conversations with users. Such a logic necessitates both simplicity and very high relevance in order not to strain the leader who is often the communication bottleneck in social systems, something that neither Canvas nor Facebook can deliver to their users by definition. Course administration is seldom simple, and mass communication is seldom relevant for all users. A commonality between Canvas and LoopMe is that both systems are hierarchical and have approval functionality. They both manage formalized learning and development processes where teachers, coaches or managers direct an experience that is (more or less) mandatory for all learners.

Table 1. Scientific social media / social learning media such as LoopMe compared to learning management systems such as Canvas and social media platforms such as Facebook.

	Learning management systems such as Canvas	Social media platforms such as Facebook	Scientific social media / social learning media tools such as LoopMe
Main purpose	Administer courses	Connect people	Facilitate action learning
Relationships	Many-to-one – Manage	One-to-many – Maximize	One-to-one – Mentor
Communication	Formal – pass/fail logic	Public – everyone sees all	Private – trustful dialog
Complexity	Complex and comprehensive	Simple but overwhelming	Simple and relevant
Structure	Hierarchical and mandatory	Flat and optional	Hierarchical and mandatory
Assessment	Summative primarily	None	Formative and summative
Quantifiability	Low	Low	High

3.7.3 Detailed comparison of characteristics unique to LoopMe

While LoopMe could perhaps be viewed as a combination of a learning management system and a social media platform, there are nevertheless four characteristics that are unique to LoopMe, and that are not found neither in Canvas nor in Facebook. These are described below, and connected to some benefits they can offer to researchers that use SSM to collect data.

Private one-to-one contextual dialogs. All three systems have many different dialog functions. In Canvas there are chatrooms, message boards, group messaging and individual messaging. In Facebook there are contextual discussions for posts and a messenger function for individual and group messaging. But neither of the two has a social flow of action-based reflections where the leader can engage in private one-to-one contextual dialogs with users such as in LoopMe. This facilitates honesty and deep reflection in LoopMe, while safeguarding discretion, intimacy and openness without risk of being humiliated in front of many people. The existence and importance of this difference was confirmed empirically in the comparison conducted at LTU in Sweden. For researchers this openness and honesty leads to less biased, more reflective and richer data being produced by the users. It also allows for the researcher to engage in trustful discussions with respondents longitudinally in real-time, in a unique and cost-effective way.

Simple and relevant. People's expectations on software in general and on social media in particular are that they exhibit maximum usability and ease-of-use. Facebook indeed fulfils this demand, whereas Canvas struggles due to the need to include a broad variety of administrative functions to fulfil the procurement requirements of large educational institutions. Another common requirement of software in general is a high level of relevancy, especially for leaders who are always short on time. Here Canvas can largely fulfil this demand, whereas Facebook instead struggles due to its mass communication ambition and its commercial agenda of wanting to expose ads. LoopMe is thus the only system of the three that manages to come across as both simple and relevant. This was confirmed empirically in the comparison between Canvas and LoopMe conducted at LTU in Sweden. For researchers, simplicity and relevance both contribute to increasing the chances of gaining access and acceptance when proposing stressed practitioners to use LoopMe to generate data for a research study.

Action-oriented mandatory tasks. It has become apparent in practical use of LoopMe that the applied action-oriented mandatory task approach leans on a quite different pedagogical foundation than learning management systems such as Canvas. The established systems are often based on (or at least used for) the widely used traditional teaching approaches, emphasizing passive learning of theoretical content (Labaree, 2005). This unique aspect of LoopMe is closely related to innovative pedagogical approaches such as 'authentic assessment' (Ellis and Bond, 2016), 'performance assessment' (Darling-Hammond, 1994), 'reflective assessment' (Bond et al., 2011) and 'task based assessment' (Biggs and Tang, 2007). For a more detailed discussion on innovative assessment approaches in relation to LoopMe, see Lackéus and Williams Middleton (2018). In LoopMe, tasks designed in an action-based manner lean on the constructive alignment principle (Biggs, 1996) of letting learners do what they need to do in order to learn what the teacher wants them to learn. Neither Canvas nor Facebook has this focus, although Canvas could perhaps be shoehorned into a more innovative pedagogical approach. Learning management systems will hopefully be developed in a not too distant future to cater for more innovative pedagogical approaches. In the comparison made at LTU in Sweden, the difference discussed here between Canvas and LoopMe was framed to be around differences in assessment regimes. Whereas the use of Canvas promoted a summative assessment focus only, the use of LoopMe successfully managed to mix summative and formative assessment within a single IT tool, offering the pedagogical advantages of formative assessment without having to miss out on fulfilling summative assessment requirements. For researchers, a focus on action-oriented mandatory tasks is what makes LoopMe particularly useful when studying behavior in its natural context. It also allows for very cost-effective longitudinal study designs, since actions taken by participants can be followed over long time periods without necessitating expensive data collection interventions. Once LoopMe has been configured and deployed, the data will come to the researcher.

