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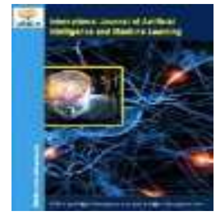

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Sustainable Street Planning: A DEMATEL Based Review of Pedestrian Flow Prediction Using Machine Learning

M. Senthil[1], S. M. Sindhu[2], J. Janani[3]

[1]Professor, Saveetha College of Architecture and Design (SCAD) Saveetha Institute of Medical and Technical Sciences (SIMATS), Chennai.
E-mail: ar.senthilmani@gmail.com ORCID: 0000-0003-4521-5665
[2]Assistant Professor, Dhanalakshmi Srinivasan University, Trichy, India. ORCID: 0009-0009-2435-1968
[3]Associate Professor, School of Planning, Architecture, and Design Excellence (SPADE) Hindustan Institute of Science and Technology (HITS), Chennai. ORCID: 0009-0005-8145-7807

Abstract

Rapid urbanization has intensified pedestrian congestion on commercial streets, where high footfall, mixed land use, and a limited right-of-way place mobility, safety, and commercial vitality in continual conflict. This paper reviews machine learning (ML) approaches to pedestrian flow prediction and reads them alongside a Decision-Making Trial and Evaluation Laboratory (DEMATEL) analysis of the factors that govern sustainable commercial street planning. The DEMATEL outputs reported here are conceptual and hypothesis-generating rather than empirically estimated causal weights: prominence and relation values synthesise the direction and strength of influence reported across the reviewed literature and are offered as testable propositions, not as demonstrated measurements. Ten evaluation factors, from walkability and accessibility through to smart infrastructure and real-time data availability, were drawn from the reviewed literature and sorted into provisional cause and effect groups by the DEMATEL procedure. Smart infrastructure, real-time data availability, accessibility, and land-use diversity appear to act as principal causal drivers, while pedestrian safety, walkability, social interaction, and urban livability appear to behave as dependent outcomes. On this basis the paper proposes a conceptual structure linking ML-based prediction to causal factor analysis and to planning decisions, and maps its contributions to Sustainable Development Goals (SDGs) 3, 9, 11, and 13. The review clarifies how predictive modelling and causal reasoning might be combined in support of pedestrian-centred street planning, and sets out priorities for future empirical work: structured expert elicitation, real pedestrian-flow data, and field application to case-based commercial corridors, through which the proposed cause-effect hierarchy can be tested rather than assumed.

Keyword: pedestrian flow prediction, sustainable cities, commercial streets, urban mobility, walkability, Sustainable Development Goals.

Introduction

More than half of the world's population now lives in urban areas, and that share is projected to rise substantially over the coming decades [1]. Commercial streets sit at the centre of this transition. They concentrate retail activity, social exchange, and movement, and they serve as the public rooms in which much of urban life takes place [2]. As footfall grows, these corridors experience recurring conflicts between walking, vehicular access, loading, and street trading. Narrow footpaths, encroachment, and uneven surfaces reduce the comfort and safety of walking precisely where pedestrian volumes are highest, and keeping such districts both economically active and pleasant to move through has become a central planning concern. The response in policy and research has been the smart sustainable city agenda, which seeks to combine digital sensing and analytics with long-standing goals of environmental quality, social inclusion, and economic vitality [3]. Mobility, within that agenda, is treated not merely as a transport problem but as a determinant of urban livability. Streets that are easy and safe to walk support local commerce, physical activity, and social contact; congested or hostile streets erode all three [4]. Pedestrian movement therefore deserves the analytical attention long reserved for vehicular traffic.

