

# Supplementary Materials

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## **Mapping Artificial Intelligence in Electric Two-Wheelers: Paradigm Evolution, Technology–Application Specialization, and Emerging Frontiers (2015–2025)**

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Dataset: 568 Direct AI–E2W publications | 2015–2025

Methodological note: the thematic analyses implement strategic-map, thematic-evolution, and trend-topic logic associated with bibliometrix/Biblioshiny in Python; the R/Biblioshiny interface was not directly executed. VOSviewer (version 1.6.20) maps provide independent cross-software structural checks rather than replacements for the canonical Python workflow or validation of a ground truth.

Settings correspond to Section 3.15 of the main manuscript: the 80 most frequent eligible normalized author keywords (effective minimum frequency = 2) were analyzed using a document-level co-occurrence matrix normalized by association strength and Louvain clustering (seed = 1234). Thematic evolution used 2015–2019, 2020–2022, and 2023–2025 windows, with weighted inclusion  $\geq 0.12$  retained for substantive lineage links; trend topics required at least four occurrences. In bibliometrix-style evolution logic, the inclusion index is the number of shared terms divided by the smaller theme size; weighted inclusion is the sum of the minimum occurrence counts of shared terms divided by the smaller total theme occurrence count. The present Python implementation follows this logic but is reported as a complementary algorithmic analysis rather than a direct Biblioshiny run.

### **S1. Strategic Thematic Map**

The strategic map distinguishes thematic size from maturity. ML–micromobility and shared operations is the largest theme but remains in the Basic quadrant, whereas the smaller neural-network/battery-intelligence theme shows the strongest internal development and occupies the Motor quadrant.

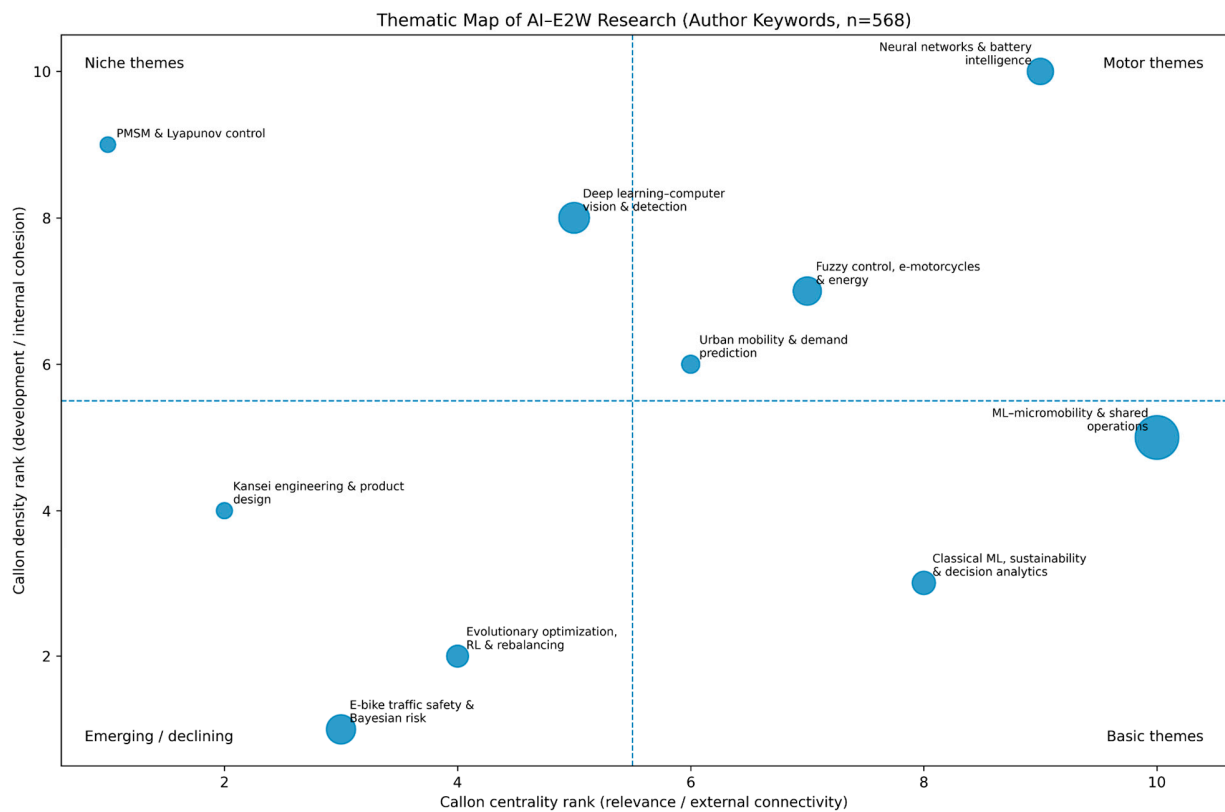


**Figure S1.** Biblioshiny-style thematic map of normalized Author Keywords in the 568-publication Direct corpus.

| Theme                                             | Quadrant           | Centrality | Density | Frequency | Top terms                                                                                                 |
|---------------------------------------------------|--------------------|------------|---------|-----------|-----------------------------------------------------------------------------------------------------------|
| ML–micromobility & shared operations              | Basic              | 0.831      | 5.248   | 262       | machine learning; electric scooter / e-scooter; micromobility; artificial intelligence; built environment |
| Deep learning–computer vision & detection         | Niche              | 0.280      | 6.780   | 117       | deep learning; object detection; convolutional neural network; computer vision; yolo                      |
| E-bike traffic safety & Bayesian risk             | Emerging/Declining | 0.147      | 3.592   | 103       | electric bicycle / e-bike; bayesian network; traffic safety; crash severity                               |
| Fuzzy control, e-motorcycles & energy             | Motor              | 0.492      | 6.053   | 95        | electric vehicle; fuzzy logic; electric motorcycle; regenerative braking; energy consumption              |
| Neural networks & battery intelligence            | Motor              | 0.760      | 9.065   | 79        | neural network; lithium-ion battery; electric two-wheeler; state of charge; safety                        |
| Classical ML, sustainability & decision analytics | Basic              | 0.604      | 4.847   | 56        | random forest; sustainability; support vector machine; deep reinforcement learning; decision tree         |
| Evolutionary optimization, RL & rebalancing       | Emerging/Declining | 0.228      | 4.038   | 47        | genetic algorithm; reinforcement learning; optimization; shared micromobility; rebalancing                |
| Urban mobility & demand prediction                | Motor              | 0.366      | 5.536   | 24        | urban mobility; demand prediction; sharing system; deep neural network; gps data                          |
| Kansei engineering & product design               | Emerging/Declining | 0.045      | 4.861   | 14        | kansei engineering; product design; data mining                                                           |
| PMSM & Lyapunov control                           | Niche              | 0.013      | 8.333   | 11        | permanent magnet synchronous motor; lyapunov stability                                                    |

