Sensing Multi Business Model Innovation via Advanced Sensor Technology

Peter Lindgren, Per Valter and Gitte Kingo

*Department of Business Development and Technology, Aarhus University,
Aarhus, Denmark*

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Abstract

The ability to innovate Business Models (BM) and do Multi Business Model Innovation (MBMI) has become more complicated today, but also a very hot topic in many businesses and even for governments. As BM's lifetime are becoming shorter and shorter, BM's are also changing typologies and a larger part of these becomes disruptive. Danish Government already in 2017 formed a disruption council – as a reflection on this evolvement – its primary task was to discuss, analyze and come up with proposals for how businesses and society should prepare for future MBMI, disruptive BM's and Business Model Ecosystems (BMES) [1–4, 6, 7, 16].

Sensing BM's seems to hold some solutions to meet this development. The academic classification of Sensing BM's and Sensing MBMI have until now been very fragmented defined. The Sensing BM and Sensing MBMI have not been clearly defined, also compared to other types of BM's and Business Model Innovation (BMI). Several businesses believe they innovate Sensing BM's (SBM), Operate Industrial 4.0 with advanced sensors – but are challenged when asked to classify SBM and SBMI.

The paper addresses – when can a BM be classified as a SBM. In relation to this topic – When can a business be classified as doing SBMI. The aim of the paper is:

- (1) to add to the development of conceptual framework models and typologies [10–12] for classifying SBM's and disruptive, radical and incremental SBM's and SBMIs.

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- (2) to add to the development of MBMI framework and language using advanced sensor and wireless technologies.

The preliminary research was supported by a BM and BMI framework [29], combined with advanced sensing technology, enabling researchers to observe and do experiments with SBM's and SBMI.

Keywords: Sensing Business Models, Sensing Business Model Innovation, Sensor Technology, Digitalization of Business Models and Business Model Innovation.

1 Introduction

The ability to sense MBMI and to “see” and “sense” what is really taking place in an MBMI process or an already operating BM – “AS IS BM” – between humans, humans and technology, technology and machines has become a very hot topic in many businesses these days.

The overall vision and purpose of the CGC B-lab is to develop a global MBMI research platform establishing a global network of sensing and digital MBMI labs and MBMI facilities with optimized MBMI conditions. These CGC B-labs should be able to in a long-term perspective to support any interaction in MBMI processes – and develop sensing BM's combined with advanced behavioral science. The aim is to make MBMI experiments for innovating persuasive BM's and carry out research on how future BM's could look like and do MBMI experiments within MBMI processes.

Making this possible business and researchers have to begin the journey by sharing and exchanging BM dimensions – with a common agreed BM language, MBMI competences, capabilities and processes – and all this in real time. Some businesses – Alibaba.com, Amazone.com, Google, Apple and Facebook are already into these BM's using digital sensors combined with digital robots, embedded with machine learning software and advanced behavioral science to support their BM Operation [24]. According to [25] businesses that have behavioral science “baked” into their way of doing business include Instagram (sold for \$1 billion to Facebook, Opower (sold for \$532 million to Oracle in 2017—currently enabling 100 global utilities to sense each other businesses) [8, 9]. These as examples of the fact that there is plenty of money in these sensing BM's. This will enable businesses

to improve their AS IS BM's and AS IS MBMI processes in a faster pace enabling them to match TO BE BM's to necessary future MBMI requirements.

The knowledge from these first experiments can be valuable to understand and create future global MBMI. "Harvesting" sensor data in real time from these MBMI experiments for research purpose will be of importance to future understanding and innovation of BM's and MBMI.

In order to reach this goal several experiments with sensing and digitization technologies have to be carried out. In CGC B-labs the research group intend to experiment and test in different areas.

1. BM with advanced sensor technologies
2. BM tools with advanced sensor technologies
3. MBMI environment with advanced sensor technologies
4. AI embedded with BM's

In this paper, we report on CGC preliminary experiments on BM and MBMI sensing framework functions in an experimental MBMI context. We further discuss how a larger experiment can be setup in future experiments. The preliminary experiments show some initial results of how humans in MBMI processes work and act – and how human and machines interact in MBMI processes. By digitalizing the MBMI environment in the CGC B-labs and digitalizing human behavior of those participating in elective experimental MBMI challenges and projects, it was possible to gain new insight in the MBMI processes and thereby contribute to proposals of how to improve MBMI environment, MBMI technology, MBMI process, development and coaching of MBMI processes.