Advances in machine learning (ML) have made it possible to anticipate pedestrian movement with growing precision. Methods first developed for vehicular traffic, among them the deep learning model of Lv et al. for large-scale flow prediction [5], have been adapted to estimate footfall from sensors, video, and mobile traces. Reliable prediction allows planners to identify when and where crowding will occur, to size footpaths and crossings accordingly, and to schedule interventions before congestion becomes acute. What prediction cannot indicate is which underlying factor a planner should address first. Commercial street planning turns on many interacting considerations—accessibility, safety, land-use mix, the quality of the public realm—and these influence one another rather than acting in isolation. Multi-criteria decision-making (MCDM) methods were developed to structure problems of exactly this kind [6]. Among them, the Decision-Making Trial and Evaluation Laboratory (DEMATEL), introduced by Gabus and Fontela [7], is distinctive: it does not merely rank criteria but maps the cause-and-effect relations among them, separating the factors that drive a system from those that mainly respond to it [8]. The property matters wherever the order of intervention, and not simply the list of priorities, is at stake.

The two strands have largely developed apart. Work on ML pedestrian prediction concentrates on accuracy and rarely connects its outputs to planning priorities, while work on urban decision analysis seldom incorporates predictive evidence about movement. Three gaps follow. The causal relations among the factors that shape walkable commercial streets are rarely made explicit; sustainability objectives tend to be appended to technical studies rather than built into them; and few studies offer a planning-oriented structure that connects prediction to decisions.

This paper addresses these gaps through a structured review. Its aim is twofold: to review ML approaches to pedestrian flow prediction, and to analyse the interrelationships among the factors governing sustainable commercial street planning using DEMATEL. The analysis is *conceptual and hypothesis-generating*. Rather than reporting causal weights derived from primary expert data, it sets out a structured set of testable propositions about how the factors relate. The contributions are (i) a synthesis of ML techniques relevant to pedestrian prediction and their planning relevance; (ii) identification of ten evaluation factors and their organisation into provisional cause and effect groups; (iii) a conceptual structure linking prediction, causal analysis, and planning decisions; and (iv) an explicit mapping of these elements to the Sustainable Development Goals [9].

II. Literature Review

A. Smart Sustainable Cities

The smart city concept emerged as cities began to use networked sensing and information systems to manage infrastructure and services [10]. Early enthusiasm was tempered by criticism that the label often privileged technology over residents; Hollands cautioned against treating instrumentation as an end in itself rather than a means to more equitable outcomes [11]. The smart sustainable city reframes the idea by placing environmental and social goals at its centre and putting digital tools in their service [3]. Three technological currents support that reframing. The first is pervasive sensing through the Internet of Things, which supplies continuous observations of how streets are used [12]; the value of IoT-enabled sensing and real-time data acquisition for intelligent decision-making has been demonstrated across a range of smart systems [13]. The second is the integration of those observations into urban models capable of representing complex systems at the scale of streets and districts [14]. The third is smart mobility, which treats walking, cycling, and public transport as first-class modes and aims to make them safe, legible, and attractive. Pedestrian-centred planning is where these currents meet the street.

These ambitions align with the global sustainability agenda [9]. Sustainable Development Goal 11 calls for inclusive, safe, and sustainable cities, with explicit attention to accessible transport and public space. SDG 9 concerns resilient infrastructure and innovation, the basis of smart sensing and analytics. SDG 13 addresses climate action, to which shifting short trips from motor vehicles to walking contributes through reduced emissions. SDG 3, on health and well-being, is advanced where safer and more walkable streets encourage physical activity and reduce exposure to traffic injury. Commercial streets, where many short trips begin and end, are a natural setting in which these goals reinforce one another.

B. Machine Learning in Urban Planning

Machine learning has become a standard tool for analysing urban movement because it can represent the nonlinear and time-varying patterns that classical models struggle to capture. Artificial neural networks and their deep variants learn hierarchical representations directly from observations [15]. Ensemble methods such as random forests combine many decision trees to produce robust estimates and to rank the importance of input variables [16], while support vector machines remain effective where labelled examples are limited [17]. For sequential data, recurrent architectures—long short-term memory networks in particular—model temporal dependence and have been applied successfully to short-term traffic prediction [18]. Reinforcement learning, which learns policies through interaction, has been used for adaptive signal control and other sequential decisions [19]; more recent work shows that such approaches can optimize complex urban systems through adaptive decision-making mechanisms [20], which bears directly on adaptive, data-responsive street management.

