Journal of Retailing and Consumer Services 53 (2020) 101799

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

Personalized digital marketing recommender engine

Rajat Kumar Behera[a], Angappa Gunasekaran[b,*], Shivam Gupta[c], Shampy Kamboj[d], Pradip Kumar Bala[a]

[a] Indian Institute of Management Ranchi, Suchana Bhawan, 5th Floor, Audrey House Campus, Meur's Road, Ranchi, 834008, Jharkhand, India
[b] School of Business and Public Administration, California State University, 9001 Stockdale Highway, Bakersfield, CA 93311, California, USA
[c] Montpellier Business School, Montpellier Research in Management, 2300 Avenue des Moulins, 34185, Montpellier, France
[d] Amity School of Business, Amity University, Noida, 201313, Uttar Pradesh, India

ARTICLE INFO

Keywords:
Personalized digital marketing
Recommender engine
Customer relationship management

ABSTRACT

E-business leverages digital channels to scale its functions and services and operates by connecting and retaining customers using marketing initiatives. To increase the likelihood of a sale, the business must recommend additional items that the customers may be unaware of or may find appealing. Recommender Engine (RE) is considered to be the preferred solution in these cases for reasons that include delivering relevant items, hence improving cart value, and boosting customer engagement. The paper describes a model for delivering real-time, personalised marketing information concerning the recommended items for online and offline customers, using a blend of selling strategies: up-selling, cross-selling, best-in-class-selling, needs-satisfaction-selling and consultative-selling. The model further defines the e-marketplace by clustering items, customers and unique selling proposition (USP), and then gathering, storing, and processing transactional data, and displaying personalised marketing information to support the customer in their decision-making process, even when purchasing from large item spaces. An experimental study using a quantitative research methodology was conducted in a mid-size healthcare retailer, based out of India, to determine the tangible benefits. The model was tested with 100 online customers and, with the adoption of the proposed methodology, the results indicated growth in average monthly revenue (33.49%), Average Order Value (AOV) (32.79%) and Items per Order (IPO) (1.93%).

1. Introduction

Digital marketing as a concept was first identified in the 1990s, principally with regard to advertising to customers (Fierro et al., 2017). However, the concept was extended with the emergence of "mobile technologies" during the 2000s and "social media" technologies from around 2010 (Fierro et al., 2017). As a result, there has been a paradigm shift in digital marketing, from advertising to everlasting customer-oriented engagement, supported by the development of a number of instruments indispensable for business competence. Since almost everybody is inadvertently engrossed within the digital age, this has become the most efficient way to reach prospective customers (Kannan, 2017). Over recent decades, corporations such as Amazon, Alibaba, eBay, Best Buy and Netflix have become the prime drivers of the modern economy (Kannan, 2017). Such corporations have highlighted the significance of building digital connectivity with their customers. Consequently, customers' percipience towards business strategies has changed due to the digital uprising (Ghotbifar et al., 2017). As a result, to succeed in the digital medium, such corporation have implemented strategies to offer focused and quantifiable ways of reaching customers, termed "digital marketing" (Lamberton and Stephen, 2016). Technically, digital marketing refers to communicating the value of items such as goods, products or services to customers, leveraging online and offline digital channels, mainly on the Internet. Essential business decisions like product development, product creation, marketing communication, buying and selling for profitability, brand management and customer relationship management have seen significant development through the application of digital technologies. Personalised digital marketing or one-to-one digital marketing is one strategy by which e-businesses leverage data analysis to deliver individual marketing messages to existing and prospective users. From a theoretical standpoint, the recommendation of personalised content to the individual customer reflects the leading step in online relationship marketing (Schubert and Ginsburg, 2000).

Recommender Engine (RE) is a system that is used in internet-facing platforms such as email, social media, Internet-enabled televisions

* Corresponding author.
E-mail addresses: rajat_behera@yahoo.com (R.K. Behera), agunasekaran@csub.edu (A. Gunasekaran), sh.gupta@montpellier-bs.com (S. Gupta), kamboj.shampy@gmail.com (S. Kamboj), pkbala@iimranchi.ac.in (P.K. Bala).

https://doi.org/10.1016/j.jretconser.2019.03.026
Received 15 September 2018; Received in revised form 23 March 2019; Accepted 30 March 2019
Available online 13 April 2019
0969-6989/

(IETVs), online shopping web portals and online mobile applications to recommend relevant items that the online customer may find appealing and is likely to purchase. It predicts the user rating of or preference for particular items, and also recommends items that the user may prefer. In the process, it collects user preferences of items such as songs, movies, travel destinations, e-learning materials, books, jokes, gadgets, applications, websites and products, and uses an algorithm to make predictions and recommendations based on those items (Bobadilla et al., 2011). This has led to the development of a sizable volume of literature on diversified topics, such as music (Lee et al., 2010; Nanopoulos et al., 2010; Tan et al., 2011), television (Yu et al., 2006; Barragáns-Martínez et al., 2010), books (Núñez-Valdéz et al., 2012; Crespo et al., 2011), documents (Serrano-Guerrero et al., 2011; Porcel et al., 2009, 2010, 2012), electronic-learning (Zaíane, 2002; Bobadilla et al., 2009), electronic commerce (Huang et al., 2007; Castro-Schez et al., 2011), market applications (Costa-Montenegro et al., 2012) and web search (McNally et al., 2011), among others. RE taps into the behaviour of customers who have rated such items (so-called items-rated customers) to make recommendations about what future customers will like most. In e-business, the most important factor is the continuing relationship with the customer. Customers buy items to satisfy their needs and each has a unique buying pattern. They love personal touchpoints such as communications over email, remembering them on their birthdays or, more importantly, being able to customize their needs. Therefore, a strategic focus must be developed over time on what to sell, what to up-sell, what to cross-sell, what to best-in-class-sell, what to needs-satisfaction-sell, and what to consultative-sell; and such strategic focus must take into consideration that customer needs are constantly changing. The challenge is to reach not only the items-rated customers, but also the cold-start and window-shopping customers. This involves the collection of sizable volume of customer data, and the process of automatic generation of recommendations at different e-shopping points. Personalised items lead to more custom tailoring than unsystematic suggestions. In addition, a constructive approach towards personalization improves the perception of shopping on digital platforms (de Pechpeyrou, 2009).

RE should suggest highly relevant, personalised items at multiple touch points in the e-shopping process across different digital channels. Failure to do so may result in customer dissatisfaction, and potential responses include change of brands, registering complaints with the retailer, or may lead to negative ratings, online or by word-of-mouth, of items and retailers as unsatisfactory (Richins, 1983). Personalised marketing in the form of recommended items would certainly make sense for every customer as e-shopping is designed for them and, consequently, it enjoys a natural advantage in brand awareness in the digital space. Personalised marketing can also drive web traffic by acquiring and retaining customers. An attempt should be made by the e-business to deploy more effective real-time and prolonged personalisation marketing tactics, always keeping in mind that the focus is to manage the customers and not the items.

The objective of the study is to present an innovative model by redefining the e-marketplace to deliver individual marketing content to the customers through data collection, processing and analysis with RE technology. In order to meet this aim, this paper proposes three step-wise research objectives:

(1) Design of the e-marketplace, achieved by: (1.1) classifying customers based on the buying pattern for effective marketing at multiple touch points in the e-shopping process; (1.2) classifying items for better recommendation to improve e-purchasing conversions; (1.3) classifying USPs to differentiate the items from those of competitors for efficient personalised recommendation; (1.4) developing a selling strategy for different customer profiles.
(2) Develop a model to deliver customized, tailored and personalised promotion and advertising of recommended items targeting items-rated, window shopping and cold-start users using a blend of selling strategies: up-selling, cross-selling, best-in-class-selling, needs-satisfaction-selling and consultative-selling.
(3) Validate the model by testing and verifying the proposed hypotheses.

Online shopping offers access to the items of a worldwide market in an e-commerce space, increases the value of customers and builds sustainable capabilities. Human nature makes consumers tend to buy items recommended by people they consider trustworthy. In the e-commerce space, the online shop utilises some sort of RE to recommend items from different categories based on the browsing history and direct available items to the customer to increase customer satisfaction and retention. Over the internet, the number of items available is overwhelming, so there is a need to prioritize, filter and deliver relevant items matching the preferences or taste of the customer by attenuating the problem of overload due to display of multiple items, which has, in the past, created problems for internet users.

When used correctly, personalisation can be a powerful tool and plays a significant role in digital marketing. If a personalised experience is offered, customers feel special and are likely to do business (Epsilon, 2018; Simonson, 2005; CyberAtlas Staff, 2002). Dynamic personalisation is most effective via email as it improves response rates (Vesanen, 2005, p.15; Nussey, 2004). Offline as well as online users may want more relevance, hence implementing personalisation in places of work, retail and catering, aligned with consumers' psychological profiles, can improve performance and user satisfaction (Stewart-Knox et al., 2016; Oulasvirta and Blom, 2008). Personalisation is an established e-commerce marketing strategy and generates uplifts in purchasing intentions towards the company, and produces additional customer benefits such as effectiveness, increase in loyalty, and early feedback (Lee and Cranage, 2011; Alatalo and Siponen, 2001; Kokko and Moilanen, 1997). Personalisation of a payment card is an important part of adding value and ensuring its proper use (Wildash, 2008).

Customer behaviour is changing, so in order to be relevant and assist in the sales process, current and future marketers need new knowledge, new skills and new approaches, not only to understand the changing and technology-enabled marketing environment, but also to understand and communicate with the new customer (Bala and Verma, 2018). Hence, different areas of academic literature have highlighted the technology necessary for future research in personalised digital marketing: customers rely on continuous assistance from other customers when interacting with sellers, especially in "digital technologies", and such technology approbation provides a push for meaningful commitment and, eventually, for existing customers to foster prospective customers (van Tonder et al., 2018). Luxury brands also make use of new technologies, but there is little research into the adoption of "internet-based technologies" in the high-end retail sector (Pantano et al., 2018; Baker et al., 2018). Advances in digital technology are expanding e-commerce dimensions and reforming the way consumers shop and buy products and services (Park and Kim, 2018). Social media platforms can be a propitious tool for retailers, but to date there is little knowledge about the influence of social media campaigns and better interaction with customers (Baum et al., 2018; Di Fatta, 2018; Alalwan et al., 2017).

In the remainder of this paper, section 2 presents the literature review; section 3 articulates the theory and propositions; section 4 discusses the proposed framework; section 5 outlines the research methodology; section 6 discusses the results; section 7 focuses on a discussion covering managerial and social implications; and section 8 concludes the study with a discussion of limitations and an agenda for future research.

2. Research background

The review is broadly classified into two areas: 1) existing conventional (standard or common) approaches to personalised digital marketing; and 2) existing RE approaches to personalised digital marketing.

2.1. Review of existing conventional approaches to personalised digital marketing

Table A1 in Appendix A presents a breakdown of the extent of coverage in this field as revealed by the literature review, as well as a synthesis of existing approaches, i.e. findings, outcomes, limitations, context and methodology. The following sub-section covers the author's self-compilation of ideas that remain unexplored in previous studies.

Literature Gaps: The importance of the brand image of luxury products is emphasised by maintaining a personal relationship with customers and developing website characteristics before the development of prescriptive suggestions (Baket et al., 2018), and promotional suggestions are "pushed" out in masses, with no classification of customers. The items were not classified, but rather brand ranking was considered, which is not aligned with customer behavior (i.e. repeat visits, additional purchases, increased trust etc.). Personalisation is an emerging trend, a necessity in e-commerce, and has different viewpoints (Dangi and Malik, 2017), but to date studies have not considered the theme of different selling strategies. Promotions, ideas and suggestions are mutually exclusive external impulse buying signals and there is a positive relationship between web sales of retailers and the number of external signals (Dawson and Kim, 2010); however, vitality of personalisation was not discussed. Quality of promotion is the most important attribute to increase the conversion rate (Di Fatta et al., 2018), but other outcomes of personalisation, such as revenue, IPO etc., were not discussed. Integration of smart phones is reconfiguring retail in digital media and changing in-store shopping behaviour (Fuentes et al., 2017), but this study was confined to mobile applications and other digital touchpoints such as social media sites – the study did not consider Internet Enabled Televisions (IETVs) or e-commerce websites, or how all digital touchpoints should work in tandem. According to Hallikainen et al. (2018), the preferred digital touchpoints are functional ones, such as e-mail, websites and search engines, but their study lacks analysis of short-term or long-term obligations, and does not determine success factors based on resources like people, time etc. While deal-prone customers are more likely to buy deal-of-the-day (DoD) items and enjoyment plays a vital role in their shopping (Ieva et al., 2018), nevertheless, conscious customers are less DoD-oriented, and this study lacks clarity regarding the implications of different DoD platforms. Personalised products and services resulting from a personalised design enhance customer satisfaction and realise sustainable consumption and production (Kaneko et al., 2018), but this paper lacks detail on the customer engagement pyramid, i.e. identifying individual customers and their goals, determining the values of the goals, etc. Satisfaction affects spending and results in more e-commerce spending according to Nisar and Prabhakar (2017), but their analysis lacks a real- or near-real time analysis. The study of Park and Kim (2018) classified customers, shopping patterns and channel preferences to understand path-to-purchase behaviour but failed to address real or near-real time analysis and only considered customers of similar priority. Young customers or customers with previous mobile purchasing experience and those with higher out-of-pocket expenditure are more likely to use mobile technology as a search and purchase channel (Singh and Swait, 2017), but this study fails to identify the factors that "delight" customers or at presenting the tailored messages in an unexpected way. Millennials preferred online coupons, side-panel ads, competitive prices and good shipping rates, and did not like pop-up advertising, according to Smith (2011), but the author does not discuss types of selling strategies. Hedonic shopping motivations primarily influence attitudes towards IETV shopping, and shopping on IETV makes shopping online more enjoyable and convenient for consumers (Wagner et al., 2017), but there is no discussion on how to influence customers on their own terms, provide customer-centred support etc. The manufacturer and the traditional retailer can use different return policies and this can lead to an increase in online sales by using revenue sharing plus mechanisms for profit sharing according to Yan and Pei (2018), but their paper lacks a discussion on USP.

Taking into consideration the work identified in Table A1 in Appendix A, and the identified literature gaps, it can be concluded that existing approaches: (1) have not looked at item segmentation or USP in order to achieve more effective customer marketing via personalization; (2) treat all customers as equal priority, and assume that all digital touchpoints perform identical marketing content delivery, which is mistaken. The clusters are mainly used to target customers with personalised offers and incentives for their preferences and needs, but (3) the studies failed to call out item suggestions using different selling strategies such as up-selling, cross-selling, best-in-class-selling, needs-satisfaction-selling, and consultative-selling. (4) None of the approaches looked at calling out to customers in real- or near-real time fashion in order to make the offers "sticky" in the minds of customers.

2.2. Review of recommender engine

In Appendix A, Table A2 presents a breakdown of the adequacy of coverage identified in the literature review as well as a synthesis of existing approaches in this area, i.e. findings, outcomes, limitations, context, and methodology, especially regarding RE. The following subsection presents the author's self-compilation of ideas unexplored in previous studies.

Literature Gaps: The study of Ansari et al. (2000) examined the merits of the collaborative filtering method and proposed Bayesian preference model, and discovered five types of information useful for making recommendations. However, the study does not look at item clustering or USP and does not factor in different sales strategies. Greater knowledge is more important in the calculation of recommendations for less knowledgeable users and this concept is at the core of the collaborative memory filtering proposed by Bobadilla et al. (2009), but they did not emphasise personalised recommendations through classifying customers or items. The study of Geuens et al. (2018) proposed a framework for supporting decisions to help e-commerce companies select the best collaborative filtering algorithms to generate recommendations based on binary purchase data online, but again did not address classifying customers or items to provide personalised recommendations. In comparison with several state-of-the- art techniques, the study by Gurini et al. (2018) described a people-to-people recommendation approach for large scale social networks to improve recommendation performance, but the study lacks a synthesis of personalised recommendations and no discussion is made regarding cold-start items and new (cold-start) customers. Hu et al. (2019) propose a new item-oriented recommendation algorithm to discover users who can purchase the target item in order to maximise revenue, but they lack a synthesis of personalised recommendation and consider all customers as equal priority. Hwangbo et al. (2018) proposed a collaborative filtering recommendation system in the real world and that shows superiority in product clicks and sales, but the study lacks a synthesis of personalised recommendation and no discussion is made regarding cold start items and customers. In contrast, Schafer et al. (1999) described how recommender systems enhance e-commerce sales in three ways: converting browsers into buyers, cross-selling and creating loyalty, and they include cold start items and cold start customers in the evaluation criteria. The study of Núñez-Valdez et al. (2018) described an electronic book recommendation system and evaluated its quality by benchmarking twelve popular machine learning algorithms, but again the study lacks personalised recommendation and no discussion was made for cold start items and cold start customers.

