Big Data Driven IMP - B2B Marketing Needs a Robot

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Abstract

B2B research and practice faces disruption from big data and a tsunami of marketing technology and digital platform developments. Over 1 million B2B sales jobs could be lost by 2020 and customers will manage 85% of their relationship with enterprises without interacting with a human" (Forrester 2011). B2B research traditionally focuses on rich description and developing insights and heuristics out of case studies (LaPlaca & da Silva 2016). Developments in big data computing and democratisation of data science (Dillon 2017) enables machine handling multimedia and multidimensional data flow (Keinert and Teich 2010), big data curation (Freitas and Curry 2016), big data annotation (ICSI 2013), analysis and increasingly prescriptive analytics (Davenport 2013) shortening the path between decision-making and action. But Behavioral Big Data (BBD; Shmueli 2017) relating to human behaviors, actions, and interactions has potential to significantly impact B2B environments and research. This paper explores the the utilisation of BBD within the framework of the Social IMP Model (Sood & Pattinson 2012; 2013) as a means of generating of IMP Models capable of "…more accurate prediction of underlying B2B phenomena" (LaPlaca & da Silva 2016) – including B2B Robots!

B2B Buyers, Sellers and Robots

Imagine the world of B2B Buyers and Sellers interacting against a backdrop of "one million US B2B salespeople jobs eliminated by 2020" (Hoar 2015) with robots (bots or voice assistants e.g. Apple Siri, Amazon Alexa or Google Voice) requesting service (knowledge and skills; Vargo and Lusch 2004) or automatically generating tender content and responses from review sites, social networks and blog sites. How long before B2B organisations hire a robot enabling buyers seek out information disrupting the sales process, answering requests for information, perform account-based marketing or managing an account for sellers (Syvänen 2018)? In 2020, the expectations are "…customers will manage 85% of their relationship with the enterprise without interacting with a human" (Gartner 2011) much sooner than most of us think.

Big Data – Plus Behavioural Big Data (BBD)

The expectation is "Big Data" drives the emerging interactions of 2020 - presenting an opportunity for thinking about the application of B2B robots while utilising the IMP model (Håkansson, 1982, p. 24).

Big Data (NIST 2017) is not just about size, but more importantly, variety of data beyond transactional data including technologies generating data via sensors, capturing, storing, managing and analysing population scale collections of data. Big Data, the Internet of Things (IoT) underpin a platform enabling smart software applications to effectively manage most customer relationship activities through a combination of human-robot interaction (HRI) and non-human-robot interaction (autonomous interactions) – effectively interactions with digital representations of all buyer and seller interactions. Behavioural Big Data (BBD) as "very large and rich multidimensional datasets on human behaviors, actions, and interactions, which have become available to companies, governments, and researchers” (Shmueli, 2017, p.57), holds the key to underpinning an IMP model with this sort of platform and interactions.

BBD requires orders of magnitude more data and computing capacity than just structured streams of big data. Digital representation and reproduction of a human walking or lifting requires multi-media and multidimensional data-sourcing and deep learning. Digital representation and reproduction of more advanced human social activities such as thinking, talking or collective development of ideas, solutions, decisions and actions significantly adds BBD and supporting digital capacity requirements. Nevertheless, advancing digital platforms are now capable of supporting development BBD-driven interactions and actions – at least at a level where routine repetitive ordering and conversations around product/service features and recommendations can be undertaken between digital systems including robots and humans.

Continued rapid digital advances will see all elements of the IMP Model digitized and datafied through a mix of human and digital actors interacting to complete B2B activities. The sheer mass, velocity and complexity of not just conventional Big Data but even more BBD will force devolvement of analysis and processing down to the platform and application level wherever interactions and activities can be routinised and recommendations for actions offer sufficient choice or variety at a reasonable cost and efficiency (or value) level.

Deep learning with BBD may not produce distinctly digital creative and new problem-solving capability (typically required to link information from many different sources for business decision-making) – but it may go near enough to digitise most of this sort of activity that is undertaken as human B2B activity in the mid-2010’s by the mid-2020’s.