Mandatory reflection, emotionality rating and tagging. The completion of a task is in LoopMe always coupled with a mandatory reflection, a mandatory emotional rating and a mandatory tagging of the experience. From a practitioner point of view, this serves to foster reflective ability, facilitate deeper learning, provide evidence for the leader that the behavioral task was completed by the user, and provide evidence of any desired effects. From a research point of view, it leans on a methodology called 'experience sampling', championed by psychology researcher Mihaly Csikszentmihalyi in the 1970s. He used short 30-seconds surveys to capture respondents' experiences directly in their natural environment, attempting to capture the 'flow' of everyday experience (Hektner et al., 2007). By capturing subjective experiences with a previously unattained precision, a high level of ecological validity was obtained. While experience sampling is a well-established methodology in social science (Reis et al., 2014), it has never been integrated into learning management systems or social media platforms. This represents a unique possibility to integrate experience sampling methodology into settings where a more traditional way to work with experience sampling would not be acceptable due to the high demands put on respondents. In the comparison conducted at LTU in Sweden, this possibility was highlighted as a very useful feature, distinguishing LoopMe from Canvas.

To conclude this comparison, LoopMe represents both a unique combination of learning management and social media, and some unique features not found in such systems. This is, however, not to deny the many opportunities for research that existing learning management systems such as Canvas and social media platforms such as Facebook represent today, and perhaps even more so in the future. Some systems that have surfaced as possible alternatives to using LoopMe will be briefly mentioned. These systems could perhaps fulfil some of the practical purposes discussed here, if deploying a new specialized SSM system such as LoopMe is not deemed a viable alternative. If scholars could arrange for data extraction from existing systems, this data could also be used for research purposes just like exemplified with LoopMe. One example is the learning management tool Socrative, which is a widely used system for student tracking and formative assessment through smartphones and tablets. Another similar example is Showbie, a learning management tool for creating and completing student assignments. Some teachers have also experimented with using Twitter in the classroom. For managers tapping into their employees' developmental processes, there have been reports about using Google Classroom or Google Apps to collect reflective data from employees related to development projects. None of these tools are, however, designed with research purposes in mind.

4 Discussion

A number of key characteristics of SSM will now be discussed more in general, such as ability to combine strengths and characteristics of different methods and ontologies, ability to triangulate across different kinds of data, ability to generate high quality research and ability to employ a longitudinal approach. This informs a discussion on whether SSM could disrupt entrepreneurship research by allowing for significantly higher efficiency in collection and analysis of primary data. Implications and limitations will then be discussed.

4.1 Some key characteristics of SSM based research

4.1.1 Combinatorial capability

The LoopMe case illustrates how SSM possesses a key quality that is ascribed to mixed-methods approaches; that of combining strengths. SSM manages to combine many of the different strengths of established methods like interviews and surveys, see Table 2. A low cost of use and a possibility to include many participants is combined with an ability to manage complex issues, to generate new ideas and patterns, to take context into account and to allow for generalization and quantification. SSM also allows for producing both qualitative text and quantitative numbers simultaneously. All text that is generated is also linked to numbers generated by for example the mandatory emotional evaluations and associated tags associated to each 'loop' submitted through LoopMe. The chart in Figure 3 illustrates this capacity to link text and numbers. SSM also allows for follow-up questions in real-time just like the interview method does, while at the same time allowing for anonymous respondents like in surveys.

If SSM can combine the strengths of interviews and surveys on a practical level as shown here, it could be argued that SSM also can combine rival ontological and epistemological stances. The LoopMe case and its scholarly applications so far illustrate that SSM can be used both for hypothesis generation and for hypothesis testing (cf. Bergman, 2008). Stated in more general terms, SSM could be used both for positivist explanatory aims and for constructivist aims of improving understanding (cf. Guba and Lincoln, 1994, p.112). The LoopMe case also shows how SSM could be used both by the disinterested value-free positivist researcher observing at a distance, and by the passionate value-laden interpretive action researcher aiming to intervene and steer participants towards desirable behaviors. Which approach is taken depends on which kinds of tasks are configured in the SSM platform and which role the researcher takes. Either she opts for the invisible observer not chatting with participants, or she opts for being a visible actor chatting in real-time with participants explicitly trying to influence their behavior.

