MODESTUM

EURASIA Journal of Mathematics, Science and Technology Education, 2026, 22(4), em2817
ISSN:1305-8223 (online)

OPEN ACCESS

Review Article

https://doi.org/10.29333/ejmste/18280

Human trajectory prediction with machine learning: An integrated systematic review and bibliometric analysis (2015-2025)

Ahmad Zaki Aiman Bin Abdul Rashid [1], Azita Laily Binti Yusof [1*]

[1] Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, MALAYSIA

Received 31 July 2025 ▪ Accepted 10 February 2026

Abstract

This paper presents an in-depth bibliometric analysis of the evolving landscape of human trajectory prediction through the lens of machine learning (ML), leveraging both bibliographic coupling and keyword co-occurrence methodologies. Drawing from a curated corpus of high-impact publications indexed in Scopus from 2015 to 2025, the study unveils the intellectual and conceptual structure of the field. The bibliographic coupling analysis identifies five dominant thematic clusters: (1) sensor-driven human activity and mobility monitoring, (2) deep learning approaches for pedestrian and crowd trajectory forecasting, (3) autonomous vehicles and intelligent driving behaviors, (4) multi-agent coordination and vehicle-to-vehicle dynamics, and (5) vision-based trajectory estimation and behavioral understanding. In parallel, the co-occurrence analysis reveals four emergent conceptual clusters centered around: (1) autonomous systems and environmental perception, (2) human-centered motion modeling, (3) predictive artificial intelligence (AI) and spatiotemporal learning, and (4) cognitive modeling and adaptive learning architectures. The findings underscore a paradigm shift toward hybrid deep learning frameworks, socially-aware multi-agent models, and explainable trajectory forecasting systems. Furthermore, the study identifies key future directions including graph-based motion prediction, privacy-preserving analytics, and real-time edge-AI deployments. This bibliometric roadmap serves as a foundational reference for scholars, system architects, and policymakers engaged in advancing intelligent mobility systems and human-machine interaction in complex environments. Beyond intelligent mobility systems, the findings offer direct implications for educational environments, particularly in smart campuses and learning analytics. ML-based human trajectory prediction can support student flow optimization, campus safety monitoring, and adaptive learning space design. This study therefore provides a conceptual and practical foundation for integrating predictive mobility analytics into educational and institutional decision-making.

Keywords: human trajectory prediction, deep learning, science mapping, pedestrian forecasting, bibliometric analysis

INTRODUCTION

The ability to accurately predict human trajectories has become a cornerstone of innovation in a range of intelligent systems, including autonomous navigation (Gorlo et al., 2024), crowd analytics, smart surveillance (Rudenko et al., 2019), urban planning (Rossi et al., 2021), and handover management in 5G networks (Ma et al., 2021). As humans move through physical spaces—both indoors and outdoors—their motion is governed by a complex interplay of goals, obstacles, interactions, and environmental context. Modeling this behavior with high fidelity is essential for designing systems that are proactive, adaptive, and socially aware.

A human trajectory can be defined as a sequence of spatial positions (often 2-dimensional or 3-dimensional coordinates) that describes the movement of a person over a period of time. Each point in the trajectory corresponds to the person's location at a specific time step, forming a path that reflects their motion dynamics and interactions with the environment or other people (Alahi et al., 2016; Gorlo et al., 2024; Huang et al., 2023;

✉ zakiaimanrashid@gmail.com ✉ azita968@uitm.edu.my **(*Correspondence)**

Contribution to the literature

- This study maps the intellectual and conceptual landscape of trajectory prediction research using ML.
- It identifies the most influential themes, techniques, and application domains.
- It highlights future directions such as transformer-based forecasting, privacy-preserving trajectory models, and real-time prediction on edge devices.

Kothari et al., 2020; Lin et al., 2024; Peng et al., 2024; Rudenko et al., 2019; Zhao et al., 2020). The definition of human trajectory prediction involves the forecasting the future positions of a person based on their observed past trajectory, often considering social and environmental factors that influence movement (Alahi et al., 2016; Gorlo et al., 2024; Huang et al., 2023; Kothari et al., 2020; Lin et al., 2024; Peng et al., 2024; Rudenko et al., 2019; Zhao et al., 2020).

In recent years, machine learning (ML)—particularly deep learning, recurrent neural networks, graph neural networks (GNNs), and transformer-based models—has revolutionized the field of trajectory prediction. These models offer the ability to capture temporal dependencies, spatial relationships (Zhou et al., 2022), and social interactions that traditional statistical models fail to represent. State-of-the-art models can now anticipate future trajectories in real-time, even in highly dynamic and multi-agent environments, enabling improved decision-making in applications such as self-driving cars (Sun et al., 2022), video surveillance (Kothari et al., 2020), and telecommunication and networks management where predicting user movement aids in resource allocation and mobility management, enhancing service quality (Wang et al., 2019).

Research Problem

Despite rapid advances in ML-based human trajectory prediction, the existing literature remains methodologically fragmented, conceptually dispersed, and application-driven, with limited integrative understanding across disciplines. Studies are scattered across computer vision, robotics, transportation, smart environments, and educational analytics, often emphasizing algorithmic performance without clarifying underlying assumptions about human behavior, interaction dynamics, context awareness, or temporal prediction horizons.

Furthermore, prior reviews in this domain predominantly focus on technical comparisons of models or application-specific surveys, lacking a systematic synthesis of conceptual dimensions and an evidence-informed mapping of research evolution over time. This gap makes it difficult for researchers—particularly those in education, learning analytics, and human-centered system design—to identify dominant paradigms, emerging trends, and underexplored research opportunities.

In educational contexts, human trajectory prediction has growing relevance for understanding student flow, classroom transitions, and campus-scale mobility patterns. Predictive models can inform smart campus design by anticipating congestion in corridors, optimizing classroom occupancy, and enhancing campus security through early detection of abnormal movement patterns. Furthermore, the integration of ML-based movement prediction with spatial layouts enables intelligent learning environments, where classroom configurations, resource allocation, and student support service adapt dynamically to observed and predicted human behavior. Despite this potential, educational applications remain underrepresented and weakly connected to mainstream trajectory prediction research.

Therefore, the central problem addressed in this study is the absence of an integrated, conceptually grounded synthesis that combines systematic review principles with bibliometric science mapping to organize, interpret, and contextualize ML approaches to human trajectory prediction over the past decade (2015-2025).

To address this gap, this paper presents a comprehensive bibliometric analysis of research on human trajectory prediction using ML from 2015 to 2025. Using data derived from Scopus, we apply bibliographic coupling and keyword co-occurrence analysis through VOSviewer to uncover dominant research clusters, conceptual structures, and thematic evolution within the field. Five bibliographic clusters—ranging from sensor-based trajectory monitoring and pedestrian forecasting to vehicle behavior modeling—are identified alongside four conceptual clusters, including predictive AI models, cognitive learning architectures, and socially aware forecasting frameworks. Similar to bibliometric approaches applied in domains such as fall prevention and gerontology-related mobility research (Azizan, 2024a), this study aims to map thematic clusters and intellectual structures in human trajectory prediction using ML techniques.

