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A Proposed Business Intelligent Framework for Recommender Systems

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Abstract: In this Internet age, recommender systems (RS) have become popular, offering new opportunities and challenges to the business world. With a continuous increase in global competition, e-businesses, information portals, social networks and more, websites are required to become more user-centric and rely on the presence and role of RS in assisting users in better decision making. However, with continuous changes in user interests and consumer behavior patterns that are influenced by easy access to vast information and social factors, raising the quality of recommendations has become a challenge for recommender systems. There is a pressing need for exploring hybrid models of the five main types of RS, namely collaborative, demographic, utility, content and knowledge based approaches along with advancements in Big Data (BD) to become more context-aware of the technology and social changes and to behave intelligently. There is a gap in literature with a research focus in this direction. This paper takes a step to address this by exploring a new paradigm of applying business intelligence (BI) concepts to RS for intelligently responding to user changes and business complexities. A BI based framework adopting a hybrid methodology for RS is proposed with a focus on enhancing the RS performance. Such a business intelligent recommender system (BIRS) can adopt On-line Analytical Processing (OLAP) tools and performance monitoring metrics using data mining techniques of BI to enhance its own learning, user profiling and predictive models for making a more useful set of personalised recommendations to its users. The application of the proposed framework to a B2C e-commerce case example is presented.

Keywords: recommender systems; business intelligence; data analytics; data mining; e-commerce

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1. Introduction

Recommender systems (RS) have been used to assist users in finding the intended items more effectively over the Internet and have been developed predominantly for enhancing users' search results. The main aim of RS is to recommend personalised items (products or services) to the users and is evolving to be more user-centric [1]. A good quality RS applies active and selective information-filtering techniques on the history of user behavior data to suggest meaningful information that can be contextualised and personalised for each end-user [2]. Since the advent of Internet and social media, several models have been proposed to achieve quality user experience for a variety of applications, and RS have been continuously improved over these years to meet diverse user requirements. With growing changes in businesses to embrace social media for global competitiveness, RS are increasingly required to improve customer relationship management along with quality of user experience [3,4]. With such a crucial role in today's context of customer-centric products and services, RS are required to assist users in various forms such as to discover, locate, and recommend the most suitable item by predicting a user's interests about various items and by even processing previous history of interactions between items and users in various business contexts.

Historically, the main purpose of recommendations for e-businesses was to improve product sales through information filtering that would help in educating consumers about the products of interest and to build a community of users around products or content. With the ever-changing society and technological advances, there is a need to re-engineer the existing RS adopting traditional methods of providing recommendations, which are predominantly text-based. Future RS are expected to leverage Big Data (BD) and incorporate business intelligent methods that can intelligently cater to diverse user requirements and business goals [4]. Recent research has identified the need for RS to hasten analysts' response to complex events such as cyber-attacks and tailor the recommendations to the intelligent community [5]. While RS have served common domain such as e-commerce traditionally, future purposes would include providing context-dependent recommendations for dynamically changing and complex situations, such as suggesting traffic routes, predicting careers, etc. In order to provide the most suitable information of high value to active users of an e-commerce business system, a customised recommender system is required [6]. Modern e-businesses would like to have intelligent and context-aware information filtering techniques adopted for its active users to find the best suitable items of interest with diverse content, such as movies, audio, books, and documents for improving quality of experience in a variety of fields [7]. Hence, it is of high importance in the design of RS to relate user perceived quality of experience.

With the Internet of Things (IoT), more and more personal information is made available and processed over the Internet, and there arises a new set of privacy and confidentiality issues [8]. Users raise various concerns with queries such as "What items are known about me?", "Is the recommendation trustworthy?", "What could be the vulnerabilities and security threats?", etc. A trust-based model is necessary for future RS. With significant advances in machine learning, artificial intelligence (AI) techniques could be employed to include trust-based business rules while mining relevant user data for identifying new and useful patterns [9,10]. These enhancements would provide a greater promise for RS to embrace business intelligence (BI). Hence, in this paper, we propose a framework for developing a business intelligent recommender system (BIRS).

The remainder of this paper is structured as follows. Section 2 sets the background concepts by summarising the pros and cons of the main types of recommender systems with similarity measures used. Section 3 proposes a BI based framework for RS with model steps for a self-monitoring BIRS. The application of the proposed BIRS framework in a B2C e-commerce use case example is presented in Section 4. Section 5 provides conclusions and future work.

2. Comparison of RS Types

A recommender system is a software agent that elicits the interests and preferences of each user to make recommendations when a variety of choices and options are made available to the user. RS are often present in e-commerce landscapes where the website provides recommendations of products and services that might be of their interest based on users' opinions [11]. Questions such as what, how and when information is gathered and processed should be considered while constructing RS based on its purpose and desired usage that lead to different types of recommender system being developed. From literature, there are five main RS types based on the recommendation techniques they employ, namely collaborative, content, demographic, utility, and knowledge based approaches [4,12,13].

