Understanding Customer Data With AI Recommender Systems In The Automotive Industry: An Abstract

INTRODUCTION

Marketing has evolved from transactional to relationship-based (Sheth and Paravatiyar, 1995a) and businesses are now focusing on developing long-term relationships rather than short-term high-volume transactions (Osman, Hemmington and Bowie, 2009). The key to relationship marketing is targeting customers as individuals with unique needs and wants which the personalisation approach would be highly effective to establish a stronger one-to-one relationship with customers (Halima et al., 2011). The concept of personalisation has always been crucial to marketing. However, the rapid advancement of artificial intelligence (AI) and information technology has heightened the significance of this phenomenon for all types of marketing initiatives (Aksoy et al., 2020). The increasing popularity of AI applications is credited to its high degree of real-time personalisation where its paradigm has shifted from a rule-based expert system to a deep-learning based (Kumar et al., 2019).

Among the various AI tools and applications used for personalised marketing, the recommender system remains widely popular as it is regarded as one of the most useful tools to provide a high degree of personalisation (Kumar et al., 2019; Zanker, Rook and Jannach, 2019). This led to the birth of "recommendation marketing" which is defined as the process in which businesses suggest a product or service based on their current and future customers' interests by leveraging on available data (Chinchanachokchai, Thontirawong and Chinchanachokchai, 2021). AI has the capability to rapidly provide reliable real-time analysis of large contextual and behavioural data beyond that of humans (Tam and Ho, 2005; Tanveer, Khan and Ahmad, 2021). Hence, businesses that deploy AI gain deeper insights into the needs of their customers (Hoyer et al., 2020) potentially allowing them to offer real-time personalised products or services (Tam and Ho, 2005) through the analysis of several data such as the customers' demographic, behaviour and transactional (Chinchanachokchai, Thontirawong and Chinchanachokchai, 2021; Huang and Rust, 2020; Verma et al., 2021). Therefore, with the deployment of AI to perform real-time tracking, data mining and dynamic content generation, hyper-personalised marketing has been made possible (Tam and Ho, 2005).

Recommender system uses machine learning algorithms such as clustering, k-nearest neighbour and matrix factorisation (Kumar et al., 2019) to predict customers' interest in the product or service (Chinchanachokchai, Thontirawong and Chinchanachokchai, 2021). However, implementing the same algorithms to different recommender systems and testing against the same measures using the same methodology, could yield different results (Said and Bellogin, 2014). The issue occurred due to "different data management procedures and slight deviations in the interpretation of the evaluation methodology and algorithmic steps" (Zanker, Rook and Jannach, 2019). Hence, existing recommender system algorithms might not be generalisable to the UK automotive industry.

Therefore, this research aims to investigate the use of a hybrid AI recommender system in providing personalised recommendations to customers in the automotive industry.

BACKGROUND

Customer Relationship Management (CRM)

In the present digital world where data is deemed as the new oil of the economy (Wieringa et al., 2021), information and data have become crucial for businesses to sustain a competitive advantage (Nguyen, Jaber and Simkin, 2020; Van Tonder and Petzer, 2018). The advancement of information technology software and tools (Valmohammadi, 2017) coupled with the rising level of competition and rapidly changing customers demand (Mosa, 2022) has led to the growing interest in CRM among practitioners and academics (Guerola-Navarro et al., 2021; Parvatiyar and Sheth, 2001). Despite the growing interest, there has not been a widely accepted definition of CRM (Nicolescu and Nicolescu, 2021) and numerous definitions regarding CRM exist. While the fragmented CRM definitions signify that a variety of different viewpoints exist (Parvatiyar and Sheth, 2001; Payne and Frow, 2005), Reinartz, Krafft and Hoyer (2004) claimed that any definition of CRM is appropriate depending on the level at which CRM is practised. Despite the fragmented definitions regarding CRM, several researchers have identified various CRM types and levels such as Strategic, Operational, and Analytical (Reiny & Buttle, 2007); Operational, Analytical, and Collaborative (Karimi, Somers and Gupta, 2001; Payne, 2005) and functional level, customer-facing level, strategic level (Kumar and Relnartz, 2006; Reinartz, Krafft and Hoyer, 2004). Buttle (2009) opined that CRM can be categorised into four types – Strategic, Operational, Analytical and Collaborative.