The key contributions of this study are as follows:

1. It maps the intellectual and conceptual landscape of trajectory prediction research using ML.
2. It identifies the most influential themes, techniques, and application domains.
3. It highlights future directions such as transformer-based forecasting, privacy-

Table 1. Search string in Scopus database

No	Keywords	Justification
1	(TITLE ((“trajectory prediction” OR “motion prediction” OR “movement forecasting”) AND (“human” OR “pedestrian”))	To identify literature related to human trajectory prediction
2	TITLE ((“machine learning” OR “deep learning” OR “LSTM” OR “GRU”)))	To identify literature related to machine learning
3	AND PUBYEAR > 2015 AND PUBYEAR < 2026	To identify the publication year

preserving trajectory models, and real-time prediction on edge devices.

The remainder of the paper is structured as follows: We first describe the methodology and data sources used for bibliometric extraction. We then present the results of the bibliographic and co-occurrence analysis. Next, we discuss thematic trends, research gaps, and future opportunities. Finally, we conclude with actionable insights for academics and practitioners in the trajectory prediction domain.

RESEARCH METHODOLOGY

Bibliometric Analysis and Science Mapping

Bibliometric analysis is a quantitative method used to evaluate and map scientific literature, helping researchers understand the structure, trends, and impact of research within a specific field (Donthu et al., 2021). It measures aspects like publication counts, citation counts, and various indices (e.g., h-index and impact factor) to evaluate the influence of articles, authors, journals and institutions (Choudri et al., 2015; Cooper, 2015; Donthu et al., 2021; Lazarides et al., 2023; Merigo & Yang, 2017). Besides quantitative assessment, another purpose of bibliometric analysis is mapping research fields where it helps identify core research themes, intellectual structures, key contributors, and emerging trends within discipline (Donthu et al., 2021; Hassan & Duarte, 2024; Kaparthi, 2005; Zupic & Cater, 2014). This analysis can be classified into two categories:

(1) science mapping and

(2) performance analysis (Noyons et al., 1999).

The first type assesses the structural and dynamic dimensions of scientific research. The second type is utilized to assess research performance based on authors, organizations, nations, and sources. The current research employs scientific mapping to reveal the chronological framework of the knowledge base about human trajectory prediction and ML. Based on the objectives, two analyses are utilized to achieve the study’s aims:

1. **Bibliographic coupling:** Bibliographic coupling occurs when two articles cite the same references. The more reference they share, the stronger their bibliographic coupling and the higher their estimated similarity (Kazienko et al., 2020). Its main purpose is to analyze the relatedness of articles, cluster research topics, and map scientific literature (Habib & Afzal, 2019). This analysis is commonly utilized in information retrieval, topic clustering, research paper recommendation systems, and systematic literature reviews (Liu, 2017).
2. **Co-word analysis:** Co-word analysis is a quantitative content analysis technique used to map and understand the relationships between concepts, topics, or research areas by examining how often pairs of words or phrases appear together in a collection of texts (Zupic & Cater, 2015). The method counts how frequently pairs of words (or phrases) appear together in documents, using this frequency to infer the strength of association between concepts (Delecroix & Eppstein, 2004).

Previous studies have shown how bibliometric science mapping can effectively uncover thematic shifts and collaborative patterns in sensor-based and exercise-focused research (Azizan, 2024b), validating its utility in revealing research dynamics in technical and health-related domains alike.

From an educational research perspective, bibliometric science mapping offers a systematic means to identify how learning environments, human behavior modeling, and AI-driven analytics intersect across disciplines. By revealing dominant research streams and conceptual linkages, bibliometric analysis supports curriculum development, interdisciplinary research planning, and evidence-based adoption of emerging technologies in education. In practical terms, such mappings enable educational institutions to identify mature techniques suitable for deployment (e.g., student flow monitoring) and emerging methods requiring further validation.

Research Design and Data Collection Procedure

On 12 June 2025, the search string in **Table 1** was created and utilized in the Scopus database to locate publications based on relevant keywords. The two main keywords are related to human trajectory prediction and ML.

The search was applied in the documents section as shown in **Figure 1** using the “search within” with type “article type” with AND operator to combine both search strings. The presence of keywords in the article title areas indicates their significance to the associated publications.

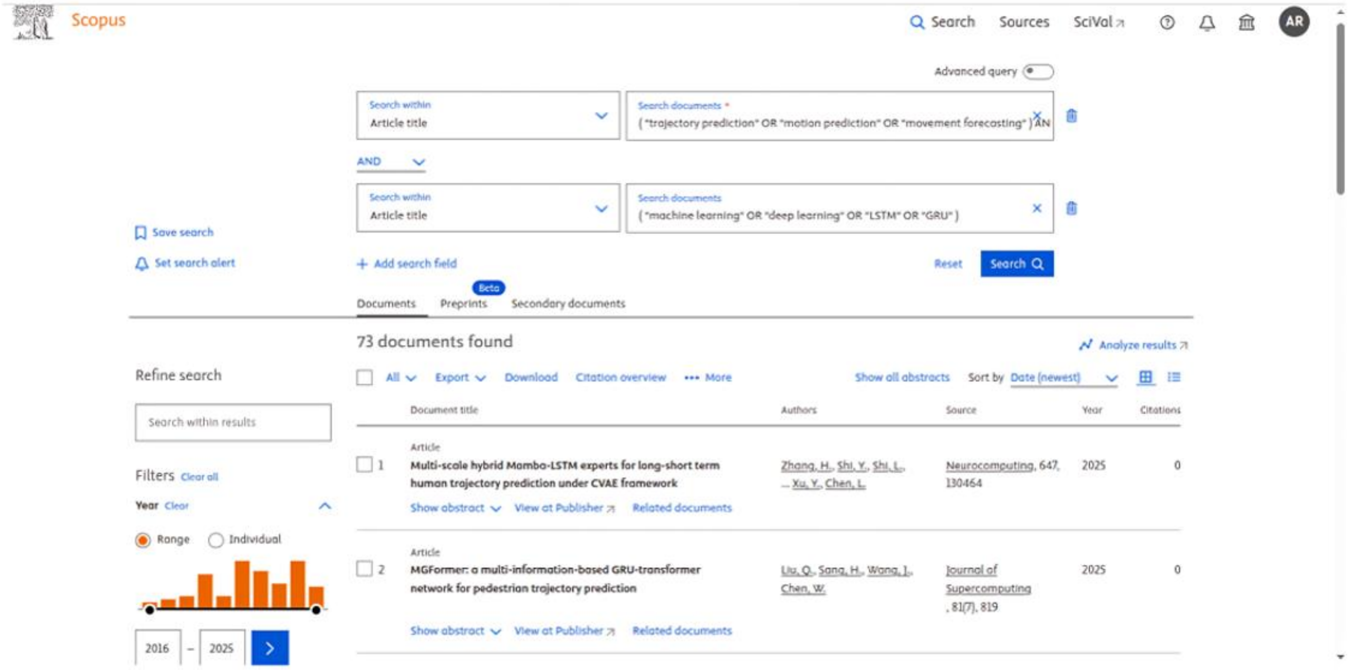

Figure 1. Searching strings in Scopus (Source: Authors' own elaboration)