Taking into consideration all the works currently available related to a Recommender Engine, we see that: (1) such platforms or systems exist, but it cannot be said that there is an existence of "Personalised Digital Marketing" using different sales strategies. (2) Many existing

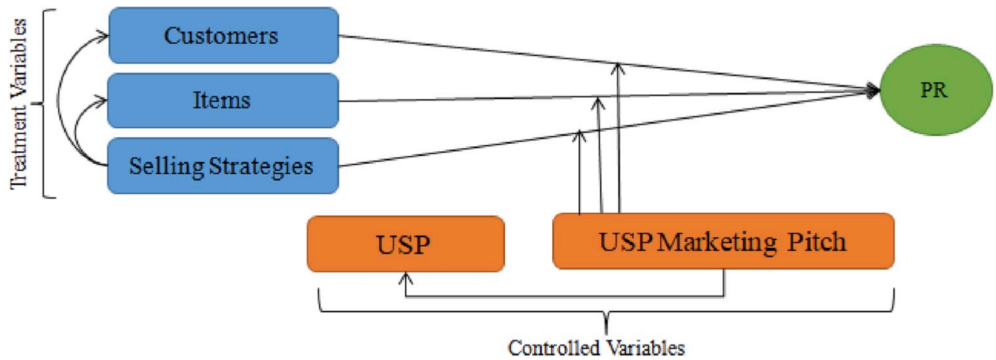

Fig. 1. Variables Co-relationship diagram.

approaches do not discuss cold start items and cold start customers, and (3), those that do address cold start items and cold start customers do not include them in the accuracy evaluation criteria, making the decisions vulnerable.

3. Theory and hypothesis development

This section describes the theoretical foundation of this study. In this study, three hypotheses (H1, H2 and H3) are proposed. Hypotheses H1 and H2 are tested and validated with primary data. Hypothesis H3 is tested and validated against the existing literature.

3.1. Variables and hypothesis conceptualization

Variables, Propositions and Hypotheses used in the study are conceptualized below.

USP: A factor that makes the item(s) or product(s) unique from the rest of the competing brands (Laskey et al., 1989). It is primarily associated with advertising.

USP Marketing Pitch: The line of talk in USP to persuade the customer to buy the item.

AOV: The average amount spent each time a customer places an order.

IPO: The number of items ordered in one transaction by one customer.

Customers/Users: The group of people who purchase items and services and are impacted by the suggestions and are likely to influence the suggestions.

Items: The set of all products, services including cold start items, that are to be suggested to the users.

Selling Strategy: The plan by the business on how to go about selling the additional items and services for possible uplift in profits. This study considers five selling strategies, namely up-selling, cross-selling, best-in-class-selling, needs-satisfaction-selling and consultative-selling. *Up-selling* is the technique to induce the customer to purchase additional items, upgrades or expensive add-on items. *Cross-selling* is the technique to induce the customer to purchase related or complementary items. *Best-in-class-selling* is the technique to induce the customer to purchase superior items in a specific segment. *Needs-satisfaction-selling* is the technique to induce the customer to purchase to satisfy a particular need, either stated or unstated. *Consultative-selling* is the technique to interact with prospects to help them understand their pain points and induces them to purchase customized items.

Conversion Rate: In the context of digital marketing, the percentage of users who purchase items on the selling site. In essence, it is the act of converting prospects to potential buying customers (Di Fatta et al., 2018).

Organisations use insight based on the user's personal and behavioral data along with similar people's actions to provide an experience that meets specific preferences, but marketers still struggle with the execution (Cmswire, 2018), leading to challenges. The challenges highlighted by different academic authors include: how is value created for the customer, how does the value concept add a new dimension, and how meaningful are the results of value creation (Wikström and Decosta, 2018)? How can businesses personalise website content, e-mail newsletters and/or mobile notifications (Ricci et al., 2015)? What are the most important security issues to be considered in the evolving electronic world, and how should businesses treat privacy concerns (Nepomuceno et al., 2014)? How do issues such as lack of face-to-face contact, demanding customers, and difficulties discovering customers' real wishes limit the efficiency of RE (Leeflang et al., 2014; Kokko and Moilanen, 1997)?

This paper makes a unique contribution in that no previous research has paid attention to the perspective wherein the recommendation is provided in the context of the various selling strategies, and how the strategies connect with the customers, items and USP. Prior studies have primarily paid attention to item-to-item similarity (i.e. "content-based filtering", "collaborative filtering" and "hybrid filtering") as the core principle behind item recommendations offered by RE (Huang et al., 2007; Adomavicius and Tuzhilin, 2005; Isinkaye et al., 2015; Krzywicki et al., 2015). Other studies have paid attention to the treatment of variables such as users and items (Isinkaye et al., 2015) for correct recommendations, whereas this study additionally includes controlled variables and selling strategies to make more accurate recommendations, as presented in Equation (1). Let F(TVs) represent the function over treatment variables and F(CVs) represent the function over controlled variables. Then Personalised Recommendation (PR) is given by:

$$PR = F(TV_s) + F(CV_s) \tag{1}$$

The co-relationship among the variables is represented in Fig. 1. From the diagram, it can be inferred that selling strategies are co-related to items and customers, and USP marketing pitch is correlated to USP, customers, items and selling strategies. In Fig. 1, PR stands for Personalised Recommendation over digital media.

3.2. Theory

Let n be the total number of online customers, and m be the total number of items. Since a one-size-fits-all approach is inappropriate for the personalised items recommendation approach, the most important consideration is to define the e-marketplace by classifying customers, items, USP, and USP marketing pitch and then applying the most influential selling strategies. Let m be the total number of items for sale, u be the total number of users, m'' be the most regular items purchased by the user u''', and m''' be the additional items recommended to u''', where $m'' \subseteq m$, $m''' \subseteq m$, $u''' \subseteq u$, and n''' is the total items (i.e. m'' plus m''') where $n''' \subseteq m$, then the total items the customer u''' is expected to purchase is n'''. The theoretical foundation of this study is based on the computation of m''', the two propositions and the three hypotheses, with the primary aim of answering the research questions.

Let PDR(C, I, USP, USP Marketing Pitch, Selling Strategies) represent the personalised digital recommendation function of a customer C, covering recommended items I, USP, USP marketing pitch and selling strategies. Then PDR is defined as:

PDR(C, I, USP, USP Marketing Pitch, Selling Strategies) = TVF(C, I, Selling Strategies) + CVF(USP, USP Marketing Pitch).Where TVF represents Treatment Variables Function, covering customer, recommended items, and Selling Strategies and CVF represents Controlled Variables Function covering USP and USP Marketing Pitch.

3.3. Hypotheses development

Hypothesis 1. (**H1**): The online revenue contribution is a key objective for digital marketing as it provides a simple measure of the performance of online sales achieved in various product categories (Chaffey and Ellis-Chadwick, 2019). A few case studies show that measuring and optimizing the measurement of digital marketing performance increased revenue from sales (Phippen et al., 2004; Dale Wilson, 2010). Hence, we hypothesize that: the more the business performs personalised digital marketing, the higher the growth rate of revenue, as represented in Equation (2). The potential synergy between the personalised digital marketing and revenue management allows control of two different components of the marketing funnel. A higher value means sustainable growth of the company.

$$\text{PDR(C, I, USP, USP Marketing pitch, Selling Strategies)} \propto \text{\% increase in Revenue} \quad (2)$$

Hypothesis 2. (**H2**): The AOV provides an estimate of the potential value of completing an order by the user and it is most likely that a high value can improve performance and increase sales (Nelson et al., 2016). An interactive shopping basket on the website can be used as a tool to increase AOV, and the secret behind AOV is to listen to own audience, provide customers with the shopping experience and the tools to become loyal evangelists (Mack, 2009). AOV measure revenue, and is the most critical point in the online retailing value chain (Singh, 2017). Hence, we hypothesize that: the more the business performs personalised digital marketing, the higher the rate of AOV, as represented in Equation (3). A higher value means an increase in the customer's purchasing habits.

$$\text{PDR(C, I, USP, USP Marketing Pitch, Selling Strategies)} \propto \text{\% increase in AOV} \quad (3)$$

Hypothesis 3. (**H3**): Alibaba broke records as the biggest items per order (IPO), pricing its offering at $68 per share and the IPO is expected to raise $21.8 billion, which values the company at $167.6 billion overtaking Visa and Facebook (Chen et al., 2014) and became so successful in e-commerce (Yazdanifard and Li, 2014). Hence, we hypothesize that: the more the business performs personalised digital marketing, the higher the rate of IPO, as represented in Equation (4). A higher value means more gained in total revenue, i.e. attracting more new customers.

$$\text{PDR(C, I, USP, USP Marketing Pitch, Selling Strategies)} \propto \text{\% increase in IPO} \quad (4)$$

In order to meet the constantly changing needs of the customer, a strategic focus must be developed and periodically reassessed on what to sell, what to cross-sell, what to up-sell, what to best-in-class-sell, what to needs-satisfaction-sell, what to consultative-sell, and which items have to be discounted. The focus may be developed when any planned business performance attribute (i.e. revenue, AOV, IPO, Conversation Rate and Staff Time Saving) is lagging behind actual performance attributes. Fig. 2 presents a radar chart showing the five-dimensional performance attributes.

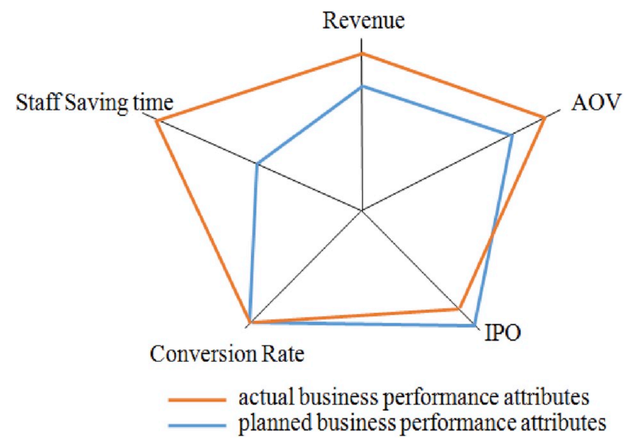

Fig. 2. Radar chart depicting phenomenon of strategic focus.

3.4. Building blocks of theory development

The building blocks of theory development are: (1) **What**: The variables are customer clusters, item clusters, USP clusters and USP marketing pitch. The constructs are % growth in revenue, % growth in AOV, % growth in IPO, growth in conversion rate and % growth in staff time saving. (2) **How**: The treatment variables such as customers, items, customer-friendly selling strategies such as up-selling, cross-selling, best-in-class-selling, needs-satisfaction-selling, consultative-selling and the controlled variables such as USP, USP Marketing Pitch are wired together to deliver personalised recommendations over digital media. The goal of personalized recommendation is to validate the hypotheses (H1, H2, H3) and outline the propositions (P1, P2). (3) **Why**: To achieve a higher performance in revenue, AOV, IPO, conversion rate and staff time saving with correct and to the possible extent, best recommendation. Finally, (4) **Who**: The Recommender Engine with the proposed framework.

4. Proposed framework

Our proposed framework, constructed using the building blocks described below, is presented in Fig. 3. The building blocks of the proposed framework are: (1) design of the e-marketplace, (2) personalised recommendation model and (3) recommendation process. The strength of the framework is to recommend items in accordance with the design of the e-marketplace, and to follow the proposed recommendation process with the adoption of the proposed personalized recommendation model.

4.1. Design of e-marketplace

In order to maximise the conversions and order values, the e-marketplace has been designed by devising a strategy set wherein customers, items and unique selling proposition (USP) are to be organised into different clusters and mapped for the marketing customisation. For better efficiency of the e-business revenue, the taxonomies proposed below must be continuously re-assessed. The proposed taxonomies are based on the study by Park and Kim (2018). In particular, the mixed use

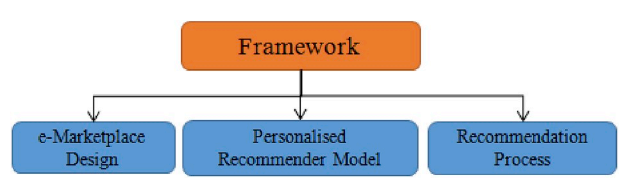

Fig. 3. Proposed Framework for Digital Marketing of Recommended Items Each of the building blocks of the framework is explained below.

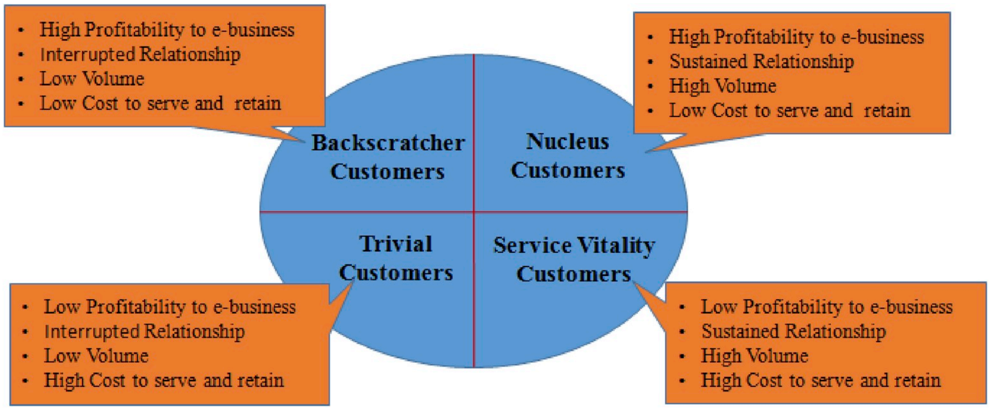

Fig. 4. Items-rated customer cluster with characteristics.

of online, offline and mobile shopping offers unprecedented challenges and opportunities for B2C companies to develop effective segmentation approaches that capture multiple shopping patterns for newly emerging consumers. A non-hierarchical clustering method is recommended for this proposed model.

Customer Cluster: The strategy is called a cluster-of-cluster of customers and the purpose behind this strategy is to identify the prospective customers from the buying patterns and to communicate marketing information of items with each as an individual. Primarily, the cluster is one of three types, namely, *items-rated*, *cold-start* and *window-shopping*. Items-rated customers are registered to the e-business and have also rated items (positively or negatively). Cold-start customers are registered to the e-business but have not rated the items, or rather items ratings are not available. Window-shopping customers are neither registered to the e-business nor have they rated the items. As Fig. 4 depicts, items-rated customers are further clustered as: (1) nucleus customers; (2) backscratcher customers; (3) service vitality customers and (4) trivial customers. The customer clusters are mutually exclusive and collectively exhaustive. Dimensional spaces of items-rated customers are: (1) volume of transactions, (2) relationship, (3) profitability to the e-business, and (4) cost of service and retaining. The clustering is based on the concept of customer segmentation (Neslin et al., 2006).

Items Cluster: The objective behind this strategy is to identify the prospective items from the buying patterns for efficient personalised recommendation, as presented in Fig. 5. The item clusters are mutually exclusive and collectively exhaustive. Dimensional spaces of items customers are: (1) cost and (2) criticality. Items are further clustered as: (1) bulk purchase items; (2) strategic purchase items; (3) critical purchase items and (4) general purchase items. The clustering is based on the concept of product classification (Korgaonkar et al., 2010).

Unique Selling Proposition (USP) Cluster: The USP propels the customers to read more about the recommended items and how the items are different from those of competitors. It also defines the e-business's unique position in the marketplace. The cluster is presented in Fig. 6. USP clusters are mutually exclusive and collectively exhaustive. USP is further clustered as: (1) hassle-free; (2) best-in-class; (3) lowest price and (4) uniquely placed. The clustering is based on the concept of necessity of a well-differentiated and consistent image in successful branding strategies (Aaker and Joachimsthaler, 2000).