These techniques underpin applications ranging from pedestrian and crowd prediction to crowd management, smart transport operations, and broader urban analytics [21]. Their common value lies in converting raw observations of movement into estimates that can inform operational and design decisions. The model of Lv et al., for instance, showed that large volumes of traffic observations could predict flow more accurately than earlier statistical methods [5]; the same logic extends to pedestrians, whose footfall, dwell, and routing can be estimated from comparable sources. Advances in AIoT and smart sensing supply the continuous urban data streams on which pedestrian flow monitoring and prediction depend [22], and edge-based deep learning architectures make low-latency analytics and real-time urban monitoring feasible, which suits them to pedestrian sensing applications in smart cities [23]. Two limitations recur. Accuracy depends heavily on the quantity and quality of observations, which are uneven across cities and especially scarce for pedestrians in commercial settings. Predictive models are also typically opaque about why movement occurs and which planning levers would change it: they indicate what is likely to happen, not which factor to address first. The second limitation is what motivates pairing prediction with a method capable of causal reasoning.

Table I summarises the principal machine-learning techniques relevant to pedestrian-flow prediction, contrasting their core idea, main limitation, and applicability. No single technique dominates. The choice depends on data volume, temporal structure, and the spatial dependence of the flow, and the accuracy of all of them is bounded, as noted above, by the quantity and quality of the available pedestrian observations.

TABLE I. MACHINE-LEARNING TECHNIQUES FOR PEDESTRIAN-FLOW PREDICTION

Technique	Core idea and strength	Key limitation	Relevance to pedestrian flow
Deep neural networks [15]	Learn hierarchical nonlinear representations from raw data	Need large labelled datasets; limited interpretability	Baseline learners for footfall from sensor and video features
Random forests [16]	Tree ensembles; robust estimates and variable-importance ranking	Weaker on sequential and temporal structure	Ranking of built-environment predictors of flow
Support vector machines [17]	Margin-based learning effective with few samples	Scales poorly to very large data; kernel-sensitive	Suited to data-scarce commercial-street settings
Recurrent / LSTM networks [18]	Model temporal dependence in sequential data	Training cost; long-horizon drift	Short-term prediction of time-varying volumes
Reinforcement learning [19], [20]	Learns adaptive control policies through interaction	Needs interaction or simulation; reward design is hard	Adaptive management of crossings and signals
Graph neural networks [26]	Represent the street network; capture spatial dependence	Data-hungry; graph construction non-trivial	Network-level prediction across dependent locations

C. Pedestrian Flow Prediction Models

Pedestrian flow has been studied through three broad families of models. Physically grounded models represent walking as the outcome of interacting forces; the social force model of Helbing and Molnár, in which pedestrians respond to attractive and repulsive influences, remains the reference point for that tradition [25]. Learning-based models instead infer movement from observations, as in the Social LSTM of Alahi et al., which predicts individual trajectories in crowded scenes by learning how nearby people influence one another [24]. Graph-based deep learning models represent the street network explicitly and capture how flows at one location depend on conditions elsewhere [26]. The observations that feed all three come from several sources: fixed sensors and automated counters provide continuous volumes at specific points; closed-circuit television analysed with computer vision yields counts, trajectories, and dwell times; geographic information systems situate these measurements within the street network and built environment; and mobile traces extend coverage across wider areas. The expansion of connected sensing within the Internet of Things has increased both the volume and the timeliness of such observations [12], [22].

For planning, the relevance of prediction lies in three outcomes. Walkability—the degree to which an environment supports comfortable and safe walking—is shaped by movement volumes and by the design that accommodates them [4], [27]. Congestion reduction depends on anticipating where crowding will form so that capacity can be provided in advance. Accessibility, the ease with which destinations can be reached on foot, is closely tied to the built-environment characteristics that empirical studies link to walking [28]. Prediction, in short, is most useful when it is read alongside the planning factors it informs, and that is precisely the reading a causal method can supply [2].

