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Value co-creation for open innovation: An evidence-based study of the data driven paradigm of social media using machine learning.

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ABSTRACT

Social media encapsulates one of the most prominent human information behaviours that has rapidly evolved to create a new data-driven paradigm that uses data-intensive digital environments to communicate, collaborate, express opinions and support decisions. This has established social media as a unique information asset for value co-creation as it empowers individuals to actively express opinions and sentiment on all facets of interactions with an external entity. Despite recent research on the theoretical underpinnings of social media in open service innovation, practical demonstrations of actionable insights are limited, mainly due to the voluminous and unstructured nature of social media data. We address this limitation by presenting an evidence-based study that uses machine learning algorithms to generate actionable insights of strategic value from this data-driven paradigm. These outcomes provide fresh perspectives and new thinking that advances social media as an emergent information asset for end-to-end open innovation and incremental value co-creation.

1. Introduction

The entire field of information from origination and collection to transformation and utilization (Borko, 1968) has undergone several paradigm shifts (Dervin & Nilan, 1986; Marchionini, 2008; Tang, Mehra, Du & Zhao, 2019). Most recently, the digitalisation and advancements of information technology have created a ubiquitous purpose for information where millions of people around the globe access, use and transmit information every second using a myriad of social media platforms (Bello-Orgaz, Jung & Camacho, 2016). This rapid development of social media has empowered individuals to express opinions, thoughts and emotions, leading to an emergent information reality that is accessible and equitable but also overwhelming and at times misrepresented (Kaplan & Haenlein, 2010). Both the scale and scope of the content generated on such platforms are evolutionary and constantly in flux – unpredictable and dynamic. For example, Facebook has 1.23 billion daily active users that create 510,000 comments every 60 s while Twitter disseminates around 500 million tweets per day (Jeff & Sally, 2019). Besides the 5Vs of Big Data (Xie, Wu, Xiao & Hu, 2016), that signify its complexity, social media is also characterized by the virality of information propagation which further establishes the emergent information reality of this medium and the increasing need for an extensive study of this data-driven paradigm (Adikari et al., 2021; Hansen, Arvidsson, Nielsen, Colleoni & Etter, 2011; Peng, Adikari, Alahakoon & Gero, 2019).

To this end, it can be established that the abundance of information in social media and its constellation of information dynamics have unveiled a 'data-driven paradigm' into the field of information research. Social media acts as a critical enabler of this paradigm shift given the proliferation of information created by users and it has been established that organizations should efficiently utilize social media and transform their business practices (Aral, Dellarocas & Godes, 2013; Georgescu & Popescul, 2015). The use of social media analytics is deemed to be imperative to enhance multiple business functions across the organization (Rathore, Kar & Ilavarasan, 2017). These digital platforms have been disruptive to organisational functions, thus requiring a change in strategy development and innovation efforts (Berthon, Pitt, Plangger & Shapiro, 2012; Sarin, Kar, Kewat & Ilavarasan, 2020). Therefore the new data-driven paradigm has not only revealed untapped sources of information but also has kindled the need to reconceptualize and reorganize the thinking and practices in a new digital age of information (Georgescu & Popescul, 2015). Due to this fact, organizations are keen to utilize the social media platforms in order to drive innovations and form strategies (Chatterjee & Kumar Kar, 2020). In this study, we narrow our focus to reconceptualizing an organization's *'open innovation'* practices in the age of social media as innovation practices constantly need to be re-aligned with external information sources. In Information systems research, open innovation is a relatively new field of study introduced by Chesbrough that uses *'inbound and outbound knowl-*

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edge' flows to improve and expand an organization's ability to innovate (Chesbrough, Vanhaverbeke & West, 2006). This brings out the necessity to incorporate information on consumers' opinions, emotions and community-driven behaviours that are widely reflected in the evolving data-driven paradigm of social media.

Based on this foundation, the authors set out to answer the following research questions:

1. How can organizations reconceptualize open innovation practices by co-creating value using consumer-generated social media data?
2. How machine learning can be utilized to capture informed insights from unstructured social media data?

In this regard, we conducted an evidence-based study that used machine learning algorithms to address the big data challenges of 36,100 discussions generated by 4300 consumers in an online social media forum. In this study, we identified diverse information-seeking behaviours of consumers, their emotions and their views about different service providers that collectively contribute towards end-to-end open innovation and incremental value co-creation. Based on this analysis, we present two contributions on this emergent information reality of social media as a data-driven paradigm. First, we establish a theoretical model to position social media as an external information source to support open innovation using Service-Dominant Logic (S-D Logic). From a theoretical perspective, S-D Logic has been used to deliberate the notion of value co-creation in social media. S-D Logic is a meta-theoretical framework that postulates the provision of competences to benefit others and the reciprocal benefit from the competencies of others through service-for-service exchange (Lusch & Vargo, 2006). Second, we propose a machine-learning framework to transform unstructured social media data into structured insights. One of the key considerations in utilizing data-driven environments is the use of 'big data' in a practical sense in order to facilitate data-driven strategies (Kar & Dwivedi, 2020). Organizations should be able to adapt data analytics and machine learning techniques to accommodate and extract useful information from data-driven paradigms (Grover, Kar & Dwivedi, 2020). Information systems research can largely benefit from the use of computational techniques to leverage informed insights from big data resources (Grover, Lindberg, Benbasat & Lyytinen, 2020). Therefore, we demonstrate the use of machine learning to automatically extract consumers' information-seeking behaviours and emotions from social media data.

The rest of the paper is structured as follows: The following section reports on the relevant theoretical notions of open service innovation and social media value creation via S-D logic. The third section presents the proposed approach, followed by an analysis in the fourth section which also discusses the outcomes of the analysis by formulating a conceptual model on how social media data can be integrated for value co-creation. The final section concludes this article by summarizing the contributions of this study and directions for future research.

2. Literature review

S-D logic shifts the focus of value creation and innovation from the production of tangible goods to the provision of intangible service (Lusch & Nambisan, 2015; Lusch & Vargo, 2006; Vargo & Lusch, 2008). It conceptualizes service as the process (and not the unit of output) of using resources to create value for another participant (referred to as an actor in the process). Knowledge and capabilities are considered as resources with the highest value for competitive advantage (Madhavaram & Hunt, 2008). S-D logic confronts the traditional value creation in services where it is stated that firms always deliver value to consumers and the participation of consumers is insignificant. S-D logic brings in a new dimension of value co-creation by emphasizing the role of the consumer in creating value to services, thus contribute towards service innovation (Grönroos & Voima, 2013). The foundational premise of value co-creation among multiple actors in S-D logic highlights three concepts relevant to big data environments such as social media platforms, they are **role changes, resource integration** and **value identification** (Xie et al., 2016).

Role changes in S-D logic refer to the varied behaviours of consumers and how they contribute different kinds of value to a service organization. Lusch and Nambisan explain three types of consumer roles; 1) ideator - who contributes knowledge based on current experiences, 2) designer - who incorporates existing knowledge to envision new services and 3) intermediary - who cross-pollinates knowledge across several ecosystems and facilitates non-obvious connections (Lusch & Nambisan, 2015). In social media, consumers take on each of the three roles as they comment, raise concerns, provide feedback and compare the service offerings of different organizations (Cheung, Lee & Rabjohn, 2008). The analysis of social media data would lead to insights on each role, and these would collectively improve services and service innovation. However, this data exists on different platforms that are created for different purposes. This silo-ed nature of data raises the need for resource integration.