## S2. Trend Topics and Recent Concentration

Bubble position indicates the weighted median year, bubble size indicates total frequency, and the horizontal line shows the observed keyword lifespan. The complete table reports the recent-period share for all retained trend topics.

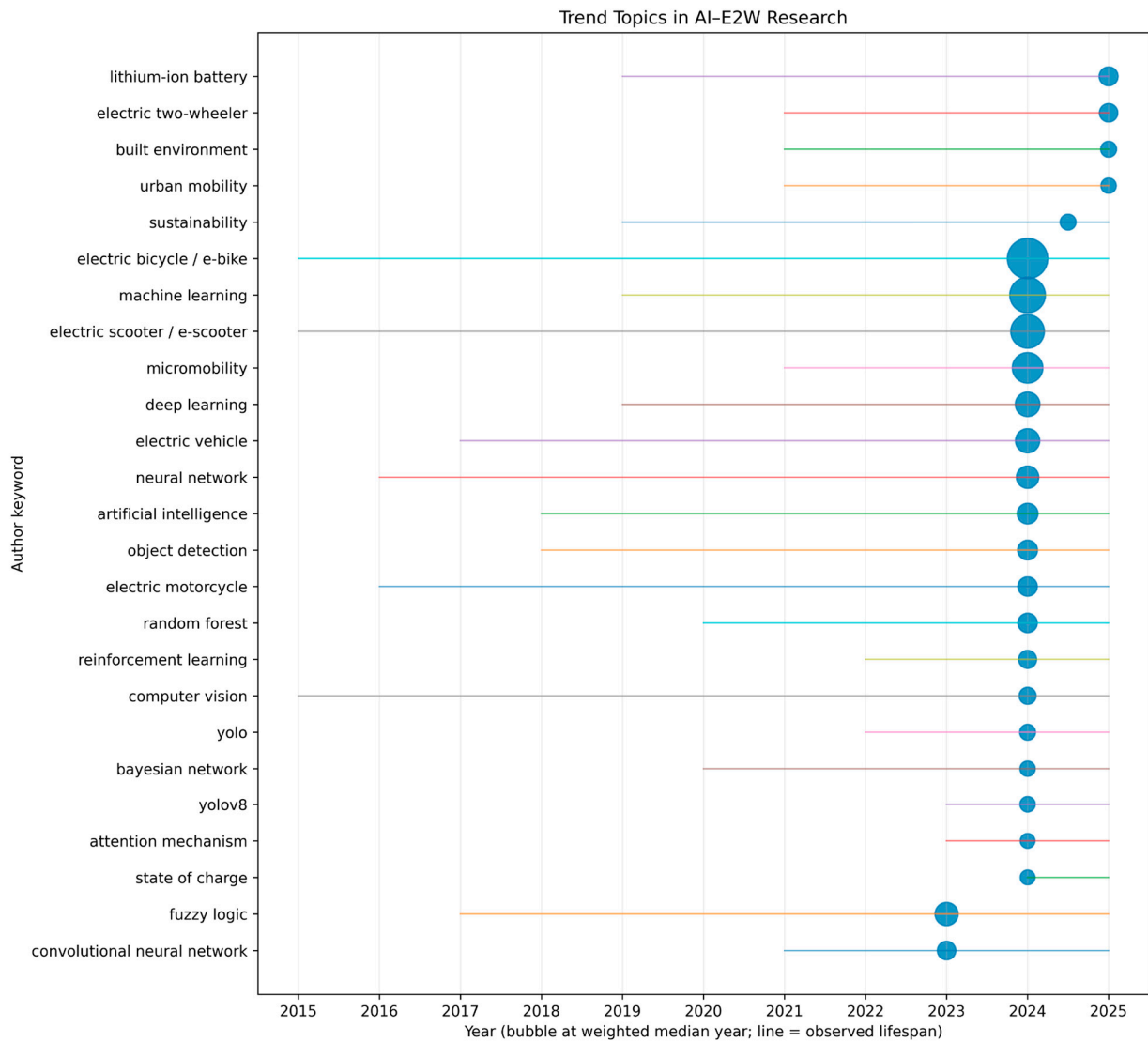


**Figure S2.** Trend topics based on normalized Author Keywords; bubble position = weighted median year, line = observed lifespan, and bubble size = total frequency.