D. DEMATEL in Urban Planning

DEMATEL was developed to study complex and interdependent problems by expressing expert judgement as a matrix of direct influences and then deriving the total influence, direct and indirect, that each factor exerts and receives [7], [34]. Two quantities are obtained for every factor from the resulting total-relation matrix: its prominence, the sum of influence given and received, and its relation, the difference between the two. Factors with positive relation values drive the system and are termed causes; those with negative values are driven by it and are termed effects [8]. The output is a cause-and-effect diagram showing not only which factors matter but how they act on one another. Such a diagram is only as strong as the expert judgements that populate the direct-influence matrix. Where those judgements have not yet been collected, as in the present review, it should be read as a structured hypothesis rather than a measured result.

The emphasis on interdependence is what makes DEMATEL suitable for urban problems, in which land use, accessibility, and safety are tightly coupled rather than independent [35]. The method is frequently combined with related MCDM techniques: the analytic hierarchy process supplies criterion weights [31], while fuzzy and grey extensions accommodate the vagueness of human judgement [29], [30]. Across transport planning, sustainability assessment, smart-city governance, and urban resilience, it has been used to distinguish root drivers from downstream symptoms so that limited resources can be directed at the former [8]. Pedestrian-centered commercial street planning has attracted comparatively little of this work, and less still in conjunction with machine learning-based prediction. This paper offers a conceptual bridge between the two while making clear that empirical confirmation remains outstanding.

III. RESEARCH METHODOLOGY

A. Research Design

The study adopts a qualitative systematic review combined with a conceptual analysis. The review assembles and synthesises the literature on ML pedestrian prediction and on DEMATEL applications; the conceptual analysis organises the resulting factors and their relations into a coherent, testable structure. The design suits the dual aim of summarising a fragmented field and proposing a way to connect its parts. By construction it yields hypotheses about causal structure rather than empirical estimates of it, and the distinction is maintained deliberately throughout the paper.

B. Data Collection

Literature was identified from Scopus, Web of Science, and Google Scholar, supplemented by peer-reviewed journals in transport, planning, and computing. The search combined the terms machine learning, pedestrian flow, smart cities, DEMATEL, sustainable streets, and urban mobility. Records were screened by title and abstract for relevance to pedestrian movement, predictive modelling, or multi-criteria evaluation in an urban context, and the studies retained after screening were read in full to extract methods, factors, and findings.

C. Identification of Evaluation Factors

Ten factors recurring across the reviewed studies were selected to represent the considerations that govern sustainable commercial street planning. They are listed in Table II.

TABLE II. EVALUATION FACTORS

Code	Evaluation Factor
F1	Walkability
F2	Accessibility
F3	Traffic Congestion
F4	Pedestrian Safety
F5	Environmental Quality
F6	Land-Use Diversity
F7	Smart Infrastructure
F8	Social Interaction
F9	Real-Time Data Availability
F10	Urban Livability

The set spans the physical environment (walkability, accessibility, environmental quality, land-use diversity), movement and safety (traffic congestion, pedestrian safety), the technological layer (smart infrastructure, real-time data availability), and social and overall outcomes (social interaction, urban livability). The factors draw on the built-environment and walkability literature [4], [27], [28], [32], on work linking urban form to walking [33], and on the smart-infrastructure literature [12], [22].

To keep the basis for factor selection explicit rather than impressionistic, Table III records how frequently each factor was supported across the reviewed sources. Only factors supported by two or more independent sources were retained; inclusion was governed by this occurrence-based screening rather than by author preference.

TABLE III. FREQUENCY OF FACTOR OCCURRENCE ACROSS THE REVIEWED SOURCES

Code	Evaluation factor	Supporting sources	No.
F1	Walkability	[4], [27], [28]	3
F2	Accessibility	[2], [28], [32]	3
F3	Traffic Congestion	[5], [18]	2
F4	Pedestrian Safety	[4], [24], [25]	3
F5	Environmental Quality	[3], [4]	2
F6	Land-Use Diversity	[27], [32], [33]	3
F7	Smart Infrastructure	[12], [13], [14], [22]	4
F8	Social Interaction	[2], [4]	2
F9	Real-Time Data Availability	[12], [22], [23]	3
F10	Urban Livability	[2], [3], [4]	3

D. DEMATEL Procedure

The relations among the ten factors are analysed with the standard DEMATEL procedure, which proceeds in five steps [7], [34]. No primary expert panel was convened for this review, so the input ratings used below are synthesised from the reviewed literature and treated as provisional. The procedure is reported in full so that it can be reproduced once primary data are gathered.

