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Can Scientific Social Media Disrupt Entrepreneurship Research?

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Abstract

This article investigates how social media can help entrepreneurship researchers in their data collection and analysis efforts. The widespread use in society of social media platforms represents a new opportunity for social scientists to collect both big and thick 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 where a research purpose is allowed to fully inform the design and development of a new social media platform. It is here labeled a 'scientific social media' (SSM) approach. A case study method is applied where the six-year development process and current functionality of an SSM platform called LoopMe is described in-depth. Generalizations from this case then lead up to an attempt to answer the question: Can SSM platforms offer disruptive benefits to entrepreneurship researchers? Some identified benefits of an SSM approach include ability to combine key strengths of established research methods and ontologies, ability to triangulate between qualitative and quantitative data in new ways and ability to conduct very cost-efficient longitudinal studies. These new benefits could contribute to alleviating a problematic rigor-relevance gap in entrepreneurship research.

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 & Landström, 2016). To bridge this gap, methodological plurality and development has been called for (Neergaard & 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 & 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 & 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 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 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 & 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 & 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 & 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 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 SSM platform ever built (see for example Garaizar & Reips, 2014), LoopMe is most likely the first SSM platform designed, built and broadly used specifically for entrepreneurship 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 some previously developed generalizations on what LoopMe is an example of. 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 & 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 & 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 however 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 & 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 & 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 & 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 & 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 US than in Europe (Neergaard & Ulhøi, 2007). It could be due to a less articulated publication pressure among European scholars, making them more open to methodological pluralism (Huse & Landström, 1997). There is also a trend towards an increasing appreciation of qualitative methods (Smith & McKeever, 2015), slowly diminishing the mono-method emphasis on a macro level across studies. On a micro level within studies the mono-method emphasis however 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 based research**

Recent research outside the field of entrepreneurship indicates that social media 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 & 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 & 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 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). 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 (Langlois & Elmer, 2013; Skeggs & 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 & Colleoni, 2012; Shumar & 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 later discussion around the question of whether SSM could disrupt entrepreneurship research.

3 The SSM platform LoopMe

An overview of the SSM 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 identified so far, followed by two sections outlining challenges so far and possible future applications. The last section defines a new category of IT systems that LoopMe could be viewed as an example of.

3.1 Overview of LoopMe

LoopMe is a social media platform originally developed for scientific purposes at Chalmers University of Technology in Sweden. 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 education technology startup placed in the regional business incubator Chalmers Innovation. Seven different assessment 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 6000 users in Sweden, Norway, Denmark, France, Italy, Ireland, UK and Turkey. The LoopMe platform is currently available to the public at the website www.loopme.io, managed by the commercial software-as-a-service company Me Analytics AB employing five people. The platform has a wide user base in Sweden and an emerging user base around Europe. The company is owned by the co-founders, by the employees and by three business angel investors. 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 business angel investment. The development cost has so far amounted to around 1 million USD spread out over four years.

LoopMe works like a system consisting of input, process and output (cf. Von Bertalanffy, 1950), see Figure 1. The input consists of a few predefined behavioral tasks that are intended to trigger personal and organizational development, and a few associated tags that users can attach to each task when it has been completed. The process entails a group of people doing and reflecting upon the completion of the tasks that a leader of some kind has assigned to them. 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 output consists of digitally documented personal learning and / or organizational development. Usage of LoopMe thus contains three phases – (1) a leader defined input, (2) users completing and reflecting upon a number of behavioral tasks, and (3) all people involved benefiting from and analyzing the output.