RS should be capable of finding things that are of interest and should help each user to explore the space of options by intelligently narrowing down the set of choices that are of added value to that particular user. To the business that provides the RS, it offers opportunities for promotion of products and services. The RS obtain useful knowledge about their users, employ techniques for incorporating persuasion, trust and customer loyalty. Businesses could make use of RS features in conjunction with digital inventories of IoT to increase privacy-based accessibility, user-friendliness and personalisation for improving their marketing and sales [6,12]. A typical recommender system is expected to use ratings, preferences, demographics, situational context of its consumers as well as the item characteristics to arrive at a 'relevance score' used to rank the items. Hence, based on the scores calculated, different types of recommender systems could derive different outcomes for the same user. While providing personalised recommendations, the RS tries to reduce information overload caused by diverse characteristics of the items by using techniques to estimate relevance and context-dependency. For instance, the goal of a collaborative RS would be to satisfy a particular user's requirement using the search query: "Find which item is popular among the peers of the user", while for a content based RS, the task would be to: "Discover more such items that the user has liked", a knowledge based RS would search for: "All items that best-fit the needs of the user", a utility based RS would use the search query: "Which is the most useful item for the user", and a demographic type RS would search for: "Any item most suitable for a particular location". There are also hybrid types that combine different techniques based on the complexity of the situation. We compare the five types of RS and identify their salient features and limitations.

Collaborative RS—Among the abovementioned RS types, collaborative types are most popular where items are recommended by making use of social media crowd sourcing and other recent socio-technological developments [14]. The system aggregates ratings of items, identifies common patterns between user ratings, and finally generates new recommendations based on inter-user correlations [15]. However, the assumption is that users give ratings to catalog items and that their preferences and likes are similar in the past and future.

Demographic RS—Similar to collaborative RS, demographic RS also employs a similar collaborative filtering technique on demographic information such as location and time of the day collected from the users, where the data does not rely on historical ratings and preferences of the users [16].

Both collaborative and demographic types of RS rely on users and not on the content. For these two RS types, a commonly employed user-based measure (*sim*) is a nearest neighbor formula using Pearson correlation, as given below [17]:

$$sim(a,b) = \frac{\sum_{p \in P} \left(r_{a,p} - \overline{r_a}\right)\left(r_{b,p} - \overline{r_b}\right)}{\sqrt{\left[\sum_{p \in P}\left(r_{a,p} - \overline{r_a}\right)^2\right]}\ \sqrt{\left[\sum_{p \in P}\left(r_{b,p} - \overline{r_a}\right)^2\right]}} \quad (1)$$

a, b: users; $r_{a,p}$: rating of user a for item p; P: set of items, rated both by a and b; $\overline{r_a}$, $\overline{r_b}$: user's average ratings.

Using the similarity measure from Equation (1), a popular prediction measure (*pred*) based on neighbour's rating is calculated by Equation (2) given below:

$$pred(a,p) = \overline{r_a} + \frac{\sum_{b \in N} sim(a,b) \times \left(r_{b,p} - \overline{r_b}\right)}{\sum_{b \in N} sim(a,b)} \quad (2)$$

All collaborative RS are based on techniques that require some form of rating feedback to be available a priori. This results in some limitations: a cold start for new users and new items, and the quality of recommendation much depends on large historical user data collected over a considerable period of time for arriving at accurate predictions.

Content based RS—Contrary to collaborative and demographic techniques where the focus is on the users, content based recommender systems focus on the items. They define items of interest according to their associated features and employ item-to-item correlations [18]. In addition, by gathering the properties of items that users have liked, the system forms users' interest and preferences. Similar to the collaborative filtering technique, this technique also requires an extensive use of the system to learn users' interests and preferences. Early stage of interaction with the recommender system would lack accuracy and quality in its recommendations and the confidence level may be low as the set of user-specified keywords collected may be small. A commonly used similarity measure (*sim*) for an unseen item matching with the user profile is calculated based on the overlap of two sets of keywords, *bi* and *bj* and is given in Equation (3) below [17]:

$$sim(bi,\ bj) = \frac{2 \times |keywords(bi) \cap keywords(bj)|}{|keywords(bi)| + |keywords(bj)|} \tag{3}$$

The above keyword based measure is simple, but has its limitations since it does not consider the difference in importance of each word. Also, longer documents provide a higher chance of occurrence of the keywords, resulting in higher match with the user profile. Therefore, a much preferred measure is based on term frequency (*TF*) that normalises document size, along with inverse document frequency (*IDF*) to reduce bias due to certain terms appearing in all documents. The overall importance of words (*OverallImp*) are calculated using Equation (4) as follows:

Given a keyword *i* and a document *j*

$$OverallImp(i, j) = TF(i, j) \times IDF(i) \tag{4}$$

where *TF* is defined in Equation (5) as follows:

$$TF(i, j) = \frac{freq(i, j)}{maxF(i, j)} \tag{5}$$

freq(*i*,*j*): number of occurrences of keyword *i* in document *j*; *maxF*(*i*,*j*) denotes the highest number of occurrences of another keyword of *j*.