The LoopMe case thus confirms a recent statement in computational social science literature that "the 'digital' may precisely provide a way out of this all-too-familiar opposition, [instead representing a] mixture of interpretative and calculative forms of analysis that occur in computationally enabled research" (Marres, 2017, p.35). Hine (2015, p.77) also highlights the possibility of viewing digital methods as a mixed-methods approach by letting "quantitative and aggregative analysis ... guide and inform fieldwork". Here SSM could represent a way to alleviate the common challenge in qualitative research of retaining control when faced with massive amounts of data (Dubois and Gadde, 2014).

Drawing on the example in Figure 3, a researcher could start a search for detailed qualitative data in a conceptually interesting cell of the quantitative matrix in Figure 3. This represents an example of "selectivity and presentation of only those details that relate to the conceptual arguments" (Siggelkow, 2007, p.23). In the example study mentioned in section 3.1, consisting of 129 848 words produced by 516 participants over eight months, such a digitally powered selectivity can be both useful and time-efficient.

Table 2. Comparison between three different methods. Interviews, SSM and surveys are compared and contrasted across a number of key dimensions.

Dimension	**Interviews**	**Scientific social media**	**Surveys**
Kind of data collected	Oral speech and body language delivered in isolation	Written text, numbers and bodily emotions delivered in social settings	Numbers but at times also written text delivered in isolation
Typical number of respondents in a study	25	250	1000
Quantifiability of results	Low	Medium	High
Preparation time consumption	Low	Low	High
Data collection time consumption	High	Low	Low
Data analysis time consumption	High	Low	Medium
Maturity of analysis toolbox	Medium	Low	High
Geographical challenges	Medium	Low	Low
Suitable for exploring complex issues?	Yes	Yes	No
Longitudinal studies possible?	Yes, but resource intensive	Yes, by default	Yes, but problems with response rate / causality
Generalizability of results	Low	Medium	High
Suitable for generation of new ideas and patterns	Yes	Yes	No
Allows for anonymous respondents	No	Yes	Yes
Context sensitivity	High	High	Low
Methodological fit	Emerging and intermediate theory	Could potentially fit all phases	Mature theory
Value for participants	Low to medium	High	Low to none
Measurement tool construction cost	Low	High	Medium

4.1.2 Triangulation capability

This study shows that SSM can offer new ways of working with triangulation across qualitative and quantitative data sets. The LoopMe case shows that an SSM platform generates large amounts of text, just like qualitative methods. But large amounts of numbers are also produced, stemming from a number of different quantification steps and characteristics. Each 'loop' in LoopMe contains mandatory quantification steps just like in a survey. The large number of users of an SSM platform also represents a triangulation possibility in its own respect. Investigations can be made around how many and which users complete which tasks, choose which tags and pick which emotional level on the mandatory 5-step Likert scale, and how this is connected to their qualitative reflections. This inherent mixed-methods characteristic developed and honed through years of meticulous software design in close collaboration between users, programmers and researchers represents a rare link between large qualitative and large quantitative data sets. Being able to link between numbers and text in both directions in the data analysis phase could be a unique and perhaps even disruptive feature of SSM that is rare in most other data collection methods. Triangulation can also be performed in real-time, allowing for a longitudinal approach to data analysis. The triangulation capability of SSM research is an example of a more general analytic capability that SSM platforms can provide through its generic and digital characteristic of containing multiple and automatic quantification steps. The analytic toolbox of SSM platforms is however in a nascent stage, representing an important area for further methodological research. While triangulations represent an obvious capability, there are probably other important analytic capabilities of SSM research waiting to be developed.

4.1.3 Research quality capability

SSM arguably allows for fulfilling many of the requirements for achieving a high level of research quality. This is the case both for positivist measures such as validity, reliability and objectivity, and for interpretive measures such as trustworthiness, credibility, dependability, transferability and confirmability (Wigren, 2007, Guba and Lincoln, 1994). Given that SSM shares theoretical roots with experience sampling (Larson and Csikszentmihalyi, 1983), it can be inferred that SSM inherits similarly high levels of ecological validity of the content produced in the 'loops' disclosed by participants through an SSM platform. This has also been confirmed in studies conducted with LoopMe (Lackéus, 2017). In terms of reliability, dependability and confirmability, the content packages in LoopMe facilitate replication of studies since corroboration studies can use the same tasks and tags on a different but similar population to see if similar results are obtained.

Having stated that the prospects for meeting high standards of research quality seem reasonably good, it is much too early to state when, how and why SSM allows for a high level of research quality. Further studies are needed to uncover which configurations of SSM based research are conducive to high research quality.

