

**CUSTOMER PROFILING TO IMPROVE SERVICE
AND MANAGEMENT OF MOBILITY ON DEMAND
(MOD) SYSTEMS**

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Degree of Master of Science

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Sri Lanka

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DECLARATION

I declare that this is my own work and this dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidate has carried out research for the Masters Dissertation under my supervision.

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ABSTRACT

A system which caters the mobility requirements/travel needs in real time with user demand is known as Mobility on Demand system (MoDS). Global companies like Uber, Lyft, and local company like PickMe can be considered as examples for a Mobility on Demand systems. With the prevailing rapid growth of these MoDS, there is an explosion in system data where massive amounts of information related to customer rides are gathered on a daily basis. Due to this enormous volume of data, there is a potential for exploiting data mining and machine learning technologies to make the service smart and improve the management functionalities of the system.

Even though there is a vast amount of data at hand, the lack of systematic modelling techniques in MoDS is delaying the businesses from achieving smart systems with improved and personalized services. However, when considering similar E-commerce systems, user profiling and segmentation can be identified as the foundation towards smart improved service and management. Hence it is crucial to form the necessary framework towards user profiling and segmentation in MoDS. Research work found in our work is two-fold. First, we introduce a systematic aggregated and anonymous analysis schemes towards user profiling and segmentation in MoDS. Starting from the feature extraction specific to the MoDS, a detailed methodology for building the profile vectors is defined by this work in the following sections.

Then consequently, we extended the methodology towards enabling recommender systems in MoDS in order to improve the service. Moreover, under the recommender system methodology, a novel deep Collaborative Filtering method is introduced, and evaluation results show that the new model is capable of outperforming the current state-of-the-art techniques for Collaborative Filtering. The outcome under the recommender system for MoD is a hybrid system which incorporates all the profile vectors built in the customer profiling phase. Evaluation of the overall recommender system with historical data shows a significant improvement in recommendations related to MoD services.

Keywords: Mobility on Demand systems (MoDS), Recommender Systems (RS), Collaborative Filtering (CF)

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LIST OF ABBREVIATIONS

Abbreviation	Description
MoDS	Mobility on Demand System
RS	Recommender System
BDA	Big Data Analytics
RFM	Recency Frequency Monetary
POI	Point of Interest
CF	Collaborative Filtering
MF	Matrix Factorization
AE	Autoencoder
AAE	Adversarial Autoencoder
VAE	Variational Autoencoder

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