And inverse document frequency (*IDF*) is defined in Equation (6) as given below:

$$IDF(i) = log\frac{N}{n(i)} \tag{6}$$

N: number of all recommendable documents; *n*(*i*): number of documents where keyword *i* appears.

While content based RS are simpler to develop, the limitations are that such measures based on keyword importance do not capture the semantics and negative user contexts. In addition, due to the diverse formats of content, keywords alone may not be sufficient to determine the importance of an item, especially with IoT.

One major advantage of the three recommendation techniques discussed so far is their suitability for long-term generalisations on users' preferences, giving them more benefits with prolonged use and more interactions with the system.

Utility based RS—The recommendations drawn by utility based RS is based on the computation of each item's utility for the user, typically based on the derived user profile. Here, the focus is on the utility rather than on the users or products, and the approach is to consider various factors such as product stock level or vendor reliability for making useful recommendations to the users [12]. An important observation is that a utility based recommender system could be more successful for short-term purposes only. For example, it could suggest a relatively more expensive item based on a match with the immediate user requirement, and may not suit well in the long-term, unless it is designed intelligently.

Knowledge based RS—The pitfalls in utility based RS can be overcome with a knowledge based recommender system that arrives at inferences by employing reasoning about its users' needs and their preferences before making suggestions [19]. It makes use of various domain knowledge such as product knowledge from domain experts and sales knowledge from sales experts, elicitation from users on their requirements for determining a more reliable recommendation [10]. A typical distance similarity (*similarity*) between the item attribute (*p*) and the user requirement (*r*) is defined in Equation (7) below:

$$similarity(p,\ REQ) = \frac{\sum_{r \in REQ}\ w_r \times sim(p, r)}{\sum_{r \in REQ}\ w_r} \tag{7}$$

$sim(p, r)$: distance of item attribute p value to the customer requirement $r \in REQ.$; w_r: importance weight for requirement r.

Knowledge occurs in different forms, and capturing relevant knowledge is the main limitation with knowledge based RS since knowledge acquisition from domain experts, users and the web could be time consuming. The advantage of knowledge based RS is the high accuracy in recommendations that get derived through fine granular preference models, which require processing BD collected from long-term interactions with the user as well as sufficient and detailed data about the user [20]. Overall, knowledge based RS would be preferred for long-term outcomes and situations that give high importance for accuracy.

One common feature between utility based and knowledge based RS is that both types provide recommendations by measuring the match between users' needs and the set of options available, which could have positive influence on the user actions. By considering the pros and cons of the abovementioned 5 types of recommender systems, in the next section, we describe the motivation of this research to adopt a hybrid methodology and propose a BIRS framework.

3. Methodology for the Proposed BIRS Framework

The methodology adopted in this paper takes a hybrid approach by intelligently combining two or more popular types of recommendation techniques described in Section 2 for implementing a BIRS. Similar research conducted previously has predominantly adopted content based methodology for recommender systems with the business focus on their products [18]. With the pervasiveness of social media, recent research studies have proposed collaborative-type recommender systems [17,21]. However, in order to meet today's dynamic and competitive business requirement, a hybrid recommender system is required to employ different techniques intelligently to best suit the given situation [16]. For instance, with a new user, the RS could employ various proportion of weights on content based technique during initial interactions, and as the user provides more information to the system, the RS progressively learns the habits, interests, and preferences of the user, and could combine knowledge based techniques as well in order to build higher confidence levels for the recommended items [16]. In addition to combining recommendation techniques, further improvement can be achieved through the incorporation of contextual information into the recommendation process as they provide additional support for multiple criteria of ratings, as well as improvement in the understanding of users and items [7]. However, the main difference between this work and others reported in literature previously is that the proposed methodology is more generic and the framework with model steps detailed here could be applied to any business situation, while previous studies are for specific situations such as proposing a recommender system for a security solution or business-business e-commerce application [5,6]. Further, the approach of capitalising BD in conjunction with BI techniques for a generic hybrid recommender framework is a novel methodology adopted in this paper.