Peppers and Rogers (1999) developed the IDIC model (Identify, Differentiate, Interact and Customised) which includes a four-step implementation process for organisations to develop a long-term one-to-one relationship with customers. The Operational CRM includes 'Identify' and 'Interact' while the Analytical CRM includes 'Differentiate' and 'Customised' (Siddiqi, Akhgar and Wise, 2002). The IDIC model was developed to reflect a 'learning relationship' that gets smarter and richer with every interaction between the business and customers (Peppers and Rogers, 1999). However, the IDIC model focuses on having more interactions that require customers to specify their needs and wants to develop the learning relationship required for the customisation of products/services. On the other hand, personalisation has now embedded the application of AI and machine learning (Zanker, Rook, and Jannach, 2019) where the algorithms continuously learn from streams of data (Kumar et al., 2019) to support businesses in personalising suitable marketing mix for customers (Arora et al., 2018) while requiring lesser interaction efforts from customers (Tiihonen and Felfernig, 2017).

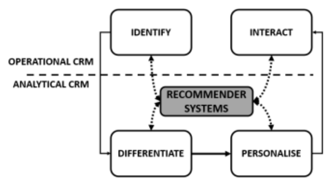

Figure 1 Author Proposed Model

The integration of advanced technology into CRM systems continues apace (Libai et al., 2020) and has evolved from a traditional CRM system with no personalisation involved to current-day AI-enabled personalisation (Khan and Iqbal, 2020). The recommender systems can be integrated into the IDIC model to create more accurate and relevant personalized messages for customers with lesser interaction efforts from customers. It has the capabilities to learn consumption patterns, customer habits, demographic data, etc. to perform appropriate real-time segmentation, prioritization and personalisation that exceeds human capabilities (Chatterjee et al., 2019).

Recommender Systems

Recommender systems are software tools that provide automated and personalised suggestions of items that are of interest to users. Recommender systems generally provide businesses with a competitive advantage and boost customer engagement (Shen, 2014) and have been deployed by several leading companies (i.e., Netflix, YouTube, Spotify, Amazon, LinkedIn, etc.) to convey personalised content or make product recommendations to their users. Recommender systems have been proven to be a valuable tool for customers to navigate the issue of information overload (Ricci, Rokach and Shapira, 2015). Therefore, recommender systems are normally directed at customers who lack the knowledge or experience to evaluate the overwhelming alternatives (Chinchanachokchai, Thontirawong and Chinchanachokchai, 2021; Ricci, Rokach and Shapira, 2015). Recommender system acts as filtering tools that use explicit (e.g., ratings) and implicit (e.g., transaction history, browsing history and search patterns) feedback (Koren and Bell, 2015) to tailor relevant content or information to users thereby reducing their time and effort required to search for this information (Roy and Dutta, 2022).

The purpose of the recommender system is to estimate the utility of an item (presented in terms of user ratings) and predict if the item is worth recommending. The recommender system finds an item for a particular user by maximising the utility function which varies according to the recommendation technique selected. Previous research has identified three main types of recommender systems - content-based, collaborative filtering and knowledge-based (Koren and Bell, 2007; Panda and Ray, 2022). However, each of these techniques is restrictive on its own, especially when several data sources are available (Aggarwal, 2016). Therefore, with a hybrid recommender system, a combination of techniques and algorithmic power from the same or various recommender systems (Aggarwal, 2016; Burke, 2007) can be applied to compensate for the disadvantage of using the other technique and to improve the performance of the recommender system, particularly the cold start problem (Ricci, Rokach and Shapira, 2015). However, careful consideration of the combination of techniques is important to ensure the success of the recommender system (Burke, 2007).