Marketing Pitch: Table 1 indicates the mapping of USP to the cluster of customers and items. The objective is to deliver the marketing attributes and features of the recommended items. Advertisements for the recommended items are to be made over the e-commerce web and mobile platforms. The recommended items are to be promoted over social media platforms and IETV (Internet-enabled television) supported by email campaigns, allowing the use of custom video messages and item images to supplement the campaign.

During email campaigning, the tips presented in Table 2 are to be kept in mind.

Selling Strategy for Customer Profile: Table 3 represents the mapping of the selling strategy to the customer cluster and items cluster. The objective is to build the customer profile in alignment with the customer cluster and items cluster from the perspective of the marketing

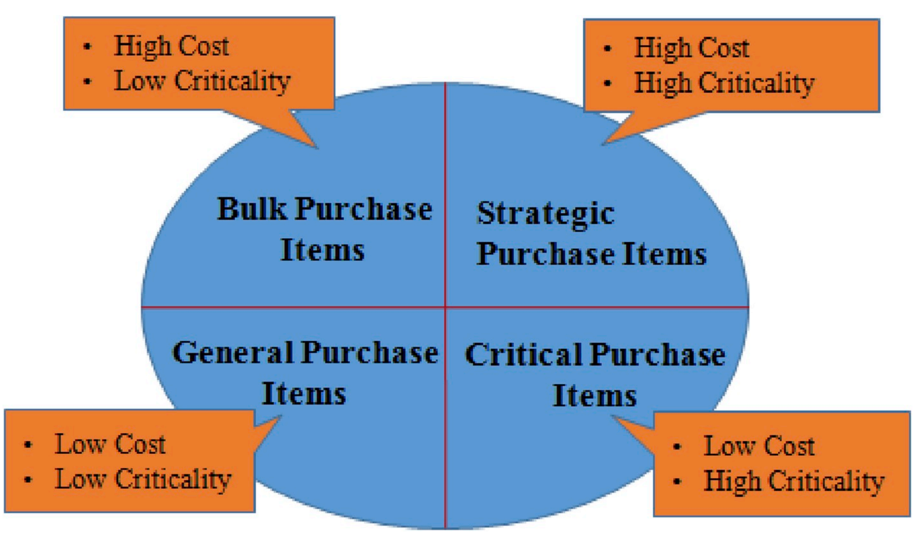

Fig. 5. Items cluster with characteristics.

Fig. 6. USP cluster with booster.

strategy. The selling strategies considered for this research are up-selling, cross-selling, best-in-class-selling, needs-satisfaction-selling and consultative-selling. Each of the selling strategies is inherently coupled with deal-of-the-day (DoD) offers and is based on the study by Ieva et al. (2018). The proposed up-selling and cross-selling selling strategies are based on the study by Dawson and Kim (2010).

4.2. Digital marketing recommendation process

The six-stage process suggests a progression of delivering recommended items, features and marketing attributes to customers. The stages are: (1) understand customers and the ratings of the items to be recommended; (2) understand the business rules defined by the domain rule setter; (3) understand the user buying pattern and build personalised preferences in real-time or near-real-time; (4) display personalised recommendation for online users; (5) display personalised recommendations for offline users and (6) understand and measure the impacts of the recommendations and adjust the personalisation strategy based on the feedback.

The process is illustrated in Fig. 7.

4.3. Proposed model

The proposed model is presented in Fig. 8 and depicts different components and interactions among those components.

4.3.1. Model touchpoints

Different touchpoints of the proposed model are as follows:

E-Commerce Web Site: The web platform where customers are expected to register and then login to purchase items and also to view the marketing attributes of the personalised recommended items. However, they can continue to purchase without registration and such customers are termed window-shoppers.

Mobile Application: The mobile platform where customers can register without using the web platform and then login to purchase items and also to view the marketing attributes of personalised recommended items. However, customers can continue to purchase without login.

IETVs: Televisions that connect directly to the internet to receive the promotion and advertisements for the personalised recommended items, based on the study by Wagner et al. (2017).

Social Media Site: The web and mobile social media platform to view the promotions of the personalised recommended items.

A customer may prefer some digital touchpoints for search and others for purchase or use a combination of search and purchase and hence, different touchpoints are proposed, based on the study of Singh and Swait (2017).

Transactional Preference Information System: The system for storage of users, items, business domain transaction data, user ratings of items and preference data (both raw and summarised) in a systematic and consistent way.

Marketing Information System: The system for storage of business rules data in a systematic and consistent way, e.g. business rules regarding cluster users, items, USP etc.

Recommender Engine: Recommends the personalised items and marketing attributes to the online users.

Auto E-mail Notifier: Recommends the personalised items and marketing attributes to the offline users. It can also involve word of mouth promotion.

4.3.2. e-Shopping touch points

The touchpoints in the e-shopping process comprise the personalised recommended items displayed in the user interface (UI) screen/page: (1) Home, (2) Item Category, (3) Item Detail, (4) Shopping Cart and (5) Order Confirmation.

4.3.3. Actors

Actors within the proposed model are as follows:

Customers or Users: Individuals or clusters of people who purchase items, rate the items and view the marketing attributes of recommended items.

Business Domain Rules Setter: Individuals or clusters of people who set the rules for the e-business, e.g. business rules to define clusters of users, items, USP etc.

4.3.4. Data model

The data model of the proposed recommendation engine is discussed in Appendix A.

4.3.5. Recommendation algorithm

The recommendation algorithms catering to different selling strategies and customers are presented in Table 4.

Table 1
USP marketing pitch.

	Cold-start customers	Window-shopping customers	Items-rated customers			
			Trivial customers	Service Vitality customers	Backscratcher customers	Nucleus customers
Strategic Purchase Items	Lowest price	Hassle-free	Uniquely Placed	Uniquely Placed	Uniquely Placed	Best-in-class
Critical Purchase Items	Uniquely Placed	Uniquely Placed	Hassle-free	Hassle-free	Uniquely Placed	Uniquely Placed
Bulk Purchase Items	Hassle-free	Lowest price	Hassle-free	Hassle-free	Uniquely Placed	Uniquely Placed
General Purchase Items	Lowest price	Lowest price	Lowest price	Lowest price	Lowest price	Hassle-free

Table 2
Email campaign tips.

Items Cluster	Tips
Strategic Purchase Items	Create desire and announce new about recommended items
Critical Purchase Items	Reinforce salespeople and enhance recommended items image
Bulk Purchase Items	Convince recommended items are the right for needs
General Purchase Items	Create awareness and take next steps about recommended items

5. Research design

A quantitative research methodology (QRM) was used for the experimental study and the data needed for the experimental study were collected from the primary source, i.e. a mid-size healthcare retailer based in India. In this QRM, the *t*-test statistical hypothesis test was used. One-tail and two-tail tests were used, keeping the significance level or tolerance level (α) to 5%. Two-tail testing was used to test the claim of revenue and AOV from the context of a known universe. One-tail testing was used to test the claim that the proposed methodology out-performs the existing methodology. As discussed in the e-marketplace design, customers are classified into items-rated, window-shopping and cold-start segments. Since window-shopping customers purchase items as guests without login to the system, personalised information is unknown and hence they are classified into an unknown universe. For this study, this unknown universe is excluded. The known universe includes items-rated and cold-start customers.

5.1. Sample selection

Convenience sampling was used and the model was trialled with 40 nucleus customers, 10 backscratcher customers, and 35 service vitality customers. Convenience sampling was used due to proximity and access to masked and basic data, and lack of access to the known universe. The customer clusters were based on the sales and profitability of the healthcare retailer. Based on the buying pattern, the study classified *nucleus customers* whose monthly transaction total is more than 50 K Indian Rupee (INR), *service vitality* customers whose monthly transaction is in the range of 10 K–50 K INR, and *backscratcher customers* whose monthly transaction is less than 10 K INR. Typically, Backscratcher customers are B2C. Items (i.e. medicines and devices) classification was done based on the MRP and criticality to B2C and B2B. Cost details of those items were not shared with the authors due to confidentiality. Since the model has proposed an items cluster, and due to lack of attributes in the primary data, an interview was conducted with a salesperson to understand the rationale on performing such clustering. After the interview, it was concluded that, for the purposes of this study, medical devices are classified under strategic purchase items and medicines purchased by B2C are classified under general purchase items. Medicines purchased by B2B customers are classified under critical purchase and bulk purchase items, depending on the cost and volume. USPs for B2B customers involved in the procurement of medical devices and medicines is classified as hassle-free. USPs for B2C customers are classified under lowest price or best-in-class, depending on the medicines. USPs for B2B customers involved in the procurement of medicines only classified under uniquely-placed. This classification was performed purely in the context of the case-study retailer, and may vary according to different industries.

In order to validate the proposed model, a binary recommendation (the item was either liked, i.e. 1, or not, i.e. 0, by the user) was considered. Let P(u,i) be the predicted recommendation and O(u,i) be the observed recommendation of a user u out of m, and for an item i out of n, then the number of correct suggestions is defined in Equation (5).

$$\#\text{correct recommendation} = \sum_{u=1}^{m}\sum_{i=1}^{k} \mathrm{p}(\mathrm{u},\ \mathrm{i}) \equiv 0(\mathrm{u},\ \mathrm{i}) \tag{5}$$

The predicted recommendation and the observed recommendation were collected for nucleus, backscratcher, and service vitality customers on strategic purchase, general purchase, critical and bulk purchase items.

5.2. Data and summary statistics

One month of convenience sample masked data (for August 2018) was collected for 100 customers before the implementation of the proposed approach, and three months (September 2018 to November 2018) of convenience sample masked data were collected for similar customers after the implementation of the proposed approach. Masked data collected from the retailer were related to revenue and AOV. Data for each month were recorded in three different date slots. Slot 1 is from the 1st to the 10th day of the month, slot 2 from the 11th to the 20th day of the month, and slot 3 from the 20th to the last day of the month.

Revenue summary statistics from the convenience sample and known universe with a 5% significance level, recorded in Aug 2018, are presented in Table 5. AOV summary statistics for the convenience sample and the known universe, with 5% significance level, recorded on Aug 2018 are presented in Table 6. Data for the known universe are presented using a descriptive statistical form with a two-tailed test. The null hypothesis (H_0) is the mean of the convenience sample, which is equal to the mean of known universe, and the alternative hypothesis (H_a) is the mean of the known universe, which is either greater or less than mean of the convenience sample. A p-value or significance level (α) less than or equal to 5% signifies 95% confidence on the upper and lower values of the known universe and indicates that there is good reason to reject the null hypothesis.

Subsequent to the deployment of the proposed approach, data were recorded for the months with the taxonomy settings presented in Table 7. These data were used to answer the following questions: (1) whether the proposed RE model results in growth in revenue and the

Table 3
Selling strategy for customer profile.

	Cold-start customers	Window-shopping customers	Items-rated customers			
			Trivial customers	Service Vitality customers	Backscratcher customers	Nucleus customers
Strategic Purchase Items	B-I-C-S	CO-S	B-I-C-S	B-I-C-S	B-I-C-S	N-S-S
Critical Purchase Items	B-I-C-S	CO-S	N-S-S	N-S-S	B-I-C-S	B-I-C-S
Bulk Purchase Items	B-I-C-S	CO-S	B-I-C-S	U-S and C-S	N-S-S	C-S
General Purchase Items	B-I-C-S	CO-S	C-S	U-S and C-S	U-S and C-S	U-S and C-S

Legend: CO-S (consultative-selling), B-I-C-S (best-in-class-selling), N-S-S (needs-satisfaction-selling), U-S (up-selling), C-S (cross-selling).

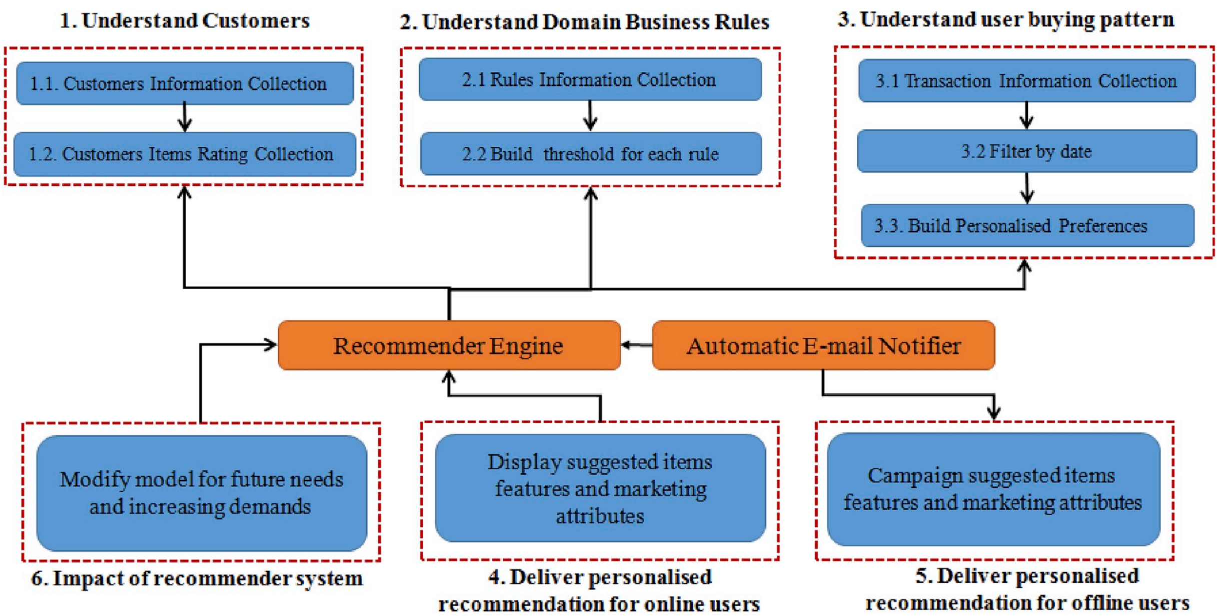

Fig. 7. Stages of digital marketing recommended process.

quantum of growth; (2) whether the proposed RE model results in growth in AOV and the quantum of growth; and (3) whether the proposed model outperforms existing recommendation approaches.

Revenue summary statistics for the convenience sample and known universe with 5% significance level, recorded from Sept 2018 to Nov 2018, are presented in Table 8. AOV summary statistics for the convenience sample and known universe with 5% significance level, recorded from Sept 2018 to Nov 2018, are presented in Table 9. Data for the known universe are presented using descriptive statistics with a two-tailed test. The null hypothesis (H_0) is that the mean of the convenience sample is equal to the mean of the known universe and the alternative hypothesis (H_a) is that the mean of the known universe is either greater or less than mean of the convenience sample. A p-value or significance level (α) less than or equal to 5% signifies 95% confidence on the upper value and lower values of the known universe and provides good reason to reject the null hypothesis.

For the performance evaluation of the model, the predicted and observed recommendation data were collected at different times and are presented in Table 10. The data was recorded by adopting A/B testing (i.e. two version of the user interface used for data capture).

According to Santra and Christy (2012), a confusion matrix contains data about the predicted and observed recommendations of the RE according to four standard terms, namely True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). TP are the cases where both predicted and observed values are 1, TN are the cases where predicted is 0 and observed is 1, FP are the cases where predicted is 1 and observed is 0, and FN are the cases where predicted is 0 and observed is 0. Data recorded for such an analysis is presented in Table 11.

Legend: NC: Nucleus Customers, BC: Backscratcher Customers, and SVC: Service Vitality Customers.

6. Results

Results of the experimental pilot study are presented below to indicate effectiveness, efficiency, testing of the propositions and performance evaluation, before a final summary.

6.1. *Effectiveness*

Effectiveness of the proposed approach is measured with the mean difference of revenue and AOV for the timeframe September to November 2018 in comparison with August 18, with a breakdown for the three different timescales. The mean difference for revenue is presented in Table 12 and AOV is presented in Table 13. The difference is highlighted in bold. It can be observed that the difference is positive in

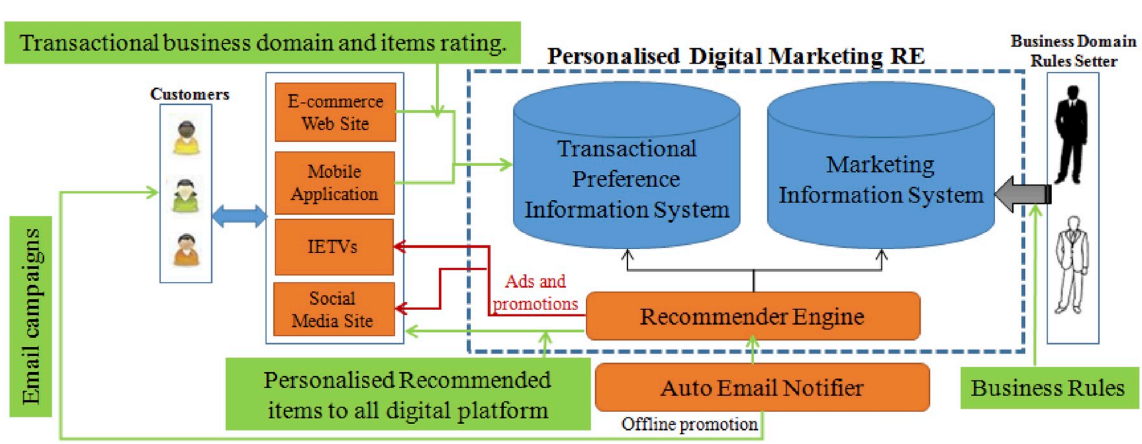

Fig. 8. Personalised digital marketing recommender system.