Although **resource integration** is equally important for consumers to accomplish co-creation, few studies have considered how different consumer roles integrate resources and how they affect the results of value co-creation (Vargo, Maglio & Akaka, 2008). We focus on the operant resources of an organization, which are human (skills and knowledge of consumers and employees), organizational (routines, cultures, competencies), informational (knowledge about markets, competitors, and technology), and relational (relationships with competitors, suppliers, and consumers) (Derozier & Hunt, 2004), and attempt to identify such resources using free-flowing social media data. Insights from social media content serve as an addition to the current informational resources of an organization. Specifically, consumers with different roles may exhibit distinct participative behavior on digital platforms, which produce different types of knowledge resources such as feedback, and innovation ideas (Xie et al., 2016). The integration of resources now leads to the need to identify value created by different groups of consumers.

Rather than an output-oriented strategy, S-D logic focuses on a process-oriented strategy that involves consumers as important actors in the process of **value identification** (Grönroos & Voima, 2013). It is also noted that the perception of values and the extent of the contribution of consumers rely on their roles and positions in the social system (Edvardsson, Tronvoll & Gruber, 2011). Different consumers may perceive the same service differently based on their own experiences, time and personality. Using the primary foundational premise of *'value is always co-created and is uniquely and phenomenologically determined by the beneficiary'* (Lusch & Nambisan, 2015) we present the applicability of the social media environment to capture insights that contribute to value co-creation.

Although the term 'value' is not clearly defined, existing literature on S-D logic considers it as value co-creation highlighting the process in which actions of both consumers and service providers are incorporated (Grönroos & Voima, 2013). When considering the value created by consumers, it is important to identify their opinions. Research on word-of-mouth (WOM) communication and the ability to influence potential consumers via WOM has shown the importance and the impact of identifying consumer opinions in organizations (Trusov, Bucklin & Pauwels, 2009). The advent of social media has reformed the concept of consumer engagement by providing digital platforms engaging millions of consumers together to discuss and share their opinions (Kaplan & Haenlein, 2010). Thus the notion of WOM has transformed into eWOM (electronic word-of-mouth) (Hennig-Thurau, Gwinner, Walsh & Gremler, 2004), where many studies show the impact of eWOM on performance and reputation of an organization (Cheung et al., 2008; Jansen, Zhang, Sobel & Chowdury, 2009). This creates a new direction of consumer-to-consumer (C2C) communication and the exchange of information about services.

In the context of value co-creation, sentiments and emotions have an important role in influencing policies and decisions (Bae & Lee, 2012).

While sentiments provide a categorization of content as positive and negative, emotions provide deep insight into authentic opinions expressed by a consumer (Wang & Pal, 2015). From an organization's perspective, it is essential to identify the emotional responses of consumers to customize and uplift the current service offerings (McColl-Kennedy, Smith & 10, 2006). Furthermore, the analysis of emotional expressions in a large social media community over a longer time period would potentially create a better understanding of consumers' perceived value of the service. The study of such deeper emotions expressed by consumers has been made possible due to social media conversations compared to traditional questionnaires and surveys (Abeysinghe et al., 2018; Chatzakou & Vakali, 2015; Chung & Zeng, 2018; Rathnayaka et al., 2019). Although there are many studies based on identifying sentiment related to products (Fang & Zhan, 2015; Hutter, Hautz, Dennhardt & Füller, 2013), detecting deep emotions from consumer conversation related to the services sector in line with theories of Information systems is currently underexplored. The integration of emotions expressed via consumer communication has the potential to generate informed insights that can be used as a strategic input for value co-creation (Novani & Kijima, 2012).

Based on this synthesis of value co-creation in S-D logic and past research, it could be argued that although organizations constantly attempt to improve and innovate their current service offerings, there is limited attention given to deriving informed insights from consumer-generated data on social media. The assumption of extant open innovation research in social media contexts has largely been that consumers intentionally generate content on social media to be used for innovation by organizations. Related research has either focused on the perceptions and motivations of consumers who contribute to organizational innovation efforts (Magnusson, Matthing & Kristensson, 2003) or on the benefits that organizations derive from these collaborations. Recent open innovation research (Mount & Martinez, 2014), however, indicates that organizations can also innovate based on social media content that has not been intentionally created for this purpose.

We believe that with the emergence of a new 'digital ecosystem' with diversified data sources, there is a necessity in Information Systems research to expand current innovation practices to capture insights generated via these digital data sources even if they are not created directly for the purpose of innovation. The integration of digital data such as social media content as a part of the consumer value co-creation would further uplift and expand the current innovation processes (Antikainen & Vaataja, 2010; Di Gangi & Wasko, 2009). This requires capturing data created with innovation purposes as well as free-flowing consumer discussions that have the potential to contribute to innovation by understanding various facets of consumer communication. Considering the importance of integrating social media into organizational strategy development, we have identified a compelling need for a robust investigation of social media content to understand its aptitude to support continuous value co-creation in services organizations that can elevate current information systems research.

3. Research methodology

This section presents the methodology adopted in our evidence-based study for demonstrating how consumer-generated social media data enables value co-creation in service organizations. We present a machine learning approach that can be used to transform social media data into actionable insights.

3.1. Data sources

We selected the Australian tertiary (university) education sector as an exemplar for this study because tertiary education is increasingly becoming a service where consumers (students) are highly active in value co-creation (Sojkin, Bartkowiak & Skuza, 2012). We selected online discussion fora and student discussion groups as two data sources. Both contain free-flowing discussions that are not created with the intention of innovation but as mere discussions between students. However, they comprise of a wide range of student conversations that are relevant for value co-creation.

Online discussion fora are organized as conversations where one person starts a conversation thread and others express their views as responses. Online fora contain general discussions related to higher education that are continuous and long-term, some extend into months. In contrast, student discussion groups are more focused on one university where they use it as a platform to discuss issues/concerns related to a particular university. The content generation in these groups is fast-paced and short-lived. Our objective was to capture both short-term and long-term discussions to monitor the differences in content generated by students, thus identifying how different platforms can generate different forms of value.

3.2. Data collection

We utilised data extraction algorithms that automatically collect data from the two data sources; online forums and discussion groups. The extraction process yielded 36,100 posts, which were organized into 2500 conversation threads generated by 4300 consumers. The extracted text corpus was augmented using the names of the universities that students have mentioned in their online conversations. A series of Natural Language Processing (NLP) techniques were used to extract the University names and abbreviations.

Each post was considered as one record in the dataset. Each record contained the following variables:

- Title of the conversation
- Content of the post
- Date and time of the post
- User ID of the person
- Message Index (Refers to the order of the conversation. Message Index 0 is assigned to the person starting the conversation, and responses are numbered accordingly)
- Universities mentioned in each post

We excluded details about users (such as screen-name and location) in order to preserve anonymity and privacy. We do not include the names of universities in any of the reported results.

3.3. The machine learning approach

A high-level illustration of the proposed approach that depicts the transformation of data sources into organisational value is presented in Fig. 1. This framework addresses the research question on how machine learning can be utilized to derive informed insights from unstructured social media data. It shows how data from different social media channels are synthesised together to extract consumer emotions, themes of discussions, behavioural patterns and significant events. The extracted insights are then integrated into the organization's innovation practices facilitating interactive value co-creation via digital channels.

To derive an understanding of the collected social media contents for their importance, we focus on automatically capturing linguistic features such as unique terms, entities, key phrases and emotional expressions that add value to the content quality (Ng et al., 2006, 2003). The machine learning framework used for insights generation (identify prominent topics, emotions and significant entities mentions) is illustrated in Fig. 2, with a sample tertiary education-related social media post for further clarity.