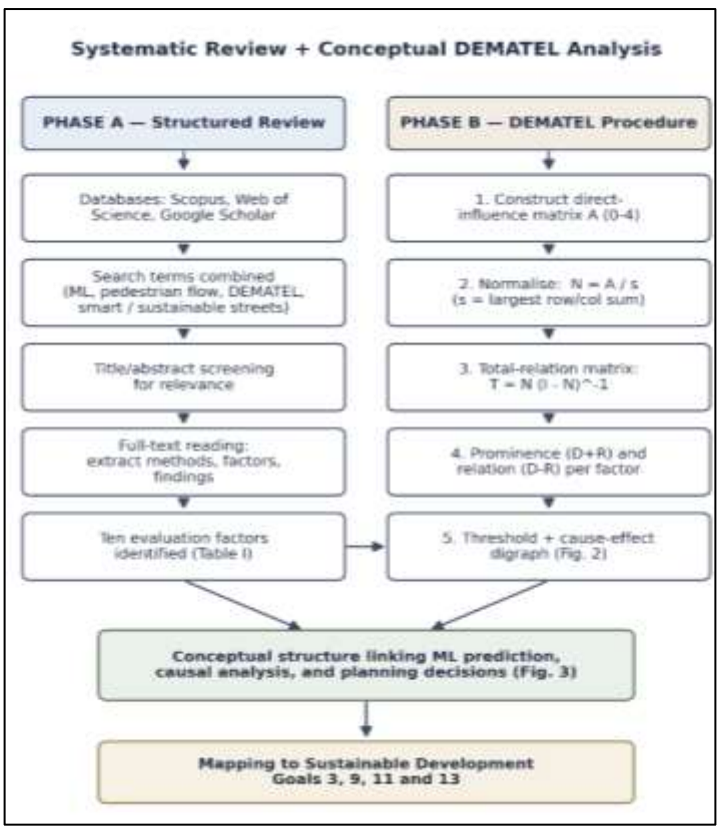

Fig. 1. Methodology of the study, combining a systematic review with the DEMATEL procedure.

1. Construct the direct influence matrix. Experts rate the direct influence of each factor on every other on a 0–4 scale, and the ratings are averaged to give matrix A.
2. Normalise the matrix. A is scaled by its largest row sum to obtain matrix N, whose entries lie between 0 and 1.

3. Develop the total-relation matrix. Direct and indirect influence are combined as $T = N(I - N)^{-1}$, where I is the identity matrix.
4. Derive prominence and relation. Row sums (D) and column sums (R) of T give prominence (D + R) and relation (D − R) for each factor.
5. Generate the causal diagram. Plotting relation against prominence, and applying a threshold to T, yields the cause–effect diagram and the significant influence paths.

IV. Proposed Conceptual DEMATEL Analysis

Applying the procedure to the ten factors yields the cause-and-effect pattern summarised in Table VI and shown conceptually in Fig. 2. Because this is a conceptual review, the prominence and relation values reported here are indicative and hypothesis-generating rather than empirically estimated causal weights. They synthesise the direction and strength of influence reported across the reviewed literature and are presented as propositions to be confirmed, revised, or rejected by expert elicitation and field data in later empirical work. What they do offer is a consistent and interpretable structure from which testing can begin.
The illustrative direct-influence ratings synthesised from the reviewed literature are reported in full in Table IV, so that every value in Table VI and Fig. 2 can be traced back to its input. Each entry gives the direct influence of the row factor on the column factor on a 0–4 scale.

