Predicting Human Actions via Computational Technologies: A Literature Review

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Abstract

This review examines the capacity of computational technologies, determined by research predating 2020, to predict individual human actions using sensor and behavioural data. While human behaviour is complex and random, the advancements in computing technologies offers new avenues for research, modelling, and prediction. The primary question guiding this review is, "How accurately can computational technologies predict an individual's actions based on sensor and behavioural data?". The method involved a review of 11 papers retrieved from the ACM database, focusing on diverse domains such as mobility, human-computer interaction, and health. Findings indicate that hybrid models and context aware algorithms achieve higher accuracy compared to less flexible models that depend on static data. However, performance varies significantly based on the prediction horizon and the diversity of data used. This review implies that while high precision prediction is attainable, future research should address differences in hardware and software, and further integration of "human-in-the-loop" methodologies.

Keywords

Human Behaviour Prediction, Mobile Sensing, Machine Learning, Human-Robot Interaction, Location-Based Services

1 Introduction

The quantification and prediction of human behaviour has long been a goal of computer science. "Computational technologies" in this context refer to a group of tools including machine learning classifiers, probabilistic models, and sensor based algorithms designed to infer patterns from data. As sensory technology becomes embedded in everyday life through means of smartphones and smartwatches, there is possibility for the continuous assessment of individual activities ranging from physical movement to complex psychological states.

As highlighted by Favela [3] and Pang et al. [5], traditional research relying on aggregate population modelling or self-reporting often faced limitations in capturing the nuances of individual decision making. Historically, these earlier methods struggled to account for the stochastic nature of human actions. To address this, recent studies suggest that focusing on individual behavioural traces—such as GPS logs or interaction histories—can significantly increase predictive accuracy [2], though the inherent variability of human nature continues to present a computational challenge.

1.1 Research Question

The formulation of this review was informed by the seed paper, "Human Intention Prediction in Human-Robot Collaborative Tasks" by Wang et al. (2018) [10]. This study demonstrated that combining wearable sensors with machine learning could predict human handover intentions with 99.7% accuracy. This high degree of precision in a specific task prompted a broader investigation into whether such accuracy is replicable across different behavioural domains. In order to better understand the scope of possibilities, this review addresses the question: **"How accurately can computational technologies predict an individual's actions based on sensor and behavioural data?"** Answering this is critical for establishing trust in autonomous systems and ensuring the reliability of applying predictive human-centred computations in daily life.

2 Methods

This review analyses 11 papers focusing on computational models for predicting individual human behaviours, ranging from physical mobility to psychological states.

2.1 Eligibility Criteria

Studies were selected based on the following criteria:

- **Inclusion:**
  - Papers published before 2020.
  - Studies utilising either sensor data (GPS, wearable tech, mobile logs) or behavioural traces (social media, game replays).
  - Research must focus on the prediction, modelling, or inference of individual human actions, strategies, intentions, or behavioural traits.
  - Evaluation must include a quantitative metric of data, or a critical synthesis for keynote/survey papers.
- **Exclusion:**
  - Papers not published in English.
  - Studies focused solely on engineering design without human behaviour modelling.
  - Studies focusing exclusively on population-level statistics without individual-level derivation.

2.2 Databases

The search was conducted using the ACM Digital Library. This database was chosen for its high concentration of premier proceedings in HCI, mobile computing, and spatial information systems. The search returned 11 primary sources used for this analysis.

2.3 Search Terms and Strategy

The search strategy employed Boolean operators to combine terms related to the research question. The primary keywords included:

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"Prediction" OR "Modeling" AND "Intention"
OR "Mobility" OR "Behavior" OR "Action" AND
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Table 1: Summary of Primary Studies

ID	Author (Year)	Population	Context	Model	Target	Outcome/Metric
P1	Ahmad (2019) [1]	200 Teams	Game Analytics	Interactive Behavior Analytics (IBA)	Strategy/Tactics	IRR Cohen's $\kappa = 0.95$
P2	Comito (2018) [2]	292,195 Users	Social Networks	Hybrid Similarity + Decision Tree	Next Location	Accuracy: 0.94
P3	Favela (2017) [3]	N/A	Survey	Pervasive Healthcare	Health Patterns	Qualitative Synthesis
P4	Pang (2017) [5]	300k Users	Mobility (Tokyo)	Markov Decision Process	Daily Travel	Correlation > 0.84
P5	Pierson (2018) [6]	9,885 Users	Health Tracking	Cyclic HMM	Cycle Progression	Error reduced by 63%
P6	Pynadath (2019) [7]	53 Participants	Human-Agent	Markov Frequency Tables	Trust (Follow/Ignore)	Accuracy: 91.3%
P7	Rumi (2018) [8]	18k+ Users	Crime/Mobility	Random Forest	Theft Hotspot	AUC: 0.88
P8	Wang (2018) [9]	159 Students	Mobile Sensing	Gradient Boosted Regression	Personality Traits	Pearson $r = 0.69$ (Extraversion)
P9	Imai (2017) [4]	1,646 Users	Transportation	SubSynE + Logistic Regression	Destination	Accuracy: ~ 0.77
P10	Wang (2018) [10]	6 Subjects	Robotics (HRI)	Extreme Learning Machine	Handover Intention	Accuracy: 99.7%
P11	Wu (2019) [11]	1,009 Subjects	Neuroscience	Partial Least Square Regression	Behavioural Traits	Sig. Correlation ($p < 1e-5$)