3.3.1. Topic analysis

To identify the main concerns (topics) of consumer discussions, we applied an unsupervised document clustering algorithm that segmented similar social media content together, enabling further exploration of the content of these posts. For a detailed analysis of such content, a

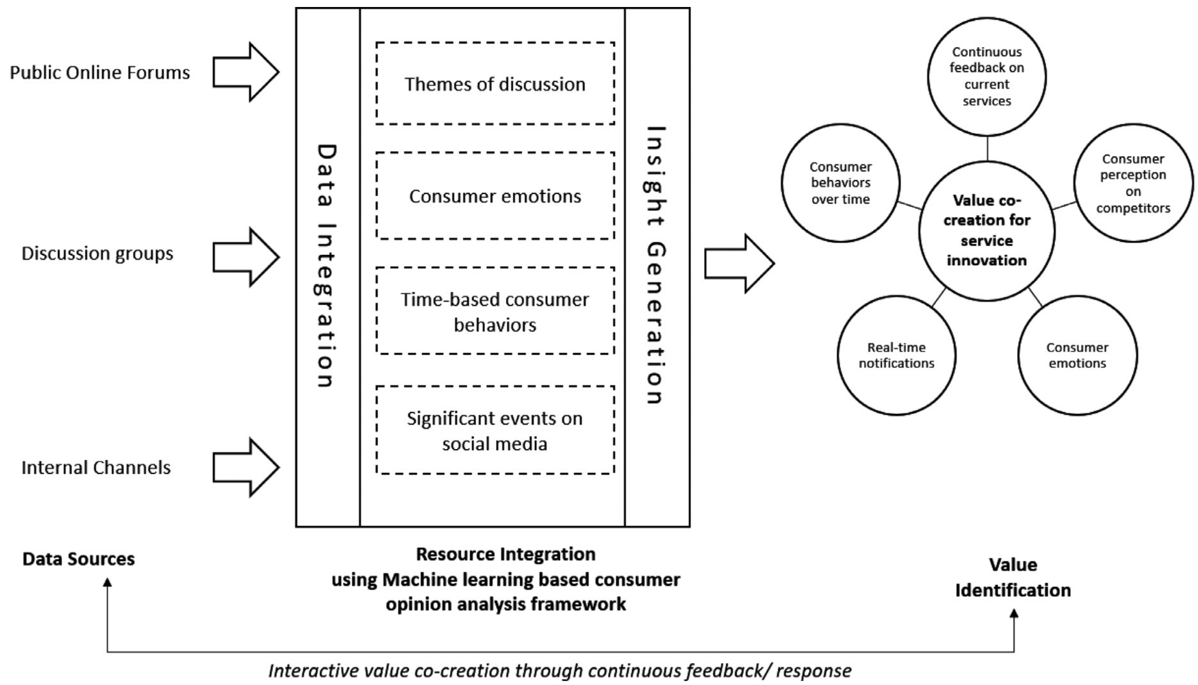

Fig. 1. The proposed approach of using a machine learning framework to extract, analyze and integrate insights generated from social media.

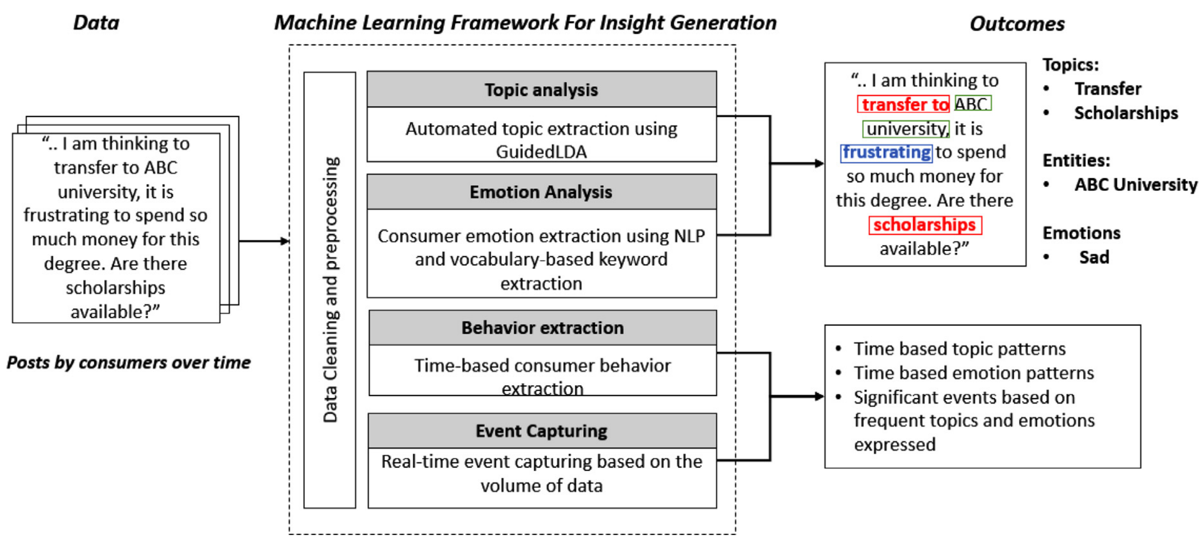

Fig. 2. Illustration of the machine learning framework for insight generation.

semi-supervised topic modeling algorithm (Guided Latent Dirichlet Allocation (Guided LDA)) was applied to extract prominent topics discussed under each category (Jagarlamudi, Daumé & Udupa, 2012). The temporal aspect of the posts was also considered to evaluate topic patterns over time. The insights generated from this are expected to contain the opinions and main themes of discussion in C2C communication thus enabling the capturing of useful information for innovation. Furthermore, the nature of the topics being discussed provided an indication of the role of the consumer as specified in S-D logic role changes –an ideator, designer or intermediary.

3.3.2. Emotion analysis

The sentiment is generally expressed as positive, negative and neutral, aggregation which leads to loss of useful information on consumer emotions. We extended the sentiment analysis into emotion analysis using the psychological emotion model proposed by Plutchik (Plutchik, 1991) as the foundation for emotion extraction. We considered the eight basic emotions *(Joy, Anticipation, Trust, Surprise, Fear, Sad, Disgust and Anger)* proposed in the aforementioned model. A series of NLP techniques were used to explore cues for emotion expressions from the textual content of the posts and consequently, emotions were mapped to the posts. Mapped consumer emotions are an invaluable metric to assess the effectiveness of organisational services. This will be an input to the value co-creation process to alter, adjust and innovate services to suit consumer expectations.

4. Results

In this section, we align the outcomes of machine-learning based insight generation with the foundational premise of S-D logic, i.e. resource integration, role changes and value identification, to demonstrate how the proposed machine learning framework generates insights for value co-creation, thereby contributing to open service innovation. The results align with the underlying theoretical premises addressing the research

	Issues related to studies	Assistance with studies	University events	Infrastructure issues	Staff related queries
JOY	11.00%	10.00%	79.00%	0.00%	0.00%
ANTICIPATION	2.00%	18.30%	55.21%	0.00%	24.45%
TRUST	20.00%	36.50%	24.89%	10.40%	8.21%
SURPRISE	34.51%	2.33%	44.87%	2.31%	15.66%
DISGUST	42.00%	8.30%	11.72%	29.10%	8.88%
ANGER	36.20%	5.20%	8.80%	28.50%	21.30%
SAD	55.88%	19.56%	14.23%	6.89%	3.21%
FEAR	61.00%	15.22%	9.20%	12.20%	2.30%

Fig. 3. Emotions associated with topics discussed by ideators.

question on how organizations could reconceptualize open innovation practices by co-creating value using consumer-generated social media data.

