A Machine Learning Approach to Model HRI Research Trends in 2010~2021

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***Abstract*—The present study collects a large amount of HRI-related research studies and analyzes the research trends from 2010 to 2021. Through the topic modeling technique, our developed ML model is able to retrieve the dominant research factors. The preliminary results reveal five important topics, handover, privacy, robot tutor, skin de deformation, and trust. Our results show the research in the HRI domain can be divided into two general directions, namely technical and human aspects regarding the use of robotic applications. At this point, we are increasing the research pool to collect more research studies and advance our ML model to strengthen the robustness of the results.**

***Keywords*—human-robot interaction, machine learning, topic modeling, research direction, trend, review**

I. INTRODUCTION

Human-robot interaction (HRI) has become an important field over the past decades. The design of robotic agents involves complex system applications and requires interdisciplinary knowledge, including computer science, robotics, artificial intelligence, information management, usability expertise, etc. Various HRI applications have been developed and utilized in numerous fields and a considerable amount of research has focused on evaluating the interaction between human operators and robotic agents. Since robotic technology is not advanced enough to satisfy all types of real-world situations, a successful collaboration occurs when the humans and robots adapt to each other and reach a mutual understanding of the shared goals. HRI research focuses on developing robotic applications in various contexts and examines how humans collaborate with robots in a variety of general and specific situations. HRI raises many research opportunities, including human-related (including psychology and cognitive science), robot-related (including robotic agents and intelligent systems), and environmental (including social norms and cultural values) aspects [1]. The present study aims to identify the important factors associated with HRI research trends, in which we collected a substantial amount of research studies published between 2010 to 2021 in six HRI-related journals or conferences and utilized the machine learning (ML) technique to model the important research topics.

II. RELATED WORKS

To examine research trends and model the relevant topics, researchers often have to conduct intensive reviews on a large amount of literature and perform the quantitative (e.g., meta-analysis) or qualitative (e.g., Delphi method) approach to validate the related factors. Various ML frameworks and topic modeling algorithms have been developed to improve the review and validation processes. Latent Dirichlet Allocation (LDA) [2] is one of the most popular topic modeling algorithms and has been widely used in various fields. However, inconsistent results are generated by the LDA that largely decreases its effectiveness. Nonnegative Matrix Factorization (NMF) [3], another widely used algorithm, utilizes multivariate analysis to extract sparse and meaningful features from a set of data vectors. However, NMF requires the constant size of input data across different time sections which could lead to potential issues in an unbalanced dataset. As the trend of HRI research may change across time, training a model with articles published in different time periods may fail to appropriately identify the emerging topics. Therefore, to capture the emerging HRI research focuses across time sequences, the corpus should be split into segments based on its published time to build topic models and to update the weight inside the models.

To avoid the aforementioned issues and identify the evolution of research topics in the HRI domain, the present research adopts a flexible online topic modeling algorithm, Deep Nonnegative Autoencoder (DNAE) [5]. The DNAE is a multiple-layer autoencoder without bias and nonlinear activation functions and imposed nonnegative constraints (Fig. 1). By minimizing the difference between the input data matrix V and the recovered matrix V', DNAE can learn the low-

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dimensional representations of the topics from the data matrix. The data matrix V will be decomposed into two matrices, H_1 and W_1, to represent the probability of a document regarding its belonging sub-topic and its weights of terms to each sub-topic. In addition, the DNAE's nonnegative constraints represent the terms and topics with its associated weights, which allow us to interpret the model weights in a more efficient manner. By continuously updating the DNAE weights, we can capture the thematic patterns and identify topics of articles and its changes over time.

III. METHODOLOGY

To train our ML model and retrieve the critical topics, a total of 4,279 full-text research articles is collected. These articles are published between 2010~2021in six HRI-related journals or conferences, including ACM/IEEE International Conference on Human-Robot Interaction (N=507), ACM Transactions on Computer-Human Interaction (N=247), Autonomous Robots (N=550), Human Factors (N=680), International Journal of Advanced Robotics Systems (N=1699), and International Journal of Social Robotics (N =626).

A. Data Preprocessing

Considering the representative and importance of the International Conference on Human-Robot Interaction (ICHRI), 507 ICHRI research articles are adopted and used as the corpus in this research, which enable us to compare the frequency of the retrieved key terms appearing in the ICHRI's publications. As Fig.2 shows, we first extracted the textual content from the proceedings published in the six selected journals and conferences to create an HRI-related dictionary that consists of 11,500 author-defined terms/keywords. We then construct a document-term matrix by breaking up the contents of articles published in the ICHRI into terms/words, filtering out 3,731 terms/words both exist in the HRI-related dictionary and the articles' content and computing their frequency of appearance in each article. Last, we transform the research articles published in ICHRI to a document-term matrix with 507 rows (articles) and 3,731 columns (terms/words).