4.1.4 Longitudinal capability

Longitudinal studies are often difficult to conduct due to time and resources needed for repeated data collection. Here SSM opens for a renewed emphasis on longitudinal studies without having to pay the price in terms of time and resources. Once an SSM platform has been successfully deployed on a population in a way that makes participants engage repeatedly, the researcher can sit back and wait for the data to be collected more or less automatically. Longitudinal data is continuously captured as participants' experiences unfold. This arguably represents a more or less disruptive feature of SSM based research, in terms of offering significant cost reductions or even new-to-the-world features for data collection. This resonates with what computational social science scholars have labeled 'natively digital methods', i.e. methods that are 'born in the new medium' of digital technologies, thus taking full advantage of these technologies (Rogers, 2009, p.5). In a first attempt to answer the research question pursued here, it is thus proposed that it is the natively digital characteristic of SSM that makes it able to contribute with disruptive improvements to entrepreneurship research. If it had been a mere digitization of existing methods such as interviews or surveys (cf. Marres, 2017), it would perhaps not have been as disruptive.

The longitudinal capability of SSM research leans on an underlying capability to trigger continuous engagement among participants. A key challenge with other methods such as surveys and interviews is to get potential participants to engage. This challenge often manifests itself in low response rates on surveys and a need to provide extrinsic motivation factors (Cook et al., 2000). Interviews are slightly more engaging for participants, since they could provide some value for participants through potentially stimulating conversations. Here, SSM offers significantly higher levels of engagement among participants. This leans on the principle of combining practitioner benefits of a social media platform with the scholarly utility of getting access to the data being generated.

4.1.5 Efficiency improvement capability

The automatic capability of SSM in both data collection and data analysis arguably contributes with new and disruptive implications for entrepreneurship research. The longitudinal characteristics allow for collecting more primary data of high quality per invested hour of scarce research time than has been possible before. This benefit is stronger the longer a study is on-going, since once an SSM platform has been deployed it keeps producing large amounts of both text and numbers without requiring the researcher to intervene more than marginally if at all. This means that the longer a researcher can afford to wait, the more efficient the data collection is. The triangulation capability and the combination of strengths from established research methods allow for more efficient, effective and automated data analysis that is almost as in-depth and context sensitive as interview research and arguably even more efficient than surveys research. A number of new-to-the-world analytic techniques are also provided through SSM, such as linking of text to numbers in novel ways and causal analysis of tasks and tags. Taken together it is proposed here that SSM indeed represents a possibility to disrupt entrepreneurship research, i.e.to allow for 5-10 times improvement in performance, a 30-50% cost reduction and new-to-the-world performance features (cf. Garcia and Calantone, 2002). Users can be studied in their natural environment, at a substantially lower cost than other methods allow for.

4.2 Implications for research

For quantitative researchers SSM provides new ways to uncover causality through hypothesis testing. By not interfering during the study and by choosing relatively generic and naturalistic tasks that participants are asked to perform, a positivist stance can be retained aiming to uncover the 'truth' of matters (cf. Guba and Lincoln, 1994). For qualitative researchers SSM provides new ways to reach a deeper understanding of environments studied, giving detailed accounts of meaning-making processes that unfold in highly contextual situations. This facilitates hypothesis generation, pattern recognition and identification of emergent ideas and concepts through analysis of thick data. SSM also allows qualitative researchers to passionately participate through an emphasis on behavioral guidance, action-taking and immersion among practitioners. A particularly useful approach for SSM could be action research, i.e. iterative intertwining of reflection with participative action, leading to generalizable understanding of underlying mechanisms (Brannick and Coghlan, 2007). For mixed-methods researchers SSM provides new concrete tools and methods for combining different data collection techniques and ontologies.

4.3 Limitations and challenges

While a promising research method, SSM also comes with some significant limitations and challenges. It seems crucial to combine practitioner benefits with research activities in order for SSM to work well. This implies a risk of conflicting agendas to hamper the process, in terms of commercial, legal and other issues. The SSM platform is a prerequisite for conducting research, resulting in a dependence on the platform owner who seldom will be the same as the research team due to very high costs and other hurdles associated to developing an SSM platform. Users of an SSM are also being taxed through enforced reflection and valuation. This could represent a problem in some settings. The adaptation of an SSM platform to a particular research question or research program has also shown to be a meticulous and time-consuming endeavor. While other research questions could probably utilize the same SSM platform as outlined in this article, it is not something that can be assumed given the strong emphasis of LoopMe on education, learning and leadership. Another challenge is who will be willing in the long run to finance the gap between what is profitable and what yields good scientific data. Any SSM platform that is appreciated by a large number of users is at risk of being taken over by commercial purposes.