4.1. Consumer role changes in social media platforms

4.1.1. Discussion groups - The role of 'Ideator'

The main characteristics of consumers in the role of 'ideator' are to contribute opinions and feedback on current service offerings. Using the machine learning approach, we have identified a group of students who have been providing feedback/ suggestions constantly related to current services and their experience within the university. This group was identified to be ideators as they presented opinions and feedback on their current student experience. Such pro-longed participation and the amount of information provided can be effectively utilised as 'digital feedback' (Chen, Wu & Yoon,). This, in turn, can be used by management to inform the strategy within the organization. Most large organisations have strategies in place, however, many are unable to engage effectively with social media strategies as the limitations (both perceived and imposed) appear cumbersome. As stated by Berthon, Pitt, McCarthy, & Kates, 2007 in Berthon, Pitt, McCarthy and Kates, (2007), firms regularly ignore or mismanage the opportunities and threats presented by creative consumers. Further research shows that 'one reason behind this ineptitude is a lack of understanding regarding what social media are and the various forms they can take (Kaplan & Haenlein, 2010). It is paramount that organisations take the time to understand how digital feedback can inform the company's strategy.

Using the machine learning framework, we have identified the key themes of discussions among the students identified as ideators in a particular academic institution. The insights enable us to identify problems in student satisfaction in real-time. It was observed that the majority of students engaged in discussions related to course work and academic subjects (29%), issues with studies (23%) and university events (23%). Among other concerns, there were discussions looking for assistance with studies (12%), complaining about infrastructure issues (8%) and staff-related issues (5%). These conversations provided direct feedback on these issues which can be considered particularly important information to senior management within the organization to inform and assist in improving student satisfaction. The topic analysis demonstrated that the majority of C2C communication has occurred when discussing issues related to specific course modules. Issues related to staff and university infrastructure have also been reported which should be given attention by management as they are directly related to the students' experience.

4.1.2. Value identification from ideators – analysis of emotions associated with topics

Identifying important topics of discussions and the associated emotions provide a clear insight into student experience which is directly linked with student satisfaction. Using the emotion analysis approach, we identified the emotions attached to each issue to generate a holistic view of the student experience. It was observed that most of the participants expressed negative emotions (Anger, Sad, Disgust) towards issues concerned with studies while positive emotions (Joy, Interest) were mostly expressed for University events. Such analysis of feedback from ideators who constantly provide feedback on existing services could be effectively integrated as input into management decisions and strategic direction and allows the opportunity to monitor the negative emotion fluctuations in a real-time manner (and act accordingly). Visualization of emotions associated with topics (Fig. 3) and examples of emotion expressions are given below.

- *"The workload in ….. is simply too much, it's stressful to handle all this at once"*
- *"Why is it so frustrating to use this system?"*
- *"Looking forward to the sports event on campus tomorrow! Going to be great!"*

As student satisfaction is mentioned as a key enabler of university performance, identifying student concerns in a near real-time can lead to improved service offerings. The fundamental premise of S-D logic specifies that the consumer is always a co-creator of value, implying that value creation is interactional. The proposed platform allows organizations to identify students with negative content and attempt to take proactive action to address these concerns as well as providing a mechanism to interact and provide advice and solutions instantly. This constant interaction with students supports incremental value co-creation and continually supports innovating current service offerings. We emphasize the incremental and instantaneous nature of value co-creation using the proposed platform as this approach can be used to investigate deeper emotional patterns and trends at near real-time, such as variations of student emotions during different academic periods, (start of the semester, exam time, and end of the semester), again, informing actionable insights for improved proactive decision making. Academic institutions could adopt this approach to continuously monitor student satisfaction levels and take the necessary actions if there is a negative atmosphere among students in the discussion group.

4.1.3. Online discussion forum - The role of 'Designer' and 'Intermediary'

In the value co-creation process, consumers who are designers and intermediary involve in service innovation by expressing their knowledge on existing services and also by cross-pollinating knowledge across several ecosystems (ROHRACHER, 2003). They allow organizations to compare their service offerings against competing service providers. It can be stated that while ideators create a view on current service offerings, designers and intermediary participants paint a wider picture of the market and inform high-level expectations of consumers. We have identified that participants in online fora are mostly designers and intermediaries, as they continuously provide their suggestions in open issues in a general manner, which offers an overview of the services provided. Given the wealth of information online, it is imperative to capture the ways consumers contribute to value co-creation and contribute to improving and innovating services. We have conducted a series of experiments to identify the insights which could be extracted from public online forums.

Initially, to recognize the prominent topics being discussed, we applied an unsupervised document clustering algorithm. The clustering results demonstrated that most of the posts were related to seeking in-

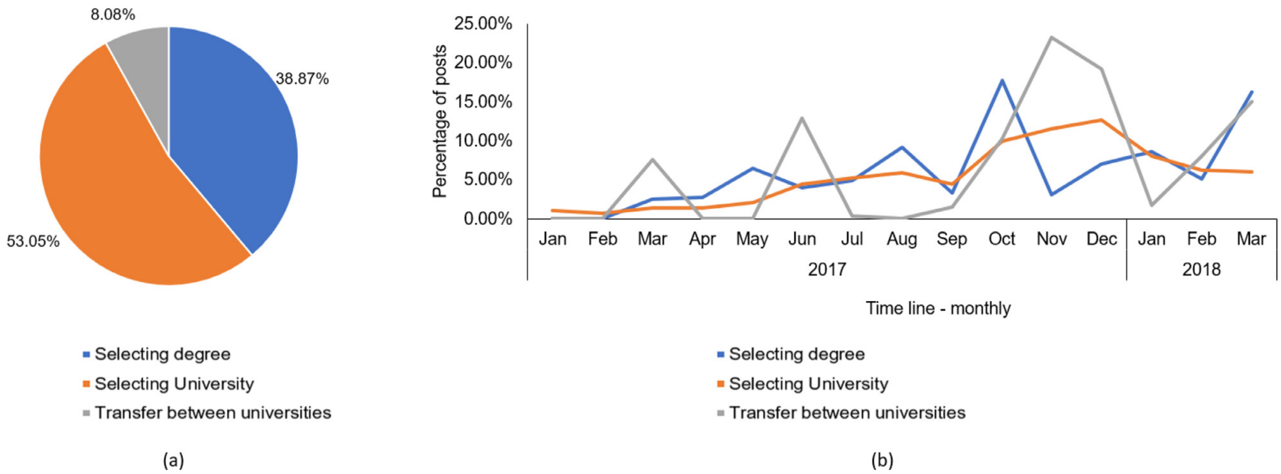

Fig. 4. Main categories of student decision making behaviors and growth over time.

formation and advice from the community. These posts were mainly associated with different decision-making behaviors of students where they compared different universities and discussed broader issues. From the results, we were able to interpret three main decision-making behaviors of students that occur in different stages of the student lifecycle.

The three prominent decision-making interests/themes identified were as follows:

1. Choosing an area of study/ degree
2. Choosing a university
3. Transferring between universities

We further examined each decision-making category to comprehend the volume, topic patterns over time, topics discussed and how this information could be useful to enhance current strategies for managing the student experience. Fig. 4 illustrates the volume of data for each decision-making behavior pattern as well as the growth of posts over time (percentage of posts per month). Topics were also analysed over time to determine trends over the last year (2017–2018).