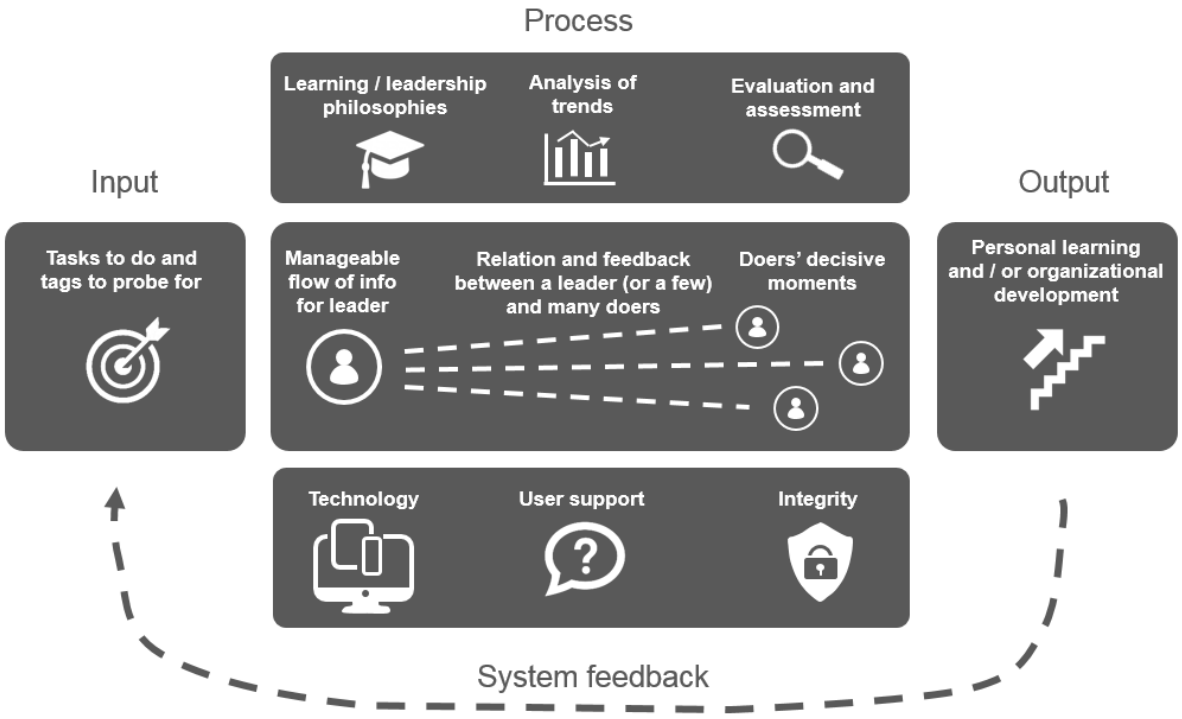

Figure 1. LoopMe as a system.

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 tag 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 a large number of 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 & 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 & Elmer, 2013).

3.2 **Development history of LoopMe**

The development of LoopMe has passed through four distinct phases over six years from 2012 to 2017, each resulting in a new major version of the platform. Example graphical designs taken from each version are shown in Figure 2. The four development phases will now be briefly outlined.