| Keyword                      | Total | First | Last | Median | Peak | Peak n | 2015–19 | 2020–22 | 2023–25 | Recent share |
|------------------------------|-------|-------|------|--------|------|--------|---------|---------|---------|--------------|
| electric bicycle / e-bike    | 87    | 2015  | 2025 | 2024   | 2025 | 27     | 12      | 18      | 57      | 65.5%        |
| machine learning             | 66    | 2019  | 2025 | 2024   | 2024 | 21     | 2       | 11      | 53      | 80.3%        |
| electric scooter / e-scooter | 58    | 2015  | 2025 | 2024   | 2025 | 19     | 4       | 14      | 40      | 69.0%        |
| micromobility                | 47    | 2021  | 2025 | 2024   | 2025 | 15     | 0       | 10      | 37      | 78.7%        |
| deep learning                | 28    | 2019  | 2025 | 2024   | 2025 | 11     | 1       | 6       | 21      | 75.0%        |
| electric vehicle             | 27    | 2017  | 2025 | 2024   | 2025 | 9      | 3       | 7       | 17      | 63.0%        |
| neural network               | 22    | 2016  | 2025 | 2024   | 2025 | 8      | 2       | 4       | 16      | 72.7%        |
| artificial intelligence      | 18    | 2018  | 2025 | 2024   | 2024 | 7      | 1       | 2       | 15      | 83.3%        |
| lithium-ion battery          | 14    | 2019  | 2025 | 2025   | 2025 | 11     | 1       | 0       | 13      | 92.9%        |
| fuzzy logic                  | 24    | 2017  | 2025 | 2023   | 2025 | 6      | 5       | 6       | 13      | 54.2%        |
| random forest                | 15    | 2020  | 2025 | 2024   | 2025 | 6      | 0       | 3       | 12      | 80.0%        |
| object detection             | 16    | 2018  | 2025 | 2024   | 2025 | 6      | 1       | 3       | 12      | 75.0%        |
| electric two-wheeler         | 13    | 2021  | 2025 | 2025   | 2025 | 7      | 0       | 2       | 11      | 84.6%        |
| reinforcement learning       | 12    | 2022  | 2025 | 2024   | 2025 | 4      | 0       | 2       | 10      | 83.3%        |
| convolutional neural network | 13    | 2021  | 2025 | 2023   | 2024 | 4      | 0       | 4       | 9       | 69.2%        |
| computer vision              | 10    | 2015  | 2025 | 2024   | 2025 | 5      | 1       | 1       | 8       | 80.0%        |
| electric motorcycle          | 15    | 2016  | 2025 | 2024   | 2025 | 6      | 2       | 5       | 8       | 53.3%        |
| yolov8                       | 7     | 2023  | 2025 | 2024   | 2024 | 3      | 0       | 0       | 7       | 100.0%       |
| sustainability               | 8     | 2019  | 2025 | 2024.5 | 2025 | 4      | 1       | 0       | 7       | 87.5%        |
| yolo                         | 8     | 2022  | 2025 | 2024   | 2024 | 4      | 0       | 1       | 7       | 87.5%        |
| built environment            | 8     | 2021  | 2025 | 2025   | 2025 | 5      | 0       | 1       | 7       | 87.5%        |
| state of charge              | 6     | 2024  | 2025 | 2024   | 2024 | 4      | 0       | 0       | 6       | 100.0%       |

| Keyword                            | Total | First | Last | Median | Peak | Peak<br>n | 2015–<br>19 | 2020–<br>22 | 2023–<br>25 | Recent<br>share |
|------------------------------------|-------|-------|------|--------|------|-----------|-------------|-------------|-------------|-----------------|
| attention mechanism                | 6     | 2023  | 2025 | 2024   | 2024 | 3         | 0           | 0           | 6           | 100.0%          |
| bayesian network                   | 7     | 2020  | 2025 | 2024   | 2025 | 3         | 0           | 1           | 6           | 85.7%           |
| urban mobility                     | 7     | 2021  | 2025 | 2025   | 2025 | 4         | 0           | 1           | 6           | 85.7%           |
| support vector machine             | 8     | 2019  | 2025 | 2024   | 2025 | 3         | 1           | 1           | 6           | 75.0%           |
| genetic algorithm                  | 14    | 2017  | 2025 | 2022   | 2022 | 3         | 2           | 6           | 6           | 42.9%           |
| yolov5s                            | 5     | 2023  | 2024 | 2023   | 2023 | 3         | 0           | 0           | 5           | 100.0%          |
| travel behavior                    | 5     | 2023  | 2025 | 2024   | 2024 | 3         | 0           | 0           | 5           | 100.0%          |
| shared micromobility               | 5     | 2024  | 2025 | 2025   | 2025 | 3         | 0           | 0           | 5           | 100.0%          |
| multi-objective optimization       | 6     | 2022  | 2025 | 2024   | 2024 | 3         | 0           | 1           | 5           | 83.3%           |
| shared mobility                    | 6     | 2022  | 2025 | 2023.5 | 2023 | 2         | 0           | 1           | 5           | 83.3%           |
| shared e-scooters                  | 6     | 2022  | 2025 | 2024   | 2024 | 2         | 0           | 1           | 5           | 83.3%           |
| deep reinforcement learning        | 7     | 2021  | 2025 | 2024   | 2024 | 3         | 0           | 2           | 5           | 71.4%           |
| optimization                       | 8     | 2020  | 2025 | 2023.5 | 2020 | 2         | 0           | 3           | 5           | 62.5%           |
| health monitoring                  | 4     | 2024  | 2025 | 2024.5 | 2024 | 2         | 0           | 0           | 4           | 100.0%          |
| electric bicycle detection         | 4     | 2023  | 2025 | 2024.5 | 2025 | 2         | 0           | 0           | 4           | 100.0%          |
| smart mobility                     | 4     | 2024  | 2025 | 2024.5 | 2024 | 2         | 0           | 0           | 4           | 100.0%          |
| shared e-bike                      | 4     | 2023  | 2025 | 2024   | 2024 | 2         | 0           | 0           | 4           | 100.0%          |
| deep neural network                | 4     | 2023  | 2025 | 2024   | 2023 | 2         | 0           | 0           | 4           | 100.0%          |
| artificial intelligence (ai)       | 4     | 2024  | 2025 | 2024.5 | 2024 | 2         | 0           | 0           | 4           | 100.0%          |
| rebalancing                        | 4     | 2023  | 2025 | 2024.5 | 2025 | 2         | 0           | 0           | 4           | 100.0%          |
| regenerative braking               | 5     | 2022  | 2025 | 2024   | 2025 | 2         | 0           | 1           | 4           | 80.0%           |
| decision tree                      | 6     | 2022  | 2025 | 2024   | 2022 | 2         | 0           | 2           | 4           | 66.7%           |
| yolov5                             | 6     | 2022  | 2025 | 2023.5 | 2022 | 2         | 0           | 2           | 4           | 66.7%           |
| traffic safety                     | 6     | 2021  | 2025 | 2024.5 | 2025 | 3         | 0           | 2           | 4           | 66.7%           |
| predictive maintenance             | 4     | 2019  | 2025 | 2024.5 | 2025 | 2         | 1           | 0           | 3           | 75.0%           |
| battery                            | 4     | 2020  | 2025 | 2023.5 | 2020 | 1         | 0           | 1           | 3           | 75.0%           |
| gradient boosting                  | 4     | 2022  | 2025 | 2024   | 2024 | 2         | 0           | 1           | 3           | 75.0%           |
| gps data                           | 4     | 2018  | 2025 | 2024.5 | 2025 | 2         | 1           | 0           | 3           | 75.0%           |
| loss function                      | 4     | 2022  | 2025 | 2023.5 | 2022 | 1         | 0           | 1           | 3           | 75.0%           |
| battery swapping stations          | 4     | 2022  | 2025 | 2025   | 2025 | 3         | 0           | 1           | 3           | 75.0%           |
| component                          | 4     | 2016  | 2025 | 2024.5 | 2025 | 2         | 1           | 0           | 3           | 75.0%           |
| bike-sharing                       | 5     | 2021  | 2025 | 2024   | 2021 | 2         | 0           | 2           | 3           | 60.0%           |
| bldc motor                         | 5     | 2021  | 2025 | 2023   | 2021 | 1         | 0           | 2           | 3           | 60.0%           |
| energy consumption                 | 5     | 2016  | 2025 | 2025   | 2025 | 3         | 2           | 0           | 3           | 60.0%           |
| demand prediction                  | 5     | 2020  | 2024 | 2023   | 2023 | 2         | 0           | 2           | 3           | 60.0%           |
| safety                             | 6     | 2021  | 2025 | 2023   | 2022 | 2         | 0           | 3           | 3           | 50.0%           |
| fuzzy logic control                | 6     | 2019  | 2025 | 2022.5 | 2019 | 2         | 2           | 1           | 3           | 50.0%           |
| fault diagnosis                    | 6     | 2019  | 2025 | 2022   | 2021 | 2         | 1           | 2           | 3           | 50.0%           |
| energy efficiency                  | 4     | 2016  | 2025 | 2021   | 2025 | 2         | 2           | 0           | 2           | 50.0%           |
| machine learning algorithms        | 4     | 2022  | 2023 | 2022.5 | 2022 | 2         | 0           | 2           | 2           | 50.0%           |
| battery pack                       | 4     | 2020  | 2025 | 2023   | 2025 | 2         | 0           | 2           | 2           | 50.0%           |
| brushless dc motor                 | 4     | 2018  | 2024 | 2023   | 2024 | 2         | 1           | 1           | 2           | 50.0%           |
| bldc                               | 4     | 2017  | 2025 | 2020.5 | 2017 | 1         | 2           | 0           | 2           | 50.0%           |
| kansei engineering                 | 6     | 2020  | 2025 | 2021.5 | 2021 | 2         | 0           | 4           | 2           | 33.3%           |
| sharing system                     | 4     | 2020  | 2023 | 2021   | 2020 | 2         | 0           | 3           | 1           | 25.0%           |
| charging station                   | 4     | 2018  | 2025 | 2021.5 | 2018 | 1         | 1           | 2           | 1           | 25.0%           |
| product design                     | 4     | 2021  | 2025 | 2022   | 2022 | 2         | 0           | 3           | 1           | 25.0%           |
| smart city                         | 5     | 2019  | 2024 | 2021   | 2021 | 2         | 1           | 3           | 1           | 20.0%           |
| permanent magnet synchronous motor | 6     | 2015  | 2015 | 2015   | 2015 | 6         | 6           | 0           | 0           | 0.0%            |
| lyapunov stability                 | 5     | 2015  | 2015 | 2015   | 2015 | 5         | 5           | 0           | 0           | 0.0%            |
| data mining                        | 4     | 2021  | 2022 | 2021.5 | 2021 | 2         | 0           | 4           | 0           | 0.0%            |