Big Data, B2B interactions and the IMP Model

Big data has the potential for complimenting an IMP model representation of B2B interactions and essential in developing predictive models of the evolution of all aspects of B2B activity including negotiations. Last century B2B categories of Buyers and Sellers as actors no longer hold in a digital world. For example, the simple identity data of gender extends from 2 to more than 71 in the Facebook digital environment (Williams 2014). From a marketing big data interaction perspective, the buying process no longer represents need fulfilment but rather an experience of co-creation whereby the unique behavioural signals of each actor need studying and interpretation. Human behaviour is made up of complex interdependencies not least of all because individuals convey actions using the multiple modes of voice, facial and eye movements, hand gesturing and body to interact on a social basis.

The granular nature of big data means the high-level outcome in an IMP model representation is not a foregone conclusion and potential exists to take action and alter the final result achieving a favourable outcome for all parties by taking necessary steps in advance of the generalisable outcome.

In the 21st century with the prevalence of social media, the IMP interaction model (Hakansson 1982) transforms into an IMP Social framework (Sood & Pattinson 2012). Amplification of the IMP Social Model for Big Data and BBD in particular is now possible – but the journey to develop almost everything from definition, curation, analysis, use and further research has been challenging.

A Brief History of B2B Research Information Collection, Analysis and Use

Since the mid-1970's B2B research and related information use has focused on gaining deeper insights into interactions mainly between individuals or groups across businesses working to create products, services or processes, expressed as networks. Research and information use has focused on methods that go deeper into offering insights into social-business interaction activities such as negotiations (e.g. sales, marketing, manufacturing, operations, delivery, support). Complex and multidimensional human behaviours and interactions have been identified and then at least translated into some heuristic outputs. Ambiguity and complexity around human behaviours and interactions are challenges to curating data such that these can be reproduced in digital algorithm form (i.e. to be used by conventional older digital systems). Complexity also comes through the substantial multidimensional and multimedia nature of such data.

Initially the main source of data collection and information use related to B2B negotiations was indepth interviews with participants in defined activities – rich descriptions in case studies. Written and audio from interviews was translated into digital text form and then analyzed through various software applications. Focus Groups and Ethnographic methods highlighted visual observation of respondents stating what they thought they might doing as behavior versus observing what they actually were seen to be doing in a situation.

Adding Video recording and analysis was a key step for researching B2B negotiations and developing enhanced heuristic outputs. An early example of video analysis of complex B2B of B2B negotiations at a macro level was undertaken by Sood and Pattinson (2010), in the form of a video mark up using the Interpersonal Negotiation Coding Scheme (Campbell 1997). A time code is inserted by a at the beginning and end (if applicable) or just at the beginning of observed behaviour in accordance with the coding scheme. The video segment between the codes captures "what is actually going on" and therefore codes the micro level activities.

At the highest level it is expected that the negotiation follows an IMP interaction between 2 parties. Each party does not automatically accept what the other party offers. At some stage during the negotiation one may indeed witness conflict resolution, joint collaboration and a decision on a final outcome. Price may not be the only deciding factor. The patterns of micro interactions across a number of negotiations help understand the macro interactions (beginning and end of time code) and provide the potential to predict in advance what is necessary to successful outcomes at each stage and help provide a data driven approach to concluding an overall negotiation.

Other areas contributing to the “bigness” of the data during a negotiation includes the capture of physiological factors automatically alongside the video with the face emotions (Ekman and Rosenberg 1997) participating in the negotiation automatically available with a boundary highlighting the face under study (Roth et al 2017) as well as attributes including age and gender (SteveMSFT et al 2018).

The emergence of Social media everywhere and effectively “social everything” (Keys & Malnight 2013) opens up novel, innovative and complex B2B scenarios in supply chain (Sood 2011) and service innovations (Lusch 2011) going well beyond human interactions. Three key use cases and scenarios (vignettes; Hakansson 1982) were developed to further inform and help discern critical aspects of newly emergent B2B network structures. Each vignette study applies the Social IMP framework (Sood and Pattinson 2012, p.121). These case studies require consideration of M2M (machine-to-machine) networks as well as participant firms, intermediaries and user community networks – See Table 1.