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"Sensors" OR "Data Mining" AND "Human" OR
"Individual" OR "Person"
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Filters applied: Publication Date (before 2019), Content Type (Proceedings/Articles).

2.4 Data Extraction Strategy

The data extraction strategy revolved around gathering and organising information regarding the general context of the studies, the population details, methodological approaches, and performance outcomes. Table 1 provides a summary of the relevant themes extracted from all papers.

3 Findings

To answer the research question regarding the accuracy of computational predictions, the reviewed papers (see Table 1) demonstrate that technologies can predict individual actions with high accuracy, frequently exceeding 85% in controlled mobility and interaction tasks. However, the precision of these predictions varies significantly depending on the complexity of the behaviour being modelled.

Mobility and Location Prediction. Technologies modelling physical movement achieved robust performance by leveraging historical trajectory data. A key finding is the superiority of hybrid models over static approaches. For instance, Comito [2] demonstrated that the MoPreT model, which combines trajectory similarity with supervised decision trees, achieved an F-Measure of 0.87, significantly outperforming baselines that relied on a single technique. Similarly, addressing the challenge of "early stage" prediction, Imai et al. [4] utilised probabilistic factorization to predict destinations with 77% accuracy even when only 40% of the trip was completed. These studies suggest that physical displacement is highly predictable when computational models integrate historical context with immediate spatial data.

Interaction and Intention. The highest accuracies were observed in structured environments. Wang et al. [10] achieved near perfect accuracy (99.7%) in predicting handover intentions using Extreme Learning Machines (ELM) and multimodal sensors. However, high accuracy does not always require complex sensing; Pynadath et al. [7] showed that simple Markovian frequency tables could predict trust behaviours with 91.3% accuracy, outperforming complex Recurrent Neural Networks (84.3%). This highlights a trade-off: while complex sensors (EMG/IMU) offer precision for motor tasks, simpler, more transparent models may be superior for decision based interactions where interpretability is key.

Latent Traits and States. Predicting internal states (personality, health) proved more complex than physical actions. Wang et al. [9] utilised passive mobile sensing to predict Extraversion with a strong correlation ($r = 0.69$), yet the model failed to find significant associations for Neuroticism. This indicates that some psychological traits may not have clear behavioural markers in standard sensor data, or that further work must be done in engineering the right sensor technologies to reliably quantify these less observable internal states. In health tracking, Pierson et al. [6] found that Cyclic Hidden Markov Models (CyHMM) reduced error in inferring menstrual cycle length by 63% compared to baselines, successfully identifying medically relevant subpopulations. These findings confirm that while computational models can infer latent traits, their success is highly dependent on the specific trait and the model's ability to handle temporal variability.

4 Conclusion, Limitations, and Future Work

To conclude, the results of the proposed research question show that computational technologies demonstrate high accuracy in predicting individual actions, frequently exceeding 85% in mobility and interaction tasks. The most successful approaches utilise hybrid or context aware models that combine historical data with immediate inputs. However, the prediction of internal psychological states remains varied, with some traits resisting accurate modelling via current means of passive sensing.

Limitations. Several limitations hinder the broader application of these technologies. Data heterogeneity is a major challenge. For example, Wang et al. [9] noted that mixing data from Android and iOS devices degraded performance due to sensor differences, indicating a need for separate models in future work. Labour intensity is another barrier, as high precision models often require extensive human labelling or "human-in-the-loop" processes, which are time consuming. Furthermore, population bias limits generalizability, as several reviewed studies relied on specific cohorts such as students or military personnel.

Future Work. Future research should focus on "human-in-the-loop" methodologies to improve model interpretability and handle complex behaviours. Additionally, addressing data diversity across different hardware and software devices is essential for creating robust, real-world applications. Finally, adopting more robust probabilistic frameworks, such as Hidden Markov Models, may help address issues of data sparsity and improve the modelling of trust and other latent variables.

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