For the RS to be successful, apart from adopting a set of good similarity and prediction measures as given in Equations (1)–(7), importance should be given to adopt the right interaction method for user persuasion as well as user trust strategies while educating users about the products [21]. Further, businesses would consider the conversion rate as a success criteria by keeping track of increase in sales margins and profit that relate to user measures such as "hit", "clickthrough", "lookers-to-bookers" rates of their online products and services. These methods could be implemented by adopting BI, which allows different kinds of user data including behaviour patterns to be stored and manipulated in a data warehouse (DW). Some of the BI tools that are commonly used for BD analytics include OnLine Analytical Processing (OLAP) and data mining [9]. The performance monitoring tools of BI could be used to continuously evaluate the recommender system and support continuous improvement in decision making while suggesting personalised recommendation to each user [22]. The decision making is based on processing two main categories of BD: (1) historical data/OnLine Analytical Processing (OLAP) data, and (2) day-to-day transaction data/OnLine Transactional Processing (OLTP) data [4]. Such a generic BIRS proposed in this paper will benefit various industries as they can intelligently align their RS to be user-centric while catering to their business goals. For example, the proposed BIRS will be able to answer the question "How did this user recommendation influence the company's revenue?", which could be visualised and monitored with the fact table containing the measure "revenue" and one of the dimension tables containing the "user recommendation" attribute. Figure 1 provides a framework of the proposed BIRS giving a pictorial representation of how the various components of the model are integrated. The model steps are described next with a generic user situation in order to illustrate the proposed BIRS process flow.

Let us suppose the requirement of the proposed BIRS is to process a particular user problem/query/interaction to provide a recommendation. The high-level model steps followed in the proposed BIRS are given below:

Step 1 The system considers a collection of inputs that contribute to decision making. The key inputs captured through web pages are:

(a) Item based inputs, such as product (or service) features, restrictions, and business context [18].
(b) Social engineering based inputs, such as community data, temporal data, location-based data, and peer ratings/feedback [23].
(c) User based inputs, such as user profile and contextual parameters including ratings, preferences, situational context, and specific demographics that relate to ratings or buying propensity/behaviour [6].

Step 2 Information in different data formats gained from Step 1 above are extracted by the system using a hybrid set of filtering techniques chosen from the five types (collaborative, demographic, content, utility and knowledge based techniques) depending on the situational context. Expert system components that include AI models are employed for identifying and filtering datasets in the data warehouse by using the previously defined expert rules and domain knowledge. The knowledge base of expert rules is also dynamically and intelligently updated using the continuous performance monitoring measures of BI.

Step 3 The machine learning component of the recommender system performs learning and prediction from the data stored in the data warehouse using OLAP databases. It applies various data mining techniques to cluster items (for e.g., by using k-means clustering based on relevance, ratings, similarity, and other factors), and then to find nearest neighbour of active users, and finally to arrive at a working dataset that is best correlated.

Step 4 Using the data warehouse (DW) component, each user's current activities as well as long-term preferences are processed by utilising OLTP/OLAP features of DW. In addition, BD processing techniques such as data mining, text mining, complex event processing, and predictive analytics are adopted in BIRS to make more accurate and valuable recommendations to the user.

Step 5 The performance monitoring component of the BIRS uses appropriate monitoring metrics that are calculated by taking inputs from OLAP/OLTP system to generate performance dashboards and a recommended set of reports. To support this, inputs from external data (e.g., competitive market analysis and seasonal analysis) are also combined to provide valuable feedback on how well the recommender system contributes towards achieving the business goals.

By integrating the BI methods, process and technologies, the RS is able to employ data warehousing and performance monitoring features to display more personalised and useful recommendations to the active user [4]. The performance of these recommendations made could also be evaluated by measuring their user acceptance rate and by comparing it with previous instances [9]. Such a continuous monitoring feature of BI helps the RS to understand how well it is contributing to the business goals and to adapt itself intelligently. In addition, performance visualisation and explanations of the recommendations made to the user contribute to the value-added functionality of RS [20]. For e.g., a measure of users' positive actions (accepted recommendations) that lead to product sales would determine their tangible benefits to the business. Similarly, by monitoring the users' negative actions (rejected recommendations), a continuous improvement of the recommender system could be achieved [24]. Finally, as a use case example, we present some of the key features of our proposed methodology and BIRS framework that were employed in a real-life industry setting.

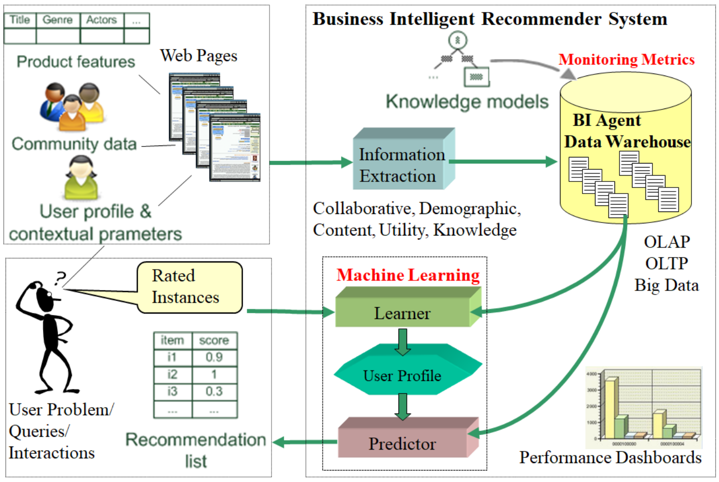


Figure 1. Proposed BIRS framework.