TABLE IV. ILLUSTRATIVE DIRECT-INFLUENCE MATRIX (0–4 SCALE)

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
F1	0	0	1	2	1	0	0	3	0	3
F2	3	0	3	3	2	1	0	3	0	3
F3	2	1	0	3	3	0	0	1	0	3
F4	3	1	2	0	1	0	0	2	0	3
F5	2	0	1	1	0	0	0	2	0	3
F6	3	3	2	1	2	0	0	3	0	3
F7	3	3	3	3	2	1	0	1	4	3
F8	2	0	0	1	1	0	0	0	0	3
F9	3	2	3	3	1	1	3	1	0	3
F10	1	0	1	1	1	0	0	2	0	0

The matrix is normalised by its largest row/column sum (s = 27) to obtain N = A / s, and the total-relation matrix is computed as $T = N (I - N)^{-1}$, shown in Table V.

TABLE V. TOTAL-RELATION MATRIX T

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
F1	0.04	0.01	0.05	0.10	0.06	0.00	0.00	0.14	0.00	0.15
F2	0.18	0.02	0.15	0.16	0.12	0.04	0.00	0.18	0.00	0.20
F3	0.12	0.04	0.03	0.14	0.14	0.00	0.00	0.09	0.00	0.17
F4	0.15	0.04	0.10	0.04	0.07	0.00	0.00	0.12	0.00	0.17
F5	0.10	0.00	0.05	0.06	0.02	0.00	0.00	0.10	0.00	0.15
F6	0.17	0.12	0.11	0.09	0.12	0.00	0.00	0.18	0.00	0.20
F7	0.22	0.14	0.19	0.20	0.15	0.05	0.02	0.14	0.15	0.25
F8	0.09	0.00	0.01	0.05	0.05	0.00	0.00	0.03	0.00	0.14
F9	0.20	0.11	0.17	0.19	0.10	0.05	0.11	0.13	0.02	0.23
F10	0.06	0.00	0.05	0.05	0.05	0.00	0.00	0.09	0.00	0.03

Summing the rows and columns of T yields the prominence (D + R) and relation (D − R) values reported in Table VI. A threshold equal to the mean of all entries of T ($\tau = 0.081$) identifies the significant influence links (47 links with $T_{ij} > \tau$) used to draw the cause–effect digraph in Fig. 2. Since the input matrix in Table IV is an illustrative synthesis of the reviewed literature rather than primary expert data, every quantity that follows is fully reproducible from Table IV yet remains a hypothesis-generating estimate rather than an empirical measurement.

TABLE VI. Indicative (Hypothesis-Generating) Prominence and Relation Values

Factor	D	R	D+R	D−R	Group
F1	0.55	1.33	1.87	−0.78	Effect
F2	1.04	0.49	1.53	+0.55	Cause
F3	0.74	0.92	1.66	−0.17	Effect
F4	0.68	1.10	1.78	−0.42	Effect
F5	0.49	0.88	1.37	−0.39	Effect
F6	1.00	0.14	1.14	+0.86	Cause
F7	1.51	0.13	1.64	+1.38	Cause
F8	0.38	1.20	1.58	−0.82	Effect
F9	1.31	0.17	1.48	+1.15	Cause
F10	0.34	1.71	2.05	−1.36	Effect

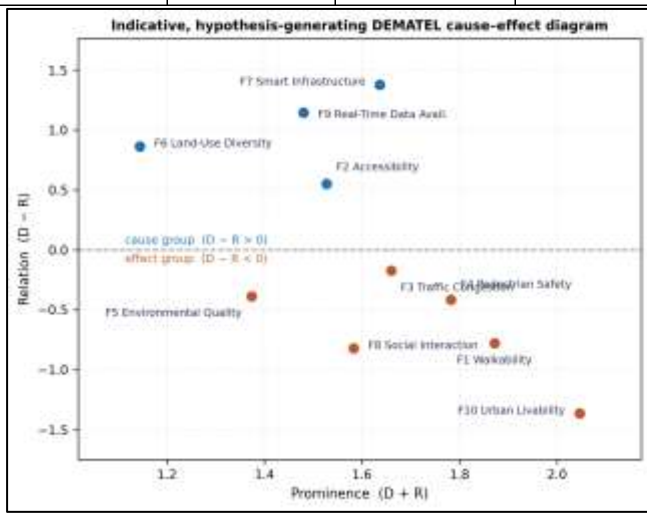

Fig. 2. Indicative, hypothesis-generating DEMATEL cause–effect diagram.