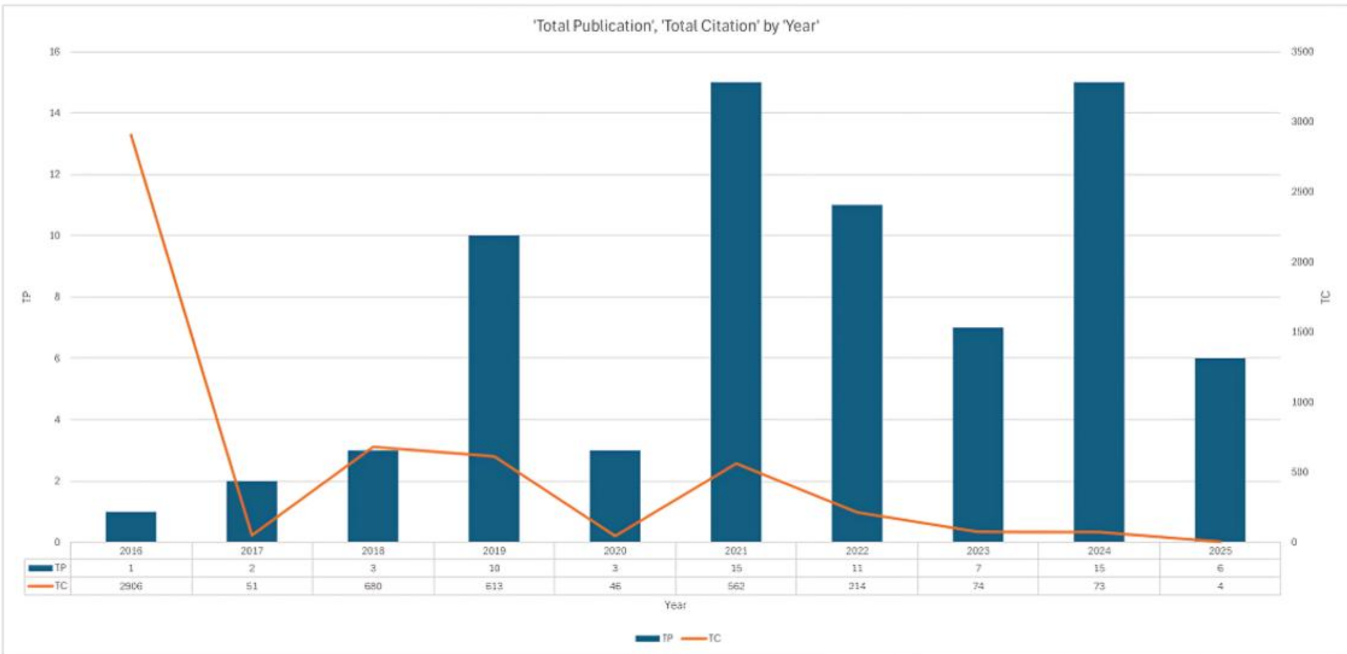

Figure 2. TP and TC on human trajectory predictions (Source: Authors' own elaboration)

Scopus is selected as the bibliographic database because of its superior quality and distinctive features (Baas et al., 2020) and offers useful bibliometric indicators and author profiles that increase its usefulness for institutional rankings and research evaluations (Ballew, 2009). While Scopus provides high-quality curated metadata, alternative data sources such as IEEE Xplore, Web of Science, and open repositories (e.g., arXiv) can complement bibliometric coverage, particularly for emerging ML techniques and early-stage educational applications. Methodological diversity can also be enhanced by integrating citation-based mapping with content-based topic modeling, longitudinal trend analysis, and hybrid qualitative-quantitative synthesis. Additionally, the analysis encompasses solely journal publications. Restricting journals would ensure that only high-quality, peer-reviewed documents are incorporated into the science mapping (Tan & Fauzi, 2023). The software VOSviewer version 1.6.18 was utilized to visualize the network (Eck & Waltman, 2014). The network of bibliometric maps is analyzed, created, and visualized using the software program.

Figure 2 shows the total publications (TP) and total citations (TC) on human trajectory predictions for a decade. The highest number of publications on the human trajectory prediction topic is in the previous year 2024 with 15 total publications while the lowest is in the year 2016. The TP shows a general increase over the decade indicating growing research interest in human trajectory predictions. The peaks are in the year of 2021 and 2024 with the highest number of publications with 15 publications each. Significant increases were seen from 2019 to 2021 and again in 2024. The lows are shown in 2016-2017 which had minimal publications with 1-2 paper published. A drop is observed in 2020 with 3 publications and 2023 with 7 publications.

The highest total number of citations for this topic was achieved in 2016 with 2906 citations despite only one publication, suggesting that a seminal or highly influential paper was published that year, while the lowest is in the current year 2025 with 4 citations. 2018 to 2019 had moderate citations with 680 and 613 citations, respectively, aligning with the growth in TP. In recent years (2023-2025), the citations are low with 74, 73, 4, citations, respectively, which is expected as citations accumulate over time and newer papers haven't yet had time to be cited extensively.

As a conclusion, the graph reveals a maturing research field with significant foundational contributions in early years, notably in 2016. The growth in publication volume from 2019 onward suggests increasing academic engagement. Citation trends emphasize the importance of quality over quantity and reflect the natural lag in scholarly impact. Future work should aim at novel interdisciplinary methods, real-world deployment, and interpretable models to retain academic and practical relevance.

Integrated Systematic Review and Bibliometric Design

This study adopts an integrated review design that combines systematic literature review procedures with bibliometric science mapping techniques, following recommendations by Donthu et al. (2021) and Zupic and Čater (2015).

The systematic review component was used to ensure transparency, reproducibility, and relevance in study selection. This involved:

1. "Database selection (Scopus),"
2. "Keyword formulation and search strategy (**Table 1**),"
3. "Inclusion and exclusion criteria (journal articles, English language, 2015-2025),"
4. "Title and abstract screening," and
5. "Full-text eligibility assessment to confirm relevance to human trajectory prediction using machine learning."

The bibliometric component was subsequently employed to analyze the selected corpus at scale.

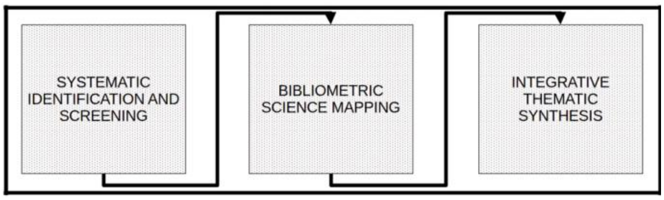

Figure 3. Overall research design (Azizan, 2024a, 2024b)

Bibliographic coupling was used to uncover the intellectual structure of the field, while keyword co-occurrence analysis revealed conceptual themes and research trends.

Finally, an integrative qualitative synthesis was conducted by interpreting bibliometric clusters through close reading of representative studies, enabling thematic labeling, cross-cluster comparison, and identification of conceptual dimensions relevant to human trajectory prediction research.

Figure 3 summarizes the overall research design. The study proceeds in three sequential phases: First, a systematic identification and screening process was conducted to ensure transparency and relevance in the selection of literature. Using a predefined search strategy and inclusion criteria, peer-reviewed journal articles on human trajectory prediction using ML published between 2015 and 2025 were identified, screened, and retained as the final corpus.

Second, bibliometric science mapping techniques were applied to analyze the intellectual and conceptual structure of the field. Bibliographic coupling was used to identify dominant research streams based on shared reference patterns, while keyword co-occurrence analysis revealed core themes and evolving research trends.

Finally, an integrative thematic synthesis was performed to interpret the bibliometric clusters through conceptual lenses related to human behavior modeling, interaction dynamics, uncertainty handling, and temporal prediction horizons. This phase enabled the translation of quantitative bibliometric patterns into meaningful insights, including implications for applied domains such as education and learning environments.