4. Use Case of BIRS framework

Recommender systems are quite popular in e-business domains [25]. B2C e-commerce websites such as Amazon are consistently looking for methods to improve their recommender systems in order to assist users in finding items quickly. Hence, in this section, we describe how our proposed BIRS framework is applied to an e-commerce setting, a website of a jewelry store that specialises in customised jewelry making. We illustrate selected features of the BIRS implemented within this real-life industry context as a use case example. Key BI features of the proposed framework applied in the RS to enhance the e-business of the jewelry store, such as (i) Search and comparison of products, (ii) User reviews, chats and forums, and (iii) Performance monitoring reports/dashboards using BI are described below:

Search and comparison of products—The search facility in e-commerce websites help customers to narrow down the products based on keywords related to the products and services. For the jewelry store website considered here, various filtering options, such as price range, gemstone used, metal type, type of occasion, and other context-dependent parameters are used and combined with comparison features of similar products to facilitate customers achieving their goals [7]. Figure 2 shows an example screen shot of an output from the search and comparison feature developed for the website.

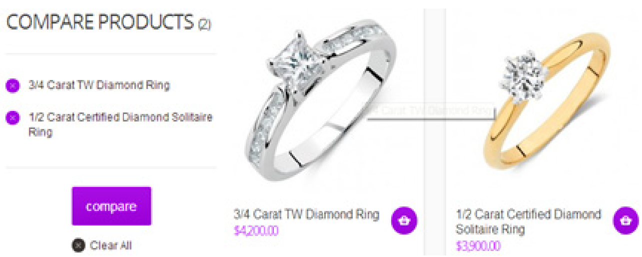


Figure 2. Context-dependent personalised comparison of related products.

A context-dependent and interactive search combined with feature-wise comparison of products empowers customers to effortlessly navigate pages, to find items of interest quickly, and to finally assist them to take positive actions based on the recommendations. The business is interested in users eventually purchasing an item. Hence, various data such as user clicks, and behavior patterns would be captured to measure conversion rates and other performance measures.

User reviews, chats and forums—Social engineering features have become a common functionality of e-commerce websites for improving customer relationships. User reviews, chats and forums are some of the many social engineering platforms that help users to get more information about their products in the pre-purchase stage. Such features create a positive influence on users in making a purchasing decision. Online chats and forums not only increase the level of customer service but also provide advanced demographic and contextual information about the user as well as community data as part of BD of the recommender system [24]. Figure 3 shows an example of the user review and online chat/forum functionality developed for the e-commerce jewelry store. The page shows contextual products and testimonials based on the user query on special event jewelry items as well as past history of user interests. On the same page, it allows a customer service staff of the jewelry store to attend to the online chat. The user can also post further queries/comments that can be filtered and approved for an entry into the jewelry store's Facebook page.