5 Conclusions

The LoopMe case has illustrated how SSM makes it possible to combine interesting research questions with an emerging set of powerful and innovative research methods grounded in computational social science. This however requires a stronger emphasis on the research question of interest to the investigation than what is allowed for when starting with the data generated by an established commercially oriented social media platform such as Facebook or Twitter, or with an established learning management system.

Current research on social media platforms is in such an early stage that it could almost be seen as a number of "empty-headed 'fishing expeditions'" (Sayer, 2010, p.245), where scholars are searching for new methods that can make use of a wide sea of available data. If entrepreneurship scholars are to take advantage of any resulting new natively digital methods, they will need to engage in a challenging and costly endeavor of designing and developing new or significantly modified social media platforms. Such platforms need to be tailored to the scholarly purpose at hand in order to get beyond a mere 'fishing trip' of recycling old digital data originally cooked for commercial purposes.

This article has identified several rewards for scholars willing to engage in the challenging task of tailoring social media to entrepreneurship research purposes. SSM allows for combining important and complementary strengths of established methods such as surveys and interviews, thus facilitating the collection of large amounts of interconnected qualitative and quantitative data. SSM also allows for new possibilities to conduct longitudinal studies, to triangulate data and to analyze data in new and time efficient ways. This implies that SSM could indeed offer disruptive advantages to entrepreneurship research in terms of significantly lowering the cost of high quality data collection efforts, providing new-to-the-world data collection and analysis techniques and bridging between qualitative and quantitative research. This could in turn help alleviating a problematic rigor-relevance gap in entrepreneurship research, by collecting data in a rigorous way that is both potentially novel to scholars and relevant to practitioners (cf. Frank and Landström, 2016). The new possibilities could be employed in many entrepreneurship related environments such as entrepreneurship and enterprise education, incubators, accelerators and other business start-up related environments. It could also be used to advance research in subfields such as venture capital, social entrepreneurship and intrapreneurship. Scholarly fields outside entrepreneurship could also use SSM to advance sociological research in diverse areas such as education, health, parenting, dieting and sustainability.

Some challenges have also been identified. Building a new social media platform tailored for scholarly purposes is costly, takes many years and requires a team with a broad set of complementary skills in research methods and information technology. Many of the generic challenges in computational social science also need to be considered, such as privacy, consent, data ownership and opt out policies.

6 References

Anderson, C. 2008. The end of theory: The data deluge makes the scientific method obsolete. *Wired magazine,* 16(7)**,** 16-07.

Arend, R. J., Sarooghi, H. & Burkemper, A. 2015. Effectuation as ineffectual? Applying the 3E theory-assessment framework to a proposed new theory of entrepreneurship. *Academy of Management Review,* 40(4)**,** 630-651.

Arvidsson, A. & Colleoni, E. 2012. Value in Informational Capitalism and on the Internet. *The Information Society,* 28(3)**,** 135-150.

Arvidsson, A. & Peitersen, N. 2013. *The ethical economy: Rebuilding value after the crisis*, Columbia University Press.

Baltar, F. & Brunet, I. 2012. Social research 2.0: virtual snowball sampling method using Facebook. *internet Research,* 22(1)**,** 57-74.

Barnes, N., Penn-Edwards, S. & Sim, C. 2015. A dialogic about using Facebook status updates for education research: a PhD student's journey. *Educational Research and Evaluation,* 21(2)**,** 109-121.

Batterham, P. J. 2014. Recruitment of mental health survey participants using Internet advertising: content, characteristics and cost effectiveness. *International journal of methods in psychiatric research,* 23(2)**,** 184-191.

Beer, M., Finnström, M. & Schrader, D. 2016. Why leadership training fails—and what to do about it. *Harvard Business Review,* 94(10)**,** 50-57.

Bergman, M. M. 2008. The straw men of the qualitative-quantitative divide and their influence on mixed methods research. *Advances in mixed methods research: Theories and applications***,** 11-21.

Bergman, M. M. 2011. The politics, fashions, and conventions of research methods. *Journal of Mixed Methods Research,* 5(2)**,** 99-102.

Biggs, J. 1996. Enhancing teaching through constructive alignment. *Higher education,* 32(3)**,** 347-364.

Biggs, J. & Tang, C. 2007. *Teaching for quality learning at university,* Berkshire, England, Open University Press.

Black, P. & Wiliam, D. 1998. Assessment and classroom learning. *Assessment in Education: principles, policy & practice,* 5(1)**,** 7-74.

Bond, J. B., Evans, L. & Ellis, A. K. 2011. Reflective Assessment. *Principal Leadership,* 11(6)**,** 32-34.