2 Experimental Setup

The main purpose of the first experiments in the CGC B-labs was to focus on the MBMI environment and embed different sensors in the MBMI environment – the B-labs.

The first experiment with an experimental setup for Sensing MBMI processes [25] was established with 1 Danish Business (Thise Dairy), 1 Norwegian business (Veas) and 1 Swedish business (Westlax). These Businesses together with 15 master and PhD students together with 3 Business Managers, 4 Business Experts and 2 MBMI coaches were involved in the experiment. 3 researchers with different focus areas (sensor/data technology, MBMI Coaching and MBMI) were further involved.

Figure 1 The MBMI B-Lab's shown in the promo video [27].

Figures 2 and 3 Student work Pitch their BM's to external experts and management.

The actors worked close together with business management on the different MBMI Challenges with the aim to create and capture “TO BE” BM's to the businesses. The research was carried out within the EU Interreg Project Biogas 2020 [26].

In the 3 CGC B-labs several sensors were installed. This experimental set-up primarily focused on testing the use of digitalization to monitor:

- IEQ data – Indoor Environment temperature, pressure, acoustic, CO₂
- Physical Health data – Heart rate of the participants
- Physiological health data – Mood of the participants – 7 different moods

Secondary, as a spinout of the data collection and Biogas 2020 TBMI Challenge

- Video pictures – 360 Degree
- Other IEQ data – Humidity, Sound
- Participants Personal profile data

Figure 4 CGC B-labs, sensor types and sensor positions.

Tertiary,

- Qualitative interviews of students, BMI coach, business, judge and audience participants via video

In Figure 4 it is shown where the different sensors were placed in the 3 B-labs. Heart rate and other Human Parameters of the participants were measured with special sensors. For the mood recognition, the data was collected as pictures of the participants' face sent to a mood recognition software, Figure 5.

This was done by an experimental 3D printed prototype and by for the experiment developed devices attached to special caps and installed with eye-tracking cameras and special battery construction securing power supply, Figure 6.

The "mode recognition caps" were wirelessly connected to a central computer in the control room installed to collect and store all incoming data – video pictures, IEQ, Heart rate, mood, video, sound data.

Table 1 shows the measured indoor climate parameters and the sensors used.

Environment data were monitored and analyzed together with heart rate and picture from participants faces. Microsoft mood recognition software was used, and the emotion was expressed as a distribution of the 8 emotion parameters: anger, contempt, disgust, fear, happiness, neutral, sadness.

Figure 5 Participants' face sent to a mood recognition software and monitor in experimental control room.

Figure 6 Participants with special mood recognitions caps.

Figure 7 Researcher showing mood recognition cap and monitoring screen in B-lab experimental control room.

Every data sample from the 3 B-labs and 3 overall monitoring areas were accessible live during the whole experiment and were stored with a timestamp for further analysis.

Table 1 Indoor climate parameters, units, uncertainty and sensor type

Indoor Climate Parameter	Unit	Uncertainty	Sensor
Temperature	°C	2–5%	Terminal Sensors
CO ₂ level	Ppm	5–10%	CO ₂ Sensors
Pressure	Pa	5–10%	Pressure Sensors
Humidity	%	5–10%	Humidity Sensors

Table 2 Human reaction parameters units, uncertainty and sensor type

Human Reaction Parameter	Unit	Sensor
Pulse	Beats pr. minute	Heart Rate Monitor
Emotion	Portraits Pictures	Face recognition Sensor

Secondary data – video and pictures were monitored with camera and 360-degree camera. Every participant in the TBMI Challenge filled out beforehand a personal profile test. The system and software of Insight was used to make the profiles.

Tertiary data were monitored and gathered as videotaped qualitative interviews and as individual and group interviews with participants during the Biogas 2020 TBMI Challenge.

This made it possible to commence analyzing the data quantitatively and qualitatively including analyses data area wise and across primary, secondary and tertiary research focus areas. This made it possible to look for explanations and correlations between different areas and research topics of interest related to the sensing MBMI process and output of the sensing MBMI process.