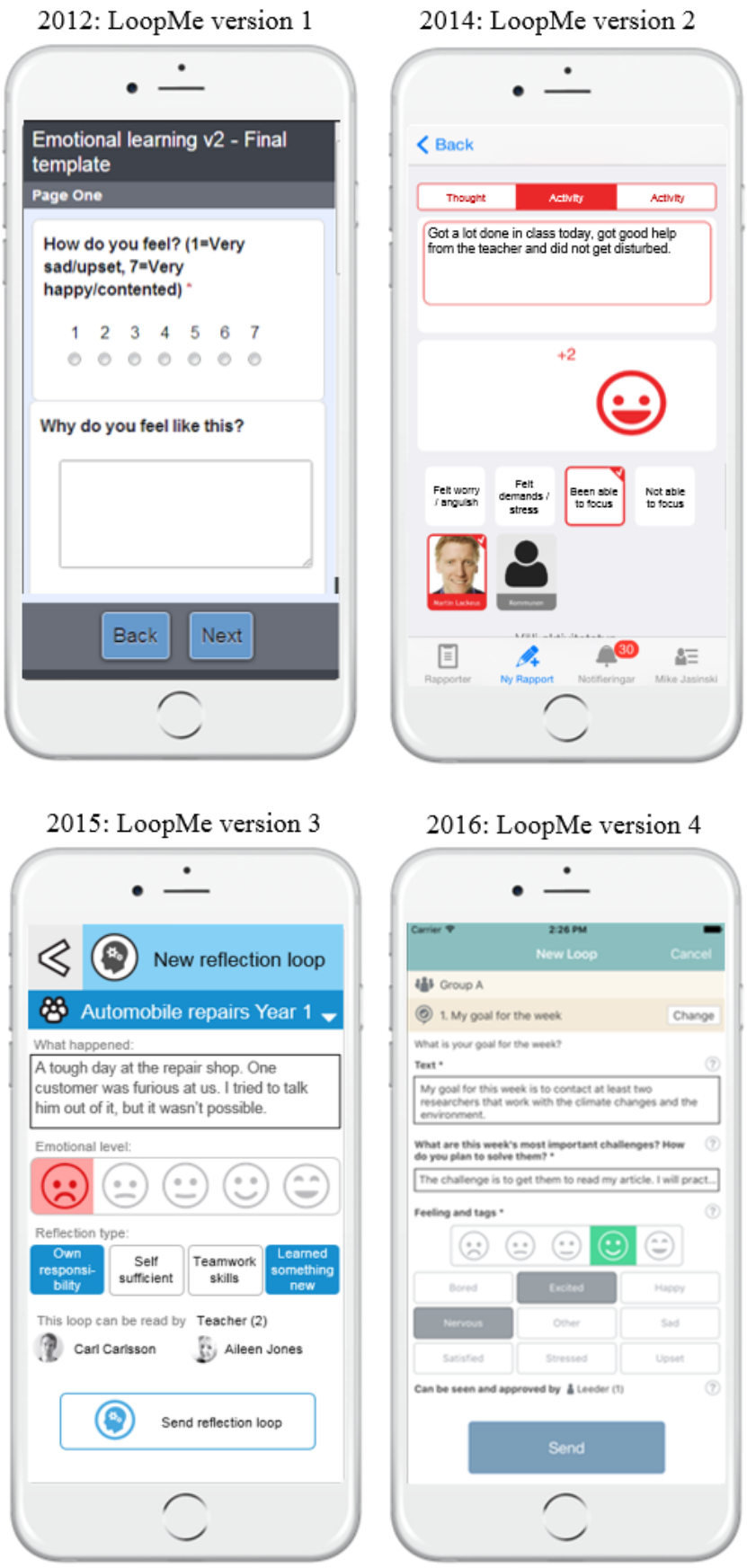

Figure 2. Historical overview showing graphical design of four different versions of LoopMe.

3.2.1 LoopMe version 1

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 from early 2012 to late 2013. 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). The survey contained two questions; "How do you feel?" and "Why do you feel like this?", see Figure 2. Responses were extracted from the commercial web survey engine used in the form of one Excel sheet for each participant. This data was then used in subsequent interviews with the participants, reducing recall bias and providing key topics to discuss with the interviewees. LoopMe thus served primarily to increase the quality of the interviews (Lackéus, 2014). 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 an in-curricular entrepreneurial project (Lackéus & Sävetun, 2014).

3.2.2 LoopMe version 2

The second version of LoopMe was designed by the research team at Chalmers University of Technology and built by a team of professional programmers employed at the start-up venture Me Analytics AB, founded in early 2014. The venture was founded with the specific aim of building LoopMe for use in a study commissioned by Swedish National Agency of Education (SNAE) on entrepreneurial 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. A key feature of this version was also to first let the user decide whether it was a thought, an action or an emotion that was to be reported to the teacher. The idea behind this was to trigger users to report not only activities but also thoughts and emotions they experienced. 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 & Sävetun, 2015; Lackéus & Sävetun, 2016).

3.2.3 LoopMe version 3

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, a number of 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. The possibility to report on an emotion was removed, since this had confused users. Instead an emotional classification was made mandatory for all loops. Due to a collaboration project initiated with a network of vocational schools in Sweden, a functionality called 'tasks' was also specified. The idea was to allow teachers to assign tasks to apprenticeship students. This would then alleviate the challenge of assessing students doing internships at workplaces. LoopMe would then allow for apprentices to complete and then reflect upon mandatory tasks. This could be viewed as a commercial influence on the development process, since the task functionality was not deemed central from a research perspective at that time. The task functionality was however not used in a large study on 500 participants initiated when the third version of LoopMe was completed in September 2015. Participants were instead asked to report to their teachers whenever they experienced an emotional event (Lackéus & Sävetun, 2017). The task functionality was not implemented in LoopMe until May 2016. Its first real-life beta test was conducted on entrepreneurship students at Chalmers University of Technology.