RESULTS AND DISCUSSIONS

The documents retrieved initially were 73 documents between the year 2015-2025 with conference proceeding (35), journal (32), and book series (6). After limiting the publications to the English language, the TP were 69. The highest publication on the topic is in 2021 and 2024, while the second highest is in 2022 followed by 2019. The highest citation was achieved in 2016 with 2906 of TC followed by 2018, 2019, and 2021. The observed clustering patterns also suggest increasing opportunities for cross-domain transfer, particularly toward education-oriented applications. Datasets derived from campus sensors, learning management systems, and smart building infrastructures represent promising yet underexplored data sources that could diversify future bibliometric and empirical analyses.

Bibliographic Coupling Results

This analysis discovered that 30 out of 73 documents met an 11-citation threshold. The threshold was determined by several trials to determine the suitable and robust network visualization in the science mapping analysis. According to Geng et al. (2020), the suggested threshold should be in between low and high. A threshold that is too low could cause under filtering and numerous redundant clusters, while a threshold that is too high might cause excessive filtering which leads to redundancy in the clusters.

Table 2 summarizes the highest-ranking documents in the bibliometric coupling.

Table 2. Top 10 documents

Publication	TC	TLS	Objectives	Insights	Contribution
Zhang et al. (2023)	18	63	1) Develop a transferable pedestrian trajectory prediction model. 2) Evaluate performance on non-transfer and transfer tasks.	The spatial-temporal-spectral LSTM model effectively predicts pedestrian trajectories by integrating spatial, temporal, and spectral information, demonstrating superior transferability across datasets and achieving faster inference speeds compared to existing state-of-the-art models, thus enhancing prediction accuracy on unseen data.	1) Proposed STS LSTM model for transferable trajectory prediction. 2) Achieved faster inference speed than state-of-the-art methods.
Zhang et al. (2020)	47	47	1) Propose a states refinement LSTM for trajectory prediction. 2) Utilize current neighbor intentions through message passing framework.	The paper proposes a states refinement LSTM for pedestrian trajectory prediction, enhancing social interaction modeling through a message passing framework and self-updating states refinement, utilizing spatial-edge LSTMs to improve prediction accuracy across multiple datasets.	1) Proposes states refinement LSTM for current neighbor intentions. 2) Introduces social-aware information selection for message passing.
Xue et al. (2021)	66	53	1) Classify pedestrian trajectories into route classes for prediction. 2) Improve trajectory prediction accuracy by incorporating destination prediction.	PoPPL classifies pedestrian trajectories into route classes and predicts destination regions using a bidirectional LSTM classification network. It generates corresponding trajectories through LSTM architectures, outperforming existing methods by incorporating potential destination prediction for improved accuracy in trajectory forecasting.	1) Classifies pedestrian trajectories into route classes for better prediction. 2) Outperforms state-of-the-art methods in trajectory prediction accuracy.
Huang et al. (2021)	26	26	1) Integrate human intention and behavioral patterns for prediction. 2) Estimate intention and predict trajectories simultaneously.	The paper proposes a framework, MIF-WLSTM, that integrates a mutable intention filter and warp LSTM to predict long-term pedestrian trajectories by estimating human intentions and generating trajectory offsets, outperforming baseline methods, especially in abnormal intention-changing scenarios.	1) Proposes MIF-WLSTM for intention estimation and trajectory prediction. 2) Outperforms baseline methods in abnormal intention-changing scenarios.
Zhou et al. (2021)	26	26	1) The main aim is to improve the prediction of pedestrian trajectories to help intelligent transportation systems, such as autonomous driving and pedestrian safety applications. 2) The paper targets not only the individual movement of pedestrians but also the interactions between them. This means predicting where a person will go by understanding both their own motion and how	1) The study shows that pedestrian trajectories are not solely determined by their destination but are also strongly influenced by the interaction with neighboring pedestrians. Recognizing and modelling these interactions is therefore key to more accurate predictions. 2) To capture the interaction details, the authors propose a graph-based approach where each pedestrian is viewed as a node and the relationships between them are represented as edges in a graph. This insight suggests that using a GCN can better encode those interactions compared to traditional methods.	1) The design of the social graph convolutional LSTM model, which uniquely combines a sequence-to-sequence LSTM-based approach with a graph convolution network to effectively capture both movement and interaction features among pedestrians. 2) The introduction of an emotion gate mechanism. This innovation acts like a feature selector, weighting how much the interaction information should influence the trajectory prediction, adjusted per

Table 2 (Continued). Top 10 documents

Publication	TC	TLS	Objectives	Insights	Contribution
			nearby pedestrians affect their path. 3) Another objective is to handle group behavior. The model is designed to recognize and predict the "walking in groups" phenomenon common in crowded scenes, where several pedestrians move together.	3) Another insight is the variability in interpersonal influence. The paper highlights that not every nearby pedestrian affects the target pedestrian in the same way; factors such as distance, relative speed, and movement direction matter. This motivated the authors to include an "emotion gate" to refine interaction features, effectively filtering out less relevant information. 4) The study also demonstrates that including a special loss function, called the companion loss, can enforce the model to maintain consistent distances among pedestrians who are walking as a group, thereby improving prediction accuracy for group scenarios.	pedestrian based on their movement history. 3)The development of a novel companion loss function. This loss function specifically promotes more accurate prediction by enforcing similar trajectory dynamics among pedestrians who are likely moving as a group, thereby capturing the group walking behavior more effectively. 4) By testing on publicly available datasets such as ETH and UCY, the model has been shown to outperform previous methods in terms of average and final displacement errors. This represents a significant step forward in both accuracy and real-time application performance.
Rossi (2021)	78	75	1)The paper sets out to improve human trajectory prediction, an important task for applications such as self-driving cars, indoor navigation, and tracking systems. 2)It aims at tackling key challenges like generalizability, multimodality (multiple plausible future paths), and human-space interactions. Rather than focusing on a single correct outcome in prediction, the study emphasizes the importance of generating a range of realistic behaviors under varying environmental constraints.	1) Generalizability issues in existing methods: - One of the major insights is that existing state-of-the-art models often use datasets (official datasets or ODs) with high linearity and low diversity, which do not reflect real-world complex human behaviors - This leads to non-replicable results when models are applied to more realistic settings such as indoor retail environments. 2) The role of environment and semantic descriptors: - The paper investigates how spatial (e.g., specific areas in a store) and temporal descriptors influence trajectory prediction, finding that human trajectories are moderately affected by spatial information and slightly by time-related factors - This emphasizes the importance of incorporating contextual clues into modeling to better mimic real-world behaviors. 3) Evaluation metric limitations: - Standard evaluation metrics like average displacement error (ADE) and final displacement error (FDE) have inherent biases dependent on trajectory length and linearity. - To overcome this, the work proposes new normalized error metrics (NM and TUE) that help in better assessing model performance across differently shaped trajectories and environments.	1) New datasets: - The introduction of retail datasets (RDs) collected from real retail environments stands out as a significant contribution, offering more realistic scenarios compared to traditional outdoor datasets. These RDs are characterized by lower linearity and greater diversity, reflecting the complex nature of indoor human movement. 2) Innovative deep learning models: - Two types of prediction models are proposed: - - Unimodal models: A standard LSTM network and an LSTM-based GAN-Uni that generate a single prediction for each trajectory. - - A multimodal model: The GAN-Tri is designed to produce three distinct predictions for each observation, capturing the inherent uncertainty and multimodality of human behavior. 3) Advanced Error Metrics: - The paper presents novel error metrics that normalize conventional measures to correct biases, making error evaluations more robust and comparable across diverse datasets. - Additionally, the trajectory uncertainty estimation provides