Fig. 4(a) highlights that most of the discussions were related to selecting a university, secondly, related to selecting a degree, while the minority were posts related to transferring between universities. However, according to Fig. 4(b), it can be perceived that discussions related to transfer between universities had grown in the recent past indicating a noteworthy rise in the discussions, therefore, can be regarded as a new trending topic. Identifying time-bound topics enables universities to gather feedback on current university strategies and associated limitations. Specifically, universities can monitor social media data on transfer between universities to closely identify issues faced by students and causes for transfers, thus taking the necessary measures to address such issues.

Moreover, in a broader sense, Fig. 4(b) confirms that the volume of data had significantly grown over time generating larger volumes of user-generated data than in the recent past. This clearly demonstrates the growth of social media discussions and engagement of the community.

When comparing the topics discussed by ideators with the topics discussed in online fora, the topics by designers and intermediaries belong to a broad spectrum. These three topics reflect key decisive points of a student's academic lifecycle which often result in the need to look for information, gain peer support and seek advice.

4.1.4. Value identification from designers and intermediary

(a) Consumer decision-making interests

Further exploration of the three identified themes of discussions was conducted to detect significant topics under each behavior category and to measure the overall student engagement. We measured the student engagement by considering the number of replies generated for these discussions. The results show the sub-topics nested under each main theme of discussion as well as how the three main themes are linked via similar sub-topics (Fig. 5). The objective of such insight is to provide a holistic view of consumer (student) discussions to an organization facilitating the understanding of consumer interests and opinions.

According to the results, when selecting a university, most of the students were concerned about fees and entry requirements (36.75%). This would be useful information for the third strategy noted earlier – growing the student base. In the category of selecting a degree, most students were seeking advice and support related to degree options (37.26%) and employability (26.02%) of the degree in question. This information can be directly related to organizational strategy focussing on student employability, which could, in turn, strengthen industry partnership programs to provide students with the necessary exposure.

(b) Consumer emotions associated with decision-making behaviors in designers and intermediaries

Emotion analysis based on the three decision-making behaviors suggested that, in general, a larger proportion of posts demonstrated positive emotions for two behaviors - selecting a university and selecting a degree. However, emotions associated with the transfer between universities were mostly negative emotions, this could be due to the complexities of transferring between universities (process) as illustrated in Fig. 6(a). With this knowledge, we extracted further reasons for negative emotions when transferring. Frustration related to decision making, hesitation about transferring credit between universities and choosing the best option were among the most discussed topics in posts containing negative emotions.

As potential implications, universities could identify such difficult decision-making points faced by students to provide them with both relevant and timely information. This would consequently improve student satisfaction in the university's approach to provide a better service offering.

Additionally, emotion analysis was used to compare different emotion patterns associated with each identified decision-making behavior towards the Group-of-eight (Go8)[1] universities and non-Go8 (other) universities. A high-level breakdown of emotions (aggregated as positive and negative) is shown in Fig. 6(b).

The aggregated positive and negative emotions show that the percentage of positive emotions related to Go8 universities is higher than other universities across all behavior categories, whereas the percentage of aggregated negative emotions were higher in other universities. The differences in emotions reveal the positive and negative aspects of

[1] https://go8.edu.au/about/the-go8

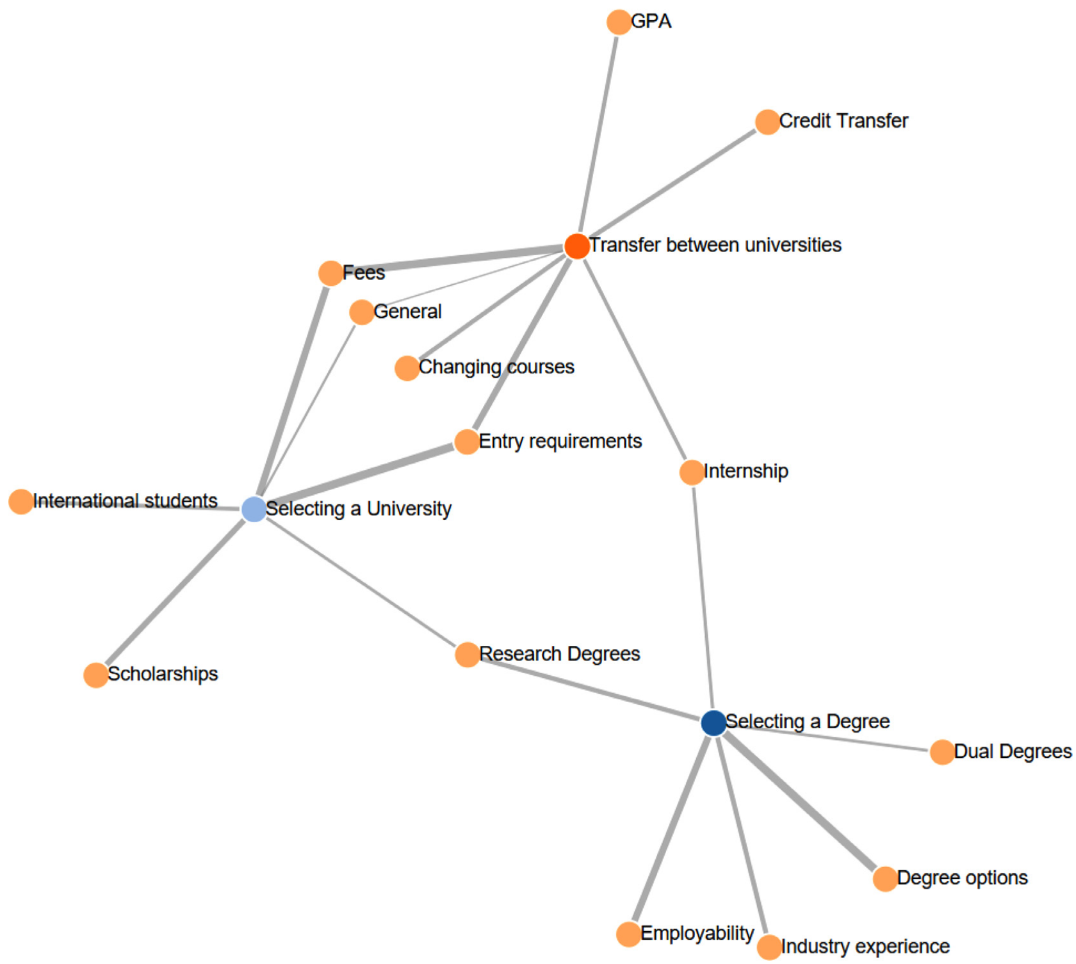

Fig. 5. Sub-topics discussed under three main themes of discussions.

each university. Such comparisons are primed for competitor analysis and benchmarking.

(c) Behaviors associated with university category – an overview of different service providers

This analysis was conducted to examine the volume of discussions relating to the identified decision-making behaviors across the Go8 and other universities as illustrated in Fig. 7.

The results show that discussions related to "Selecting a degree" and "Transfer between universities" were higher in Go8 universities, whereas discussions related to "Selecting university" was higher in other universities. Fig. 5 showed that many discussions in the "Selecting University" category mentioned entry requirements and fees. We believe this analysis would enable universities to compare current standing with respect to student perceptions.