### S3. Independent VOSviewer Keyword Co-Occurrence Structural Check

The VOSviewer keyword map serves as a cross-software structural check. Its broad concentrations correspond to the canonical Python structures for shared mobility/machine learning, e-bike safety/computer vision, battery intelligence, and powertrain/control. Exact cluster assignments are not expected to be identical because the mapping environments use different normalization and visualization procedures.

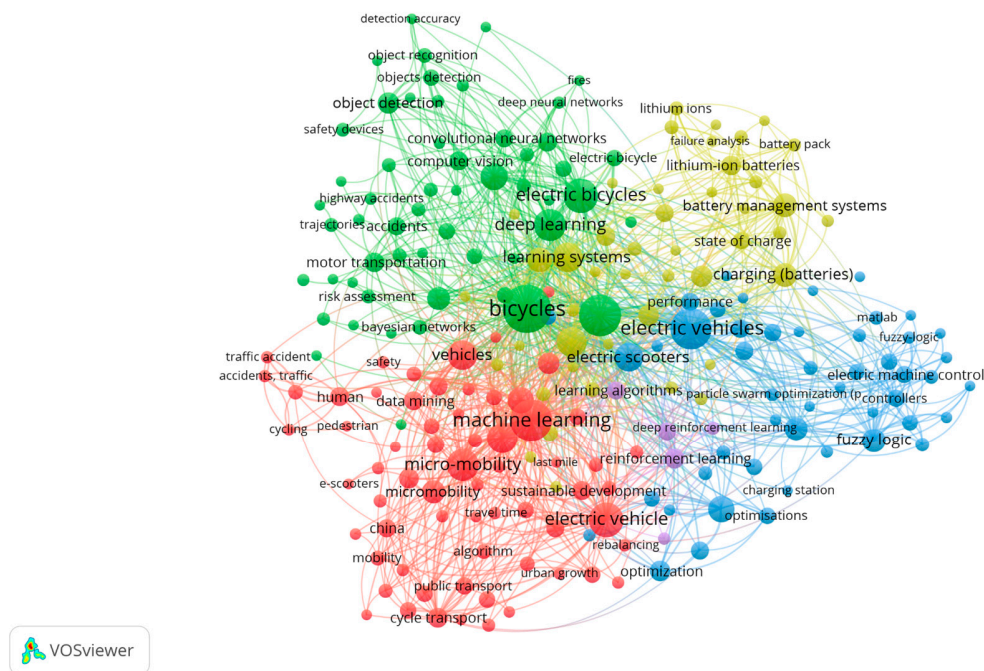


**Figure S3.** Independent VOSviewer keyword co-occurrence map of the Direct AI-E2W corpus.

#### S4. Independent VOSviewer Cited-Reference Co-Citation Structural Check

The VOSviewer co-citation map provides a complementary visualization of the intellectual structure. It preserves broad separation among micromobility/behavioral foundations, machine-learning methodology, safety-oriented work, and computer-vision/ITS references. The layout is optimized for readability without changing the underlying interpretation.