Table 4
Recommendation algorithm appendix.

Sr No.	Recommendation Algorithm	Appendix
1	Create personalised marketing pitch for a customer	C
2	Create personalised marketing pitch for a window-shopping customer	D
3	Create personalised marketing pitch for a cold-start customer	E
4	Create personalised marketing pitch for an items-rated customer	F
5	Create personalised marketing pitch using best in class selling strategy	G
6	Create personalised marketing pitch using needs satisfaction selling strategy	H
7	Create personalised marketing pitch using up-selling strategy	I
8	Create personalised marketing pitch using cross-selling strategy.	J
9	Recompute the revised price of the recommended items using DoD	K

Table 5
Revenue summary statistics recorded for aug 2018

Monthly Slot	Parameter▼	NC	BC	SVC
1st	*Convenience Sample*			
(1st–10th)	Mean	101.03	4.6	21.46
	SD	11.16	3.38	13.71
	Max	119	10	44
	Min	78	0	1
	Known Universe			
	p-Value	< 0.001	< 0.001	< 0.001
	Upper	104.59	5.99	26.16
	Lower	97.45	3.20	16.74
2nd	*Convenience Sample*			
(11th–20th)	Mean	102.43	3.6	27.37
	SD	19.42	3.34	14.05
	Max	131	10	50
	Min	78	0	3
	Known Universe			
	p-Value	< 0.001	< 0.001	< 0.001
	Upper	107.19	4.97	32.19
	Lower	97.65	2.22	22.54
3rd	*Convenience Sample*			
(21st–last day)	Mean	106.18	4.36	24.29
	SD	21.23	2.98	15.64
	Max	181	10	50
	Min	80	0	2
	Known Universe			
	p-Value	< 0.001	< 0.001	< 0.001
	Upper	112.96	5.59	29.65
	Lower	99.38	3.12	18.91

Legend: SD: standard deviation, NC: Nucleus Customers, BC: Backscratcher Customers, and SVC: Service Vitality Customers.

Table 6
AOV Summary Statistics recorded for Aug 2018

Monthly Slot	Parameter▼	NC	BC	SVC
1st	*Convenience Sample*			
(1st–10th)	Mean	9.03	2.24	5.26
	SD	6.58	1.76	2.76
	Max	20	5	10
	Min	0	0	1
	Known Universe			
	p-Value	< 0.001	< 0.001	< 0.001
	Upper	11.12	2.96	6.20
	Lower	6.92	1.51	4.30
2nd	*Convenience Sample*			
(11th–20th)	Mean	11.70	2.6	6.06
	SD	6.51	1.53	2.36
	Max	20	4	10
	Min	1	0	1
	Known Universe			
	p-Value	< 0.001	< 0.001	< 0.001
	Upper	13.78	3.23	6.86
	Lower	9.61	1.96	5.24
3rd	*Convenience Sample*			
(21st–last day)	Mean	9.30	1.96	5.09
	SD	5.98	1.65	2.77
	Max	20	5	10
	Min	0	0	1
	Known Universe			
	p-Value	< 0.001	< 0.001	< 0.001
	Upper	11.21	2.63	6.03
	Lower	7.38	1.28	4.13

Legend: SD: standard deviation, NC: Nucleus Customers, BC: Backscratcher Customers, and SVC: Service Vitality Customers.

all cases and hence it can be concluded that the proposed approach is effective.

6.2. Efficiency

Efficiency of the proposed approach is measured with the existing UBCF (Sarwar et al., 2000) and the IBCF (Deshpande and Karypis, 2004; Dou et al., 2016). The mean of revenue and AOV for the time-frame September, October and November 2018, with a breakdown across the three different timescales, was measured as per the taxonomy shown in Table 14. The mean for revenue is presented in Table 12 and AOV is presented in Table 15.

It can be observed that the mean of our proposed approach is greater than the existing approaches and hence it can be concluded that the proposed approach is efficient. The comparison for revenue is presented in Table 16 and that for AOV is presented in Table 17.

6.3. Performance evaluation and comparison

The study by Portugal et al. (2018) reveals that Precision, Recall, F-measure and Accuracy are the most commonly used performance metrics used for performance evaluation. Each performance metric is

Table 7
Timing of taxonomy setting.

Month	Monthly Slot	Approach
Sept 18	1st (1st-10th)	Our proposed approach
	2nd (10th-20th)	User based collaborative filtering (UBCF)
	3rd (20th-last date)	Item based collaborative filtering (IBCF)
Oct 18	1st (1st-10th)	IBCF
	2nd (10th-20th)	Our proposed approach
	3rd (20th-last date)	UBCF
Nov 18	1st (1st-10th)	UBCF
	2nd (10th-20th)	IBCF
	3rd (20th-last date)	Our proposed approach

defined in the study by Santra and Christy (2012) and the results obtained from applying these metrics are presented below.

$$\text{Accuracy(RE)} = \frac{\text{TP} + \text{FN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}}$$

$$\text{Re call(RE)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Precision(RE)} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Table 8
Revenue summary statistics recorded from Sept 2018 to Nov 2018

Month	Monthly Slot	Parameter▼	NC	BC	SVC
Sep 18	1st	*Convenience Sample*			
	(1st – 10th)	Mean	137.15	6.44	32.82
		SD	22.691	3.652	15.664
		Max	185	13	64
		Min	91	0	8
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	144.43	7.94	38.20
		Lower	129.91	4.93	27.44
	2nd	*Convenience Sample*			
	(11th – 20th)	Mean	136.22	5.08	33.17
		SD	21.882	3.510	14.055
		Max	177	12	59
		Min	79	0	4
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	143.22	6.52	37.99
		Lower	129.22	3.63	28.34
	3rd	*Convenience Sample*			
	(21st – last day)	Mean	138.2	6	31.42
		SD	27.366	3.188	16.516
		Max	214	13	64
		Min	86	0	5
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	146.95	7.31	37.10
		Lower	129.44	4.68	25.75
Oct 18	1st	*Convenience Sample*			
	(1st – 10th)	Mean	131.45	5.52	29.14
		SD	20.673	3.501	14.352
		Max	164	12	58
		Min	90	0	1
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	138.06	6.96	34.07
		Lower	124.83	4.07	24.21
	2nd	*Convenience Sample*			
	(11th – 20th)	Mean	135.27	4.76	34.08
		SD	25.525	3.192	14.494
		Max	190	11	63
		Min	84	0	7
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	143.43	6.07	39.06
		Lower	127.11	3.44	29.10
	3rd	*Convenience Sample*			
	(21st – last day)	Mean	138.65	5.04	29.68
		SD	28.508	3.128	16.3
		Max	221	11	59
		Min	92	0	5
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	147.76	6.33	35.28
		Lower	129.53	3.74	24.08
Nov 18	1st	*Convenience Sample*			
	(1st – 10th)	Mean	129.37	5.64	29.91
		SD	21.695	3.352	15.38
		Max	175	12	58
		Min	91	0	3
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	136.31	7.02	35.19
		Lower	122.43	4.25	24.62
	2nd	*Convenience Sample*			
	(11th – 20th)	Mean	136.17	4.92	33.88
		SD	21.871	3.377	15.101
		Max	182	11	63
		Min	97	0	7
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	143.16	6.31	39.07
		Lower	129.18	3.52	28.69
	3rd	*Convenience Sample*			
	(21st – last day)	Mean	139.25	5.48	33.88
		SD	33.996	3.124	16.453
		Max	239	12	64
		Min	85	1	9
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	150.12	6.76	38.08
		Lower	128.37	4.19	26.77

Legend: SD: standard deviation, NC: Nucleus Customers, BC: Backscratcher Customers, and SVC: Service Vitality Customers.

Table 9
AOV Summary Statistics recorded from Sept 2018 to Nov 2018

Month	Monthly Slot	Parameter	NC	BC	SVC
Sep 18	1st	*Convenience Sample*			
	(1st – 10th)	Mean	11.42	4.48	6.94
		SD	6.64	1.682	2.848
		Max	24	7	13
		Min	2	1	1
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	13.54	5.17	7.92
		Lower	9.3	3.78	5.96
	2nd	*Convenience Sample*			
	(11th – 20th)	Mean	12.17	3.12	6.31
		SD	6.586	1.66	2.08
		Max	21	5	10
		Min	1	0	2
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	14.28	3.80	7.02
		Lower	10.06	2.43	5.59
	3rd	*Convenience Sample*			
	(21st – last day)	Mean	12	2.52	6.37
		SD	6.168	1.782	2.766
		Max	24	6	12
		Min	3	0	2
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	13.97	3.25	7.32
		Lower	10.02	1.78	5.42
Oct 18	1st	*Convenience Sample*			
	(1st – 10th)	Mean	11.7	2.76	6.78
		SD	6.509	1.832	3.218
		Max	24	6	13
		Min	1	0	1
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	13.78	3.51	8.17
		Lower	9.61	2	5.39
	2nd	*Convenience Sample*			
	(11th – 20th)	Mean	14.32	3.04	7.91
		SD	6.486	1.513	2.728
		Max	23	5	12
		Min	3	0	3
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	16.39	3.66	9.09
		Lower	12.25	2.41	6.73
	3rd	*Convenience Sample*			
	(21st – last day)	Mean	11.85	2.44	6.65
		SD	6.286	1.733	2.515
		Max	24	5	12
		Min	1	0	2
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	13.86	3.15	7.73
		Lower	9.83	1.72	5.56
Nov 18	1st	*Convenience Sample*			
	(1st – 10th)	Mean	11.44	2.92	6.60
		SD	6.692	1.777	3.011
		Max	24	6	12

(*continued on next page*)

Table 9 (*continued*)

Month	Monthly Slot	Parameter	NC	BC	SVC
		Min	1	0	1
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	13.64	3.65	7.91
		Lower	9.24	2.18	5.3
	2nd (11th – 20th)	*Convenience Sample*			
		Mean	12.26	3.08	7.13
		SD	6.391	1.552	2.865
		Max	21	5	12
		Min	1	0	2
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	14.36	3.72	8.36
		Lower	10.16	2.43	5.89
	3rd (21st – last day)	*Convenience Sample*			
		Mean	11.94	3.84	6.73
		SD	6.277	1.7	2.865
		Max	23	6	12
		Min	3	1	2
		Known Universe			
		p-Value	< 0.001	< 0.001	< 0.001
		Upper	14.01	4.54	7.87
		Lower	9.88	3.13	5.6

Legend: SD: standard deviation, NC: Nucleus Customers, BC: Backscratcher Customers, and SVC: Service Vitality Customers.

Table 10
Predicted and observed recommendation data collection timing.

Month	Monthly Slot	Approach
Sept 18	1st (1st-10th)	Our proposed approach
Oct 18	3rd (20th-last date)	UBCF
Nov 18	2nd (10th-20th)	IBCF

Table 11
Predicted and observed recommendation recorded data.

Month & Slot	Approach	Customer	TP	TN	FP	FN
Sept 18 and 1st	Our proposed approach	NC	1360	80	80	112
		BC	17	0	1	2
		SVC	294	14	17	25
		Sum	1671	94	98	139
Oct 18 and 3rd	UBCF	NC	1155	70	70	98
		BC	13	0	0	2
		SVC	281	13	17	24
		Sum	1449	83	87	124
Nov 18 and 2nd	IBCF	NC	1245	75	75	105
		BC	15	0	0	2
		SVC	299	14	18	26
		Sum	1559	89	93	133

$$\mathrm{F} - \mathit{Measure}(RE) = 2 * \frac{\text{Precision}(\text{RE}) * \text{Re call}}{\text{Precision}(\text{RE}) + \text{Re call}}$$

Table 18 presents a comparison of the performance of our approach against the existing approaches (UBCF, IBCF).

6.4. Summary of results

In summary, the results of the study suggests that the presence of personalised recommendations in digital channels leads to a more positive perception towards the business operating parameters such as sales, revenue, AOV etc. Personalisation appears to have an important positive customer relationship impact. Tables 19–21 present the relationship of our proposed approach to revenue, AOV, and IPO respectively.

Table 12
Effectiveness test for revenue.

Month	Monthly	Customer Segmentation Mean		
	Slot	NC	BC	SVC
Aug 18	1st	101.02	4.6	21.45
	2nd	102.425	3.6	27.37
	3rd	106.17	4.36	24.28
Sep 18	1st	137.17	6.44	32.82
		35.78%	**40%**	**53%**
	2nd	136.22	5.08	33.17
		33.06	**41.11%**	**21.29%**
	3rd	138.2	6	31.42
		30.16	**37.61%**	**29.41%**
Oct 18	1st	131.45	5.52	29.14
		30.12%	**20%**	**35.82%**
	2nd	135.27	4.76	34.08
		32.07%	**32.22%**	**24.53%**
	3rd	138.65	5.04	29.68
		30.59%	**15.60%**	**22.24%**
Nov 18	1st	129.37	5.64	29.91
		28.06%	**22.61%**	**39.41%**
	2nd	136.17	4.92	33.88
		32.95%	**36.67%**	**23.80%**
	3rd	139.25	5.48	32.42
		31.15%	**25.69%**	**33.53%**

Legend: NC: Nucleus Customers, BC: Backscratcher Customers, and SVC: Service Vitality Customers.

Table 13
Effectiveness test for AOV.

Month	Monthly	Customer Segmentation Mean		
	Slot	NC	BC	SVC
Aug 18	1st	9.02	2.24	5.27
	2nd	11.7	2.6	6.05
	3rd	9.3	1.96	5.08
Sep 18	1st	11.42	4.48	6.94
		26.59%	*100%*	*32.07%*
	2nd	12.17	3.12	6.31
		4.06%	*20%*	*4.25%*
	3rd	12	2.52	6.37
		29.03%	*28.57%*	*25.28%*
Oct 18	1st	11.7	2.76	6.78
		29.64%	*23.21%*	*29.02%*
	2nd	14.32	3.04	7.91
		22.44%	*16.92%*	*30.64%*
	3rd	11.85	2.44	6.65
		27.42%	*24.49%*	*30.80%*
Nov 18	1st	11.44	2.92	6.60
		26.84%	*30.36%*	*25.71%*
	2nd	12.26	3.08	7.13
		4.81%	*18.46%*	*17.72%*
	3rd	11.94	3.84	6.73
		28.47%	*95.92%*	*32.51%*

Legend: NC: Nucleus Customers, BC: Backscratcher Customers, and SVC: Service Vitality Customers.

Fig. 9 presents the performance comparison of the proposed model with IBCF and UBCF.

6.5. Test summary

Table 22 depicts a summary of the test results of this study.

Hypothesis H1 (based on revenue) and Hypothesis H2 (based on AOV) are tested and presented in Tables 14 and 15, respectively. Hypothesis H3 (based on IPO) is tested mathematically with the existing theory: IPO = Sales/AOV, wherein sales are the major source of revenue. The statically significant of all three hypotheses is strong as the p-value is less than 0.001.

Table 14
Efficiency test for revenue.

Approach	Customer	Revenue			Mean
		Month and Monthly Slot			
Our proposed approach		Sep-1st	Oct-2nd	Nov-3rd	
	NC	137.17	135.27	139.25	137.23
	BC	6.44	4.76	5.48	5.56
	SVC	32.82	34.08	32.42	33.1
UBCF		Sep-2nd	Oct-3rd	Nov-1st	
	NC	136.22	138.65	129.37	134.74
	BC	5.08	5.04	5.48	5.2
	SVC	33.17	29.68	32.42	31.75
IBCF		Sep-3rd	Oct-1st	Nov-2nd	
	NC	138.2	131.45	136.17	135.27
	BC	6.0	5.52	4.92	5.48
	SVC	31.42	29.14	33.88	31.48

Legend: NC: Nucleus Customers, BC: Backscratcher Customers, and SVC: Service Vitality Customers.