From a student's perspective, it is crucial that adequate information is available so that a well-informed decision can be made (Simões & Soares, 2010). Gaining information about a university's service offerings is vital in the determination of which institution to study at and which degree to follow. If universities can predict what factors influence their applicants' decisions, they can have a competitive advantage to attract students to their institutions. Resources can be focused on the right areas and potential applicants could have an improved experience (Sojkin et al., 2012). Digital platforms such as online forums create an avenue for service innovation where it enables actors (students) to easily discover and compare service offerings which lead to innovative and scalable service offerings (Mikusz, 2017). Service providers, therefore, could exploit these insights to identify complaints, concerns of consumers and to improve the current services on offer to provide a better overall consumer experience. In the considered university sector, such insights derived via digital feedback from students could be used to improve the employability of current degree programs offered by universities by introducing career development programs and industry partnerships. The universities could publish and promote the courses they offer (with respect to career opportunities) addressing the major concerns of students. In addition, pre-career workshops could be conducted to promote certain degrees and in turn, the university. This would potentially attract the attention of students and lead to growing the student base.

4.1.5. Real-time monitoring

Interactive communication between the service organization and the consumer can largely benefit the perceived value. However, interacting on a real-time basis is a challenge, given the large volume of data being generated at a higher frequency. Therefore, we extended the machine learning framework for real-time monitoring, by creating notifications when there is a significant event occurring on the targeted social media platform. Since the data collection and analysis happen in a real-time manner, it was possible to filter feedback with importance based on the content and emotion expressions. Real-time notifications were enabled to notify authorities if/when any significant digital activity was detected relating to the specified organization be it positive or negative. The results of the analysis were visualized and updated instantaneously for organization management to gage useful insights from user's digital activity and data. The propensity for proactive decision-making in organizations with near real-time consumer feedback provides a unique opportunity for incremental service co-creation.

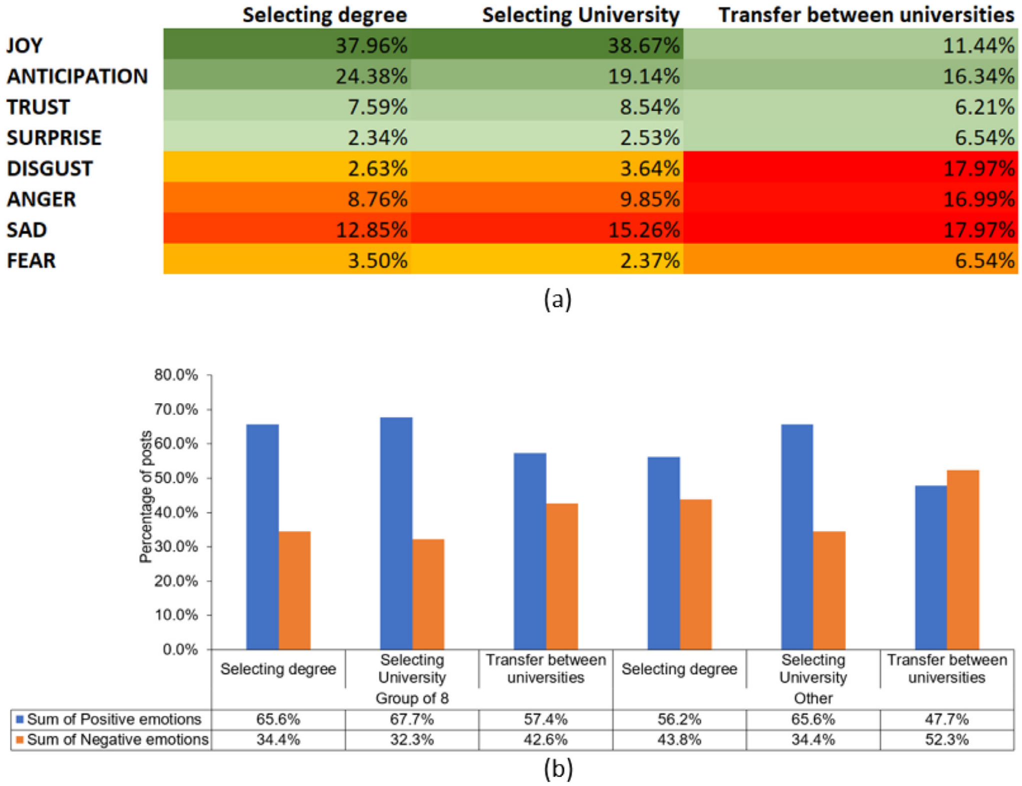

Fig. 6. Emotion analysis (a). Variation of emotions associated with different decision-making behaviors in designers and intermediaries, (b). Aggregated emotions related to university category.

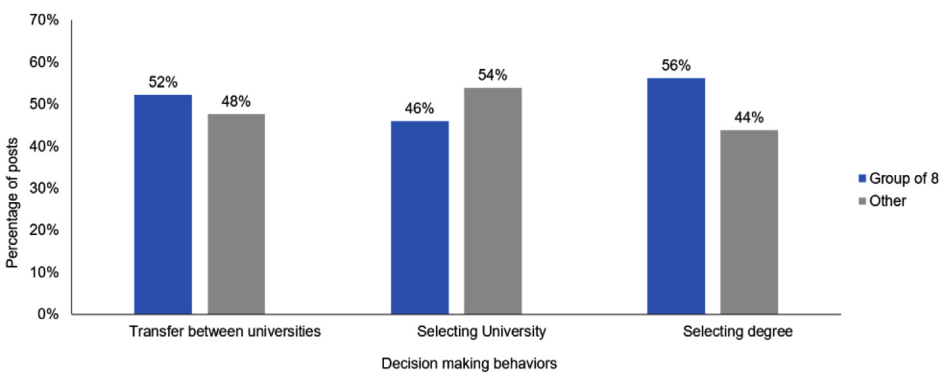

Fig. 7. Behaviours associated with university categories.

4.2. Validating the proposed approach based on the tertiary education scenario

Following the development of this approach for transforming social media content into insights and analysis, it was deemed necessary to conduct a post-hoc analysis to validate the study with appropriate in-field domain expertise. For this purpose, we selected the tertiary education sector and senior executive management of an academic institution as domain experts. The main purpose was to understand the consumer-oriented aspects considered by the organization when developing and innovating strategies for growth and sustainability and to observe how the results from the proposed social media analysis can bring upon further benefits. We conducted structured interviews with five senior executive management, who have significant experience (10+years) in organizational strategy development. From these interviews, several key focus areas were determined to use as the basis for strategy formation. The focus areas are listed below. From many strategic areas, management presented three main student-oriented aspects they consider when formulating strategies (marked in bold).

- **Student experience**
- **Student employability**
- **Grow student base**
- Research excellence
- Industry partnerships
- Operational excellence
- Investing in people & infrastructure

Interviewees acknowledged the importance of consumers (students) opinions when formulating strategies as their opinions and feedback serve as direct inputs to the strategic planning of the organization. The analysis using the proposed approach enabled extracting informed insights related to student experiences, the concerns of students regarding employability and enrolments (growth). With this, it is apparent that integrating social media content serves as a useful external body of knowledge into open service innovation practices of an organization (Fig. 8).