Brannick, T. & Coghlan, D. 2007. In defense of being "native": The case for insider academic research. *Organizational research methods,* 10(1)**,** 59-74.

Bryman, A. 2006. Paradigm peace and the implications for quality. *International Journal of Social Research Methodology,* 9(2)**,** 111-126.

Bygrave, W. D. 2007. The entrepreneurship paradigm (I) revisited. *In:* NEERGAARD, H. & ULHØI, J. P. (eds.) *Handbook of qualitative research methods in entrepreneurship.* Cheltenham, UK: Edward Elgar Publishing, pp. 17-48.

Conte, R., Gilbert, N., Bonelli, G., Cioffi-Revilla, C., Deffuant, G., Kertesz, J., Loreto, V., Moat, S., Nadal, J.-P. & Sanchez, A. 2012. Manifesto of computational social science. *The European Physical Journal Special Topics,* 214(1)**,** 325-346.

Cook, C., Heath, F. & Thompson, R. L. 2000. A meta-analysis of response rates in web-or internet-based surveys. *Educational and psychological measurement,* 60(6)**,** 821-836.

Cope, J. 2005. Researching entrepreneurship through phenomenological inquiry: philosophical and methodological issues. *International Small Business Journal,* 23(2)**,** 163-189.

Coviello, N. E. & Jones, M. V. 2004. Methodological issues in international entrepreneurship research. *Journal of Business Venturing,* 19(4)**,** 485-508.

Cuban, L. 1990. Reforming again, again, and again. *Educational researcher,* 19(1)**,** 3-13.

Darling-Hammond, L. 1994. Performance-based assessment and educational equity. *Harvard Educational Review,* 64(1)**,** 5-31.

Dubois, A. & Gadde, L.-E. 2014. "Systematic combining"—A decade later. *Journal of Business Research,* 67(6)**,** 1277-1284.

Edmondson, A. C. & McManus, S. E. 2007. Methodological fit in management field research. *Academy of Management Review,* 32(4).

Ellis, A. K. & Bond, J. B. 2016. *Research on educational innovations, 5:th edition,* Abingdon, UK, Routledge.

Elmore, R. F. 1996. Getting to scale with good educational practice. *Harvard educational review,* 66(1)**,** 1-27.

Fiske, S. T. & Hauser, R. M. 2014. Protecting human research participants in the age of big data. National Acad Sciences.

Flyvbjerg, B. 2006. Five misunderstandings about case-study research. *Qualitative inquiry,* 12(2)**,** 219-245.

Frank, H. & Landström, H. 2016. What makes entrepreneurship research interesting? Reflections on strategies to overcome the rigour–relevance gap. *Entrepreneurship & Regional Development,* 28(1-2)**,** 51-75.

Fuchs, C. 2014. Digital prosumption labour on social media in the context of the capitalist regime of time. *Time & Society,* 23(1)**,** 97-123.

Garaizar, P. & Reips, U.-D. 2014. Build your own social network laboratory with Social Lab: A tool for research in social media. *Behavior research methods,* 46(2)**,** 430-438.

Garcia, R. & Calantone, R. 2002. A critical look at technological innovation typology and innovativeness terminology: a literature review. *Journal of Product Innovation Management,* 19(2)**,** 110-132.

Guba, E. G. & Lincoln, Y. S. 1994. Competing paradigms in qualitative research. *In:* DENZIN, N. K. & LINCOLN, Y. S. (eds.) *Handbook of qualitative research.* Thousand Oaks, CA: Sage Publishing, pp. 105-117.

Harms, R., Marinakis, Y. & Walsh, S. T. 2015. Lean startup for materials ventures and other science-based ventures: under what conditions is it useful? *Translational materials research,* 2(3)**,** 035001.

Hattie, J. 2008. *Visible learning: A synthesis of over 800 meta-analyses relating to achievement*, routledge.

Hatton, N. & Smith, D. 1995. Reflection in teacher education: Towards definition and implementation. *Teaching and teacher education,* 11(1)**,** 33-49.

Hedström, P. & Ylikoski, P. 2010. Causal mechanisms in the social sciences. *Annual Review of Sociology,* 36(49-67.

Hektner, J. M., Schmidt, J. A. & Csikszentmihalyi, M. 2007. *Experience sampling method - Measuring the Quality of Everyday Life,* London, Sage Publications.

Hine, C. 2015. *Ethnography for the internet: Embedded, embodied and everyday*, Bloomsbury Publishing.

Huse, M. & Landström, H. 1997. Preface: European entrepreneurship and small business research: methodological openness and contextual differences. *International Studies of Management & Organization,* 27(3)**,** 3-12.