The first three versions of LoopMe were all based on the idea that users would determine if and when they wanted to report something to their leaders, just like in most established social media platforms. This worked well in research oriented projects where teachers and other key stakeholders could keep reminding the participants to produce data when something relevant happened. It however proved to be difficult to get more than around 20-30% 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 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 commercial agenda, making mandatory tasks a standard functionality for all users. While users beyond vocational schools 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

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. While making tasks mandatory resolved the issue of people in a group not using LoopMe, it was still up to each user to decide when to make a loop. The division into thought loops and action loops was also removed, since it had shown to cause confusion for users. These changes all 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 task packages, consisting of ready-made sets of 3-20 tasks that any leader could pick up and distribute to a group of users. The fourth version of LoopMe was completed in August 2016. It has not yet been used in a large research study, but has instead been used regularly by paying customers in various practice-oriented projects.

While the fourth version of LoopMe could be interpreted as a research oriented agenda reluctantly ceding to a commercially oriented agenda, this was actually not what ended up happening. The two potentially conflicting purposes instead ended up strengthening each other. The introduction of a task oriented structure in LoopMe opened up for a more powerful way to collect and analyze data. The mandatory tasks allowed for a more fine-grained design of participant behavior. The logical link between tasks and tags allowed for an unexpected opportunity to quantify causality between independent variables (i.e. tasks) and dependent variables (i.e. tags and 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 commercial 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 commercial needs. Users' willingness to engage with a social media platform and thus pay for using it is arguably a key factor determining the amount of scholarly useful data the platform can collect.

3.3 **Three applications of LoopMe extensively tried so far**

LoopMe has so far been used extensively for the three following purposes; (1) as a tool for teachers / coaches to follow and assess learners in a social learning environment, (2) as a tool at the school, university or workplace for managers to steer and follow organizational change, learning and development processes, and (3) as an educational 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 to improve and assess social learning experiences

Teachers have used LoopMe to design action-based learning experiences by breaking the 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 correspond to the 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, he or 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 his or 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. Adjustments or added explanations can be made based on feedback from learners. Individual learners getting stuck can be identified through their negative reflections on tasks, 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).

LoopMe represents a new approach to a number of key assessment and evaluation aspects that have been discussed extensively in educational research. One such key aspect is formative assessment, i.e. process based assessment aimed at improving teaching and learning through direct feedback to and from teachers (Isaacs et al., 2013; Black & Wiliam, 1998). Towards the end of a course or module, LoopMe summarizes which learners have completed which tasks, allowing also for a summarized action-based assessment. This is often called summative assessment, i.e. outcome oriented assessment towards the end of a module or program (Isaacs et al., 2013). Another key aspect is teacher professional development. Teachers can use information received from learners for fact based discussions among colleagues, evaluating collectively how their teaching works (cf. Timperley et al., 2008). All data in LoopMe can be downloaded to an Excel document for more in-depth analysis by a teacher individually or together with colleagues.

3.3.2 LoopMe used in school / university development projects

A common challenge in educational development projects is that the envisioned changes seldom reach the classrooms (Elmore, 1996; Cuban, 1990). 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. School / university managers have used LoopMe to break down a development project into those actionable tasks that teachers need to do in order for positive change to occur in practice in the classrooms. 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 a teacher completes a task, he or she is required to reflect upon the event and tag the experience. School / university managers will then be able to follow all teachers over time as they complete the tasks, what impact each task makes in relation to desired project outcomes and how the teachers reflect around it. This is the formative assessment component; school / university managers formatively assessing their teaching staff for the purpose of reaching desired project outcomes. When using LoopMe this way, school / university 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. The data in LoopMe can be downloaded to an Excel document for more in-depth analysis of the development project.

LoopMe has also been 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 teachers have completed and reflected upon all tasks. This is the summative assessment component; school / university managers holding teachers accountable for participating in change projects, at least giving the stipulated activities a chance. Since school / university development often involves a significant amount of organizational learning (Elmore, 1996), the reflection and trustful dialogue that LoopMe facilitates between school / university leaders and teachers is also useful. In a school / university development project it is rather the teacher that is the primary learner, together with the manager who also needs to be able to quickly learn from both setbacks and progress and adapt a development project accordingly.

Given that educational institutions are also workplaces, the above example implies that LoopMe could probably facilitate organizational learning in general. Any situation where an employee needs to act in order to learn and develop could probably be facilitated by LoopMe in similar ways.