Table 2 (Continued). Top 10 documents

Publication	TC	TLS	Objectives	Insights	Contribution
					insights into how prediction errors accumulate over time, reflecting model reliability.
Korbmacher (2022)	83	83	1) Compare deep learning and knowledge-based models for trajectory prediction. 2) Explore future directions for hybrid modeling approaches.	The paper reviews and compares deep learning methods with classical knowledge-based models for pedestrian trajectory prediction, highlighting the superior accuracy of deep learning while noting the potential of hybrid approaches to address deep learning's lack of explainability.	1) Compares deep learning and knowledge-based trajectory prediction methods. 2) Reviews literature and explores technical differences between approaches.
Yang (2024)	16	64	1)Model human-human interactions' relative importance in trajectories. 2) Predict pedestrian trajectories using interaction-aware LSTM architecture.	The IA-LSTM model introduces a novel interaction module that utilizes a corr-entropy-based mechanism to assess the importance of human-human interactions, enhancing trajectory prediction in crowded environments by effectively modeling dynamic interactions and personal spaces among pedestrians.	1) Introduced a mechanism to measure interaction importance among pedestrians. 2) Developed an interaction-aware LSTM architecture for trajectory prediction.
Song (2021)	115	56	1) Predict pedestrian trajectories in dense crowds. 2) Improve spatiotemporal interaction modeling using tensors and convolutional LSTM.	The paper proposes a deep convolutional LSTM network for pedestrian trajectory prediction, utilizing tensors to represent environmental features. This approach enhances the learning of spatiotemporal interactions, resulting in more realistic trajectory estimations, particularly in dense crowds during evacuation and counterflow scenarios.	1) Proposes convolutional LSTM for pedestrian trajectory prediction. 2) Utilizes tensors for better spatiotemporal interaction learning.
Xue (2020)	66	99	1) Predict pedestrian trajectories using observed trajectory data only. 2) Improve prediction performance with temporal attention mechanisms.	The paper presents the LVTA model, which predicts pedestrian trajectories using observed trajectory data, incorporating location and velocity LSTM layers with temporal attention mechanisms. It achieves competitive performance on benchmark datasets, demonstrating good generalizability without retraining for new scenes.	1) Introduces LVTA for trajectory prediction using observed data only. 2) Achieves competitive performance on benchmark datasets without rich context.

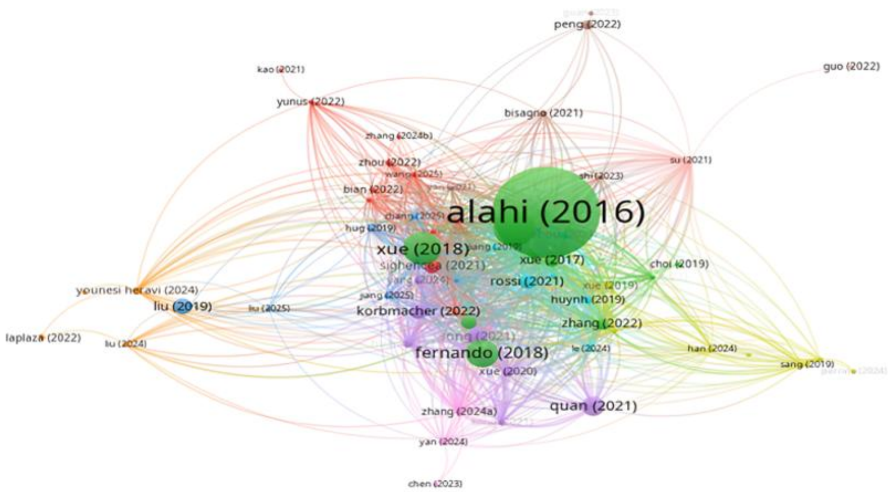

Figure 4. Network visualization of human trajectory prediction (Source: Authors' own elaboration)

Since bibliographic coupling relies on shared citations among documents, the list uses total link strength (TLS) to determine the document's relevance.

Figure 4 illustrates the bibliographic coupling network map. The network detected five clusters that are clearly independent of each other.

Table 3. Summary of the current themes on human trajectory prediction and ML

CNC	Cluster label	N	Representative publication
1 (red)	Sensor-based human activity and trajectory monitoring	11	Akabane et al. (2020), Bian et al. (2022), Korbmacher et al. (2024)
2 (green)	Deep learning for pedestrian and crowd trajectory forecasting	11	Alahi et al. (2016), Xue et al. (2021), Zhang et al. (2022)
3 (blue)	Autonomous vehicles and intelligent driving behavior	9	Archana et al. (2024), Hug et al. (2019), Shi et al. (2019)
4 (yellow)	Multi-agent systems and vehicle-to-vehicle interaction	8	Han et al. (2024), Marchellus et al. (2022), Tonchev et al. (2021)
5 (purple)	Vision-based human trajectory and behavior understanding	7	Huang et al. (2021), Korbmacher et al. (2022), Xue et al. (2020)

Note. CNC: Cluster number and color & N: Number of publications

The following assesses current patterns and future developments in human trajectory prediction and ML. The authors categorize and label clusters based on their qualitative views on representative articles and synthesized research streams in each network. The authors' judgments of the cluster label were consistent and inter-rater reliable (Eagan et al., 2020). The reliability and impartiality of the results are improved by guaranteeing that the clusters' topic is consistent across several authors.

Table 3 summarizes the five bibliographic clusters identified through bibliographic coupling analysis. Cluster 1 in red, consisting of a total of 11 documents is labelled as "Sensor-based human activity and trajectory monitoring." Akabane and Kato (2021) proposed a method for pedestrian trajectory prediction using a pre-trained ML model called social long short-term memory (LSTM), which enhances tracking accuracy for human-following mobile robots by utilizing similar dataset from a large dataset to train the prediction model. Bian et al. (2022) proposed a hybrid method combining musculoskeletal model and motion using IMU data, achieving a knee joint angle RMSE of 2.93°, significantly outperforming other methods based solely on ANN or LSTM. Korbmacher and Tordeux (2024) introduce a novel dataset from the festival of lights 2022, emphasizing density's role in enhancing trajectory prediction accuracy through a two-stage processing approach and a collision-based error metric, ultimately improving algorithmic performance in dense environments.

Cluster 2 in green consists of 11 documents labelled as "Deep learning for pedestrian and crowd trajectory forecasting." Alahi et al. (2016) proposes a social LSTM model for predicting human trajectories in crowded spaces, which outperforms traditional approaches by learning common sense rules and conventions from existing human trajectory datasets. PoPPL proposed by Xue et al. (2021) classifies pedestrian trajectories into route classes and predicts destinations using a bidirectional LSTM classification network. It generates corresponding trajectories through LSTM architectures, outperforming existing methods by incorporating potential destination prediction for improved accuracy in trajectory forecasting. Zhang et al. (2022) proposed a states-refinement LSTM for pedestrian trajectory prediction, enhancing social interaction modeling through a message passing framework and self-updating states refinement, utilizing spatial-edge LSTMs to improve prediction accuracy across multiple datasets.