Table 15
Efficiency test for AOV.

Approach	Customer	AOV			Mean
		Month and Monthly Slot			
Our proposed approach		Sep-1st	Oct-2nd	Nov-3rd	
	NC	11.42	14.32	11.94	12.56
	BC	4.48	3.04	3.84	3.78
	SVC	6.94	7.91	6.73	7.19
UBCF		Sep-2nd	Oct-3rd	Nov-1st	
	NC	12.17	11.85	11.44	11.82
	BC	3.12	2.44	2.92	2.82
	SVC	6.31	6.65	6.60	6.52
IBCF		Sep-3rd	Oct-1st	Nov-2nd	
	NC	12	11.7	12.26	11.98
	BC	2.52	2.76	3.08	2.78
	SVC	6.37	6.78	7.13	6.76

Legend: NC: Nucleus Customers, BC: Backscratcher Customers, and SVC: Service Vitality Customers.

Table 16
Revenue comparison of proposed approach with existing approaches.

Customer	Proposed Approach	UBCF	IBCF
NC	137.23	134.74	135.27
BC	5.56	5.2	5.48
SVC	33.1	31.75	31.48

Table 17
AOV comparison of proposed approach with existing approaches.

Customer	Proposed Approach	UBCF	IBCF
NC	12.56	11.82	11.98
BC	3.78	2.82	2.78
SVC	7.19	6.52	6.76

Table 18
Performance comparison of proposed approach with existing approaches.

RE	Accuracy	Recall	Precision	F-Measure
Our Approach	90.410%	92.320%	94.460%	93.378%
UBCF	90.247%	92.117%	94.336%	93.213%
IBCF	90.288%	92.139%	94.370%	93.242%

7. Discussion

This study aimed to understand how personalised recommendations in digital channels can fuel growth in revenue, AOV, IPO, and several findings were illuminated.

As we continue to step into the digital age, personalisation is a powerful and influential tool in which businesses discern what the customer wants to purchase before the individual thinks of it. While basic personalisation is relatively easy to realise, multidimensional personalisation, where an item recommendation shows up to the right customer, in the right place, at the right time and communicates the precise marketing content, is a little harder to achieve. But it is worthwhile, it is the focus of this study, and the results justify pursuing it.

It can be concluded from Table 19 that revenue experienced a significant and positive effect for the organization, with average monthly revenue showing 33.49% growth in a three-month time period. Our result on summarized revenue is in line with previous studies (Day, 1994, 2014; Wang et al., 2007; Morgan et al., 2009; Wiles et al., 2012; Rodgers and Thorson, 2018; Lee and Hosanagar, 2018). Moreover, this study paid attention to different customer clusters and clocked revenue growth per each cluster. It was observed that customers with high transaction, and sustain relationship with the seller contributes more revenue. It can be concluded from Table 20 that AOV experienced a significant and positive effect, and the average monthly AOV exhibits a 32.79% growth in the three-month time period. Our result on AOV is in line with the study by Lee and Hosanagar (2014). Moreover, this study paid attention to different customer clusters and clocked AOV growth per each cluster. It was observed that customers that results into high profitability to the business contributes more AOV. It can be concluded from Table 21 that IPO exhibited a significant and positive effect, and the average monthly IPO is measured at 1.93% growth over the three-month time period. Our result on IPO is in line with the study of Hargreaves (2011). Moreover, this study paid attention to different customer clusters and clocked IPO growth per each cluster. It was observed that customers that results into high profitability to the business and performs high transaction, contributes more IPO. It can be concluded from Fig. 9 that our proposed method outperforms the previous state-of-the-art, the IBCF and UBCF methodologies.

Previous researchers have emphasised the importance of personalisation (Kaynama and Black, 2000) and observed the helpfulness of personalised content to the quality of service in e-business and how it plays a role in affecting customer satisfaction (Szymanski and Hise, 2000) and buying intention (Shim et al., 2001). Our findings are in line with the above studies in terms of the observed growth in revenue and AOV, but in conjunction with different selling strategies. As such, this study attempted to shed light that personalised digital marketing: (1) brings traffic to the e-business by accomplishing customised e-mail messages and targeted blasts; (2) provides relevant information by analysing the customer's present use and previous browsing history, the engine can deliver appropriate suggestions. The data is gathered in real-time, so the engine can respond as the shopping habits change. (3) It engages users when individualised item suggestions are made by diving even more deeply into the items without the user needing to carry out search after search. (4) It increases AOV by showing tailored alternatives. (5) It reduces work and overload by utilising an engine to automate the e-purchasing process, reducing the workload for IT staff and budgeting. (6) It can boost number of items per order when the customer is shown options that fulfil their interest.

7.1. Theoretical contributions

In this digital age, scholars in numerous research areas have explored RE extensively, for example, in management, computer science, physics, sociology and so on (Lü et al., 2012). A series of studies has shown that the internet and the use of ICTs have completely transformed marketing strategies for business (Pires et al., 2006; Simintiras et al., 2015; Shiau et al., 2017). Research consistently suggests that marketing abilities can help to create an enduring competitive edge and contribute to companies' long-term profit and revenue growth (Day,

Table 19
Result summary for revenue.

Customer	Revenue								% Mean diff
	Month and Monthly Slot								
	Aug-1st	Aug-2nd	Aug-3rd	Mean	Sep-1st	Oct-2nd	Nov-3rd	Mean	
NC	101.25	102.24	106.17	103.22	137.17	135.27	139.25	137.23	32.95
BC	4.6	3.6	4.36	4.18	6.44	4.76	5.48	5.56	33.01
SVC	21.45	27.37	24.28	24.36	32.82	34.08	32.42	33.1	35.88
Revenue Mean				43.92				58.63	**33.49**

1994, 2014; Day, 2011; Wang et al., 2007; Morgan et al., 2009; Wiles et al., 2012). In increasingly competitive markets, determining which marketing proficiencies to develop and how these proficiencies should be promoted has become a notable, if elusive, question. In line with the above studies, we have identified the RE based approach to recommend personalised items. The findings are consistent with the above studies from the viewpoint of revenue, but may not hold true for profit, specifically for the customer clusters *service vitality* and *trivial*. Such customers always look for the opportunity to purchase items at a discounted rate. To improve sales and increase market capture, retailers often take a back-foot on profitability.

Till now, numerous "recommendation algorithms" have been presented. However, little focus was paid to studying and closely examining the effect of delivering marketing content with a recommendation process that accommodates different selling strategies. Very good recommendation of items, meeting expected accuracy, can be achieved only for items-rated customers. However, e-business can't reach its maximum potential by targeting only items-rated customers, but must attract new customers, retain them and encourage them to take specific actions to achieve an increase in the conversion rate. Hence, it is vital to recommend items correctly and appropriately, meeting individual needs and interests, and delivering individualised messages and offerings. In this paper, we have studied the relevance of such customer clusters and find that a correlation exists between the items and USPs, and such a correlation leads to the delivery of individualised messages and offerings to current or prospective customer base. To our knowledge, our paper is one of the first attempts to offer personalisation services using customer-friendly selling strategies such as up-selling, cross-selling, best-in-class-selling, needs-satisfaction-selling and consultative-selling with inherently coupled DoD offers.

7.2. Managerial implications

The current study offers insights for marketers and managers who may be interested in taking advantage of the benefits of the recommender engine and explains why they should pay attention. However, the greatest promise of recommendation engines will be realised by building a self-improving system, i.e. given a sufficient stream of data it can better satisfy customers over time.

In everyday life, we choose, for example, a bank based on suggestions by recommendation letters, word of mouth (WoM) and reviews printed in newspapers or general surveys. However, such a method (Mooney, 2018; Hamel, 2018) is often slow to diffuse and it can take an even longer time to build a relationship with customers. Further, it is limited in the number of potential customers, is inefficient in thoroughly tracking the amount of business generated, is inefficient at preventing bad experiences, and does not offer advice and direction to customers. Overall, such method clearly lacks personalisation. Personalised marketing is not only important for selling the items, but also in creating long-term customers.

The model developed in this study has major managerial consequences. The model including personalisation can enable a research company to appreciate the importance of personalised marketing in order to improve its marketing processes and dynamic capabilities in order to gain a permanent competitive advantage (Dangi and Malik, 2017).

The results indicate that marketing in one digital channel could lead to higher costs in another digital channel, therefore the profits and benefits generated by various digital touchpoints should not be evaluated in isolation (Kumar et al., 2016).

However, personalisation is an essential and necessary condition for achieving an online performance benchmark. The personalised marketing content should be designed with consideration of the lasting goal of building the brand.

From the various findings, it can be inferred that the personalised marketing is not homogenous across demographic boundaries. When designing a personalised marketing scheme to achieve efficiency and effectiveness, there are other attributes and their attributes that the Business Domain Rules Setter should consider. For example, it can be refined by considering the employment categories of customers, such as government worker, non-government worker, self-employed, and jobless.

An e-business can reasonably be recommended to implement the system described, with the expectation that it and would bring adequate returns to justify the investment. The increasing importance of providing a personalised online experience is highlighted in a survey by Econsultancy and Monetate (2013), in which 94% of companies said that personalisation is critical to current and future successes. In addition, research found that improved business performance and customer experience are the main drivers for customising the website experience for two-thirds (66%) of customer side respondents. The proof of the pudding is in the eating, and personalisation can elevate the

Table 20
Result summary for AOV.

Customer	AOV								% Mean diff
	Month and Monthly Slot								
	Aug-1st	Aug-2nd	Aug-3rd	Mean	Sep-1st	Oct-2nd	Nov-3rd	Mean	
NC	9.02	11.7	9.3	10	11.42	14.32	11.94	12.56	25.60
BC	2.24	2.6	1.96	2.26	4.48	3.04	3.84	3.78	67.26
SVC	5.25	6.05	5.08	5.46	6.94	7.91	6.73	7.19	31.68
AOV Mean				5.9				7.84	**32.79**

Table 21
Result summary for IPO.

Customer	IPO							
	Month and Monthly Slot							Mean
	Aug-1st	Aug-2nd	Aug-3rd	Mean	Sep-1st	Oct-2nd	Nov-3rd	
NC	11.22	8.73	11.41	10.45	12.01	9.44	11.66	11.04
BC	2.05	1.38	2.22	1.88	1.43	1.56	1.42	1.47
SVC	4.08	4.52	4.77	4.46	4.72	4.30	4.81	4.61
IPO Mean				**5.60**				**5.71**

Average Monthly IPO = (5.71 – 5.60)/5.60 = 1.93%.

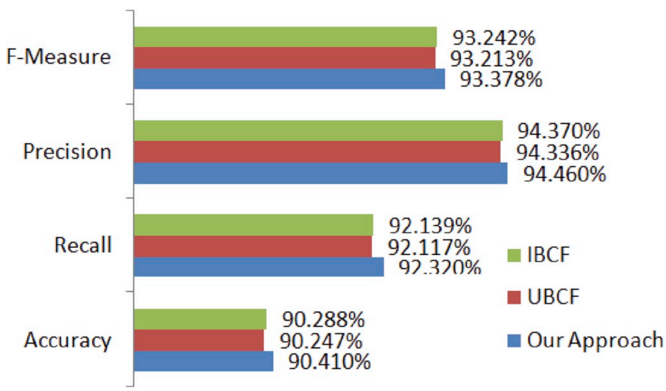

Fig. 9. Performance comparison of proposed model.

Table 22
Test summary.

Hypothesis/Proposition	Supported in Study	Statically Significant
Hypothesis H1 (Revenue)	Yes	Yes (Strong)
Hypothesis H2 (AOV)	Yes	Yes (Strong)
Hypothesis H3 (IPO)	Yes	Yes (Strong)

company to great heights. Even if the company does not yet have an online presence, it should be possible to start small and still work effectively. Increasingly, companies are attempting to improve their ROI using this technology in their marketing campaigns.

7.3. Social implications

RE can help customers to discover a wide range of items, including books, films, foods, music, electronic appliances, clothes etc, and because of the high commercial value of these items, it has been successfully deployed in the retail industry, for example in Amazon's product recommendations, iTunes music recommendation, Netflix's film recommendation, etc. By creating “social friendship” it boosts happiness and reduces stress, thus improving the consumer's self-confidence and self-worth.

Sometimes, the customer purchases RE-suggested items by accident (e.g. the item is on sale and seems like good value for a customer; the customer purchases, and if it's not the right color or fit, they return it). A well-designed returns policy implementation in the RE leads to an increase in purchases and results in a positive effect on customer behavior.

Sensitive personal information must be treated with great care, as misuse or security breaches can result in identity theft, financial fraud, and other problems that collectively have an adverse impact on people, businesses and governments, for example, in the form of a government fine, forced resignation, etc. Therefore, RE must ensure the security of such personal information.

8. Conclusion

The paper has presented a new approach involving real-time personalised marketing of items in digital media using RE, making use of a blend of selling strategies including up-selling, cross-selling, best-in-class-selling, needs-satisfaction-selling, and consultative-selling. The proposed framework comprises three building blocks, namely e-marketplace design, the marketing model, and the recommendation process. In designing the e-marketplace, different clusters were formed, namely, customers, items and the USP, and then the marketing pitch and selling strategies were proposed. A 6-stage process was proposed depicting the progression of delivering recommended items' features and marketing attributes to the customers. A model was proposed highlighting the different components, actors, data model, and the recommendation algorithm. The theoretical background of the model and the building blocks of the theory were presented along with five propositions. The study revealed that items should be recommended to the customer based not on assumptions or guesswork, but rather based on their buying pattern, i.e. items that have been repeatedly investigated, or observed, and purchased. Personalised marketing will make the customer feel as if their mind has been read and have a mammoth impact on the overall e-shopping experience across different digital channels. The conclusion can be drawn that personalisation marketing in digital channels can bring benefits to the business. Some small scale business has so far failed to clearly understand the benefits of personalisation on performance. Such businesses must appreciate that personalisation includes the performance of personalised marketing, personalised marketing out-turn, customer value and market value. Both the value for the customer and the value for the marketer increase in terms of both profit and cost margin.

8.1. Limitations

The study has presented several interesting insights. However, it has few limitations. A small data set was considered for the experimental study and was captured from one healthcare retailer operating in multiple locations in India. The research was limited to a particular set of technology. Privacy concern is the barrier in online shopping and should be investigated and is beyond the purview of this study. Other limitations are addressed in the future research agenda.

8.2. Future research agenda

Organisations have different approaches to personalisation. The real goal of personalisation is to increase the probability of organisation success through customer satisfaction by improving performance at the touchpoints. Businesses should perhaps introduce new types of personalisation slowly while keeping an eye on technical challenges. Over time, it is recommended to monitor the roles of customers. Further research is definitely warranted, and questions that researchers might consider are: how to measure the attitudes of the customers towards personalisation? What are the other real benefits that can be achieved through personalisation? Moreover, it is important to analyse the circumstances under which personalisation does not bring benefits to the organisation, along with how hyper-personalisation techniques or tools can be adopted by the companies – going beyond the customer data to determine how it can tailor future shopping experiences, how hyper-personalisation techniques can deliver better results in comparison to personalisation techniques. We put forward two propositions based on our work that can be tested using primary or secondary data for future work.

Proposition 1 (P1): To improve digital marketing performance, conversation rate plays a significant role (Chaffey and Patron, 2012). Hence, the proposition is: the more the business performs personalised digital marketing, the greater is the increase in conversion rate, as represented in Equation (6). A high rate of conversion means that people want what they offer and they can easily get it.

$$\text{PDR(C, I, USP, USP Marketing Pitch, Selling Strategies)} \propto \text{increase in Conversion Rate} \ldots \quad (6)$$

Proposition 2 (P2): Skinner (2000) states that by saving time and reducing staff numbers, sellers can achieve cost savings in "finding new customers" and reducing "administration costs." Hence, the proposition is: the more the business performs personalised digital marketing, the higher the rate of staff time saving, as represented in Equation (7). Using support staff to assess each and every customer can be difficult, daunting and time-consuming and the key is to save their time. A higher value means greater reduction of operational expenses such as cost of recruiting, hiring and training, and improving productivity through a variety of means, yielding the best possible returns.

$$\text{PDR(C, I, USP, USP Marketing Pitch, Selling Strategies)} \propto \text{\% Staff Time saving} \ldots \quad (7)$$

The authors hope that this paper will guide and inspire future research on personalised marketing focusing on Recommender Engine. We hope that the problems presented in this paper will help the marketing function to discuss the next generation of recommendation technologies for more effective personalised recommendations.