3 Results and Analysis

The data collected from the experiment in the Biogas 2020 TBMI Challenge experiment in Skive were:

- 1 million+ CO₂, temperature, humidity, pressure measurements.
- 1 million+ heart rate measurements.
- 1 million+ face pictures for post processing with face detection and emotion detection algorithms.
- 3 Terabyte+ 360 degree 4K archived video. 50 Gigabyte+ sound –
- 1 video film on the whole TBMI Biogas 2020 BMI process taken by a special professional film team
- Change recording digital bee board.
- 15 personal profiles
- 15 interviews with Biogas 2020 TBMI Challenge participants

Figure 8 Livestream monitoring of temperature and pressure in B-lab.

- 3 video interviews with Biogas 2020 TBMI Challenge business representatives from Veas Norway, Thise Dairy, Denmark, West Lax, Sweden
- 2 interviews with TBMI Challenge coaches – video recorded
- 4 interviews with Biogas 2020 TBMI Challenge Judges from India, Norway, Sweden and Denmark – video recorded
- 1 interview with researchers behind technology and engineering setup of the experiment
- Interviews with audience watching the Biogas 2020 TBMI Challenge from outside.

3.1 Live Monitoring

During the experiment, all data was successfully accessible via live streaming.

Figure 8 above shows samples of temperature and pressure in B-lab of one of the B-labs (Thise Dairy Biogas 2020 TBMI Group and Challenge) showing how the data was visible at a control screen in the control center of the experiment.

3.2 Indoor Environment and Human Bond Communication Data

The data presented in this paper is representing samples and sections of the whole data set as these are still being analyzed. However, it is already possible to report on some of the measurements in the dataset. The data showed clearly

that the temperature had an impact on the participants BMI activity level in the B-labs. When cold air floated into the B-labs, immediately it was possible to see on the monitors that the participants reacted with changed BMI activities and in this case, BMI work and intensity decreased. The impact of the cold air began time wise differently in the 3 B-labs as the temperature dropped not equally and at the same time in the 3 B-labs. It also was shown that the cold air had different impact on the participants – some reacted more than others did.

As in two previous experimental test carried out in 2015 and in 2016 it was not possible to register that the CO₂ level in the B-labs had any impact on the participants' work and intensity of work. Further, our analysis did not verify that the humidity and pressure level in the B-labs has any impact on participants' work and intensity of work.

3.3 3D Video Monitoring and Tracking of BMI Participants Movement

In the experiment 3D videos of the BMI participants and their movement in the B-labs were also monitored and analyzed. In Figure 9 an example of this measurement including the business expert members is shown. This enabled the researchers to see how the participants use the BMI tools and their interaction with the BMI tools and the B-lab.

Combined with the personal profile data measured with Insight personal profile test, we are now analyzing movements, personal profile and environment climate parameters to see if there is any correlation here.

Figure 9 3D videos of BMI and judge participants in one B-lab.

Figure 10 General Insight personal profile.

4 Next Experimental Setup

The next experiments aim at improving the experimental set-up with more and better MBMI sensors. The next experiments will be carried out in spring 2019 in over 30 B-labs at the same time and are expected to give improved knowledge on SBM and sensing MBMI processes. CGC wants to harvest MBMI sensing mega data that can give more valuable and optimal dataset for deeper understanding of human and machine interaction and impact on MBMI, MBMI participants and the MBMI process. Further, we expect to be able to contribute to the first MBMI coach supporting dashboard.

MBMI coaches' influence on the MBMI process has shown to be very important and correlated with the output of MBMI processes. Today most MBMI coaches carry out their support on behalf of experience, "feelings" and their personal sensing of the participants mood and body language. This might be changed and improved with the support of advanced sensing technologies.

Testing an explorative set-up measuring different MBMI parameters, human and machine reaction in small-scale real world MBMI settings, brought us closer towards the goal of establishing an advanced global network of interconnected MBMI environments. The experiments however showed that there is still some improvements to be achieved.

Figure 11 A sketch of a part of the future coach dashboard measuring BMI data from B-labs.

Challenge of Data Paring. After the experiment we experienced that “Data paring” was a very large challenge as this was not prepared carefully enough before the experiment was carried out. Data paring means that sound, video, environmental measurement data e.g. were not prepared to be paired. This had to be amended afterwards – which was very time consuming.