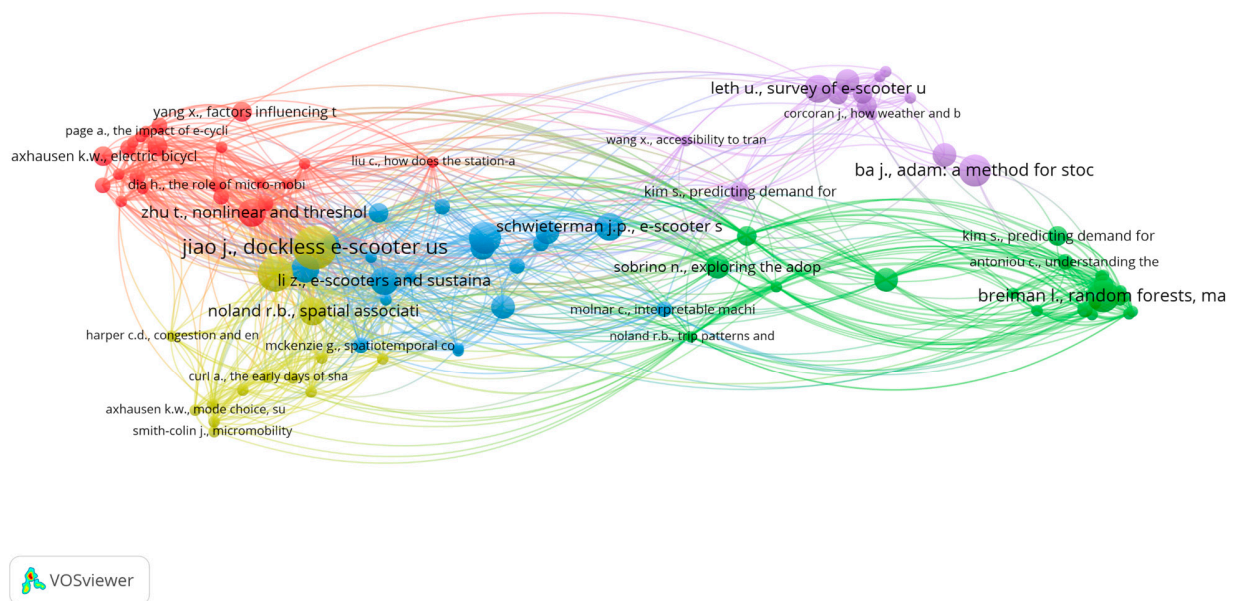


**Figure S4.** Independent VOSviewer cited-reference co-citation visualization of the Direct AI-E2W corpus.

## S5. Theme-Lineage Evidence

Figure 6 in the main manuscript presents the thematic-evolution visualization. The table below archives all non-zero consecutive-period links and identifies whether each was retained as a substantive lineage under the weighted-inclusion threshold.

| From period | From theme                                             | To period | To theme                                        | Shared terms                                                           | Weighted inclusion | Substantive | Lineage       |
|-------------|--------------------------------------------------------|-----------|-------------------------------------------------|------------------------------------------------------------------------|--------------------|-------------|---------------|
| 2015–2019   | PMSM, adaptive control & e-scooter engineering         | 2020–2022 | E-bike/e-scooter neural analytics & safety      | electric scooter / e-scooter                                           | 0.182              | Yes         | Merge         |
| 2015–2019   | E-bike energy, optimization & fuzzy control            | 2020–2022 | E-bike/e-scooter neural analytics & safety      | electric bicycle / e-bike                                              | 0.545              | Yes         | Split + Merge |
| 2015–2019   | E-bike energy, optimization & fuzzy control            | 2020–2022 | Genetic optimization, battery swapping & RL     | genetic algorithm                                                      | 0.133              | Yes         | Split         |
| 2015–2019   | E-bike energy, optimization & fuzzy control            | 2020–2022 | Electric-motorcycle AI & motor design           | electric motorcycle                                                    | 0.154              | Yes         | Split         |
| 2015–2019   | Fuzzy-logic electric-vehicle control                   | 2020–2022 | E-bike/e-scooter neural analytics & safety      | electric vehicle                                                       | 0.375              | Yes         | Split + Merge |
| 2015–2019   | Fuzzy-logic electric-vehicle control                   | 2020–2022 | Fuzzy/PSO control & charging                    | fuzzy logic                                                            | 0.625              | Yes         | Split         |
| 2015–2019   | Neural-network modelling                               | 2020–2022 | E-bike/e-scooter neural analytics & safety      | neural network                                                         | 0.400              | Yes         | Merge         |
| 2020–2022   | E-bike/e-scooter neural analytics & safety             | 2023–2025 | ML, micromobility & built-environment analytics | electric scooter / e-scooter                                           | 0.226              | Yes         | Split + Merge |
| 2020–2022   | E-bike/e-scooter neural analytics & safety             | 2023–2025 | Deep learning, computer vision & YOLO safety    | convolutional neural network; object detection; traffic safety; yolov5 | 0.177              | Yes         | Split + Merge |
| 2020–2022   | E-bike/e-scooter neural analytics & safety             | 2023–2025 | E-bike smart mobility & predictive maintenance  | electric bicycle / e-bike; fault diagnosis                             | 0.323              | Yes         | Split         |
| 2020–2022   | E-bike/e-scooter neural analytics & safety             | 2023–2025 | Battery/SoC intelligence & E2W neural models    | neural network                                                         | 0.065              | No          | Weak link     |
| 2020–2022   | E-bike/e-scooter neural analytics & safety             | 2023–2025 | Fuzzy/deep-RL control & regenerative braking    | electric vehicle                                                       | 0.156              | Yes         | Split + Merge |
| 2020–2022   | Data-driven product design & shared-mobility analytics | 2023–2025 | ML, micromobility & built-environment analytics | demand prediction                                                      | 0.062              | No          | Weak link     |