Appendix A

Table A1
Literature Review of existing conventional approach of digital marketing.

Reference	Findings	Outcomes	Limitations	Context	Methodology
Baker et al., 2018	Demonstration on how luxury companies can utilize Information Technology (IT) for marketing strategies and improvement of brand equity, customer satisfaction and corporate performance by the systemic approach in using IT.	The preservation of the unique image of the luxury brand in the Internet's mass media is a fundamental challenge.	The literature on the luxury firms is fragmented and the study addresses the internet dilemma instead of cause-effect relationship.	Luxury brand items in luxury firms and embracing with internet technologies.	Qualitative investigation.
Dangi & Malik (2017)	Described the concept of personalization by synthesising various perspectives on personalization by analysing key themes, components and approaches in literature and highlighted customers' attitudes towards personalization.	Personalisation in marketing offers tremendous opportunities in the years ahead.	The study was based on the literature survey and some other important papers may have been missed.	Personalisation in e-commerce	Extensive and critical literature review
Dawson & Kim (2010)	Proposed that internet retailers repeatedly carry out "up-selling" and "cross-selling" promotions through items recommendations.	Types of external impulse trigger signals that have often been used on websites for apparel.	Sample websites are used for the content analysis and such sample cannot be generalized to all apparel web sites.	Investigation of external cues on apparel web sites.	Focus group interviews.
Di Fatta et al., 2018	Strategy focusing on quality or promotion and prevention of those facets from being mixed into the website offer is the key factor in improving the conversion rate.	The impact of conversion rates of mainstream and luxury products differ.	Information loss during data aggregation and some antecedent factors affecting the amount of traffic were not considered.	Identification and analysis of the factors in improving the conversion rate for web retailers.	Exploratory regression analysis and qualitative comparative analysis.
Fuentes et al. (2017)	Examined and conceptualized how smartphone integration as a digital device reconfigures the retail landscapes of stores and their implications for retailers and consumers. The integration of the digital device reorganizes shopping activities, and as a result, new information landscapes, social landscapes and experience landscapes unfolded.	Shopping activities have been reconfigured using smart phones.	The study didn't call out the negative implication of mobile shopping	Retail digitization by examining how the integration of smart phones into in- store shopping reconfigures retail stores.	Combination of observations and interviews.
Hallikainen et al. (2018)	Among all digital touch points such as "websites, email, search engines, chat, social networks, photo and video content communities, discussion forums and blogs", digital touch points "email, websites, and search engines" are favored and the greatest difference lies in their readiness for overall technology.	The retailers should dedicate assets to the digital touch points that are most beneficial.	The choice of digital touchpoints limits the findings and a number of other options remain open. The digital touchpoints were studied at a general level and more deep attention is required into specific digital services	Individuals preferences for digital touchpoints in four distinct segments such as anti-digital, anti-social media, majority, and digital channel.	Extensive study.
Ieva et al. (2018)	Value sensible customers are less focused on deal-of-the-day (DoD), while dealers are further verisimilar to buy DoD, and enjoyment plays an	Younger customers buy supplemental DoD when they enjoy a pleasant shopping experience.	Did not test more complex relationships among independent variables and the outcome. The analysis is limited to the student population of a single university.	DoD website shopping.	Online survey

(*continued on next page*)

Table A1 (*continued*)

Reference	Findings	Outcomes	Limitations	Context	Methodology
	important role in young consumers shopping behavior.				
Kaneko et al. (2018)	Development of a design methodology to support providers of personalization.	The methodology of personalization design does not depend on human skills.	The relationship between each strategy and each pattern of personalization steps is not shown.	Personalization of products and services.	Case Study
Kim (2018)	Examined the effects of the presentation of digital products on the processing and behavioral intention of customer information in e-retail settings and concluded verbal stimuli varying in items descriptions were more effectual in evoking imagery and rambling processing than viewable stimulus varying in size.	How the digital environment influences the internal processes and the consumer's intention.	Relatively small sample size and lacks external validity, and thus generalization to other contexts needs caution.	e-retailing	Experimental study
Nisar & Prabhakar (2017)	For United States based e-commerce retailers, customer satisfaction affects consumer spending. The relationship between satisfaction of customers and consumer expenditure is positive, with increased e-satisfaction leading to more e-commerce. There is a direct link between "e-service quality, e-satisfaction and e-loyalty" when it comes to consumer online spending.	In United States, there is a high correlation between "Customer Satisfaction Index" and the "Customer Price Index".	Further analysis of technology-based service capabilities.	Customer satisfaction in e-commerce market	Regression and panel-data analysis
Pantano et al. (2018)	Retail industry is witnessing increasing number of technologies such as digital, mobile, absorptive and enveloping technologies to provide online platform for direct purchase from home 24/7	Sellers influence customers and their emotional involvement with the items and the shop.	Study was limited to five luxury companies adopting smart technologies and reinforced the generalizability of results. The selected companies didn't have innovation department to act digital ideas through the marketing strategies.	Smart retailing	Qualitative Approach
Park & Kim (2018)	Classified customers with their shopping patterns and channel preferences using data from Korean and US, who are on their path to purchase. Path-to-purchase factor is assessed to determine the differences between Korean and US consumers with regard to their shopping patterns.	Korean and U.S. consumers shopping patterns are considerably different.		Customer classification with respect to shopping patterns and channel preferences	Association Rule Mining and Social Network Analysis
Reydet & Carsana (2017)	Impact of digital design factors and the positive effect of mediation on two key marketing outcomes: commitment and customer loyalty. Digital factors have been shown to have an undeviating effect on positive effects but to have deviating influence on attitude. Between digital displays and these results, positive effects play a mediating role.	Digital design styles have favorable influences on customers and are capable of providing a service environment meeting needs of the customers.	There is a need to retest the framework to evaluate the temporal impact of digital design.	Influence of digital design factors and the mediating effect of positive effect on customer commitment and loyalty	Survey and quantitative approach.
Singh & Swait (2017)	Mobile and desktop devices differ in the digital channel in their usefulness in the search dimension. The chances of selecting channel combinations with mobile increases owing to the convenience of searching while the desktop is attractive due to perceived price comparison search gains.	Young consumers with previous mobile purchasing experience and higher "out- of- pocket" costs are prone to use mobile as a purchasing channel.	Lack of deeper insights into the extent of device switching and the time spent in each channel due to non-availability of longitudinal data on consumer search.	Mobile internet channel	Survey of random sample
Smith, 2011	Examined various commonly used marketing strategies in digital media and ascertains preferred ones by Millennials in influencing behavior.	Millennials can visit a website with relentless prices and good shipping rates on repeated occasions and write an online product review if an incentive is given.	Study was conducted on sample dataset and future research to include broader samples.	Marketing strategies that are commonly used in digital media.	Survey
Wagner et al. (2017)	Retailer could create online shopping more pleasant and convenient for customers by providing Internet-enabled television (IETVs) shopping app.	The strongest predictor of IETV's shopping outlook is parsimonious motivation.	The study was limited to a specific technology set and to a typical living room, and not a laboratory study.	Investigation of motivational factors of customer's attitudes and intention towards IETV.	Quasi-experimental study
Yan & Pei (2018)	Developed a new competition model "O2O (online to offline)" to address the use of competitive return policies to coordinate O2O distributions among the manufacturers. The traditional supply chain for retailers where	Fierce return policies can be used to coordinate and advance all supply chain players performance.	Manufacturer's brand reputation was not considered in the development of model and manufacturer's brand reputation to influence return policies decision was not examined.	Return policy adoption by firms to build long-term relationship with customers.	Quantitative research methodology.

(*continued on next page*)

Table A1 (*continued*)

Reference	Findings	Outcomes	Limitations	Context	Methodology
	the manufacturer opens a competitive online channel.				

Note: Few cells in the limitations column are left blank, as the author(s) did not explicitly call out in the study.

Table A2
Literature Review of Recommender Engine

Reference	Findings	Outcomes	Limitations	Context	Methodology
Ansari et al. (2000)	Examined the merits of content and/or collaborative filtering methods, and suggested the preference models offer excellent alternatives in marketing, and explain a Bayesian preference model for making recommendations with statistical integration of five types of information.	Recommend movies using Markov chain Monte Carlo methods with viable alternatives of collaborative filtering methods.		Recommendation of documents and products to consumers.	A collection of statistical methods
Bobadilla et al. (2009)	Explained that better knowledgeable users have a greater influence in the calculation of the recommendations than less knowledgeable users. To achieve the objective, new equations related to memory-based collaborative filtering were designed.	The e-learning recommender systems enable the importance of the recommendations generated by each user to be weighed according to their level of knowledge.	Experiments with an e-learning database were not carried out	e-learning recommender systems	Memory-based collaborative filtering based on statistical methods
Geuens et al. (2018)	Provided a framework in possibly guiding the marketers in the development of better “recommendation systems” and their attempts to find an appropriate “recommendation algorithm” to avoid trial and error procedures.	Finds the very accurately model and also provides an indication of different models diversity and calculation times.	A direct-imputation technique was not tested due to limitation in input matrix.	Recommendation based on binary purchase data for e-commerce companies.	Experimental Design
Gurini et al. (2018)	Proposed “people-to-people” system for recommending in social networks and the recommendation depends on identifying the attitudes of the users “sentiment, volume, and objectivity”.	The accuracy and diversity of the recommender increases with attitudes and temporal characteristics.		Recommendation in social network.	Extensive Offline experimentation
Hu et al. (2019)	Proposed a new “item-based recommendation” algorithm by capturing the “latent vector” of each item in unblemished space and capturing the dissimilarities and overlapping between consumers.	Improve the “quality and scalability” of the “item-based recommendation” through the development of a multi-view model.	The method used for the estimation is not optimal and further research is required to improve the efficiency of optimization process.	Items oriented recommendation.	Experimentation on three types of real-world datasets, namely movie, music and joke.
Hwangbo et al. (2018)	Developed a real-world recommendation utility by extending “item-based collaborative filtering” and reflecting the specific characteristics of the Korean based fashion industry.	When recommending fashion items, time and intent to buy are important.	The experiments cannot explain the effects of the use of online and offline data and the effects of preference decline over time.	Implementation of collaborative filtering recommendation system in a large Korean fashion company.	Experimentation with A/B test
Li (2009)	Proposed ECRec, a “collaborative filtering” based E-commerce recommender system.	ECRec has better portability, maintainability and open architecture characteristics.	Recommendation quality of ECRec	Recommender system for E-commerce website.	Conceptual
Liu et al. (2017)	Developed a new recommendation algorithm, i.e. a “P-FMSM”, founded on “mixed similarity” and “pair preference”.	Integrating two canonical approaches with two elements in a principle way recommends far better than up-to-the-minute methods.	Future study is to study the mixed similarity model in an extremely sparse case.	Novel recommendation algorithm with implicit feedback of user.	Experimental with public datasets
Mocean & Pop (2012)	Defined a new system, Marketing Recommender System (MRS) that serves marketing and uses techniques and methods of the digital market.	Link MRS, as a system with marketing information system and recommendation systems.		A recommendation system serving marketing using techniques of the digital economy.	Conceptual
Núñez-Valdez et al. (2018)	Described an e-book recommendation system and the approach is based on “implicit feedback”.	Benchmarked twelve popular “machine learning algorithms” in the evaluation of quality of the system output.	Limited sample size and the development of NLP in future research for the comments and other actions classification.	Recommendation system for e− books	Experimental
Sarwar et al. (2000)	Investigated several methods for analyzing large-scale purchase and preferential data in order to provide customers with useful recommendations. Various methods for different sub-processes and compositions are applied on large-scale data sets to evaluate the recommendation performance and quality.	Dimensionality reduction techniques promise that Collaborative Filtering based algorithms will be able to scale to large data sets while producing high quality recommendations.	Future work is required to understand how dimensionality reduction works well for specific application.	Recommendation System in e-commerce.	Experimentation on e-commerce and movie data.
Schafer et al. (1999)	Finds that recommendation engine increase electronic-commerce gross revenue in three ways namely, “browsers into buyers”, “cross-sell” and “loyalty”.	Recommender systems generate value both for electronic-commerce sites and their clients.		Recommender systems for e-commerce sites	Conceptual
					Experimental

(*continued on next page*)

Table A2 (*continued*)

Reference	Findings	Outcomes	Limitations	Context	Methodology
Šeleng et al. (2018)	Presented an approach addressing the defiance of inter- company cooperation by compiling e− mails as a tool to share information and automating the process of the insight gained from e-mails and their attachments.	The solution proposed is an advantage for collaborating companies.	Lack of focus on quantitative analysis	Inter-enterprise collaboration challenges.	

Note: Few cells of limitations column are left blank, as the author(s) didn't call out in the study.

Appendix B

Data model of the proposed personalised recommender engine for digital marketing is as follows:

Customer: ID, name, password, DOB (Date of Birth), DOR (Date of Registration), email, contact_no, address, employement_category, marital_status.

Item: ID, name, description, unit_price, cluster, image, video_message, return_policy, brand_message$_1$ … brand_message$_n$, feature 1 … feature$_n$.

Customer_Item_Rating: Customer_ID, Item_ID, rating.

USP: USP_ID, cluster, description, attribute$_1$ … attribute$_n$.

Purchase_Item: ID, Item_ID, purchase_date, qty, total_price.

Transaction: ID, Purchase_Item_ID, customer_ID, customer_cluster.

Item_DoD: ID, Item_ID, valid_from, valid_to, min_order_value, create_date, discount_value, discount_unit, max_discount_amount.

Personalised_Marketing_Pitch: Item_ID, item_cluster, Customer_ID, customer_cluster, USP_ID, USP_Cluster, USP_attribute$_1$ … USP_attribute$_n$, item_image, item_video_message, item_feature$_1$, …item_feature$_n$, item_brand_message$_1$, …item_brand_message$_n$, item_rating.

Appendix C

Algorithm 1. Create personalised marketing pitch for a customer.

```
Description: It returns the personalised marketing pitch by capturing recommended items for a customer using various selling strategies, outlined in Table 3. When a customer launched the shopping web portal or shopping mobile application or social media site, or IETV, or in case of offline email marketing, below algorithm should be invoked. This acts as the entry point for the overall system
Input: A customer Ck
Output: List of marketing pitch capturing personalised recommended items for the customer Ck
Procedure Recommend-Items (Ck: customer).
 BEGIN
 Let C is the list of customers stored in Transactional Preference Information System
 Let I is the list of items stored in Transactional Preference Information System
 //creating an empty data model list of type Personalised _Marketing_Pitch
 CREATE EMPTY PERSONALISED_MARKETING_PITCH data entity list V
 IF (Ck IS EMPTY OR Ck IS NULL) THEN//recommend for window-shopping customers
   SET WS = optional statement by customers on specific query
   CALL Algorithm 2 (V, WS)//Calling consultative selling strategy
   CALL Algorithm9 (V)//Check deal of the day and re-compute the items
   RETURN V//returns marketing pitch list capturing recommended items to the customer
 END IF
 FOR EACH Customer Ci ε C do
   IF (Ci NEQ Ck) THEN//if the customer Ci is not matching to customer Ck
     CONTINUE
   ELSE
     FOR EACH item Ij ε I do
       IF (Ck RATED POSITIVELY Ij) THEN//items are rated by the users
         POPULATE Ij and Ij USP fields to V
       END IF
     END FOR
     IF (V IS NOT EMPTY)
       SORT V by items rating for each cluster in descending order
       CALL Algorithm 3 (Ck, V)//recommendation for items-rated customers
     ELSE
       CALL Algorithm 4 (Ck, V)//recommendation for cold-start customers
     END IF
     CALL Algorithm9 (V)//Check deal of the day and re-compute the items
     RETURN V//returns marketing pitch list capturing recommended items to the customer
   END IF
 END FOR
END
```

Complexity Analysis: The worst case time complexity of the algorithm is O (m*n) where n is the number of registered users and m is the number of items available for sale. In case of huge data volume, it is recommended to use the distributed and parallel execution computing environment for faster delivery of personalised marketing contents.