3.3.3 LoopMe used for research

The 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 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 a large number of users. The dialogue that a completed task can spur between users adds to the qualitative analysis. It is possible to get very detailed data on how people experience a particular activity if it can be articulated as a task in LoopMe. The researcher can follow the experiential process as it unfolds in real-time, allowing for timely questions to be posed directly to the relevant users. 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 users, as well as all dialogues that have taken place.

The primary scholarly application of LoopMe has so far been in research on entrepreneurship and enterprise education. The practical benefits of LoopMe for teachers and students outlined in sections 3.3.1 and 3.3.2 have allowed LoopMe to be deployed on large student populations and with a high level of activity among users. LoopMe has allowed learners to share their daily experiences with people they trust, such as teachers, coaches and managers. Through written consent from each learner 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 categorized data on critical learning events, thought patterns and actual behaviors impacting learning and progress. The many learners involved have acted as participant observers who notify the research team of any significant events occurring within or outside the classroom. It has been both positive and negative events in relation to the intended outcomes. In any given classroom where more than approximately 10% of the students are active users of LoopMe, most events that are relevant for research purposes will likely be reported through LoopMe by at least one student. This allows for researchers to get a clear view of what happens, and what doesn't happen, in the classroom as well as in the minds of the students. Free text reflections and tags give a detailed account of what has happened. Absence of reflections or tags on a certain topic represents evidence of what is not happening. The responses from teachers to students on various critical events also adds to the data on what happens and does not happen in the learning environment. LoopMe thus generates both quantitative and qualitative data.

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 learner must categorize every completed task in the learning process 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 educational intervention leads to desired learning outcomes. Each cell containing a percentage number in such a matrix can be investigated further by studying a large number of qualitative free text reflections associated to it, where many users 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, uncovering how, when and why action-based entrepreneurial education can develop entrepreneurial competencies (Lackéus, 2016; 2017).