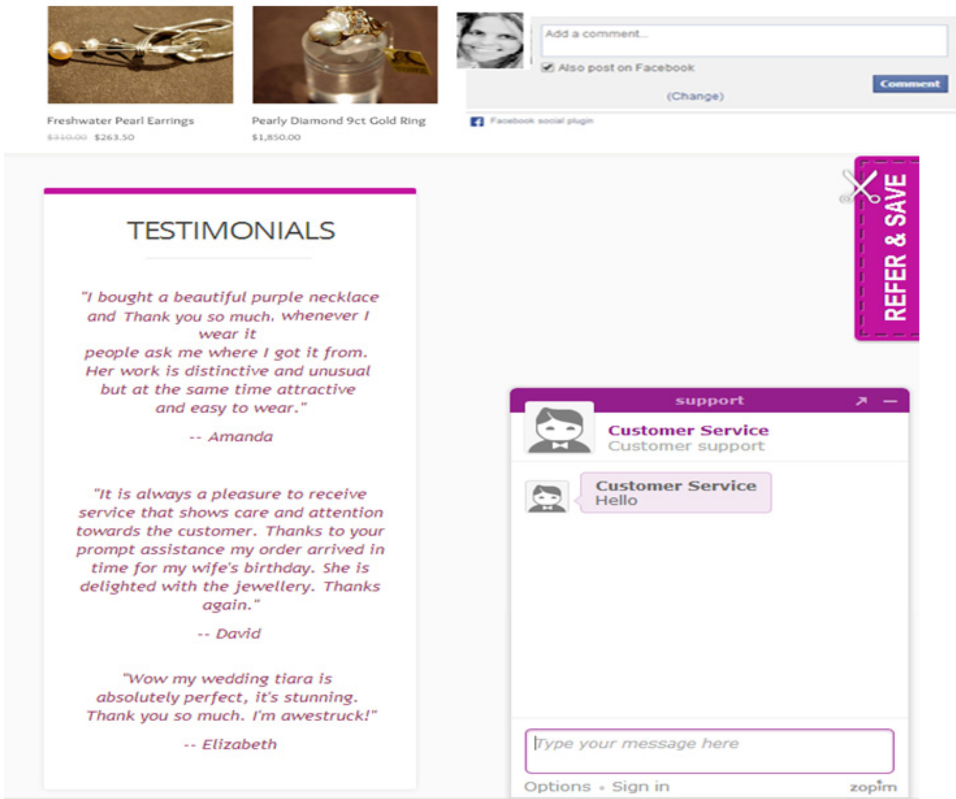
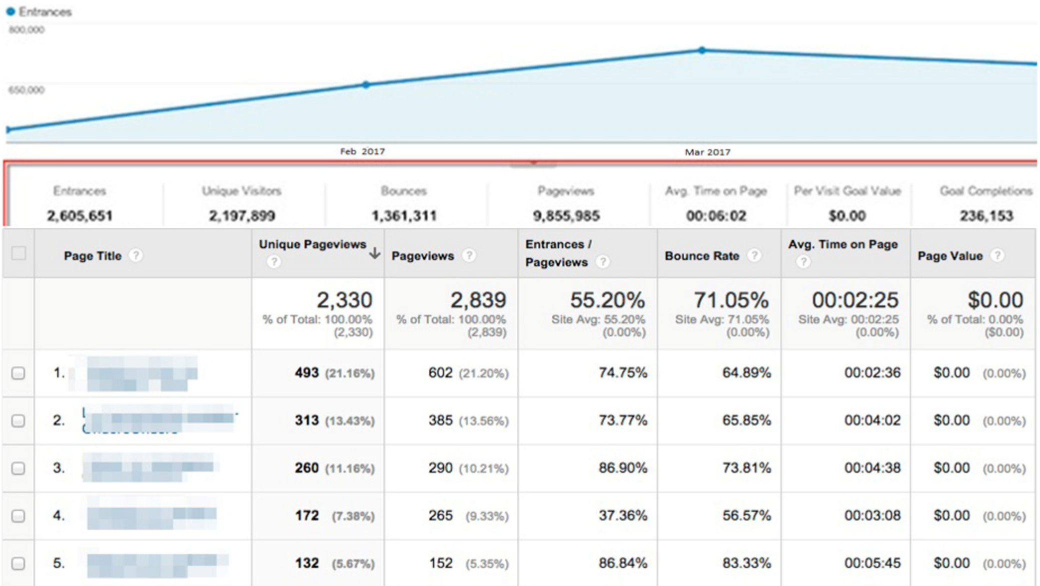


Figure 3. Social engineering inputs for recommender system.

Performance monitoring reports/dashboards—By including performance monitoring reports in BIRS, continuous monitoring metrics of BI such as content efficiency, keyword usage, e-commerce traffic, browser performance, etc., can help in evaluating the RS in relation to achieving the business goals [4]. For e.g., the content efficiency analysis report as shown in Figure 4 for the jewelry website helps to identify the content that delivers the most business value or the type of content (text, videos, pictures, etc.) that best engages the user. The report considers useful metrics for each page of the website, such as unique visitors, goal completions, goal conversion rate, e-commerce conversion rate, etc. to judge whether they need to make improvements to their collaboratively tagged resources and campaigns/product promotions that relate to their business revenue [11,26]. For the jewelry store use case, the revenue performance measures (for e.g., per visit goal value) were deliberately zeroed in on in order to preserve business privacy and to conduct an unbiased pilot study of the functionality of the proposed BIRS. In reality, such performance measures can be used to track marketing content results and correlate the campaigning efforts to the actual return on investment (ROI).



Entrances	Unique Visitors	Bounces	Pageviews	Avg. Time on Page	Per Visit Goal Value	Goal Completions
2,605,651	2,197,899	1,361,311	9,855,985	00:06:02	$0.00	236,153

	Page Title	Unique Pageviews	Pageviews	Entrances / Pageviews	Bounce Rate	Avg. Time on Page	Page Value
		2,330 % of Total: 100.00% (2,330)	2,839 % of Total: 100.00% (2,839)	55.20% Site Avg: 55.20% (0.00%)	71.05% Site Avg: 71.05% (0.00%)	00:02:25 Site Avg: 00:02:25 (0.00%)	$0.00 % of Total: 0.00% ($0.00)
1.		493 (21.16%)	602 (21.20%)	74.75%	64.89%	00:02:36	$0.00 (0.00%)
2.		313 (13.43%)	385 (13.56%)	73.77%	65.85%	00:04:02	$0.00 (0.00%)
3.		260 (11.16%)	290 (10.21%)	86.90%	73.81%	00:04:38	$0.00 (0.00%)
4.		172 (7.38%)	265 (9.33%)	37.36%	56.57%	00:03:08	$0.00 (0.00%)
5.		132 (5.67%)	152 (5.35%)	86.84%	83.33%	00:05:45	$0.00 (0.00%)

Figure 4. Content efficiency analysis reports.