Factors plotted above the dividing line form the proposed cause group; those below form the proposed effect group. The positions are conceptual and await empirical confirmation. The horizontal axis is prominence (D + R) and the vertical axis is relation (D − R); the dividing line is D − R = 0. Influence links are drawn for entries of T above the threshold $\tau = 0.081$ (47 links).

Under this provisional structure, four factors emerge as the proposed principal causes, each with a positive relation value: smart infrastructure (F7), real-time data availability (F9), land-use diversity (F6), and accessibility (F2). These are the hypothesised levers through which planners shape the street. Smart infrastructure and real-time data make movement observable and manageable [12], [13], [22]; accessibility determines how easily the street can be reached on foot [28]; and land-use diversity generates the mix of destinations that sustains pedestrian activity throughout the day [32]. With the exception of land-use diversity, their relatively high prominence suggests that they are also strongly connected to the rest of the system. The remaining factors are hypothesised to behave as effects. Pedestrian safety (F4), walkability (F1), social interaction (F8), and urban livability (F10) record negative relation values, as do traffic congestion (F3), which lies closest to the dividing line, and environmental quality (F5). These are the outcomes planners ultimately care about but, on this reading, cannot manipulate directly; the proposition is that they improve when the causal factors are addressed. Urban livability, with the most negative relation value, appears as the clearest downstream result—a synthesis of safety, comfort, and vitality rather than an independent lever.

The practical message, stated as a hypothesis rather than a finding, concerns sequence. Investment in sensing, accessibility, and a varied land-use mix should propagate through the system to raise safety, walkability, and livability, whereas attempts to improve the effect factors directly, without addressing their causes, are likely to disappoint. ML-based prediction enters at this point as the means of observing the causal layer, supplying the real-time picture of movement on which the management of smart infrastructure and accessibility depends. Whether the proposed ordering holds is precisely the question that primary expert elicitation and field measurement must settle.

V. Findings and Discussion

The review supports several observations, which we separate into evidence drawn from the ML literature and propositions arising from the conceptual DEMATEL structure. First, ML, and deep learning in particular, has substantially improved the accuracy with which movement can be predicted, by learning nonlinear spatial and temporal patterns that earlier methods could not represent [5], [18], [26]. For pedestrians, this means that crowding can increasingly be anticipated rather than merely recorded after the fact. That is an empirical observation grounded in the reviewed studies.

Second, the conceptual DEMATEL analysis offers a hypothesis about the relationships among planning factors. Separating proposed causes from proposed effects places the technological and access-related factors upstream of the experiential outcomes, and so reframes prediction as part of the causal layer rather than an isolated technical exercise: on this view, the value of an accurate footfall estimate is realised only when it informs the accessibility and infrastructure decisions that shape the street. The reframing is the paper's central contribution—moving pedestrian prediction from a pure forecasting task toward a decision-support role in street design—but the specific cause-effect ordering that underpins it remains provisional.

Third, the structure points to the importance of integrated planning. If the factors are indeed interdependent, interventions evaluated in isolation may have limited or even counterproductive effects: a widened footpath not matched by crossing capacity, for example, may simply displace congestion. Treating the street as a coupled system, with prediction informing the causal factors, offers a more coherent basis for design—again, a proposition to be tested rather than a demonstrated result.

Fourth, smart infrastructure recurs as the most prominent proposed causal factor, consistent with its role in making the other factors observable and adjustable [12], [14], [22]. Four themes summarise the discussion: evidence-informed planning, in which prediction supports design; human-centred streets, in which pedestrian experience is the objective; sustainable mobility, in which walking is prioritised; and smart governance, in which institutions act on continuous information about how streets perform.