Appendix D

Algorithm 2
Create personalised marketing pitch for a window-shopping customer.

Description: It returns the personalised marketing pitch by capturing recommended items for a window-shopping customer using consultative-selling strategy. Aim of the e-business is to convert window-shopping to speed-shopping as fast as possible, hence it is essential to define conversion quotient first and then take one step at a time to formulate a revised strategy. Since such customers are not registered and their items ratings are unknown, so 2 approaches can be followed initially. In default case, items with lesser price or items with larger discounted price can be recommended. If such customer provides wants through search option or posing questions in the shopping digital touchpoints such as web portal or mobile application etc, items matching to the wants should be recommended with the appropriate marketing pitch. This algorithm is called from Algorithm 1.
Input: PERSONALISED_MARKETING_PITCH list V and/or what statement (abbreviated as WS) by window-shopper.
Output: List of marketing pitch capturing recommended items for the window-shopper
Procedure Recommend-for-Window-Shopper-Customers (V: PERSONALISED_MARKETING_PITCH, WS: statement)
BEGIN
  Let I be the list of items stored in Transactional Preference Information System
  IF (WS IS NULL OR WS IS EMPTY) **THEN**
    FOR EACH cluster of item CI_j ε I do
      SORT items in CI_j BY unit price and popularity in ascending order
      POPULATE items fields to V
      POPULATE item's USP fields to V
    END FOR
  ELSE
    FOR EACH item I_j ε I do
        IF (NAME(I_j) **MATCHES** WS **OR** DESCRIPTION(I_j) **MATCHES** WS) **THEN**
          POPULATE I_j fields and I_j USP fields to V
        END IF
      END FOR
    END IF
    RETURN V//returns marketing pitch list capturing recommended items to the customer
END

Appendix E

Algorithm 4
Create personalised marketing pitch for a cold-start customer.

Description: The algorithm uses best-in-selling strategy and is called from Algorithm 1
Input: A customer C_k and PERSONALISED_MARKETING_PITCH LIST V
Output: List of marketing pitch capturing recommended items of a cold-start customer
Procedure Recommend-for-Cold-Start-Customers (C_k: customer, V: PERSONALISED_MARKETING_PITCH)
BEGIN
  Let I be the list of best selling items for a given date range
  FOR EACH item I_j ε I do
    POPULATE I_j fields and I_j USP fields to V
  END FOR
  RETURN V//returns marketing pitch list capturing recommended items to the customer
END

Appendix F

Algorithm 3
Create personalised marketing pitch for an items-rated customer.

Description: The algorithm uses different selling strategies, outlined in Table 3 and is called from Algorithm 1. In addition to the recommendation of the rated items, it does recommendation of supplementary items
Input: A customer C_k and PERSONALISED_MARKETING_PITCH list V
Output: List of marketing pitch capturing recommended items of an items-rated customer
Procedure Recommend-for-Items-Rated-Customers (C_k: customer, V: PERSONALISED_MARKETING_PITCH)
BEGIN
  Let I be the list of items available in V
  SET CC_k = CLUSTER (C_k)//In real-time, compute customer cluster for a given date range
  FOR EACH item I_j ε I do
    SET CI_j = CLUSTER (I_j)//finding the cluster of the item I_j
    IF (CI_j **MATCHES** "Strategic") **THEN**
      IF (CC_k **MATCHES** "Nucleus") **THEN**
        CALL Algorithm6 (C_k, V, I_j)//call needs-satisfaction-selling strategy
      ELSE
          CALL Algorithm5 (C_k, V, I_j)//call best-in-class selling strategy
        END IF
  ELSE IF (CI_j **MATCHES** "Critical") **THEN**
    IF (CC_k **MATCHES** "Trivial" OR CC_k **MATCHES** "Service Vitality") **THEN**
      CALL Algorithm6 (C_k, V, I_j)//call needs-satisfaction-selling strategy
    ELSE
      CALL Algorithm5 (C_k, V, I_j)//call best-in-class selling strategy
    END IF

(*continued on next page*)

Algorithm 3 (*continued*)

```
  ELSE IF (CI_j MATCHES "Bulk") THEN
    IF (CC_k MATCHES "Trivial") THEN
      CALL Algorithm5 (C_k, V, I_j)//call best-in-class selling strategy
    ELSE IF (CC_k MATCHES "Service Vitality") THEN
      CALL Algorithm7 (C_k, V, I_j)//call up-selling strategy
      CALL Algorithm-CS (C_k, V, I_j)
    ELSE IF (CC_k MATCHES "Backscratcher") THEN
      CALL Algorithm6 (C_k, V, I_j)//call needs-satisfaction-selling strategy
    ELSE
      CALL Algorithm8 (C_k, V, I_j)//call cross-selling strategy
    END IF
  ELSE//this is the case of general purchase item
    IF (CC_k MATCHES "Trivial") THEN
      CALL Algorithm8 (C_k, V, I_j)//call cross-selling strategy
    ELSE
      CALL Algorithm7 (C_k, V, I_j)//call up-selling strategy
      CALL Algorithm8 (C_k, V, I_j)//call cross-selling strategy
    END IF
  END IF
  END FOR
  RETURN V//returns marketing pitch list capturing recommended items to the customer
END
```

Appendix G

Algorithm 5
Create personalised marketing pitch using best in class selling strategy.

Description: The algorithm uses best in class selling strategy, outlined in Table 3 and is called from Algorithm 3. In addition to the recommendation of the rated items, it does recommendation of supplementary items similar to the given item cluster
Input: A customer C_k, an item I_j and PERSONALISED_MARKETING_PITCH list V
Output: List of marketing pitch capturing recommended items of an items-rated customer
Procedure Recommend-using-BICS (C_k: customer, V: PERSONALISED_MARKETING_PITCH, I_j: item)

```
BEGIN
  Let I be the list of best selling items available for a given date range
  SET CI_j = CLUSTER (I_j)//cluster of the item I_j
  FOR EACH item I_k ε I do
  SET CI_k = CLUSTER (I_k)//finding the cluster of the item I_k
    IF (CI_j MATCHES CI_k AND I_k NOT EXIST in V) THEN
      POPULATE I_k and CI_k fields to V
    END IF
  END FOR
  RETURN V
END
```

Appendix H

Algorithm 6
Create personalised marketing pitch using needs satisfaction selling strategy.

Description: The algorithm uses needs satisfaction selling strategy, outlined in Table 3 and is called from Algorithm 3. In addition to the recommendation of the rated items, it does recommendation of supplementary items similar to the given item cluster
Input: A customer C_k, an item I_j and PERSONALISED_MARKETING_PITCH list V
Output: List of marketing pitch capturing recommended items of an items-rated customer
Procedure Recommend-using-NSS (C_k: customer, V: PERSONALISED_MARKETING_PITCH, I_j: item)

```
BEGIN
  Let I be the list of items purchased by C_k for a given date range
  SET CI_j = CLUSTER(I_j)//cluster of the item I_j
  FOR EACH item I_k ε I do
  SET CI_k = CLUSTER(I_k)//finding the cluster of the item I_k
    IF (CI_j MATCHES CI_k AND I_k NOT EXIST in V) THEN
      POPULATE I_k and CI_k fields to V
    END IF
  END FOR
  RETURN V
END
```

Appendix I

Algorithm 7
Create personalised marketing pitch using up-selling strategy.

Description: The algorithm uses up-selling strategy, outlined in Table 3 and is called from Algorithm 3. In addition to the recommendation of the rated items, it does the recommendation of supplementary items rated by subset of customers based on the similarity of the given customer. The algorithm uses neighborhood-based collaborative technique (Isinkaye et al., 2015)
Input: A customer C_k, an item I_j and PERSONALISED_MARKETING_PITCH list V
Output: List of marketing pitch capturing recommended items of an items-rated customer
Procedure Recommend-using-US (C_k: customer, V: PERSONALISED_MARKETING_PITCH, I_j: item)
BEGIN
  Let C is the list of customers stored in Transactional Preference Information System
  SET C^H = NEIGHBOR (C_k, C)//neighborhood-based technique to obtain C_K neighbor from C
  SET CI_j = CLUSTER (I_j)//cluster of the item I_j
  FOR EACH customer C_j ε C^H do
    SET I = ITEMS-RATED-POSITIVELY (C_j)//list of items rated positively by C_k
    FOR EACH item I_k ε I do
      SET CI_k = CLUSTER (I_k)//finding the cluster of the item I_k
    IF (CI_j **MATCHES** CI_k **AND** I_k **NOT EXIST** in V) **THEN**
        POPULATE I_k fields and CI_k fields to V
      END IF
    END FOR
  END FOR
  RETURN V
END

Appendix J

Algorithm 8
Create personalised marketing pitch using cross-selling strategy.

Description: The algorithm uses up-selling strategy, outlined in Table 3 and is called from Algorithm 3. In addition to the recommendation of the rated items, it does the recommendation of supplementary items (belonging to different items cluster) rated by subset of customers based on the similarity of given customer. The algorithm uses neighborhood-based collaborative technique (Isinkaye et al., 2015)
Input: A customer C_k, an item I_j and PERSONALISED_MARKETING_PITCH list V
Output: List of marketing pitch capturing recommended items of an items-rated customer
Procedure Recommend-using-CS (C_k: customer, V: PERSONALISED_MARKETING_PITCH, I_j: item)
BEGIN
  Let C is the list of customers stored in Transactional Preference Information System
  SET C^H = NEIGHBOR (C_k, C)//neighborhood-based technique to obtain C_K neighbor from C
  FOR EACH customer C_j ε C^H do
    SET I = ITEMS-RATED-POSITIVELY (C_j)//list of items rated positively by C_k
    FOR EACH item I_k ε I do
      IF (I_k NOT EXIST in V) **THEN**
        POPULATE I_k fields and CI_k fields to V
      END IF
    END FOR
  END FOR
  RETURN V
END

Appendix K

Algorithm 9
Re-compute the suggested items as per deals of the day offer.

Input: PERSONALISED_MARKETING_PITCH data entity V
Output: PERSONALISED_MARKETING_PITCH data entity V with revised price
Procedure DoD (V: PERSONALISED_MARKETING_PITCH)
BEGIN
  FOR EACH item I_k ε V do
    IF (I_k **EXIST** in DoD) **THEN**//If the items exists in deals of the day offer
      RECOMPUTE I_k//Re-compute the item with offers associated with the items
    END IF
  END FOR
  RETURN V
END

Recommendation of the items catering to different customers is presented in Fig. 10.

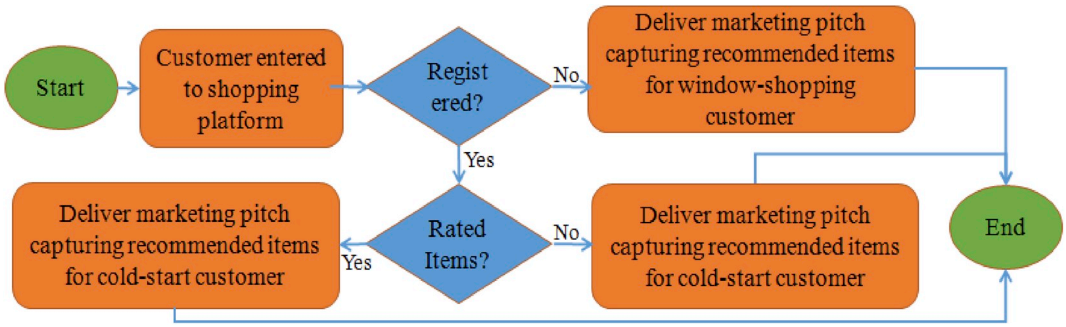

Fig. 10. Items recommendation for different cluster of customers.

References

Aaker, D.A., Joachimsthaler, E., 2000. Brand Leadership: the Next Level of the Brand Revolution.

Adomavicius, G., Tuzhilin, A., 2005. Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Trans. Knowl. Data Eng. (6), 734–749.

Alalwan, A.A., Rana, N.P., Dwivedi, Y.K., Algharabat, R., 2017. Social media in marketing: a review and analysis of the existing literature. Telematics Inf. 34 (7), 1177–1190.

Alatalo, T., Siponen, M.T., 2001. Addressing the personalization paradox in the development of electronic commerce systems. In: Post-proceedings of the EBusiness Research Forum (eBRF). Finland, Tampere.

Ansari, A., Essegaier, S., Kohli, R., 2000. Internet Recommendation Systems.

Baker, J., Ashill, N., Amer, N., Diab, E., 2018. The Internet dilemma: an exploratory study of luxury firms' usage of internet-based technologies. J. Retail. Consum. Serv. 41, 37–47.

Bala, M., Verma, M.D., 2018. A critical review of digital marketing. J. Homepage 8 (10). http://www.ijmra.us.

Barragáns-Martínez, A.B., Costa-Montenegro, E., Burguillo, J.C., Rey-López, M., Mikic-Fonte, F.A., Peleteiro, A., 2010. A hybrid content-based and item-based collaborative filtering approach to recommend TV programs enhanced with singular value decomposition. Inf. Sci. 180 (22), 4290–4311.

Baum, D., Spann, M., Füller, J., Thürridl, C., 2018. The impact of social media campaigns on the success of new product introductions. J. Retail. Consum. Serv.

Bobadilla, J.E.S.U.S., Serradilla, F., Hernando, A., 2009. Collaborative filtering adapted to recommender systems of e-learning. Knowl. Base Syst. 22 (4), 261–265.

Bobadilla, J., Ortega, F., Hernando, A., Alcalá, J., 2011. Improving collaborative filtering recommender system results and performance using genetic algorithms. Knowl. Base Syst. 24 (8), 1310–1316.

Castro-Schez, J.J., Miguel, R., Vallejo, D., López-López, L.M., 2011. A highly adaptive recommender system based on fuzzy logic for B2C e-commerce portals. Expert Syst. Appl. 38 (3), 2441–2454.

Chaffey, D., Ellis-Chadwick, F., 2019. Digital Marketing. Pearson UK.

Chaffey, D., Patron, M., 2012. From web analytics to digital marketing optimization: increasing the commercial value of digital analytics. J. Direct, Data Digital Mark. Pract. 14 (1), 30–45.

Chen, L., Solomon, B., Mac, R., 2014. Alibaba's IPO Pop Makes Jack Ma the Richest Man in China. Forbes, (Forbes #400). Retrieved March 28, 2019 from. http://www.forbes.com/sites/briansolomon/2014/09/19/alibabas-ipo-pop-makes-jack-ma-the-richest-man-in-china/.

Cmswire, 2018. The Challenges of Delivering Personalized Customer Experiences. Retrieved from. https://www.cmswire.com/digital-experience/the-challenges-of-delivering-personalized-customer-experiences/.

Costa-Montenegro, E., Barragáns-Martínez, A.B., Rey-López, M., 2012. Which App? A recommender system of applications in markets: implementation of the service for monitoring users' interaction. Expert Syst. Appl. 39 (10), 9367–9375.

Crespo, R.G., Martínez, O.S., Lovelle, J.M.C., García-Bustelo, B.C.P., Gayo, J.E.L., De Pablos, P.O., 2011. Recommendation System based on user interaction data applied to intelligent electronic books. Comput. Hum. Behav. 27 (4), 1445–1449.

CyberAtlas Staff, 2002. Personalization Makes for Satisfied Consumers. Retrieved from. http://cyberatlas.internet.com/markets/retailing/article/0,,6061_989061,00.html.

Dale Wilson, R., 2010. Using clickstream data to enhance business-to-business web site performance. J. Bus. Ind. Mark. 25 (3), 177–187.

Dangi, H., Malik, A., 2017. Personalisation in marketing: an exploratory study. Int. J. Internet Mark. Advert. 11 (2), 124–136.

Dawson, S., Kim, M., 2010. Cues on apparel web sites that trigger impulse purchases. J. Fash. Mark. Manag.: Int. J. 14 (2), 230–246.

Day, G.S., 1994. The capabilities of market-driven organizations. J. Mark. 37–52.

Day, G.S., 2011. Closing the marketing capabilities gap. J. Mark. 75 (4), 183–195.

Day, G.S., 2014. An outside-in approach to resource-based theories. J. Acad. Mark. Sci. 42 (1), 27–28.

de Pechpeyrou, P., 2009. How consumers value online personalization: a longitudinal experiment. Direct Mark. An Int. J. 3 (1), 35–51.

Deshpande, M., Karypis, G., 2004. Item-based top-n recommendation algorithms. ACM Trans. Inf. Syst.(TOIS) 22 (1), 143–177.