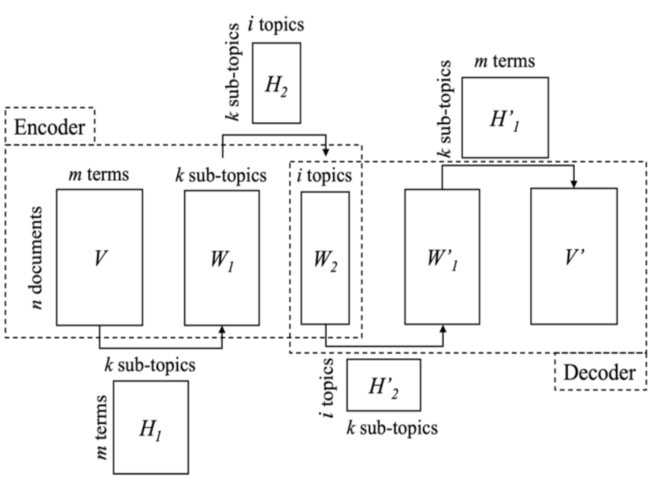

Fig. 1. DNAE framework.

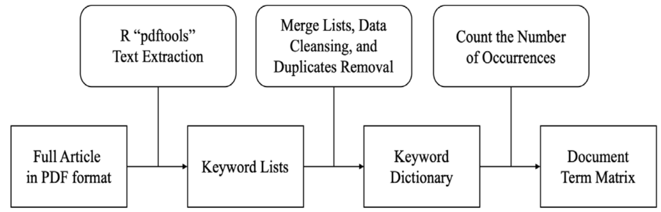

Fig. 2. Flowchart of data preprocessing.

B. Model Building

To discover the evolution of research trends in the HRI domain across the last decade, we need to update the DNAE's weights with new data in sequence. Since there are only dozens of articles published in the same year, we splice corpus with three years as a slice to make sure the sizes of data in slices are big enough to support the inherent topics. Then, we combine the current slice with the previous year to avoid the catastrophic inference problems which cause inconsistency between topics discovered from adjacent time slices [4]. In the experiment, we empirically define the DNAE's structure with three hidden layers (number of neurons are 15, 5, 15) and train the model with data in the four-time slices sequentially. With this model architecture, we first compress the 3,731 terms into 15 sub-topics, then the 15 sub-topics were compressed into 5 topics. After models are trained, we extract weights from matrices H_1 and H_2 in the encoder part of each time slice. Since the weights extract from the DNAE are nonnegative, terms with bigger weights are more important to a topic. So, we can discover the transition of important terms in a topic across time intuitively

IV. RESULT AND DISCUSSION

Regarding the reconstruction error of the DNAE measured by the Root Mean Square Error (RMSE), we set the model to classify the articles into 5 topics, took three years as a unit, and trained a total of four DNAE models. Table 1 shows the top-3 terms that appear in different topics from 2010 to 2021.

TABLE I. TOP-3 TERMS OF RETRIEVED TOPICS

	2010-2012	2013-2015	2016-2018	2019-2021
topic_1	grip force, load force, object transfer	handover, handovers, shared attention gaze	sex robots, priming, human human handover	sex robots, object transfer, vehicle automation
topic_2	older adults, older adult, assisted living	privacy, privacy preferences, teleoperated robots	privacy, privacy preferences, monitoring device	infrasound, media spaces, privacy preferences
topic_3	head motion, dialogue acts, nodding generation	gaze shifts, averted gaze, nodding generation	undo, robotic tutors, range sensors	language learning, second language learning, robot abuse
topic_4	nao, robot action ontology, japanese wikipedia ontology	skin deformation, path following, robot action ontology	skin deformation, skin stretch, path following	texture, skin deformation, motion synthesis
topic_5	personalization, service, services	trust, trust models, trust in automation	trust, trust scale, trust models	trust, decision aids, process control

Among the top terms in topic 1, the concepts are related to handover(s), human-human handover, and object transfer, which represent the importance of objects handover in the HRI fields. More specifically, the trend shifts from examining the force of gripping or loading an object to identifying how to direct human-robot shared attention gaze during the process regardless of its embodiment. Starting from the third segment (2016-2018), the research trend focuses more on the physical embodiment in HRI, which may suggest the emerging use of humanoid robots. The transfer of research focus from object handovers to sex robots also reflects that people's expectations for a robot are no longer limited to mechanical aids (such as automated logistics). In addition to the physical assistance, providing emotional support is equally important.

Another observation worth noting is the term 'privacy' in topic 2. The result shows that the popularity of the term 'privacy' in topic 2 has been high from 2014 to 2019, but suddenly cooled down in 2019, leading us to propose two possible conjectures. First, research has shown that people considerably support the privacy-encroaching policies and the use of contact-tracing technology to address the coronavirus disease of 2019 (COVID-19) [6], [7], indicating that the COVID-19 pandemic may have raised the public acceptance of privacy invasion. The global pandemic inevitably forced people to accept the feeling of lacking control over personal data, therefore the value of research on privacy in topic 2 decreased. Second, the terms in topic 2 such as 'monitoring device', 'teleoperated robots' and 'media space' revealed that topic 2 is related to in-door monitoring and domestic robots. This explained the reason why the popularity of the term 'privacy' in topic 2 suddenly cooled down since the research on privacy in topic 2 emphasized the privacy issues of remote surveillance while the public concern on privacy has shifted to mobile tracking technology under the influence of COVID-19.