| From period | From theme                                             | To period | To theme                                        | Shared terms                                            | Weighted inclusion | Substantive | Lineage       |
|-------------|--------------------------------------------------------|-----------|-------------------------------------------------|---------------------------------------------------------|--------------------|-------------|---------------|
| 2020–2022   | Data-driven product design & shared-mobility analytics | 2023–2025 | Battery/SoC intelligence & E2W neural models    | safety                                                  | 0.094              | No          | Weak link     |
| 2020–2022   | Data-driven product design & shared-mobility analytics | 2023–2025 | Classical ML, e-motorcycles & sustainability    | decision tree; random forest                            | 0.156              | Yes         | Merge         |
| 2020–2022   | ML/DL prediction & smart-city mobility                 | 2023–2025 | ML, micromobility & built-environment analytics | machine learning                                        | 0.393              | Yes         | Split + Merge |
| 2020–2022   | ML/DL prediction & smart-city mobility                 | 2023–2025 | Deep learning, computer vision & YOLO safety    | deep learning                                           | 0.214              | Yes         | Split + Merge |
| 2020–2022   | ML/DL prediction & smart-city mobility                 | 2023–2025 | E-bike smart mobility & predictive maintenance  | bike-sharing                                            | 0.071              | No          | Weak link     |
| 2020–2022   | ML/DL prediction & smart-city mobility                 | 2023–2025 | Battery/SoC intelligence & E2W neural models    | electric two-wheeler                                    | 0.071              | No          | Weak link     |
| 2020–2022   | Micromobility RL & multi-agent operations              | 2023–2025 | ML, micromobility & built-environment analytics | micromobility                                           | 0.625              | Yes         | Split + Merge |
| 2020–2022   | Micromobility RL & multi-agent operations              | 2023–2025 | Fuzzy/deep-RL control & regenerative braking    | deep reinforcement learning                             | 0.125              | Yes         | Split + Merge |
| 2020–2022   | Genetic optimization, battery swapping & RL            | 2023–2025 | RL/GA shared-micromobility rebalancing          | genetic algorithm; optimization; reinforcement learning | 0.733              | Yes         | Merge         |
| 2020–2022   | Electric-motorcycle AI & motor design                  | 2023–2025 | ML, micromobility & built-environment analytics | artificial intelligence                                 | 0.154              | Yes         | Split + Merge |
| 2020–2022   | Electric-motorcycle AI & motor design                  | 2023–2025 | Classical ML, e-motorcycles & sustainability    | electric motorcycle                                     | 0.385              | Yes         | Split + Merge |
| 2020–2022   | Fuzzy/PSO control & charging                           | 2023–2025 | Fuzzy/deep-RL control & regenerative braking    | fuzzy logic                                             | 0.500              | Yes         | Split + Merge |
| 2020–2022   | Fuzzy/PSO control & charging                           | 2023–2025 | RL/GA shared-micromobility rebalancing          | bldc motor                                              | 0.167              | Yes         | Split + Merge |

## S6. Cross-Method Triangulation Summary

The summary table compares field-level evidence from the canonical Python workflow, independent VOSviewer maps, and the Biblioshiny-style Python analysis. The interpretation column uses descriptive terms only: 'Convergent' indicates the same broad structure is visible across all three analytical layers; 'Partially convergent' indicates broad agreement with cross-domain bridging; and 'Method-specific / niche' indicates evidence concentrated in a smaller stream rather than a field-wide pattern.

| Knowledge structure                    | Python canonical evidence                                          | VOSviewer visual evidence                                                         | Biblioshiny-style evidence                                                                         | Cross-method interpretation |
|----------------------------------------|--------------------------------------------------------------------|-----------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------|-----------------------------|
| Shared E2W mobility / machine learning | Shared e-scooter mobility, forecasting & behavior cluster          | Dense machine-learning / micromobility / e-scooter concentration                  | Basic theme: ML–micromobility & shared operations; Motor theme: urban mobility & demand prediction | Convergent                  |
| Computer vision / safety               | E-bike AI, safety, vision & design cluster                         | Deep learning / CNN / computer vision / object detection cluster                  | Niche theme: deep learning–computer vision & detection; emerging e-bike safety/Bayesian-risk theme | Convergent                  |
| Battery / state intelligence           | Battery intelligence & data-driven management cluster              | Lithium-ion batteries / BMS / state-of-charge / charging concentration            | Motor theme: neural networks & battery intelligence                                                | Convergent                  |
| Powertrain / control                   | E2W powertrain, energy & computational control cluster             | Fuzzy logic / electric-machine control / controllers / optimization concentration | Motor theme: fuzzy control, e-motorcycles & energy; niche PMSM/Lyapunov control                    | Convergent                  |
| Reinforcement learning / operations    | Coupling fronts around shared-fleet operations, rebalancing and RL | RL / optimization nodes bridging shared mobility and charging/control             | Emerging theme: evolutionary optimization, RL & rebalancing; strong 2020–2022→2023–2025 lineage    | Partially convergent        |
| Design / HMI                           | AI×application lift shows NLP/GenAI specialization in design/HMI   | Not a dominant visual concentration                                               | Emerging/declining niche: Kansei engineering & product design                                      | Method-specific / niche     |

## S7. AI-Family and E2W Application-Domain Coding Dictionary

The coding system is non-exclusive. A value of 1 indicates that a technology family or application domain is substantively used or analyzed in the paper; a mere background mention is insufficient. The table reports the operational rules used in the revision-stage reproducibility audit.