The e-commerce traffic analysis report provides information about the websites that are sending the best traffic using metrics such as new versus existing page visits, bounce rate, and per-visit revenue [15]. An example e-commerce traffic analysis report from various sources, including organic traffic from search engines, referrals, etc. is given in Figure 5. Similarly, heat map applications that use overlays to show the percentage of visitors clicking a link, mapping of other traffic sources to user behavior, etc. could be incorporated into the website in order to see the hotspots on each page.

With the prevalence of IoT, the use of different technologies by users can be monitored too. For example, performance of different client browsers that users adopt when they visit the store's website could be analysed. A browser performance report generated for the jewelry website showing which browsers are winners and which ones might have problems is illustrated in Figure 6. Even usage of each keyword in the browser could be analysed in terms of its correlation with business revenue and the resulting monetary value. Other metrics such as e-commerce conversion rate that shows the rate of conversion of every keyword search to a successful customer order could be analysed.

With social media playing an important role in consumer behavior, data collected from social networks relating to page likes, reach (organic or paid), visits, posts, and people who are connected to the user, etc. form BD inputs to the proposed BIRS. Analysis of such BD with various metrics using the data analytics tools of BI provides useful insights, similar to Facebook insights, to track user interactions [23]. Such a feature of social engineering based insights dashboard provides social ranking to connect relevant users. Similarly, social strength measures of user experience are of added-value to the retailers and businesses. Figure 7 shows the social engineering based insights dashboard for the jewelry e-commerce website. Today, several platforms such as Google analytics and HubSpot web analytics are emerging to provide such performance measurement reports for monitoring the digital marketing efforts of the business. How much time, effort and money should be spent in setting up such tracking features of BI would very much depend on how the business can integrate such applications within their RS and how effectively they can use the data for future business decisions.

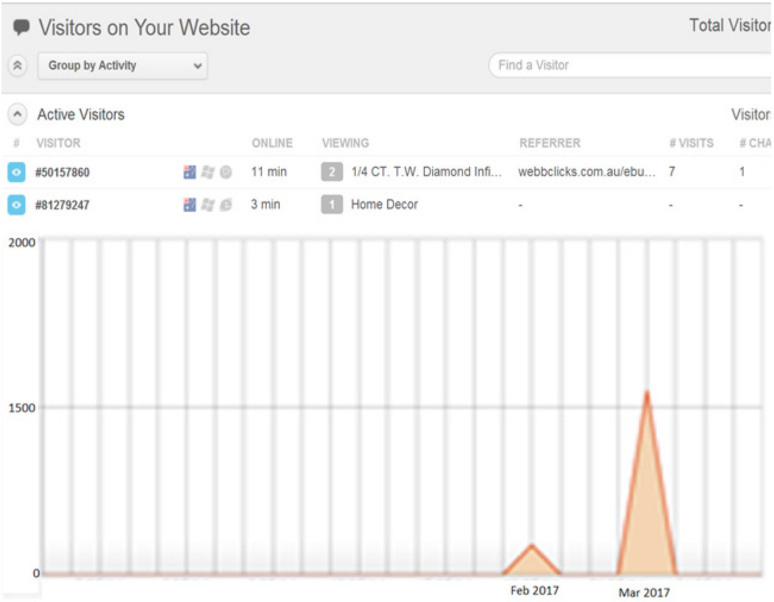
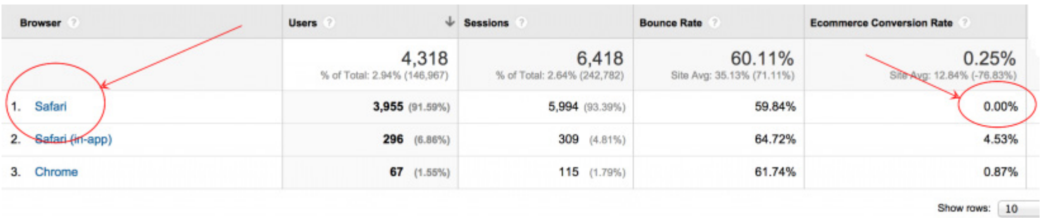


Figure 5. Example e-commerce traffic analysis report.