Taken together, the shift this paper represents is the movement of pedestrian prediction from a pure forecasting task toward a decision-support role in street design. The open question, which we state explicitly, is whether the proposed cause-effect hierarchy holds when it is tested with real experts, real pedestrian-flow data, and real streets. The contribution is therefore best understood as a promising conceptual bridge between ML-based pedestrian prediction and planning prioritization, whose central DEMATEL result remains provisional rather than demonstrated.

Drawing these threads together, the paper proposes the conceptual structure shown in Fig. 3, which links ML prediction with DEMATEL analysis in the service of sustainable commercial street planning. Observations of movement are collected from sensors, video, and mobile traces; ML models convert them into predictions of pedestrian flow; DEMATEL situates those predictions within a hypothesised set of cause-and-effect relations among planning factors; and the resulting understanding is intended to inform urban decision-making, which in turn shapes the design and management of commercial streets.

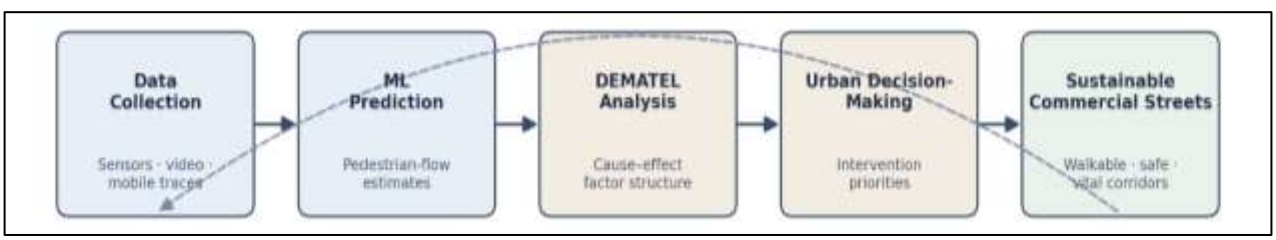

Fig. 3. Proposed conceptual structure linking prediction, causal analysis, and planning decisions: Data Collection → ML Prediction → DEMATEL Analysis → Urban Decision-Making → Sustainable Commercial Streets.

The arrangement is intended to be iterative: decisions change the street, the street is observed anew, and the cycle repeats. Prediction contributes the empirical picture; DEMATEL contributes the causal reasoning that, once empirically grounded, would turn that picture into priorities. The pairing addresses the limitation noted earlier—that predictive models are accurate but silent on which factor to act upon—by attaching a causal interpretation to predictive output. Until that interpretation is validated, it should be applied as a working hypothesis guiding data collection rather than as a settled prescription.

VI. Conclusion

The review shows that ML, and deep learning in particular, has improved the prediction of urban movement, and it argues that DEMATEL is well suited to identifying the causal structure among planning factors. The two claims differ in epistemic status: the first is an empirical observation supported by the reviewed studies, the second a methodological proposal whose application here is conceptual and hypothesis-generating. Organising ten factors into provisional cause and effect groups suggests that smart infrastructure, real-time data availability, accessibility, and land-use diversity may drive the system, while pedestrian safety, walkability, social interaction, and livability may follow from them. The prominence and relation values reported are indicative and should not be read as empirically estimated causal weights. The proposed structure links prediction to causal analysis and to planning decisions, and connects both to Sustainable Development Goals 3, 9, 11, and 13. The contribution is conceptual: a coherent way of combining predictive evidence with causal reasoning for pedestrian-centred street planning, and an indication of where intervention may be most effective. Establishing the indicative DEMATEL values empirically, through structured expert elicitation, is the obvious next task, together with fuzzy or grey extensions of the analysis to handle uncertainty in judgement. The decisive test is whether the proposed cause-effect hierarchy holds with real experts, real pedestrian-flow data, and real streets. Integration with geographic information systems would situate the analysis spatially, and emerging urban digital twins could allow interventions to be tried before implementation. Embedding these tools within governance processes would move the approach from analysis toward continuous management. Until that empirical programme is carried out, the cause-effect hierarchy presented here is best regarded as a provisional, testable hypothesis rather than a demonstrated result.

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