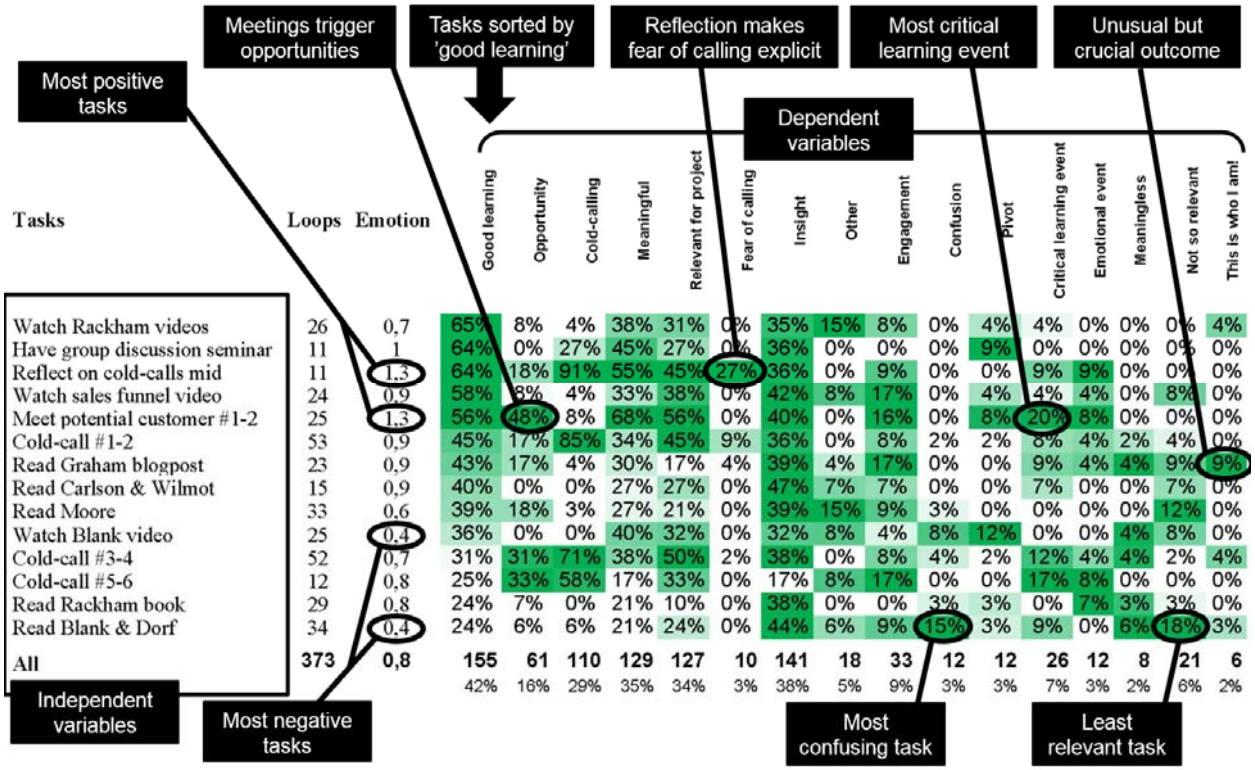

Figure 3. Rich data collected through LoopMe, aggregated into statistics relating authentic tasks to learning outcomes.

Most of the written reflections provided by learners 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 learners and 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 users, he / 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 participants 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 person with unique insights or experiences relevant to the research question pursued, follow-up questions can be asked in real-time.

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). 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 reduces 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 completely reliant on leaders (such as teachers or managers) possessing the authority to make task fulfilment mandatory for all members in a group. If such a mandatory prerequisite is not present or utilized, the likely usage ratio of LoopMe is around 5-15% 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.

Informed consent is another challenge with LoopMe. This is a well-known challenge in social media based research (Fiske & Hauser, 2014). 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 implies that access to a complementary team of 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 hundreds or even thousands of skilled programmers has also raised the public's expectations around usability, simplicity, design and attractiveness of social media 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 entrepreneurial 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 a large number of 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 a large number of entrepreneurs that they prescribe entrepreneurial action to and give personal advice to on their journey towards entrepreneurial success. While it is perhaps not easy to imagine why tycoons would want to do this, it is easier to imagine the richness of the resulting datasets on real-life entrepreneurial processes. 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 a large number of colleagues at an established corporation. This kind of data could be of interest to corporate entrepreneurship and corporate strategy scholars. A more generic possibility is for any entrepreneurship researcher who can make do with the 5-15% of users in any given group that will likely volunteer to complete tasks and then reflect upon their experiences with free text and tags.

Beneath 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 **A new category of IT systems that LoopMe is an example of: 'Social Learning Media'**

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. A need was perceived to articulate or define a new category of IT systems that LoopMe could be viewed as an example of. This category was labeled "Social Learning Media" (SLM), i.e. social media for social learning, see Table 1. SLM is here defined as a digital and mobile communication platform that allows for simple and relevant one-to-one dialogue between a leader and many learners, revolving around mandatory action-oriented tasks that a leader defines and that learners perform and then reflect upon. This makes SLM a more narrow concept than SSM, since social learning is arguably not the only possible purpose one could tailor a social media platform for. The specific example of LoopMe is thus both an SLM and an SSM at the same time. Practitioners would probably prefer to see it as an SLM, whereas scholars would perhaps rather see it as an SSM.

Table 1. Social learning media contrasted to learning management and social media.

	Learning management	Social media	Social learning media
Purpose	Administer courses	Connect people	Facilitate 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 primarily
Quantifiability	Low	Low	High

SLM leans theoretically on authentic assessment, reflective assessment, learning analytics and experience sampling. Authentic assessment is about letting students perform meaningful real-life tasks and assess them based on task accomplishment (Isaacs et al., 2013). Reflective assessment is about assessing students by letting them reflect on their experiences (Bond & Ellis, 2013). Learning analytics is about improving learning environments by collecting electronic data generated by students as they learn (Martin & Sherin, 2013). Experience sampling is a research procedure for studying people's thoughts, actions and emotions in real-life settings (Larson & Csikszentmihalyi, 1983).

Based on careful empirical study of LoopMe viewed as a paradigmatic case, seven defining characteristics of SLM are proposed below. They arguably also apply to a large extent to SSM. According to Flyvbjerg (2006), a paradigmatic case is a case that highlights more general characteristics of a new phenomenon that sets a new standard.

3.6.1 Digital and mobile communication

Just like established social media relies on digital communication that can take place on the go in the mobile, SLM also relies on digital communication that can take place on any kind of digital platform, such as a smartphone, a tablet or the web browsed on a laptop or in a phone. This is a key aspect of a new category of assessment methods labeled 'e-assessment' (Stödberg, 2012).