Di Fatta, D., Patton, D., Viglia, G., 2018. The determinants of conversion rates in SME e-commerce websites. J. Retail. Consum. Serv. 41, 161–168.

Dou, Y., Yang, H., Deng, X., 2016. A survey of collaborative filtering algorithms for social recommender systems. In: Semantics, Knowledge and Grids (SKG), 2016 12th International Conference on (pp. 40-46). IEEE.

Econsultancy & Monetate survey, 2013. Retrieved from. https://econsultancy.com/94-of-businesses-say-personalisation-is-critical-to-their-success/.

Epsilon research, 2018. Retrieved from. http://pressroom.epsilon.com/new-epsilon-research-indicates-80-of-consumers-are-more-likely-to-make-a-purchase-when-brands-offer-personalised -experiences/.

Fierro, I., Cardona Arbelaez, D.A., Gavilanez, J., 2017. Digital marketing: a new tool for international education. Pensam. Gest. (43), 241–260.

Fuentes, C., Bäckström, K., Svingstedt, A., 2017. Smartphones and the reconfiguration of retailscapes: stores, shopping, and digitalization. J. Retail. Consum. Serv. 39, 270–278.

Geuens, S., Coussement, K., De Bock, K.W., 2018. A framework for configuring collaborative filtering-based recommendations derived from purchase data. Eur. J. Oper. Res. 265 (1), 208–218.

Ghotbifar, F., Marjani, M.R., Ramazani, A., 2017. Identifying and assessing the factors affecting skill gap in digital marketing in communication industry companies. Indep. J. Manag. Prod. 8 (1), 001–014.

Gurini, D.F., Gasparetti, F., Micarelli, A., Sansonetti, G., 2018. Temporal people-to-people recommendation on social networks with sentiment-based matrix factorization. Future Gener. Comput. Syst. 78, 430–439.

Hallikainen, H., Alamäki, A., Laukkanen, T., 2018. Individual preferences of digital touchpoints: a latent class analysis. J. Retail. Consum. Serv.

Hamel, G., 2018. Pros & Cons of Word of Mouth Marketing. Retrieved from. https://smallbusiness.chron.com/pros-cons-word-mouth-marketing-52484.html.

Hargreaves, I., 2011. Digital Opportunity: a Review of Intellectual Property and Growth: an Independent Report.

Hu, Q.Y., Huang, L., Wang, C.D., Chao, H.Y., 2019. Item orientated recommendation by multi-view intact space learning with overlapping. Knowl. Base Syst. 164, 358–370.

Huang, Z., Zeng, D., Chen, H., 2007. A comparison of collaborative-filtering recommendation algorithms for e-commerce. IEEE Intell. Syst. 22 (5).

Hwangbo, H., Kim, Y.S., Cha, K.J., 2018. Recommendation system development for fashion retail e-commerce. Electron. Commer. Res. Appl. 28, 94–101.

Ieva, M., De Canio, F., Ziliani, C., 2018. Daily deal shoppers: what drives social couponing? J. Retail. Consum. Serv. 40, 299–303.

Isinkaye, F.O., Folajimi, Y.O., Ojokoh, B.A., 2015. Recommendation systems: principles, methods and evaluation. Egypt. Inform. J. 16 (3), 261–273.

Kaneko, K., Kishita, Y., Umeda, Y., 2018. Toward developing a design method of personalization: proposal of a personalization procedure. Procedia CIRP 69, 740–745.

Kannan, P.K., 2017. Digital marketing: a framework, review and research agenda. Int. J. Res. Mark. 34 (1), 22–45.

Kaynama, S.A., Black, C.I., 2000. A proposal to assess the service quality of online travel agencies: an exploratory study. J. Prof. Serv. Mark. 21 (1), 63–88.

Kim, M., 2018. Digital product presentation, information processing, need for cognition and behavioral intent in digital commerce. J. Retail. Consum. Serv.

Kokko, T., Moilanen, T., 1997. Personalisation of services as a tool for more developed buyer-seller interactions. Int. J. Hosp. Manag. 16 (3), 297–304.

Korgaonkar, P., Becerra, E., O'Leary, B., Goldring, D., 2010. Product classifications, consumer characteristics, and patronage preference for online auction. J. Retail. Consum. Serv. 17 (4), 270–277.

Krzywicki, A., Wobcke, W., Kim, Y.S., Cai, X., Bain, M., Mahidadia, A., Compton, P., 2015. Collaborative filtering for people-to-people recommendation in online dating: data analysis and user trial. Int. J. Hum. Comput. Stud. 76, 50–66.

Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R., Kannan, P.K., 2016. From social to sale: the effects of firm-generated content in social media on customer behavior. J. Mark. 80 (1), 7–25.

Lamberton, C., Stephen, A.T., 2016. A thematic exploration of digital, social media, and mobile marketing: research evolution from 2000 to 2015 and an agenda for future inquiry. J. Mark. 80 (6), 146–172.

Laskey, H.A., Day, E., Crask, M.R., 1989. Typology of main message strategies for

television commercials. J. Advert. 18 (1), 36–41.
Lee, C.H., Cranage, D.A., 2011. Personalisation–privacy paradox: the effects of personalisation and privacy assurance on customer responses to travel Web sites. Tourism Manag. 32 (5), 987–994.
Lee, D., Hosanagar, K., 2014. Impact of Recommender Systems on Sales Volume and Diversity.
Lee, D., Hosanagar, K., 2018. How Do Product Attributes Moderate the Impact of Recommender Systems? Available at: SSRN 3250189.
Lee, S.K., Cho, Y.H., Kim, S.H., 2010. Collaborative filtering with ordinal scale-based implicit ratings for mobile music recommendations. Inf. Sci. 180 (11), 2142–2155.
Leeflang, P.S., Verhoef, P.C., Dahlström, P., Freundt, T., 2014. Challenges and solutions for marketing in a digital era. Eur. Manag. J. 32 (1), 1–12.
Li, C., 2009. Research on E-commerce recommendation service using collaborative filtering. In: Knowledge Acquisition and Modeling, 2009. KAM'09. Second International Symposium on, vol. 2. IEEE, pp. 33–36.
Liu, M., Pan, W., Liu, M., Chen, Y., Peng, X., Ming, Z., 2017. Mixed similarity learning for recommendation with implicit feedback. Knowl. Base Syst. 119, 178–185.
Lü, L., Medo, M., Yeung, C.H., Zhang, Y.C., Zhang, Z.K., Zhou, T., 2012. Recommender systems. Phys. Rep. 519 (1), 1–49.
Mack, D., 2009. Customer Experience: Lessons for Loyalty. White Paper. Retrieved from. http://design1online.com/downloads/whitepapers/BrandLoyalty_Scene7_Whitepaper.pdf.
McNally, K., O'Mahony, M.P., Coyle, M., Briggs, P., Smyth, B., 2011. A case study of collaboration and reputation in social web search. ACM Trans. Intell. Syst. Technol. (TIST) 3 (1), 4.
Mocean, L., Pop, C.M., 2012. Marketing recommender systems: a new approach in digital economy. Inf. Econ. 16 (4).
Mooney, L., 2018. The Disadvantages of Word of Mouth Advertising. Retrieved from. https://smallbusiness.chron.com/disadvantages-word-mouth-advertising-26133.html.
Morgan, N.A., Slotegraaf, R.J., Vorhies, D.W., 2009. Linking marketing capabilities with profit growth. Int. J. Res. Mark. 26 (4), 284–293.
Nanopoulos, A., Rafailidis, D., Symeonidis, P., Manolopoulos, Y., 2010. Music box: personalized music recommendation based on cubic analysis of social tags. IEEE Trans. Audio Speech Lang. Process. 18 (2), 407–412.
Nelson, D.A., Williams, R., McCoy, R., Valentine, N., Dalley, S., Pace, B.P., 2016. U.S. Patent Application No. 14/538. pp. 685.
Nepomuceno, M.V., Laroche, M., Richard, M.O., 2014. How to reduce perceived risk when buying online: the interactions between intangibility, product knowledge, brand familiarity, privacy and security concerns. J. Retail. Consum. Serv. 21 (4), 619–629.
Neslin, S.A., Grewal, D., Leghorn, R., Shankar, V., Teerling, M.L., Thomas, J.S., Verhoef, P.C., 2006. Challenges and opportunities in multichannel customer management. J. Serv. Res. 9 (2), 95–112.
Nisar, T.M., Prabhakar, G., 2017. What factors determine e-satisfaction and consumer spending in e-commerce retailing? J. Retail. Consum. Serv. 39, 135–144.
Núñez-Valdéz, E.R., Lovelle, J.M.C., Martínez, O.S., García-Díaz, V., De Pablos, P.O., Marín, C.E.M., 2012. Implicit feedback techniques on recommender systems applied to electronic books. Comput. Hum. Behav. 28 (4), 1186–1193.
Núñez-Valdez, E.R., Quintana, D., Crespo, R.G., Isasi, P., Herrera-Viedma, E., 2018. A recommender system based on implicit feedback for selective dissemination of ebooks. Inf. Sci. 467, 87–98.
Nussey, B., 2004. The Quiet Revolution in Email Marketing. iUniverse.
Oulasvirta, A., Blom, J., 2008. Motivations in personalisation behaviour. Interact. Comput. 20 (1), 1–16.
Pantano, E., Passavanti, R., Priporas, C.V., Verteramo, S., 2018. To what extent luxury retailing can be smart? J. Retail. Consum. Serv. 43, 94–100.
Park, J., Kim, R.B., 2018. A new approach to segmenting multichannel shoppers in Korea and the US. J. Retail. Consum. Serv. 45, 163–178.
Phippen, A., Sheppard, L., Furnell, S., 2004. A practical evaluation of Web analytics. Internet Res. 14 (4), 284–293.
Pires, G.D., Stanton, J., Rita, P., 2006. The internet, consumer empowerment and marketing strategies. Eur. J. Market. 40 (9/10), 936–949.
Porcel, C., Herrera-Viedma, E., 2010. Dealing with incomplete information in a fuzzy linguistic recommender system to disseminate information in university digital libraries. Knowl. Base Syst. 23 (1), 32–39.
Porcel, C., Moreno, J.M., Herrera-Viedma, E., 2009. A multi-disciplinary recommender system to advice research resources in university digital libraries. Expert Syst. Appl. 36 (10), 12520–12528.
Porcel, C., Tejeda-Lorente, A., Martínez, M.A., Herrera-Viedma, E., 2012. A hybrid recommender system for the selective dissemination of research resources in a technology transfer office. Inf. Sci. 184 (1), 1–19.
Portugal, I., Alencar, P., Cowan, D., 2018. The use of machine learning algorithms in recommender systems: a systematic review. Expert Syst. Appl. 97, 205–227.
Reydet, S., Carsana, L., 2017. The effect of digital design in retail banking on customers' commitment and loyalty: the mediating role of positive affect. J. Retail. Consum. Serv. 37, 132–138.
Ricci, F., Rokach, L., Shapira, B., 2015. Recommender systems: introduction and challenges. In: Recommender Systems Handbook. Springer, Boston, MA, pp. 1–34.
Richins, M.L., 1983. Negative word-of-mouth by dissatisfied consumers: a pilot study. J. Mark. 47 (1), 68–78.
Rodgers, S., Thorson, E., 2018. Special Issue Introduction: Digital Engagement with Advertising.
Santra, A.K., Christy, C.J., 2012. Genetic algorithm and confusion matrix for document clustering. Int. J. Comput. Sci. Issues (IJCSI) 9 (1), 322.
Sarwar, B., Karypis, G., Konstan, J., Riedl, J., 2000. Analysis of recommendation algorithms for e-commerce. In: Proceedings of the 2nd ACM Conference on Electronic Commerce. ACM, pp. 158–167.
Schafer, J.B., Konstan, J., Riedl, J., 1999. Recommender systems in e-commerce. In: Proceedings of the 1st ACM Conference on Electronic Commerce. ACM, pp. 158–166.
Schubert, P., Ginsburg, M., 2000. Virtual communities of transaction: the role of personalization in electronic commerce. Electron. Mark. 10 (1), 45–55.
Šeleng, M., Dlugolinský, Š., Hluchý, L., Gräther, W., 2018. Improving inter-enterprise collaboration with recommendation tool based on lightweight semantics in emails. Procedia Comput. Sci. 138, 486–491.
Serrano-Guerrero, J., Herrera-Viedma, E., Olivas, J.A., Cerezo, A., Romero, F.P., 2011. A google wave-based fuzzy recommender system to disseminate information in University Digital Libraries 2.0. Inf. Sci. 181 (9), 1503–1516.
Shiau, W.L., Dwivedi, Y.K., Yang, H.S., 2017. Co-citation and cluster analyses of extant literature on social networks. Int. J. Inf. Manag. 37 (5), 390–399.
Shim, S., Eastlick, M.A., Lotz, S.L., Warrington, P., 2001. An online prepurchase intentions model: the role of intention to search: best overall paper award—the sixth triennial AMS/ACRA retailing conference, 2000☆ 1. J. Retail. 77 (3), 397–416.
Simintiras, A.C., Dwivedi, Y.K., Kaushik, G., Rana, N.P., 2015. Should consumers request cost transparency? Eur. J. Market. 49 (11/12), 1961–1979.
Simonson, I., 2005. Determinants of customers' responses to customized offers: conceptual framework and research propositions. J. Mark. 69 (1), 32–45.
Singh, N., 2017. The Transformation of Retailing.
Singh, S., Swait, J., 2017. Channels for search and purchase: does mobile Internet matter? J. Retail. Consum. Serv. 39, 123–134.
Skinner, S., 2000. Business-to-business e-commerce: Investment perspective. Durlacher Research, London.
Smith, K.T., 2011. Digital marketing strategies that Millennials find appealing, motivating, or just annoying. J. Strateg. Mark. 19 (6), 489–499.
Stewart-Knox, B.J., Markovina, J., Rankin, A., Bunting, B.P., Kuznesof, S., Fischer, A.R.H., van der Lans, I.A., Poínhos, R., de Almeida, M.D.V., Panzone, L., Gibney, M., 2016. Making personalised nutrition the easy choice: creating policies to break down the barriers and reap the benefits. Food Policy 63, 134–144.
Szymanski, D.M., Hise, R.T., 2000. E-satisfaction: an initial examination. J. Retail. 76 (3), 309–322.
Tan, S., Bu, J., Chen, C., Xu, B., Wang, C., He, X., 2011. Using rich social media information for music recommendation via hypergraph model. ACM Trans. Multimed Comput. Commun. Appl 7 (1), 22.
van Tonder, E., Saunders, S.G., Lisita, I.T., de Beer, L.T., 2018. The importance of customer citizenship behaviour in the modern retail environment: introducing and testing a social exchange model. J. Retail. Consum. Serv. 45, 92–102.
Vesanen, J., 2005. What is Personalization?: A Literature Review and Framework.
Wagner, G., Schramm-Klein, H., Steinmann, S., 2017. Consumers' attitudes and intentions toward Internet-enabled TV shopping. J. Retail. Consum. Serv. 34, 278–286.
Wang, E., Klein, G., Jiang, J.J., 2007. IT support in manufacturing firms for a knowledge management dynamic capability link to performance. Int. J. Prod. Res. 45 (11), 2419–2434.
Wikström, S., Decosta, P.L.E., 2018. How is value created?–Extending the value concept in the Swedish context. J. Retail. Consum. Serv. 40, 249–260.
Wildash, S., 2008. Personalisation—adding the value to cards. Card. Technol. Today 20 (9), 10–11.
Wiles, M.A., Morgan, N.A., Rego, L.L., 2012. The effect of brand acquisition and disposal on stock returns. J. Mark. 76 (1), 38–58.
Yan, R., Pei, Z., 2018. Return policies and O2O coordination in the e-tailing age. J. Retail. Consum. Serv.
Yazdanifard, R., Li, M.T.H., 2014. The review of Alibabaâ€™ s online business marketing strategies which navigate them to present success. Glob. J. Manag. Bus. Res. 14 (7).
Yu, Z., Zhou, X., Hao, Y., Gu, J., 2006. TV program recommendation for multiple viewers based on user profile merging. User Model. User-Adapted Interact. 16 (1), 63–82.
Zaíane, O.R., 2002. Building a recommender agent for e-learning systems. In: Computers in Education, 2002. Proceedings. International Conference on (pp. 55-59). IEEE.