Shapeways	
Shapeways.com with headquarters in New York is the largest 3D printing marketplace and community of over 1 million creators. From a B2B perspective Shapeways users include designers and a marketplace of over 3,000 shops. The company provides an alternative to buying expensive 3D printers instead provisioning online the largest online 3D printing manufacturing facility in the world (30 to 50 industrial 3D printers). The service model allows users to generate objects in ceramics, plastic or stainless steel. The printers are capable of producing 100 products daily or 3-5 M million products annually (Shapeways 2013). The Shapeways' network of printers represents a distributed manufacturing capability. A unique B2B relationship is the SoundCloud and Shapeways partnership resulting in the co- creation of an iPhone case with a sculpture generated from the sound selection made by the user (Kosner 2013). Users actually upload 3D files (see table 1) representing the digital description of the object to the Shapeways online service to produce the goods at the printer location of choice	
Product/service exchange	3D models in Alumide, plastic, stainless steel, sterling silver, sandstone and ceramics. 10-15 days for plastic or steel and ceramic models or goods
Information exchange	3D file formats (STL, Collada, OBJ, X3D, VRML2) representing the digital description of the object
Financial exchange	Price per cubic cm and handling fees
Social exchange	Shapeways community and monthly live chat
Cooperation	netfabb software provides output to co-ordinate production of goods
Adaptations	Shapeways community Personalisation
Conway Multimodal	
Conway Multimodal is an example of a transportation company leveraging social media technology for supply chain management by using Twitter broadcasting capability to relay freight loads to the carriers following on Twitter. Twitter in effect connects the networks of carriers with the loads available. Conway Multimodal is part of Conway, a $5.6 billion Michigan based freight transportation and logistics company with 500 locations across North America and in 20 countries. The subsidiary is a non-asset-based transportation provider with over 15,000 3rd party carrier relationships with around 100 employees (Conway Multimodal, 2013).	
Product/service exchange	Freight load
Information exchange	@ConwayTweetLoad uses Twitter to match carrier with freight needs every 15 minutes. Available freight loads are sent to Twitter and mobiles (https://twitter.com/ConwayTweetLoad). Additional load information is available via the Twitter link transmitted.
Financial exchange	Contracts are handled through the traditional process
Social exchange	Employment trends, tips and jobs (https://twitter.com/True2BlueJobs)
Cooperation	Twitter provides the opportunity for carriers to match with freight
Adaptations	Twitter messages represent information regarding the freight not the actual transaction
Proctor and Gamble (P&G Open Innovation Strategy)	
Proctor and Gamble (Proctor & Gamble 2013) Open Innovation Strategy implementation:Connect + Develop links external innovators and companies with P & G. The online portal facilitates partnerships sharing R&D, consumer knowledge and marketing know-how. Over 2,000 successful agreements are in effect (Proctor & Gamble 2013).	
Product/service exchange	Intellectual property e.g. patent

Information exchange	http://www.pgconnectdevelop.com/ Links P&G business with innovation ideas via submission process and innovation portal
Financial exchange	Determined by type of partnership e.g. academic, joint venture, trademark and licensing
Social exchange	Online idea submission process
Cooperation	P&G Global distribution, experts, sales, consumer understanding and manufacturing
Adaptations	P&G Co-Creation Channel for crowdsourcing and evaluating ideas

Table 1: IMP Social Model Examples (Adapted from: Sood and Pattinson, 2013)

Sood and Pattinson (2013) also outlined a *Social Layered Model for Social Media Driven Online B2B Service Capabilities and Activities* underpinned by (from base to top) 1. The Internet of Things (IoT), 2. Social technologies, and 3. Social Media.

Big Data, BBD, Marketing Data Science and Martech

At about the same time (2012-2014), Big Data emerges alongside these business and social disruptors – which in turn unleashed a tsunami laced with marketing data science thinking and curation of information and a new field of technologies, tools and applications – *Marketing Technology (Martech)* – growing from less than 150 in 2011 to over 6,800 marketing technology solutions in 2018 (Brinker, 2018). The race is certainly on to develop the technologies and applications to automate marketing activities.