3.6.2 Private one-to-one dialogs

Since learning is a deeply personal and sometimes intimidating process requiring honesty and deep reflection, any digital communication that supports learning needs to safeguard discretion, intimacy and openness without any risk of being humiliated in front of many people. SLM thus needs to include a way for students and teachers to engage in private one-to-one dialogs.

3.6.3 Simple and always relevant

People's expectations on software in general and on social media in particular are that they exhibit maximum usability and ease-of-use. This rules out most levels of complexity. SLM thus needs to be extremely simple to use if it is to be adopted by a wide base of users. Having stressed teachers / coaches / managers as key users also requires SLM to be highly relevant, even void of any irrelevant information.

3.6.4 Hierarchical and mandatory with approval

Education and training is based on formalized learning processes where teachers, coaches or managers direct an experience that is mandatory for learners. Therefore SLM needs to be hierarchical in its structure. The communication that takes place in an SLM also needs to be partly mandatory, since there is a minimum level of action-taking and communication that each learner needs to engage in. This also means that an approval function must be a key part of an SLM tool. For an SSM tool it might however not be necessary.

3.6.5 Action-oriented mandatory tasks

Formally described mandatory tasks that are described the same way for all learners constitute the spine of a SLM platform. Without such tasks there is little reason for learners to engage with an SLM platform. This aspect of SLM has been discussed under the terms 'authentic assessment' (Ellis & Bond, 2016) 'performance tasks' (Darling-Hammond, 1994) and 'assessment tasks' (Biggs & Tang, 2007). In an SLM, tasks should be designed in an action-based manner, leaning 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. How such tasks are completed could vary significantly between students.

3.6.6 Mandatory task based reflection and tagging

The completion of a task is coupled with a mandatory reflection and tagging of the experience that serves to increase reflective learning, facilitate deeper learning and provide evidence for the teacher that the task

was indeed completed. This aspect of an SLM has been discussed in literature under the term 'reflective assessment' (Bond et al., 2011).

3.6.7 Voluntary reflective discussion

When a task is marked as completed by the learner and reflected upon, it can at times trigger a digital dialogue connected to that specific completed task (i.e. a chat) if and whenever the teacher chooses to engage in such a dialogue. This represents a possibility for the teacher to perform an extended qualitative assessment of whether the student has performed the task in a way that fulfils the requirements put up by the teacher.

4 Discussion

A number of key characteristics of SSM will now be discussed, 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 methods 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 hypotheses 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 & 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 & Gadde, 2014). Focusing on precisely those quotes that are linked to a conceptually interesting cell in the matrix in Figure 3 shown previously could allow for "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 could arguably be quite useful.

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	Witten 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	500	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	High	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 many 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 represents 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 & Lincoln, 1994). Given that SSM shares theoretical roots with experience sampling (Larson & 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 task 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 up for a renewed emphasis on longitudinal studies without having to pay the price in terms of time and resources. Once a 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 primary 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. 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 & 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 & 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 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 & 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 an expensive, meticulous and time consuming endeavor. While other research questions could perhaps 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 and learning. 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 amount 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. Current research on social media 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 a number of 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 also bridging between qualitative and quantitative research. This could in turn help alleviating a problematic rigor-relevance gap in entrepreneurship research (cf. Frank & 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 health, parenting, dieting, leadership and sustainability.

Some challenges have also been identified. Developing a 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 taken into account, 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.

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.

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. & Ellis, A. K. 2013. The Effects of Metacognitive Reflective Assessment on Fifth and Sixth Graders' Mathematics Achievement. *School Science and Mathematics,* 113(5), 227-234.

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.

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.

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.

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.

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.

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.

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.

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

Martin, T. & Sherin, B. 2013. Learning analytics and computational techniques for detecting and evaluating patterns in learning: An introduction to the special issue. *Journal of the Learning Sciences,* 22(4), 511-520.

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.

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.

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.

Stödberg, U. 2012. A research review of e-assessment. *Assessment & Evaluation in Higher Education,* 37(5), 591-604.

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.

Timperley, H., Wilson, A., Barrar, H. & Fung, I. 2008. Teacher professional learning and development.

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.

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*.