| Code | Category | Assign 1 when... | Do NOT assign 1 when... | Typical examples |
|------|----------|------------------|-------------------------|------------------|
|------|----------|------------------|-------------------------|------------------|

| Code | Category                                     | Assign 1 when...                                                                                                                                                                                                      | Do NOT assign 1 when...                                                                                                                                                              | Typical examples                                                                                                |
|------|----------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------|
| AI1  | Computational intelligence / metaheuristics  | Assign 1 when the study substantively uses fuzzy logic, ANFIS, genetic/evolutionary algorithms, particle-swarm/swarm intelligence, expert-system or closely related computational-intelligence/metaheuristic methods. | Do not code 1 when such methods are only mentioned in the background or references; static optimization without an AI/CI method is not enough.                                       | fuzzy logic; ANFIS; genetic algorithm; evolutionary algorithm; particle swarm optimization                      |
| AI2  | Classical machine learning                   | Assign 1 when conventional supervised/unsupervised ML is substantively used for prediction, classification, clustering or decision analytics.                                                                         | Do not code deep neural networks here merely because they are 'machine learning'; use AI3 for deep/neural architectures. Co-code only if both classical ML and DL are actually used. | random forest; SVM/SVR; decision tree; Bayesian network; KNN; gradient boosting; XGBoost                        |
| AI3  | Deep learning / neural networks              | Assign 1 when neural-network or deep-learning models are substantively used.                                                                                                                                          | Do not code 1 for generic 'AI' or 'machine learning' unless a neural/deep architecture is identifiable.                                                                              | ANN; DNN; CNN; RNN; LSTM; GRU; autoencoder; deep neural network                                                 |
| AI4  | Computer vision / perception                 | Assign 1 when image/video-based perception, recognition or object-detection is a substantive method or task.                                                                                                          | Do not code 1 for non-visual sensor prediction. This category can be co-coded with AI3 when a deep vision model is used.                                                             | computer vision; object detection; image recognition; YOLO; vehicle/helmet/rider detection                      |
| AI5  | Reinforcement learning                       | Assign 1 when the study uses reinforcement learning for sequential decision-making, control, routing, rebalancing, charging or related tasks.                                                                         | Do not code 1 for ordinary supervised learning or one-shot optimization.                                                                                                             | reinforcement learning; deep RL; Q-learning; DQN                                                                |
| AI6  | Graph learning                               | Assign 1 when graph-based machine/deep learning is substantively used.                                                                                                                                                | Do not code ordinary network analysis or graph-theory optimization as graph learning unless a learning model on graphs is used.                                                      | graph neural network; GNN; graph attention network; GAT                                                         |
| AI7  | Explainable / federated / trustworthy AI     | Assign 1 when explainability, federated/distributed privacy-preserving learning, interpretability, fairness or trustworthy-AI methods are substantive.                                                                | Do not code general statements about ethics/privacy unless an explicit method or analytical component is present.                                                                    | XAI; SHAP; LIME; federated learning; privacy-preserving learning; trustworthy AI                                |
| AI8  | NLP / generative AI / transformers           | Assign 1 when NLP, generative AI, LLMs or neural transformer architectures are substantively used.                                                                                                                    | Do not treat electrical transformers as AI. Do not code ordinary keyword analysis as NLP unless a substantive NLP/text-learning method is used.                                      | natural language processing; generative AI; LLM; language model; vision transformer; transformer neural network |
| APP1 | Battery / energy / range intelligence        | Assign 1 when the E2W problem centers on battery state/health/faults, energy consumption/management, range prediction or battery intelligence.                                                                        | Exclude studies where batteries are incidental and the primary problem is charging-station/fleet infrastructure.                                                                     | SoC/SoH; battery fault diagnosis; voltage prediction; energy consumption; range prediction                      |
| APP2 | Charging / battery swapping / infrastructure | Assign 1 when charging, charging-station siting/operation, swapping networks, battery exchange or related infrastructure is substantive.                                                                              | Exclude purely internal battery-state estimation with no charging/swapping/infrastructure component.                                                                                 | charging station; battery swapping; exchange network; charging infrastructure                                   |
| APP3 | Powertrain / motor / control                 | Assign 1 when the study centers on motors, controllers, powertrain, regenerative braking, vehicle energy-management control or propulsion control.                                                                    | Exclude high-level fleet routing or user behavior unless vehicle control is also a substantive focus.                                                                                | BLDC/PMSM; motor control; powertrain; regenerative braking; vehicle control                                     |
| APP4 | Safety / perception / rider assistance       | Assign 1 when the E2W problem concerns crash/risk/safety, detection of riders/vehicles/helmets, rider protection, perception or assistance.                                                                           | Exclude generic travel-demand studies unless safety/risk/perception is a substantive outcome.                                                                                        | helmet detection; crash severity; rider protection; object detection; risk assessment                           |
| APP5 | Shared mobility / fleet / demand             | Assign 1 when shared e-bike/e-scooter systems, fleet operations, demand prediction, rebalancing, service availability or fleet management are substantive.                                                            | Exclude private-user adoption studies with no shared/fleet operational component.                                                                                                    | bike/scooter sharing; demand forecasting; rebalancing; fleet operations                                         |

| Code | Category                                          | Assign 1 when...                                                                                                                                                     | Do NOT assign 1 when...                                                                                                        | Typical examples                                                                           |
|------|---------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------|
| APP6 | Consumer / adoption / marketing / user experience | Assign 1 when the study focuses on consumers/users, adoption/acceptance, satisfaction, retention, marketing, reviews or user experience.                             | Exclude system-level mode-choice/urban-planning work unless consumer/adoption/UX is a substantive analytical focus.            | adoption; acceptance; satisfaction; app reviews; retention; marketing; UX                  |
| APP7 | Routing / logistics / delivery / planning         | Assign 1 when routing, delivery, logistics, dispatch, route choice or operational planning is a substantive problem.                                                 | Exclude general built-environment/mode-choice analysis unless there is an explicit routing/logistics/planning decision.        | vehicle routing; food delivery; dispatch; route optimization; logistics                    |
| APP8 | Design / HMI / product development                | Assign 1 when product/form design, human-machine interface, concept generation, ergonomics or product-development decisions are substantive.                         | Exclude motor/controller engineering design unless product/HMI/form development is a substantive user-facing/design objective. | Kansei engineering; product form; concept ideation; HMI; product development               |
| APP9 | Urban planning / built environment / mode choice  | Assign 1 when the study centers on built environment, land use, mode choice/substitution, accessibility, urban context or planning/policy-oriented spatial analysis. | Exclude fleet-demand studies with no substantive urban/built-environment/mode-choice component.                                | built environment; land use; mode choice; mode substitution; accessibility; urban planning |