Cluster 3 in blue with 9 document is labelled as "Autonomous vehicles and intelligent driving behavior." Archana et al. (2024) proposed a CNN-gated recurrent unit (GRU) architecture for pedestrian trajectory prediction, addressing challenges like complex movement patterns and unpredictable events. It outperforms models like LSTM and social LSTM, achieving ADE/FDE scores of 0.46/0.61 of the ETH/UCY dataset. Hug et al. (2019) proposed the LSTM-MDL model captures data statistics but struggles with endpoint predictions due to instability from multiple paths at junctions. This highlights the model's limitations in reliability for pedestrian trajectory prediction, despite its ability to represent data effectively. Shi et al. (2019) presents a novel pedestrian prediction model that integrates detection, multi-target tracking, and a circular neighborhood approach, utilizing two LSTMs to enhance interaction information and improve trajectory prediction accuracy, addressing dataset acquisition challenges and manual labeling issues.

Cluster 4 in yellow consists of 8 documents is labelled as "Multi-agent systems and vehicle-to-vehicle interaction." Han et al. (2024) proposed an improved social LSTM model for pedestrian trajectory prediction, addressing issues like data redundancy and coordinate transformation. It utilizes YOLOv5 for detection and deep sort for tracking, achieving over 90% accuracy and effective collision location identification. Tonchev et al. (2021) proposed a method for human motion prediction using a gated recurrent unit (GRU) network optimized with graph convolution, analyzing previous poses within a 1 to 2-second time window, achieving state-of-the-art results on public datasets. Marchellus and Park (2022) surveyed deep learning methods for 3D human motion prediction, defining the problem, classifying existing approaches, and evaluating their characteristics. It also highlights unresolved issues and suggests future research directions to enhance prediction accuracy and naturalness.

Cluster 5 in purple with 7 documents is labelled as "Vision-based human trajectory and behavior understanding." Huang et al. (2021) proposed a framework, MIF-WLSTM, that integrates a mutable intention filter and Warp LSTM to predict long-term pedestrian trajectories by estimating human intentions and generating trajectory offsets, outperforming baseline methods, especially in abnormal intention-changing scenarios. Korbmacher and Tordeux (2022) reviewed and compared deep learning methods, such as LSTM and CNN, with knowledge-based models for pedestrian trajectory prediction, highlighting their technical differences, applications, and the potential of hybrid approaches to enhance prediction accuracy and interpretability. Xue et al. (2020) introduced the LVTA model, which predicts pedestrian trajectories using observed trajectory data, incorporating location and velocity LSTM layers with temporal attention mechanisms. It achieves competitive performance on benchmark datasets, demonstrating good generalization without retraining for new scenes.

Future bibliographic coupling analysis could be extended by incorporating multiple bibliographic databases to capture disciplinary diversity, particularly education-focused and human-centered computing venues. Moreover, cluster interpretations may vary across domains; for example, clusters emphasizing interaction modeling may align with autonomous driving in engineering contexts but correspond to collaborative learning and classroom dynamics in educational research.

Table 4. Top 15 keywords on human trajectory prediction

Rank	Keyword	Occurrences	TLS
1	Forecasting	58	272
2	Trajectory prediction	50	235
3	Pedestrian trajectories	47	226
4	Trajectories	47	239
5	LSTM	42	211
6	Deep learning	30	142
7	Pedestrian trajectory prediction	18	99
8	Motion estimation	15	50
9	Motion prediction	13	41
10	LSTM	11	57
11	Human	10	66
12	Pedestrian	10	70
13	Attention mechanisms	9	49
14	Prediction methods	9	51
15	Humans	7	46

Co-Word Analysis

34 out of 653 keywords are presented by the co-word analysis using the same database, reaching a threshold of 5. Similar to the last analysis, the threshold was determined following multiple attempts to generate the most suitable and reliable network map. From this analysis, it can be concluded that the highest co-occurring keywords are "forecasting" (58 occurrences), "trajectory prediction" (50 occurrences), "trajectories" (47 occurrences), and "pedestrian trajectory prediction" (47 occurrences). **Table 4** displays the top 15 keywords on human trajectory prediction and ML.

Figure 5 illustrates the structure of the network. Four clusters are clearly visible, indicating that the topic has created four distinct research streams. The most pertinent topics are represented by the labels assigned to the four clusters once they have been refined.

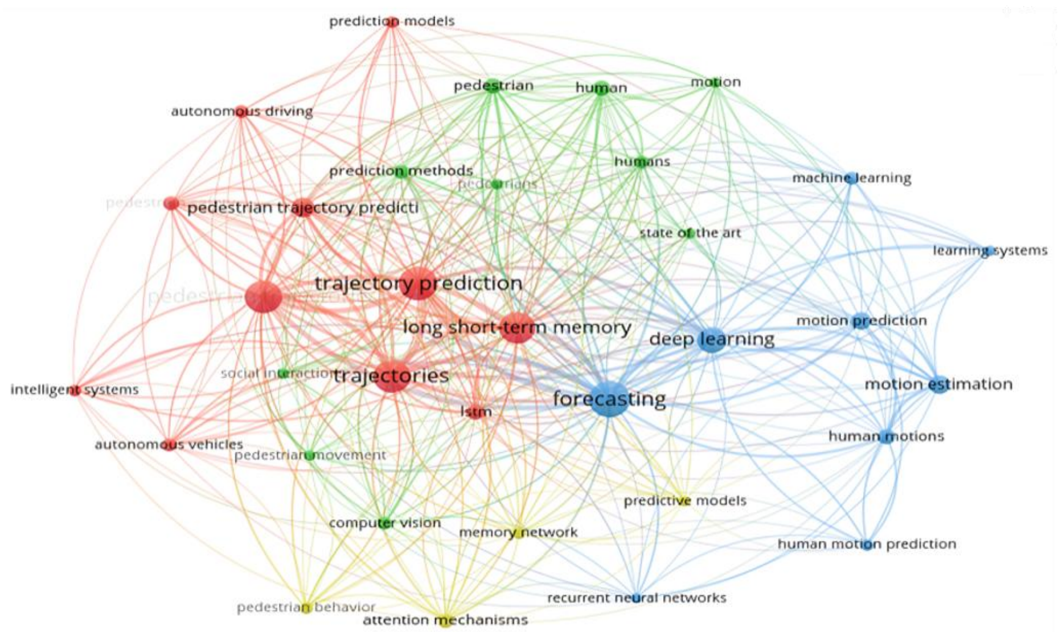

Figure 5. Co-word analysis on human trajectory prediction (Source: Authors' own elaboration)

Cluster 1 in red with 11 keywords is labelled as "Sequential deep learning for pedestrian path forecasting and collision avoidance." Shi and Xiao (2023) proposed DTG-LSTM which integrates Delaunay triangulation with LSTM networks to enhance pedestrian trajectory prediction by capturing complex dynamics and topological relationships. It employs an encoder-decoder structure and shows promising accuracy in preliminary evaluations on ETH and UCY datasets. Zhang and Ni (2023) introduces spatial-temporal-spectral LSTM model effectively predicts pedestrian trajectories by integrating spatial, temporal, and spectral information, demonstrating superior transferability across datasets and achieving faster inference speeds compared to existing state-of-the-art models, thus enhancing prediction accuracy on unseen data. Quan et al. (2021) proposed a novel holistic LSTM model that incorporates multiple information sources, including vehicle speed and pedestrian intentions, using extra memory cells and a gated shifting operation to enhance pedestrian trajectory predictions and improve safety.