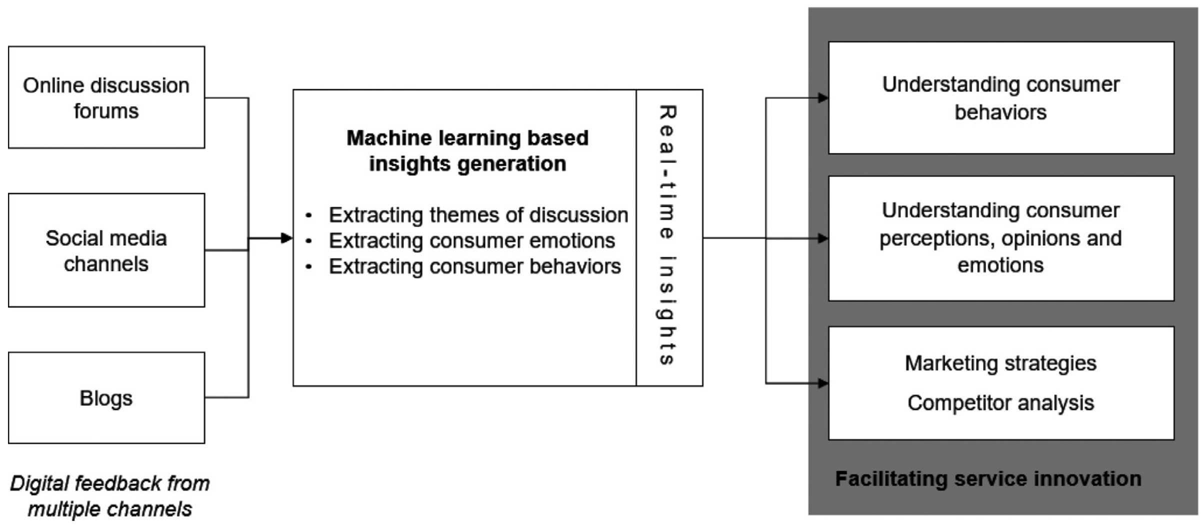

Fig. 8. A social media based open service innovation approach to improving strategy development within a university.

5. Discussion

5.1. Contribution to theory

It has been established that social media has enabled the emergence of a data-driven paradigm, subsequently creating a plethora of consumer-generated data (Chen, Fay & Wang, 2011). This has led to re-establishing the dynamics in organizations and practices (Kapoor et al., 2018). Given the multitude of opportunities that can be derived using this asset of consumer opinions, past literature emphasize the importance of integrating such data across the entire innovation funnel of an organization from ideation, research and development to commercialization[45]. However, there should be a structured methodology advocated by technology to integrate data-intensive environments such as social media into the current innovation practices of organizations (Kar & Dwivedi, 2020). Such methodology should be timely and encapsulate the ability to conveniently align consumer opinions into the decision-making process (Kushwaha, Kar & Dwivedi, 2021).

As contribution to the study of information systems, we present the following model (Fig. 9) which addresses the research question on how organizations can reconceptualize open innovation practices by co-creating value using consumer-generated social media data. This conceptual model presents the process of infusing value extracted from data intensive environments such as social media into the organization's service innovation efforts as a useful knowledge resource. The informed insights derived from consumer opinions and emotions serve as digital feedback to the continual innovation process in an organization (Dong & Wu, 2015). Using the proposed model, we aim to establish and bring a new perspective to current service innovations research, by integrating social media conversations and consumer emotions expressions as continuous input to organizations innovation practices. This will enhance the consumer involvement in the innovation process of the organization at a larger scale than traditional consumer surveys (Trusov et al., 2009). The continual extraction of knowledge from social media using automated techniques such as machine learning elevates the current service innovation operations and promotes incremental value co-creation and agility of innovation practices. The proposed theoretical model serves as a conceptualization of incremental value co-creation via digital resources which can be used to reconceptualize organizations innovation practices.

The proposed theoretical model demonstrates how insights generated via social media can be integrated into organisations open service innovation practices as a potential asset of consumer knowledge. The extracted insights contain information about consumers' discussions, views, and emotions which will provide an opportunity to closely observe the perceptions of the consumers.

Furthermore, by integrating both long-term conversation and more immediate student discussions we demonstrated how different data sources generate different consumer expectations and behaviors thereby contributing to value co-creation in diverse aspects. In the context of our case study, the analysis of the general discussions provided insights for long-term strategy development and innovation, whereas analysis of short-term student discussion group revealed current issues of students thus enabling proactive decision-making. Using the real-time analysis of social media content, it is possible to monitor consumer activities in near real-time and identify pitfalls of services in near real-time manner (Nallaperuma et al., 2019; Peng et al., 2019). The continuous engagement will result in an incremental and iterative process of value co-creation which will ultimately be useful for innovation capabilities. More specifically, this iterative value co-creation would drive the potential to adopt agile innovation practices as organizations could customize and improve services with constant and near real-time consumer feedback. These insights coupled with the organization's information sources present a valued opportunity for open service innovation research.

The practicality of integrating big data resources and how such unstructured social media data can be transformed into insights with business value, are largely overlooked as formidable challenges (Kumar, Kar & Ilavarasan, 2021). Especially extracting insights is problematic when the content is not generated with the purpose of innovation, hence useful insights should be particularly mined from the large pool of unstructured, textual data that are inherently complex to assess (Bazzaz Abkenar, Haghi Kashani, Mahdipour & Jameii, 2021). To this end, in this study, we address the research question on how machine learning can be utilized to derive informed insights from unstructured social media data by proposing a machine learning framework that is able to extract structured insights from free-flowing social media conversations. We present the applicability of using machine learning to aid the process of value identification by extracting useful insights with respect to consumers' discussion topics, behaviors over time and especially automated emotion analysis using social media, which otherwise would remain a major challenge for organizations (Verma, Sharma, Deb & Maitra, 2021). We demonstrated how organizations can automate the insight generation process from big data by using machine learning capabilities.

We emphasize on key outcomes of the study; (1) using a case study in tertiary education we established how social media content could be leveraged for end-to-end open innovation in service organizations, (2)