Deep Learning and associated applications have the capacity to capture rich multidimensional and multimedia BBD flows from particular human, social, and business interaction scenarios – and then to translate that into digital representation as actions and operations that a digital platform or possibly a robot could execute. Using an analogy of big data precision farming, the Swagbot “robot” herds cattle using familiar recorded voices and feeds them (ABC 2016), while the “Ripper” robot identifies specific plants and sprays or weeds around them (Anderson et al 2018). Not unlike the new advancing agricultural, industrial and special purpose robots driven by big data, B2B activities require robots or analogous systems driven by big data to truly advance knowledge and generate scenarios for new forms of interactive service. B2B marketing needs a robot and now! Big data streams of B2B interactions complimenting trillions of sensors (Bogue 2014) run the risk of drowning the marketer in data. According to Phillips (2013), by 2020, there will be four times more digital data in bytes than grains of sand existing on the entire planet.

Gartner’s (2011) vision “By 2020, customers will manage 85% of their relationship with the enterprise without interacting with a human” is in progress, with chatbots and recommendations systems supporting both B2C and B2C sales and ordering activities, becoming more common. Advances in Martech applications include big data and AI applications focused on salespersons activities (e.g. Salesforce Einstein, 2018) – but they may take much longer to really imitate than expected. The future form of an IMP or B2B robot is yet to be fully understood but is developing.

Humanoid robots as retail shop assistants are appearing but so far with significant teething problems. ‘Fabio” the shop robot assistant developed by Heriot-Watt University was developed in late 2017 and while novel and charming to many customers in a food store in Edinburgh, it struggled and was outperformed significantly by its human colleagues (Parker, 2018). Extending development to robots and or systems undertaking B2B sales negotiations will require relentless innovation and development – but if Watson can already help support physicians with medical functions just five years after winning *Jeopardy!* (IBM, 2016) then surely it – and its “colleagues” can be developed to perform at least some key B2B marketing and selling functions within the next five years (to around 2023-2025).

An interesting variation on the Gartner (2011) prediction may be that by 2025, significant aspects of B2B relationships will be managed without interacting with a human!

A BBD enhanced IMP Social Model not only sets up scenarios for platform level and robotic B2B relationships and activities, but also for generating dynamic “Big Data IMP” models at the most basic levels of buyer seller human interactions.

Dynamic “Big Data IMP” Model Generation

B2B research dating back to the original work of the IMP Project Group (Håkansson 1982) has been mostly available as rich descriptions but not typically as measurements. Big data presents for the first time since the conception of the IMP model an opportunity for measuring the fit of a company or industry to the IMP model itself.

How does 'big data' affect the IMP model and prediction? B2B content is available from transaction data and unstructured data in the form of buyer seller conversations, online social networks (OSNs) including LinkedIn, Twitter and B2B communities (e.g. Element14, IdeaExchange, IFSEC Global, and SuccessFactors) and even security video, support the IMP model for B2B parties under study. Furthermore, the researcher expectation is that as long as the human or machine generated data does not undergo manipulation, the B2B information flows lead to a schema consistent and exactly predictable from the IMP model. Data flows can be identified, measured and mapped into the IMP Model. The predictive nature of the model emanates from behavioural data signals well beyond primitive social exchanges including website (own media) signals (Fanplyr 2018; Knipp 2017), intent data (Niemiec 2017, Meistrell 2017, Gutierrez 2016,), social signals (Matias 2017) and more macro business signals (Seave 2015).

A key output could be a customized IMP Model – perhaps a dynamic Big Data IMP Model Canvas as a visual representation and a supporting app with embedded heuristics and algorithms. The actual form the overall prediction takes represents a nascent stream of research hitherto unexplored and may well require evaluation by a panel of judges to help discern the rating and value applicable to each individual IMP variable comprising the IMP Social big data sets. Visualising and operationalizing enhanced Social BBD IMP Models for different B2B scenarios, contexts, at group, firm, interfirm and networks levels represents a great opportunity for B2B researchers to stay with and contribute to new and emerging B2B interactions, activities and networks – and to develop them. Discussion in this paper highlights opportunities to explore enhanced Social BBD IMP Models with respect to human and non-human interaction, and for dynamic, measurable and customizable B2B model generation – see Figure 1.