Cluster 2 in green consists of 10 keywords and labelled as "Human-centered movement understanding." Choi et al. (2024) produce a smart door system that uses vision sensors and ML to predict pedestrian trajectories, enhancing automatic door functionality by reducing malfunctions and improving safety compared to traditional infrared sensor-based systems, with potential applications in smart cities. Yan et al. (2021) proposed PSA-GRU which utilizes a person-social twin-attention network based on GRU to enhance pedestrian trajectory prediction by incorporating significant historical trajectory nodes and social interaction information, improving both prediction accuracy and computational efficiency on UCY and ETH datasets. Peng et al. (2022) proposed SRA-LSTM model, which incorporates social relationship attention to enhance human trajectory prediction by considering the influence of social relationships among pedestrians, utilizing a social relationship encoder and attention mechanisms for improved accuracy in trajectory forecasting.

Cluster 3 in blue consists of 9 keywords and labelled as "Predictive AI and human motion modeling." Zhang and Zheng (2021) proposed a multilayer perceptron (MLP)-social-GRU which is a data-driven pedestrian trajectory predictor that utilizes a MLP and GRU to analyze motion patterns and simulate relationships between pedestrians, outperforming models like LSTM and social LSTM on ETH and UCY datasets. Xue et al. (2021) proposed PoPPL which classifies pedestrian trajectories into route classes and predicts destination regions using a Bidirectional LSTM classification network. It generates corresponding trajectories through LSTM architectures, outperforming existing methods by incorporating potential destination prediction for improved accuracy in trajectory forecasting. Xu et al. (2018) introduce collision-free LSTM enhances traditional LSTM by incorporating a repulsion pooling layer, enabling it to learn both temporal trajectory information and pedestrian interactions, thus improving human trajectory prediction and achieving state-of-the-art performance on public datasets.

Cluster 4 in yellow consists of 4 keywords and labelled as "Cognitive architectures and learning mechanisms." Sighencea et al. (2021) reviewed recent deep learning methods for pedestrian trajectory prediction, highlighting advancements in sensors, processing techniques, datasets, performance metrics, and practical applications, while identifying research gaps and suggesting future research directions in this critical area of computer vision. Liu et al. (2025) introduce the MGFormer model which combines pose, optical flow, and trajectory information using a novel multi-information evaluation fusion module. This cross-information fusion attention mechanism effectively evaluates the quality of each information source before melding them, ensuring robust trajectory prediction. Song et al. (2020) proposed a convolutional LSTM network for pedestrian trajectory prediction, utilizing tensors to represent environmental features. This approach enhances the learning of spatiotemporal interactions, resulting in more realistic trajectory estimations, particularly in dense crowds during evacuation and counterflow scenarios.

In educational settings, the identified co-word clusters align closely with applications such as campus security monitoring, student transportation planning, and movement-based engagement analysis. Keywords related to social interaction and motion estimation are particularly relevant for modeling group learning behaviors, peer collaboration, and safe navigation within institutional environments. **Table 5** shows the summary of future trends on human trajectory prediction and ML.

IMPLICATIONS

The findings of this bibliometric study offer substantial implications for both academia and practice. First, by identifying dominant themes such as deep learning for pedestrian forecasting, sensor-based monitoring, and multi-agent interactions, the study provides a clear research taxonomy that can guide new entrants and seasoned scholars alike in navigating the multidisciplinary landscape of human trajectory prediction. The visualization of bibliographic coupling and co-word networks allows for a nuanced understanding of the intellectual structure and emerging hotspots in the domain.

Second, the integration of science mapping with ML contexts supports evidence-based decision-making for funding agencies and academic institutions in prioritizing impactful research directions. Policymakers

Table 5. Summary of future trends on human trajectory prediction and machine learning

CNC	Cluster label	N	Representative keywords
1 (red)	Sequential deep learning for pedestrian path forecasting and collision avoidance	11	Autonomous driving, autonomous vehicles, intelligent vehicles, intelligent transportation systems
2 (green)	Human-centered movement understanding	10	Pedestrian prediction, pedestrians, pose estimation, social interaction, trajectory prediction
3 (blue)	Predictive AI and human motion modeling	9	Deep learning, forecasting, human motion prediction, human trajectory prediction
4 (yellow)	Cognitive architectures and learning mechanisms	4	Attention mechanisms, memory network, pedestrian trajectory prediction, scene understanding

Note. CNC: Cluster number and color & N: Number of publications

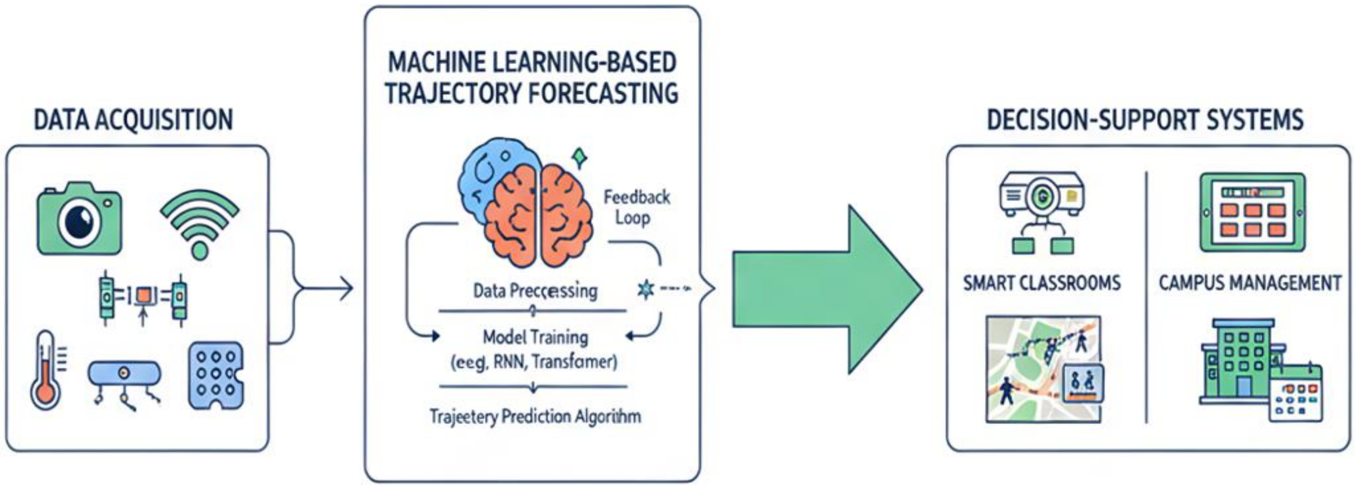

Figure 6. Educational application pipeline for human trajectory prediction (Source: Authors' own elaboration, using Google Gemini)

and developers of intelligent systems—including autonomous vehicles, surveillance systems, and 5G mobility networks—can leverage these insights to align technological innovations with user-centered mobility patterns and social dynamics. Finally, this study underscores the growing need for explainability, transferability, and real-time processing in predictive models, encouraging interdisciplinary collaboration between AI researchers, human behavioral scientists, and application engineers.

Conceptual Framework for Human Trajectory Prediction

To enhance analytical depth and theoretical coherence, this study proposes a conceptual framework that organizes ML-based human trajectory prediction research along five core dimensions:

1. Behavioral assumptions–Deterministic vs. probabilistic modeling of human intent.
2. Context awareness–Use of environmental semantics, maps, and scene understanding.
3. Interaction modeling–Individual, social, group, and multi-agent dynamics.
4. Uncertainty and multi-modality–Single-path vs. multi-future trajectory prediction.
5. Temporal horizon–Short-term reactive vs. long-term strategic forecasting.