Browser	Users	Sessions	Bounce Rate	Ecommerce Conversion Rate
	4,318 % of Total: 2.94% (146,967)	6,418 % of Total: 2.64% (242,782)	60.11% Site Avg: 35.13% (71.11%)	0.25% Site Avg: 12.84% (-76.83%)
1. Safari	3,955 (91.59%)	5,994 (93.39%)	59.84%	0.00%
2. Safari (in-app)	296 (6.86%)	309 (4.81%)	64.72%	4.53%
3. Chrome	67 (1.55%)	115 (1.79%)	61.74%	0.87%

Show rows: 10

Figure 6. Browser performance report.

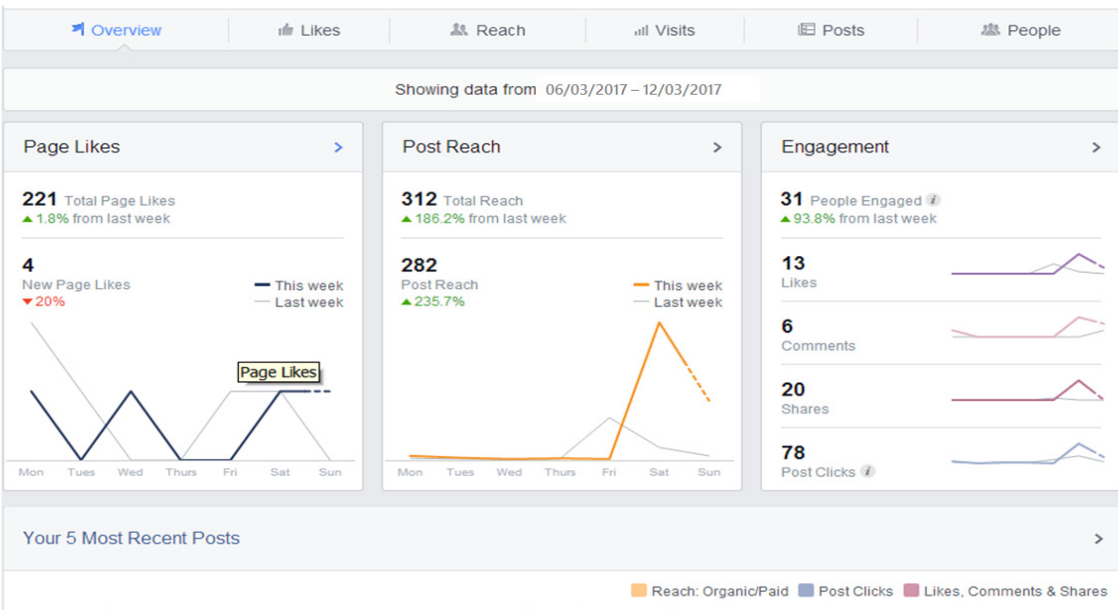


Figure 7. Social engineering based insights dashboard for an e-commerce store.

With business data available in a wide range of formats, BD analytics could be leveraged since new categories of data architectures of nonrelational data coexist with traditional relational databases [27]. Several reporting features of BI can be utilised by the recommender system of an e-commerce store to continuously monitor and evaluate the performance of the website against their business key performance indicators (KPI). Such metrics and visibility about the performance of the store could serve as change-enablers that help businesses to dynamically respond effectively to changing customer needs.

5. Conclusions and Future Work

Traditionally, a significant amount of research explored the five main types of recommender techniques (collaborative, demographic, content, utility and knowledge based). As they exhibit complementary advantages and disadvantages, hybrid models were proposed for specific industry scenarios. With new paradigms of social engineering and advancement in BD analytics, the dynamic changes in user behaviour and community data could affect the performance of the RS models adopted so far. Hence, there is a need to monitor and continuously improve these RS models to serve two purposes: (1) to enhance user's quality of experience and (2) to relate RS performance measures with business goals. This paper proposed the use of BI concepts to address this requirement.

BI tools could be used to employ BD data analytics for determining RS monitoring metrics, which has been recently in the limelight. Particularly lacking in literature is the use of BI in RS to intelligently monitor and measure the effectiveness of its recommendations made to the user and how they relate to business goals. In this paper, we proposed a generic framework for Business Intelligent Recommender System that takes a step forward to fill this gap. The proposed framework made use of OLAP reporting tools with BD to monitor RS performance and its correspondence to business KPIs. We discussed the components of the proposed recommender system and its application to a B2C e-commerce website as a use case example. The BIRS implemented for an industry setting was able to generate many performance dashboards making use of huge data on the Web. These features provided a more trusted and context-aware set of recommendations to users with dynamically changing social and demographic circumstances as well as intelligent insights to businesses. Since the proposed BIRS framework is generic in nature, it could be applied to any industry setting, which motivates future work to perform a comparative study of the effectiveness of the framework applied to different real-world businesses.

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