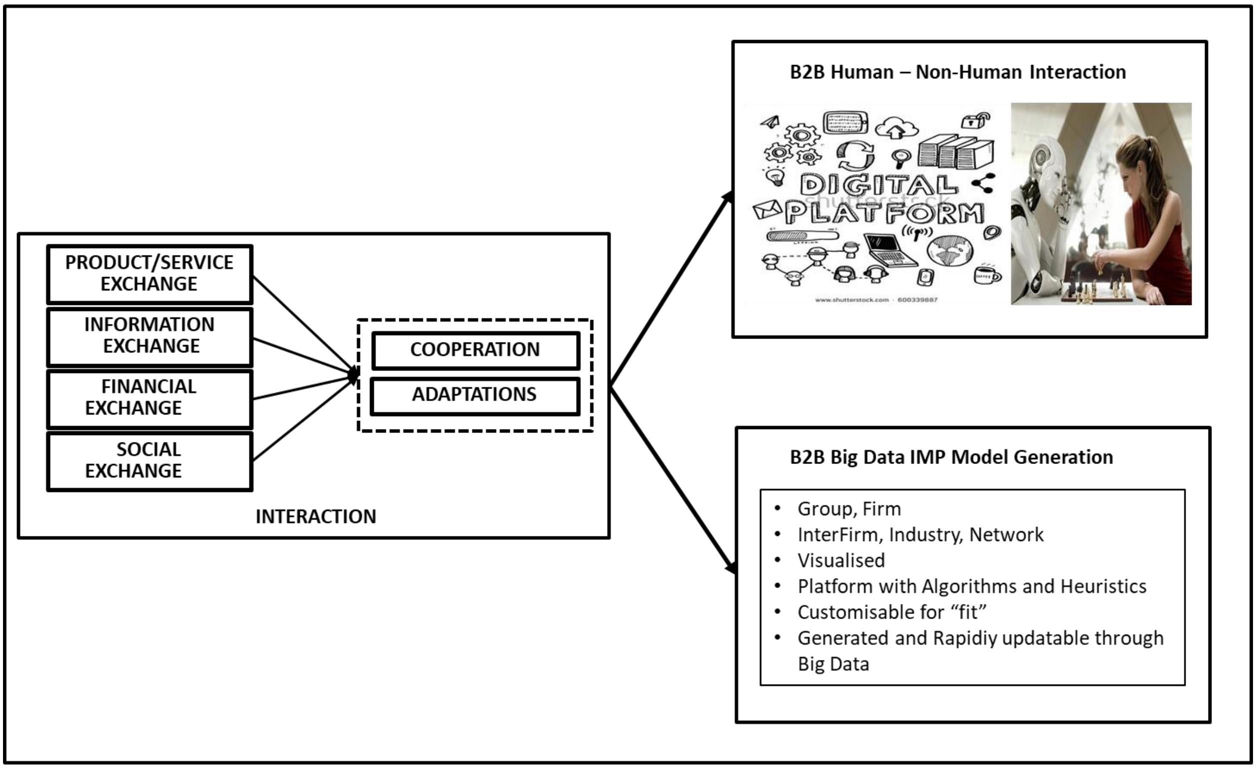

Figure 1: Big Data IMP Model ; Interactions and Model Generation (Adapted from Sood and Pattinson, 2012; Shutterstock, 2018; Small Biz Diamonds, 2012)

Will a Social BBD IMP Model be a foundation or template for B2B model generation for many different contexts and scenarios? Will Watson and his chatbots and apps be supporting B2B sales teams, or our research groups – or will Watson be the Key Interaction Manager? These are key B2B research and development challenges as we head into the third decade of the 21st Century.

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