Challenge on measurement of Mood. The first step to prepare the software for mood recognition was downloading the FER2013 dataset available on Kaggle [28] for training purpose. The picture in the dataset was 48×48 pixel 8 bit grayscale of faces more or less centered and occupies the same space within the image. The dataset consists of 35887 samples in total where each is labelled in one of the following seven categories: (0 = Angry, 1 = Disgust, 2 = Fear, 3 = Happy, 4 = Sad, 5 = Surprise, 6 = Neutral). The dataset was a csv file where the format and separators are “emotion, pixels, usage.” After downloading the dataset, we carry out the exploratory data analysis on the entire dataset to generate a better understanding of the data using it for training our model. Table 3 shows what the data looks like by listing the first ten rows of the FER2013 [28] dataset showing the three columns emotion, pixels and usage: Table 4 shows a listing of the numbers of samples in each of the seven categories – happy, neutral, sad, fear, angry, surprise and disgust.

As Madalina Buzau [29] also notices and mentions in her research, there is an imbalance between the number of samples in each of the seven emotion

Table 3 Data listing of the first ten rows of the FER2013

Emotion		Pixels															Usage
0	0	70	80	82	72	58	60	63	54	58	60	48	89	115	121	...	Training
1	0	151	150	147	155	148	133	111	140	170	174	182	15	...			Training
2	2	231	212	156	164	174	138	161	173	182	200	106	38	...			Training
3	4	24	34	36	30	32	23	19	20	30	41	21	22	32	34	21	1 ...
4	6	4	0	0	0	0	0	0	0	0	0	3	15	23	28	48	50 58 84...
5	2	55	55	55	55	55	54	60	68	54	85	151	163	170	179	...	Training
6	4	20	17	19	21	25	38	42	42	46	54	56	62	63	66	82	1 ...
7	3	77	78	79	79	78	75	60	55	47	48	58	73	77	79	57	5 ...
8	3	85	84	90	121	101	102	133	153	153	169	177	189	1	...		Training
9	2	255	254	255	254	254	179	122	107	95	124	149	150	...			Training

Table 4 Listing of the numbers of samples in each of the seven categories happy, neutral, sad, fear, angry, surprise and disgust

Emotion		Number of Samples
0	Happy	8989
1	Netural	6198
2	Sad	6077
3	Fear	5121
4	Angry	4953
5	Surprise	4002
6	Disgust	547

categories and it will make it difficult for the system to learn the representation of the emotions with a small number of samples. It is obviously easier to learn the representation of the emotions with the higher number of samples. Therefore, we notice that the network has more opportunity to learn the emotion category happy with its 8989 samples than to learn the emotion category disgust with its 547 samples.

Challenge on Battery power for Mode sensor cap. The sensors needed energy – in this case, the cameras placed on the prototyped mode recognition caps. Batteries were prepared for maximum 6 hours operations and this challenged the system and the MBMI process. It is not appropriated and effective to have participants and researchers to power the caps each 6 hour as it might interrupt and disturb the MBMI process

Election of partners. The selection of participants was done as an open invitation but could be improved to maximize the MBMI teams and process with electing teams and process to the MBMI specific task.

Internet connection and data storage. The internet connection was a challenge as the main internet connection to the experiment hall broke down – outside the experimental area. An unexpected amount of data was harvested and data storage capacity was a challenge. Data storage capacity had therefore to be improved – “on the fly” – while the experiment was taking place.

The research however continues to be supported and increased in next experiment with embedding sensors in BM tools and MBMI frameworks, advanced sensing technologies being created much smaller and hopefully invisible, nonintrusive to the BMI participants.

5 Discussion

Experts view SBM and SMBMI processes as a strategic road that will lead to many interesting future BM's — one that builds upon SMBMI strategy by leveraging new SBM operations and maximizing profits on behalf of advanced sensing technologies. AS IS BM's will also be potential to be changed or transformed to sensing BM's.

Meanwhile, the ability to do SMBMI fast, efficient and effective becomes more and more urgent – but also becomes challenging – to keep competitiveness and survival of many businesses. Examples of some of the “small” challenges to overcome are indicated above.

SMBMI appears to be important as digitalization and virtualization of BM's are generally placing substantial stress on establish businesses and BMES – and becomes more and more power full. As a consequence sensing MBMI and the competence of doing sensing MBMI have by some expert been said to become obligatory for any business.