Isaacs, T., Zara, C., Herbert, G., Coombs, S. J. & Smith, C. 2013. *Key concepts in educational assessment,* London, UK, Sage Publications.

Kelley, K., Clark, B., Brown, V. & Sitzia, J. 2003. Good practice in the conduct and reporting of survey research. *International Journal for Quality in Health Care,* 15(3)**,** 261-266.

Kember, D. 1999. Determining the level of reflective thinking from students' written journals using a coding scheme based on the work of Mezirow. *International Journal of Lifelong Education,* 18(1)**,** 18-30.

Kennedy, H., Moss, G., Birchall, C. & Moshonas, S. 2015. Balancing the potential and problems of digital methods through action research: Methodological reflections. *Information, Communication & Society,* 18(2)**,** 172-186.

Kolb, D. A. 1984. *Experiential learning: Experience as the source of learning and development,* Englewood Cliffs, NJ, Prentice Hall.

Kosinski, M., Matz, S. C., Gosling, S. D., Popov, V. & Stillwell, D. 2015. Facebook as a research tool for the social sciences: Opportunities, challenges, ethical considerations, and practical guidelines. *American Psychologist,* 70(6)**,** 543.

Labaree, D. F. 2005. Progressivism, schools and schools of education: An American romance. *Paedagogica historica,* 41(1-2)**,** 275-288.

Lackéus, M. 2014. An emotion based approach to assessing entrepreneurial education. *International Journal of Management Education,* 12(3)**,** 374-396.

Lackéus, M. 2016. *Value creation as educational practice - towards a new educational philosophy grounded in entrepreneurship?* Doctoral thesis, Chalmers University of Technology.

Lackéus, M. 2017. Can entrepreneurial education escape being caught between marginal ('the Devil') and irrelevant ('the Deep Blue Sea') practices? . *ECSB Entrepreneurship Education Conference.* Cork, Ireland on May 10-12.

Lackéus, M. & Sävetun, C. 2014. Att mäta det omätbara. Gothenburg, Sweden: Framtidsfrön i Väst.

Lackéus, M. & Sävetun, C. 2015. Elevperspektiv från tre entreprenöriella lärmiljöer i svensk grundskola - en effektstudie genomförd på uppdrag av Skolverket. Göteborg: Chalmers Publication Library.

Lackéus, M. & Sävetun, C. 2016. Koncept kontra skola: En studie av åtta entreprenöriella lärmiljöer - En effektstudie på uppdrag av Region Skåne. Gothenburg: Chalmers Publications.

Lackéus, M. & Sävetun, C. 2017. Entreprenöriell utbildning som värdeskapande lärande - en tredje väg? En effektstudie av värdeskapande lärande på uppdrag av Skolverket. Gothenburg: Chalmers University of Technology.

Lackéus, M. & Sävetun, C. 2019. Assessing the Impact of Enterprise Education in Three Leading Swedish Compulsory Schools. *Journal of Small Business Management,* in press(

Lackéus, M. & Williams Middleton, K. 2018. Assessing experiential entrepreneurship education: Key insights from five methods in use at a venture creation program. *In:* HYAMS-SSEKASI, D. & CALDWELL, E. (eds.) *Experiential Learning for Entrepreneurship - Theoretical and Practical Perspectives on Enterprise Education.* pp.

Langlois, G. & Elmer, G. 2013. The research politics of social media platforms. *Culture Machine,* 14(

Larson, R. & Csikszentmihalyi, M. 1983. The experience sampling method. *New Directions for Methodology of Social & Behavioral Science*.

Lazer, D., Pentland, A. S., Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., Christakis, N., Contractor, N., Fowler, J. & Gutmann, M. 2009. Life in the network: the coming age of computational social science. *Science (New York, NY),* 323(5915)**,** 721.

Leitch, C. 2007. An action research approach to entrepreneurship.

Madsen, A. K. 2015. Tracing Data—Paying Attention. *In:* KORNBERGER, M., JUSTESEN, L., MADSEN, A. K. & MOURITSEN, J. (eds.) *Making Things Valuable.* Oxford, UK: Oxford University Press, pp. 257.

Mansoori, Y. & Lackéus, M. in press. Comparing Effectuation to Discovery-Driven Planning, Prescriptive Entrepreneurship, Business Planning, Lean Startup and Design Thinking. *Accepted for publication in Small Business Economics*.

Marres, N. 2017. *Digital sociology: The reinvention of social research*, John Wiley & Sons.