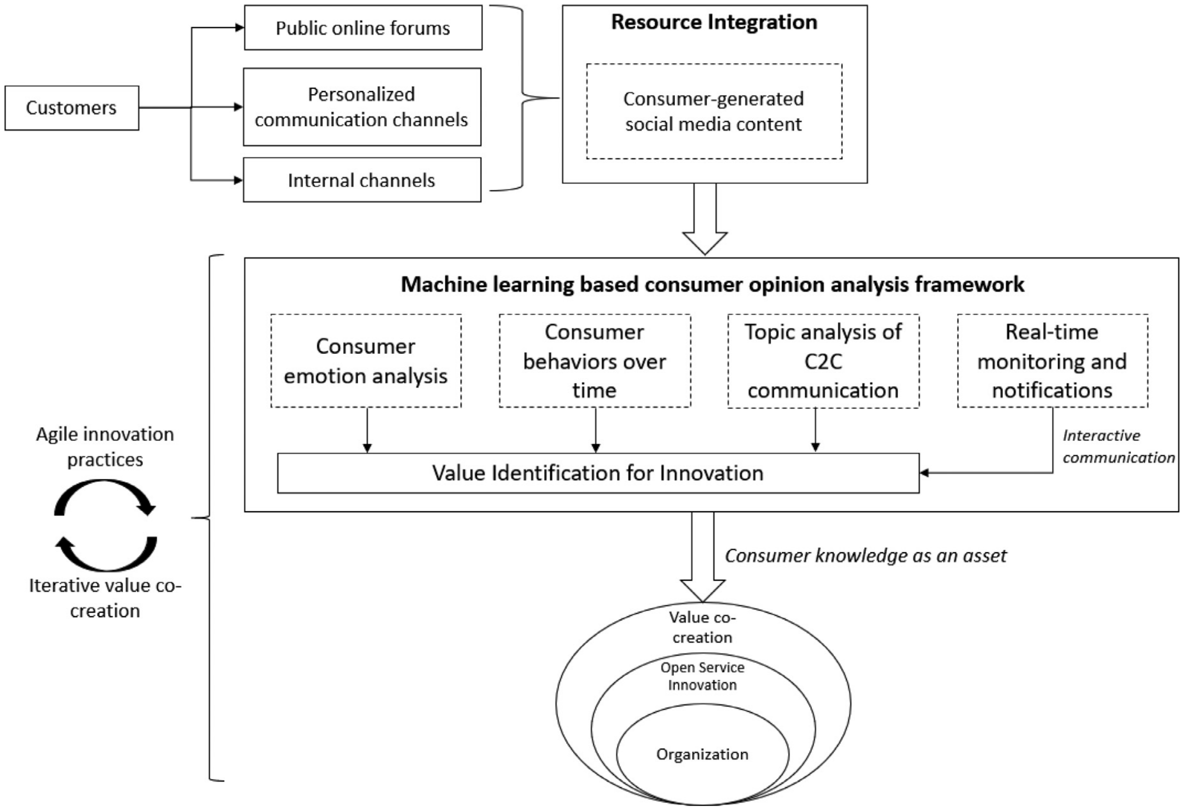

Fig. 9. The proposed theoretical model for continuous value co-creation via data-intensive social media environments.

by identifying diverse, informative insights generated by free-flowing C2C communication, we demonstrated the use of social media data and machine learning as digital enablers and (3) we present the applicability and the feasibility of using machine learning based approaches to autonomously transform unstructured free-flowing social media conversations into insights with value for innovation These outcomes demonstrate the practicality of using social media content for innovation purposes and the use of machine learning to extract consumer emotions and behaviours which are otherwise difficult to assess from free-flowing data. Next, (4) by presenting a theoretical model encapsulating the impact and effectiveness of insights generated via social media, we position social media content as a useful external source of data and as a consumer-generated knowledge asset for open innovation. This provides a theoretical perspective to current innovation research as the integration of digital feedback channels unveils a new perspective to gain consumer insights which can be used to improve innovation efforts. The outcomes derived from such digital channels can support continuous and incremental value co-creation, thus effectively supporting the service innovation process of an organization. This is particularly important given the drive towards adopting agile organization practices to improve the human-centered design (HCD) as the proposed model contributes and supports the notion to provide iterative value creation to improve innovation via real-time digital feedback channels (Gabrielli & Zoels, 2003).

5.2. Implications to practice

We anticipate that the results of the study have many implications. Institutions need to identify means of addressing the challenges of increasingly complex competitive environments if they are to both explore and expand business (Smith, Binns & Tushman, 2010). Student demand and their rapidly changing needs place immense pressure on Higher Education Institutes. This pressure and the means to respond in a timely and efficient manner is an arduous task “without re-engineering and streamlining their operations to better serve their consumers” (Gunasekaran, Talluri & Sarkis, 2007). Higher education institutions to be competitive from an agility standpoint, they must adapt and build strong relationships with potential and current students with haste to develop responses to both unstructured and competitive markets. A company cannot become internally agile unless its external relationships with the supply chain are also agile (Gunasekaran et al., 2007). Giving weight to our study and subsequent analysis that institutions need to leverage digital feedback in a different manner. Agile practices, HCD principles, and virtual enterprises can assist in ‘countering pressures and effectively meeting consumer demands and mass customization requirements’ (Gunasekaran et al., 2007).

The insights generated via social media content could be integrated as a consumer-based knowledge asset into the current service innovation life cycle of an organization. This will potentially enhance the current practices and enable insights from a larger consumer base. In addition, organizations no longer have to limit their data sources; using social media they could tap into data generated by consumers worldwide, enabling the expansion of innovation efforts in a global context. As a short-term implication, organizations could monitor the fluctuations of emotions expressed by consumers on social media channels and take proactive actions (Saheb, Amini & Alamdari, 2021). Given the virality and contagious nature of negative feedback on social media (Blackshaw, 2008), it would be important to use real-time insights for proper management of negative responses. As long-term implications, organizations would be able to derive benefit by gaining insights on how consumers’ emotions have changed over time. This could be compared with other organizations as well, since identifying diverse negative aspects seen by consumers would give the opportunity to improve current service offerings. We present the integration of emotions as a salient practical implication as it provides grounds to understand the consumer more closely.

6. Conclusions

Over the last few decades, the digitalisation has created a paradigm shift in the field of information. The information has transitioned to a digital variation and is more user oriented. Social media platforms have largely contributed to this fact given the proliferation of user-generated information. Information is no longer static, but ubiquitous and widely available via multiple channels. Therefore, organizations should leverage user-generated information to gain competitive advantage and most importantly to innovate. In this study, we demonstrated how an organization's open innovation practices can be re-structured and re-conceptualised to reflect the use of social media as a knowledge source.

By demonstrating the practicality and the feasibility of using consumer-generated social media content, our study makes four contributions to the body of knowledge on open innovation. First, by providing a detailed account of the process through which one of the case organizations leverages social media content to innovate, our study responds to calls for improved understanding of the end-to-end open innovation process in service context (Mount & Martinez, 2014). Second, by identifying the mechanisms through which social media data (that has not been created for innovation purposes) influences the trajectories of organizational innovation activities, we contribute to the understanding of digital technologies as important enablers of open innovation (Demirkan & Delen, 2013). Third, by developing a real-time machine learning framework to create informed consumer insights from voluminous, unstructured social media data, we demonstrate the applicability of machine learning for knowledge extraction. Fourth, by proposing a theoretical model to demonstrate the integration of value generated by social media as a strategic asset to uplift current open service innovation practices in an organization by encouraging continuous value creation through consumer opinions. We used the service-dominant logic as a theoretical perspective to explain how consumers can co-create innovation without being actively involved in organizational innovation processes and we have contributed to a better understanding of individuals as an external source of innovation (Xie et al., 2016). This provides a new perspective to current continuous value co-creation in IS research by positioning the use of social media as a key aspect of value co-creation and the integration of advanced technical capabilities in the knowledge extraction process. We presented the applicability of the proposed approach by using a case study in tertiary education and emphasizing the use of machine learning in extracting insights from social media data which are not created explicitly for innovation purposes. We further authenticate the applicability of the approach by conducting interviews with key personnel in a selected tertiary education institution to validate the usefulness of the derived insights from a service innovation perspective.

A potential improvement would be to integrate a module that can determine the quality of data. This could be aligned with the data collection process in order to filter fraudulent data and spam (Nasir, Khan & Varlamis, 2021). Incorporating such filtering in the data collection process would increase the accuracy and quality of data. As a further course for future research, the proposed approach could be further extended to incorporate machine learning based prediction capabilities which would enrich the decision-making and management of organization strategies. Organizations could use such capability to predict consumers' responses to different changes in service as well as to predict patterns over time.

It is evident that organizations should embrace new technologies and transform organizational practices to harness the value of big data environments such as social media. The practical use of machine learning for enhanced decision-making capabilities is still in its infancy within organizations, and this encourages many novel research directions. We believe that the proposed theoretical framework to position social media in the service innovation sphere and outcomes of the study have the potential to broaden the IS research capabilities by using social media and technological advancements to support organizational efforts in service innovation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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