6 Conclusion

The understanding of SBM and SMBMI—according to our proposal—has to be seen as different to simple BMI not using advanced sensors. The paper present a first attempt to a new conceptual model for classifying SBM and SBMI. The SBMI framework could in the future be able to facilitate more businesses and academia's to classify different degrees of SBM and SBMI by “making” it possible to “download,” “see,” “sense,” “analyze,” “understand,” “act,” “do” and communicate on the different constructions of SBM's, SBMI and SBMI processes. The knowledge of SBMI's degree of disruptions must however be “learned” and investigated by more and different business cases – and a classification tool.

7 Further Research

We are now analyzing more SBM and SBMI cases individually and how they are interrelated. We are also setting up a new experiment including amended technology setup, new and more sensing technology together with more Business case. This is a rather time consuming work, which we are convinced can be reduced, when we learn more about the appropriate digital tools and big data analytics related to our specific research needs and requirements. Simultaneously we are setting up new experiments in the spring 2019 where we will have in one experiment about 50 B-labs/Bee-cubes operating simultaneously in 50 different BMES and geographical destinations.

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Biographies

Peter Lindgren holds a full Professorship in Multi business model and Technology innovation at Aarhus University, Denmark – Business development and technology innovation and is Vice President of CTIF Global Capsule (CGC). He has researched and worked with network based high speed innovation since 2000. He has been head of Studies for Master in Engineering – Business Development and Technology at Aarhus University from 2014–2016. He has been researcher at Politecnico di Milano in Italy (2002/03), Stanford University, USA (2010/11), University Tor Vergata, Italy (2016/2017) and has in the time period 2007–2011 been the founder and Center Manager of International Center for Innovation www.ici.aau.dk at Aalborg University, founder of the MBIT

research group and lab – <http://btech.au.dk/forskning/mbit/> – and is cofounder of CTIF Global Capsule – www.ctifglobalcapsule.com. He works today as researcher in many different multi business model and technology innovations projects and knowledge networks among others E100 – <http://www.entovation.com/kleadmap/>, Stanford University project Peace Innovation Lab <http://captology.stanford.edu/projects/peace-innovation.html>, The Nordic Women in business project – www.womeninbusiness.dk/, The Center for TeleInFrastruktur (CTIF) at Aalborg University www.ctif.aau.dk, EU FP7 project about "multi business model innovation in the clouds" – www.Neffics.eu, EU Kask project – www.Biogas2020.se. He is author to several articles and books about business model innovation in networks and Emerging Business Models. He has an entrepreneurial and interdisciplinary approach to research.

His research interests are multi business model and technology innovation in cross interdisciplinary networks, multi business model typologies, sensing and persuasive business models.

Per Valter holds a Scientific Assistant position at Department of Business Development and Technology, Aarhus University, Denmark. Where his main research field areas are Digitization of Business Models and Entrepreneurship and Multi Business Model Innovation and Technology Experimental Interaction in relation to Digitalization of Business Models. He has successfully been founding several startup companies and grown them to exit's stage and was awarded "Børsen Gazelle" in 2013 and 2014 for creating and leading one among the fastest growing companies in Denmark, in addition to these business achievements he is a Graduate in Computer Science and holds an Executive MBA – Master in Management of Technology and an MSc in Business and Management Research at Henley University of Reading and are currently Doctor of Business Administration Programme Member at Henley Business School University of Reading, He is an experience teacher on Bachelor and Master level in addition to supervising on Master level. a PhD

Student at Business Development and Technology at Aarhus University. He is researcher at the CGC – Århus University

His research interests are artificial Intelligence, deep learning and sensing in multi business model and technology innovation projects in cross inter disciplinary networks.

Gitte Kingo is Research Assistant at Århus University, Btech at the CGC – research center. She has published in IEEE Explorer and at IFKAD and GWS conferences mainly on topics of Multi Business Model Innovation, team building, Coaching of Multi Business Model and Technology Innovation projects. She won the Best Paper Award in WPMC/GWS 2018 Conference in Chang Rai, Thailand. She has a Master in Learning and Change processes and also a Master in Informations- and Communication Technology in learning processes (MIL) both from Aalborg University in Denmark.

Her research interests are teambuilding, coaching and coach processes in multi business model and technology innovation in cross inter disciplinary networks.