McDonald, S., Gan, B. C., Fraser, S. S., Oke, A. & Anderson, A. R. 2015. A review of research methods in entrepreneurship 1985-2013. *International Journal of Entrepreneurial Behavior & Research,* 21(3)**,** 291-315.

McMullen, J. S. 2017. Are you pivoting away your passion? The hidden danger of assuming customer sovereignty in entrepreneurial value creation. *Business Horizons,* 4(60)**,** 427-430.

Molina-Azorín, J. F., López-Gamero, M. D., Pereira-Moliner, J. & Pertusa-Ortega, E. M. 2012. Mixed methods studies in entrepreneurship research: Applications and contributions. *Entrepreneurship & Regional Development,* 24(5-6)**,** 425-456.

Neergaard, H. & Ulhøi, J. P. 2007. *Handbook of qualitative research methods in entrepreneurship,* Cheltenham, UK, Edward Elgar Publishing.

Onwuegbuzie, A. J. & Leech, N. L. 2005. On becoming a pragmatic researcher: The importance of combining quantitative and qualitative research methodologies. *International journal of social research methodology,* 8(5)**,** 375-387.

Phellas, C. N., Bloch, A. & Seale, C. 2011. Structured methods: interviews, questionnaires and observation. *Researching society and culture,* 3(

Reis, H. T., Gable, S. L. & Maniaci, M. R. 2014. Methods for studying everyday experience in its natural context. *In:* REIS, H. T. & JUDD, C. M. (eds.) *Handbook of Research Methods in Social and Personality Psychology.* Cambridge, UK: Cambridge University Press, pp. 373.

Roberts, J. W. 2015. *Experiential Education in the College Context: What it Is, how it Works, and why it Matters*, Routledge.

Rogers, R. 2009. *The end of the virtual: Digital methods*, Amsterdam University Press.

Rosa, P. J. 2013. Recent trends in leading entrepreneurship research: The challenge for European researchers. *Entrepreneurship Research Journal,* 3(1)**,** 35-43.

Sayer, A. 2010. *Method in social science: A realist approach,* New York, NY, Routledge.

Schroeder, R. 2014. Big Data and the brave new world of social media research. *Big Data & Society,* 1(2)**,** 2053951714563194.

Schön, D. A. 1983. *The Reflective Practitioner, How Professionals Think In Action,* New York, Basic Books.

Selwyn, N. & Robson, K. 1998. Using e-mail as a research tool. *Social research update,* 21(6).

Shah, D. V., Cappella, J. N., Neuman, W. R., Shah, D. V., Cappella, J. N. & Neuman, W. R. 2015. Big data, digital media, and computational social science: Possibilities and perils. *The ANNALS of the American Academy of Political and Social Science,* 659(1)**,** 6-13.

Shumar, W. & Madison, N. 2013. Ethnography in a virtual world. *Ethnography and Education,* 8(2)**,** 255-272.

Siggelkow, N. 2007. Persuasion with case studies. *Academy of management journal,* 50(1)**,** 20-24.

Skeggs, B. & Yuill, S. 2016. The methodology of a multi-model project examining how Facebook infrastructures social relations. *Information, Communication & Society,* 19(10)**,** 1356-1372.

Smith, S. M. & McKeever, E. 2015. Using constant comparison as a method of analysis in entrepreneurship research. *In:* NEERGAARD, H. & LEITCH, C. M. (eds.) *Handbook of Qualitative Research Techniques and Analysis in Entrepreneurship.* Cheltenham, UK: Edward Elgar Publishing, pp. 52-73.

Suddaby, R., Bruton, G. D. & Si, S. X. 2015. Entrepreneurship through a qualitative lens: Insights on the construction and/or discovery of entrepreneurial opportunity. *Journal of Business Venturing,* 30(1)**,** 1-10.

Tumasjan, A., Sprenger, T. O., Sandner, P. G. & Welpe, I. M. 2010. Predicting elections with twitter: What 140 characters reveal about political sentiment. *ICWSM,* 10(1)**,** 178-185.

Weltevrede, E. 2016. *Repurposing digital methods - The research affordances of platforms and engines.* Doctoral Thesis, University of Amsterdam.

Wigren, C. 2007. Assessing the quality of qualitative research in entrepreneurship. *In:* NEERGAARD, H. & ULHØI, J. P. (eds.) *Handbook of qualitative research methods in entrepreneurship.* Cheltenham, UK: Edward Elgar Publishing, pp. 383.

Wilson, R. E., Gosling, S. D. & Graham, L. T. 2012. A review of Facebook research in the social sciences. *Perspectives on psychological science,* 7(3)**,** 203-220.

Von Bertalanffy, L. 1950. An outline of general system theory. *British Journal for the Philosophy of Science*.