Despite the advantages of implementing a recommender system, businesses ought to be mindful that their focus should not be solely on the accuracy of prediction (i.e., the issue of over-fitting) (Kunaver and Požrl, 2017; Zanker et al., 2019). This may result in an over-fitting problem where customers constantly receive similar information/recommendations (Lin et. al., 2021) which leads to a lack of interest in the information/recommendations and customers may potentially treat such information as spam over time (Wang, Gong, Li and Yang, 2016). Moreover, predictive models with a focus on accuracy tend to recommend popular products frequently purchased or viewed by users which limit businesses' ability to recommend other novel/less popular products and potentially leads to loss of business opportunities (Lin et. al., 2021). Businesses need to identify the appropriate balance between accuracy and diversity for their recommender system. As every piece of information communicated to the customer influences their behaviour and engagement with the business, businesses must understand the consequences of their communication with customers to allow for a more planned recommender design (Ricci, Rokach and Shapira, 2015).

METHODOLOGY

The proposed methodology would require a three-steps approach, as appended.

1. Developed an appropriate hybrid recommender system;
2. Conduct lab-based testing of the recommender system with a group of participants; and
3. Launched the recommender system on the actual website to understand how actual customers behave towards suggestions made by a hybrid recommender system.

The key requirements of the recommender algorithm are data and preparation of the dataset (Thomas and Vaidhehi, 2018). Therefore, the research begins with identifying relevant data points required. As the research is industry-driven, customer data (e.g., demographic, transaction and web session/behaviour) and product specification information will be obtained from the client. Once the available data has been consolidated, the research will proceed to the data processing stage which is crucial to ensure the reliability of results. Data cleaning, integration, normalisation (i.e., data has varying scales, does not follow a Gaussian distribution, etc.), simplification and dimensionality reduction are included in this stage of the process (Yao et al., 2019). Next, the research would select, develop and fine-tune the appropriate model. Lastly, the model will be evaluated based on accuracy metrics (i.e., Mean square error, root mean square error and precision-recall metric).

The use of lab-based testing is to minimise the risk and allows for further refinement to improve the performance of the recommender system. Participants will be recruited to test the model and provide the necessary feedback for further refinements. As discussed in the previous chapter, critiques have been raised on the evaluation of a recommender system solely based on its predictive power (Lin et. al., 2021). Therefore, at this stage, the research can test for the click-through rate to understand if the recommender system successfully made appropriate recommendations (i.e., accurate, diverse and novel). Lastly, the model will be implemented on the client website and results will be analysed to understand how customers react to personalised suggestions made by a hybrid recommender system for infrequent and expensive purchases as well as to study the click-through rate as well as the adoption and conversion rate. While the click-through rate is helpful to determine whether customers would click on the recommendations, it might not be the appropriate proxy to access the true relevance of the suggestions. “Catchy or insufficient link texts” that irritate or mislead customers could be the result of an unexpected increase in click-through rate (Zanker, Rook and Jannach, 2019). Therefore, the adoption and conversion rate move beyond the basic click-through rate by accessing the duration that customers take to browse the page/suggested item (adoption) or the proportion of customers adding the product to their cart/checking out (conversion).

IMPLICATIONS FOR THEORY AND PRACTICE

This research aims to bridge the recommender system research gap between marketing and computer science in the form of user studies. As recommender systems are implemented with the primary goal of increasing sales and revenue (Aggarwal, 2016) as well as enhancing customers' online experience and engagement (Chinchanachokchai, Thontirawong and Chinchanachokchai, 2021), it is important to understand the impact of a recommender system on developing a long-term relationship with customers while shifting the focus from mass-customisation to mass-personalisation.

References Available Upon Request