The five bibliographic clusters identified in this study can be mapped onto these dimensions. For example, deep learning-based pedestrian forecasting emphasizes interaction modeling and uncertainty, while sensor-based monitoring focuses on short-term, deterministic prediction. Vision-based approaches integrate context awareness and behavioral inference, whereas multi-agent systems emphasize coordination and collective dynamics.

This framework provides a unifying lens for interpreting prior work, comparing modeling assumptions, and identifying conceptual gaps—particularly in domains such as education, where long-term intent modeling, ethical considerations, and interpretability are critical.

In the context of educational application, Figure 6 illustrates an example educational application pipeline for human trajectory prediction, linking data acquisition (e.g., cameras, Wi-Fi, and sensors), ML-based trajectory forecasting, and decision-support systems for smart classrooms and campus management. Such visual frameworks support the translation of abstract modeling techniques into actionable educational tools.

LIMITATIONS

Despite its contributions, this study has several limitations that warrant acknowledgment. First, the bibliometric analysis was confined to the Scopus database, which, although comprehensive, may exclude relevant works indexed in IEEE Xplore, Web of Science, or arXiv preprints, potentially limiting the inclusiveness of the literature landscape. Future research should include these databases (IEEE Xplore, Web of Science, or arXiv preprints) for expanding the total number of papers for the research. Second, the keyword co-occurrence and bibliographic coupling are dependent on author-supplied metadata, which can vary in quality and consistency. This might lead to under-representation of certain emerging or interdisciplinary concepts not adequately indexed or labeled (Liu & Hsu, 2019; Nandy et al., 2024; Weinberg, 1974). Future research should introduce data preprocessing and standardization through keyword cleaning, keyword normalization, and control vocabularies. Hybrid approaches through combination of multiple data sources can also be included in the future research where author keywords is supplemented with automatically extracted terms such as TF-IDF, RAKE, KeyBERT, and modeling of abstract and topic through the usage of LDA and BERTopic in order to identify latent themes.

Third, the reliance on citation-based metrics like TLS may inadvertently prioritize older, highly cited papers while under-representing recent yet impactful studies with lower citation counts due to recency. Relying solely on citation-based metrics should be avoided in the future research and focus on other metrics such as collaboration metrics which consists of co-authorship analysis which measures collaboration between multiple parties (authors, institutions, and countries), collaboration index which calculate the average number of authors per paper, and international collaboration rate which shows the percentage of paper co-authored internationally. Lastly, while the study provides a macro-level thematic analysis, it does not offer a micro-level content analysis or empirical synthesis (e.g., effect sizes and algorithmic comparisons), which could further enrich the interpretation of predictive model effectiveness across different application contexts. Future research should include micro-level focus such as analyzing specific sections (e.g., methodologies and conclusions) of papers rather than just titles or abstracts, and introducing empirical synthesis which systematically categorize findings, theories, or empirical results across studies.

Educational Implications and Applications

Although human trajectory prediction research is often situated in technical domains, its implications for educational research and practice are substantial. In learning environments such as schools, universities, libraries, and smart campuses, trajectory prediction models can support learning analytics, student flow optimization, safety monitoring, and inclusive space design.

From a research perspective, the reviewed models offer methodological tools for analyzing student movement patterns, collaborative learning behaviors, and engagement dynamics in physical and hybrid learning spaces. For example, socially-aware and multi-agent trajectory models can be adapted to study peer interaction, group formation, and movement-based participation.

Practically, predictive trajectory analytics can inform the design of intelligent educational infrastructures, such as adaptive classroom layouts, automated crowd management during large academic events, and early-warning systems for safety and accessibility.

Importantly, the study highlights critical research gaps relevant to education, including the lack of explainable models, ethical data governance, and long-term intent prediction. Addressing these gaps will enable responsible integration of AI-driven trajectory prediction into educational contexts aligned with human-centered and learner-focused values.

However, the deployment of trajectory prediction systems in educational environments raises critical ethical concerns, including student privacy, informed consent, data ownership, and algorithmic bias. Ensuring data anonymization, transparency in model decision-making, and compliance with institutional data governance policies is essential for responsible adoption.

FUTURE RESEARCH AVENUES

Building on the identified trends and thematic clusters, future research in human trajectory prediction using ML should explore the following directions:

1. **Graph-based predictive modeling:** The increasing complexity of social and spatial interactions necessitates the adoption of GNNs (Feng et al., 2024) and transformer-based frameworks that can more effectively capture contextual dependencies and long-term intent estimation.
2. **Privacy-preserving mobility analytics:** As trajectory data is inherently sensitive, future models should integrate privacy-preserving mechanisms such as federated learning (Benhelal et al., 2024; Tao et al., 2024), differential privacy, and secure multi-party computation to protect user identity while maintaining predictive accuracy.
3. **Edge-AI and real-time deployment:** Research should also focus on lightweight, energy-efficient trajectory prediction models (Ghoul et al., 2022) suitable for deployment of edge devices in smart

environments, transportation systems, and mobile robotics.

4. **Benchmarking for diverse environments:** There is a growing need for standardized datasets that represent heterogeneous conditions—indoor/outdoor, crowded/sparse, urban/rural—to evaluate model generalizability and real-world applicability.
5. **Human-robot interaction and ethics:** With increasing integration of trajectory prediction in assistive technologies, ethical considerations such as algorithmic fairness, transparency, and social acceptability should be incorporated into the model design lifecycle.
6. **Educational AI applications:** Future studies should investigate trajectory prediction for smart classroom management, student engagement forecasting, and adaptive learning space utilization. Ethical-by-design frameworks and privacy-aware analytics should be embedded into educational AI systems to balance innovation with responsibility.

CONCLUSIONS

This bibliometric analysis provides a decade-long panoramic view of the evolving research landscape in human trajectory prediction using ML. Through the application of bibliographic coupling and co-word analysis, the study systematically uncovers five major research clusters and four conceptual themes that define the intellectual and methodological frontiers of the field.

The results indicate a paradigm shift from simple statistical models to socially aware, context-rich, and AI-driven prediction systems, underpinned by innovations in deep learning architectures and multi-agent modeling. The convergence of disciplines such as robotics, computer vision, transportation, and behavioral modeling is shaping a robust and dynamic research ecosystem.

This paper contributes not only by mapping the trajectory of scholarly efforts but also by identifying actionable insights and research gaps that can inform future investigations. It serves as a critical resource for academics, engineers, and policymakers aiming to design intelligent systems capable of anticipating human movement in an ethical, accurate, and contextual aware manner.

In educational and institutional contexts, the responsible use of trajectory prediction demands careful consideration of ethical obligations, data protection, and human-centered design principles. By aligning technological advancement with educational values, future research can ensure that predictive mobility systems enhance learning environments while safeguarding trust and inclusiveness.

Author contributions: Both authors contributed equally into the creation of this article. Both authors agreed with the results and conclusions.

Funding: This paper is part of research work supported by Ministry of Higher Education (MOHE) for funding under the FRGS Grant File no.: FRGS/1/2024/TK07/UITM/02/6 and Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam.

Ethical statement: The authors stated that the study does not require any ethical approval. It is based on existing literature.

AI statement: The manuscript utilizes AI-based tools such as Google Gemini to create the figure in Figure 6 based on text provided by the authors.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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