The major focus of Topic 3 is relatively fuzzy, however, the dominant concepts are surrounded by the human-robot learning contexts, including robot tutors and (second) language learning. The other terms such as gaze shifts, range sensors, or robot abuse may indicate the relevant topics that arose in the learning contexts.

The term 'skin deformation' in topic 4 reflects the research trend of augmented reality (AR) and virtual reality (VR) that has risen in recent years. Being an essential method to create realistic character animation [8], the high research interest in skin deformation remained since 2013 representing the market demand of 3D characters to a certain extent. With the big investment into the development of the metaverse, it can be expected that the research enthusiasm in this field will still have a great potential for growth in the future.

The word 'trust' has continuously occupied an important position in research on topic 5 from 2013 to 2021. Research on topic 5 progressively shifted to its derivatives, including trust, trust in automation, trust scales, and trust models. Such changes may be attributed to the advancements of automation. The fast-paced development of application in various domains encourages researchers to focus on the actual implementation of the theory instead of extensive discussions such as the measures and leading factors of human-robot trust.

To observe the evolution of terms in the topic accurately, we present the popularity of terms in different topics in the heat maps. Fig. 3 and 4 reveal a stable trend of the retrieved terms; however, the robot tutor (topic 5) is relatively unstable (Fig. 5), as it appears in multiple topics over the years. This suggests the retrieved terms may intertwine with other terms to generate the associated concepts in other topics, however, its contributions are not as significant as the original topic (i.e., the term 'robot tutors' contributes more influence in topic 3 than the other topics).

Our results show the research in the HRI domain can be divided into two general directions, namely technical and human aspects regarding the use of robotic applications. The first group aims to examine the interaction between human operators and robotic agents, where topic 1 addresses human-robot handovers, topic 3 highlights the emerging use of robot tutors, and topic 4 affirms the importance of robot appearance. The second group presents a research perspective with emphasis on user perception of privacy (topic 2) and trust (topic 5), which reveals the associated factors influencing user behavioral intention to interact with robotic agents. The results suggest the overall research trends in ICHRI are relatively balanced across both human and robot aspects.

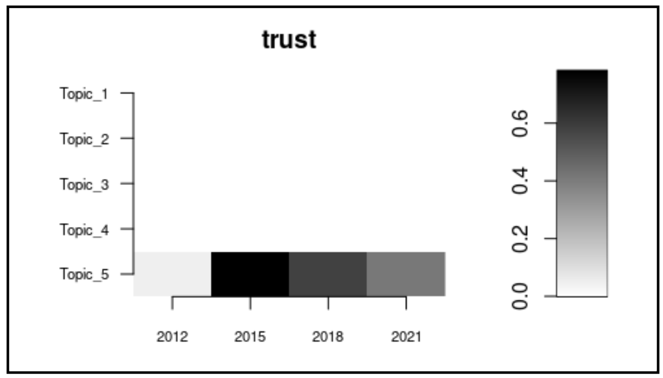

Fig. 3. The popularity of the trust-related topic across 2012-2021.

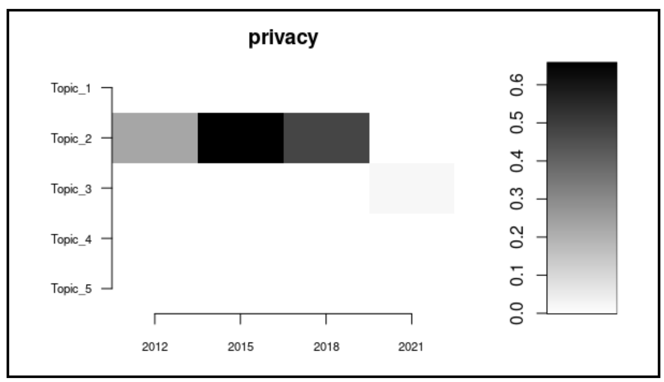

Fig. 4. The popularity of the privacy-related topic across 2012-2021.

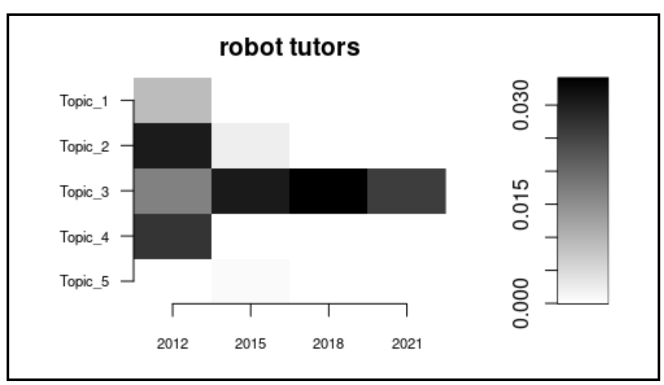

Fig. 5. The popularity of the robot tutors-related topic across 2012-2021.

As HRI-related research and the associated research has attracted significantly more attention in recent years, the present research collects a large number of relevant studies and identifies the important topics. Currently, we are increasing the research pool to collect more research studies and advancing our ML model to strengthen the robustness of the results.

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