## S8. Rule-to-Human Reproducibility Audit of Metadata Coding

A proportional stratified random sample of 114 Direct-corpus records was independently coded from titles, abstracts, and keywords. One record (S050) was excluded because the exported title and abstract were internally mismatched, leaving  $n = 113$  evaluable records. The independent human coding is treated as the reference for precision/recall/F1. Cohen's kappa is reported as a rule-to-human agreement statistic, not as two-human inter-rater reliability. Low-prevalence categories can yield unstable kappa despite high raw agreement.

| Category | Rule + | Human + | Agreement | Cohen $\kappa$ | Precision | Recall | F1    |
|----------|--------|---------|-----------|----------------|-----------|--------|-------|
| AI1      | 31     | 30      | 0.991     | 0.978          | 0.968     | 1.000  | 0.984 |
| AI2      | 37     | 33      | 0.965     | 0.917          | 0.892     | 1.000  | 0.943 |
| AI3      | 45     | 44      | 0.920     | 0.833          | 0.889     | 0.909  | 0.899 |
| AI4      | 22     | 23      | 0.973     | 0.917          | 0.955     | 0.913  | 0.933 |
| AI5      | 5      | 5       | 1.000     | 1.000          | 1.000     | 1.000  | 1.000 |
| AI6      | 2      | 3       | 0.991     | 0.796          | 1.000     | 0.667  | 0.800 |
| AI7      | 3      | 4       | 0.991     | 0.853          | 1.000     | 0.750  | 0.857 |
| AI8      | 2      | 3       | 0.991     | 0.796          | 1.000     | 0.667  | 0.800 |
| APP1     | 22     | 20      | 0.894     | 0.649          | 0.682     | 0.750  | 0.714 |
| APP2     | 19     | 12      | 0.938     | 0.740          | 0.632     | 1.000  | 0.774 |
| APP3     | 45     | 27      | 0.823     | 0.604          | 0.578     | 0.963  | 0.722 |
| APP4     | 41     | 39      | 0.823     | 0.613          | 0.732     | 0.769  | 0.750 |
| APP5     | 19     | 23      | 0.947     | 0.825          | 0.947     | 0.783  | 0.857 |
| APP6     | 17     | 14      | 0.850     | 0.365          | 0.412     | 0.500  | 0.452 |
| APP7     | 8      | 9       | 0.920     | 0.428          | 0.500     | 0.444  | 0.471 |
| APP8     | 3      | 6       | 0.938     | 0.194          | 0.333     | 0.167  | 0.222 |
| APP9     | 13     | 23      | 0.876     | 0.544          | 0.846     | 0.478  | 0.611 |

## S9. Broad-versus-Narrow AI-Definition Sensitivity

The broad study boundary retains computational intelligence/metaheuristics together with contemporary ML/DL/CV/RL and newer AI families. A narrow contemporary-AI sensitivity set was reconstructed by retaining records assigned to at least one of AI2–AI8 and treating AI1-only records as a legacy computational-intelligence boundary. Because the original record-level coding file was not retained, this is explicitly a post-hoc reconstructed sensitivity analysis rather than a replacement for the original Table 6 counts.

| Period    | Direct n | Narrow contemporary-AI n | Narrow share | AI1-only legacy n | Legacy share |
|-----------|----------|--------------------------|--------------|-------------------|--------------|
| 2015–2019 | 56       | 29                       | 51.8%        | 21                | 37.5%        |
| 2020–2022 | 136      | 97                       | 71.3%        | 31                | 22.8%        |
| 2023–2025 | 376      | 301                      | 80.1%        | 55                | 14.6%        |
| All years | 568      | 427                      | 75.2%        | 107               | 18.8%        |

In the reconstructed sensitivity coding, the rank ordering of the nine application-domain counts was highly similar between the broad and narrow sets (Spearman  $\rho = 0.967$ ,  $p < 0.001$ ). Because several application domains showed lower human agreement in S8, this rank comparison is treated as secondary sensitivity evidence rather than a new substantive result.

## S10. Emerging-Frontier Threshold Sensitivity

The baseline recent-topic rule can amplify very small counts. Sensitivity was therefore evaluated across nine combinations: minimum total occurrence = 4/6/8 and recent-period share = 60%/70%/80%. The persistence score is the number of combinations satisfied. Scores  $\geq 6$  are labeled robust emerging signals; lower scores are labeled candidate signals. In particular, an  $n = 4$  term with 100% recent share can satisfy only the three settings using the minimum frequency of 4, so it is not treated as equally robust as a higher-frequency term.

| Keyword                      | Total | 2023–25 n | Recent share | Persistence / 9 | Interpretation            |
|------------------------------|-------|-----------|--------------|-----------------|---------------------------|
| machine learning             | 66    | 53        | 80.3%        | 9               | Robust emerging signal    |
| artificial intelligence      | 18    | 15        | 83.3%        | 9               | Robust emerging signal    |
| lithium-ion battery          | 14    | 13        | 92.9%        | 9               | Robust emerging signal    |
| random forest                | 15    | 12        | 80.0%        | 9               | Robust emerging signal    |
| electric two-wheeler         | 13    | 11        | 84.6%        | 9               | Robust emerging signal    |
| reinforcement learning       | 12    | 10        | 83.3%        | 9               | Robust emerging signal    |
| computer vision              | 10    | 8         | 80.0%        | 9               | Robust emerging signal    |
| sustainability               | 8     | 7         | 87.5%        | 9               | Robust emerging signal    |
| yolo                         | 8     | 7         | 87.5%        | 9               | Robust emerging signal    |
| built environment            | 8     | 7         | 87.5%        | 9               | Robust emerging signal    |
| micromobility                | 47    | 37        | 78.7%        | 6               | Robust emerging signal    |
| deep learning                | 28    | 21        | 75.0%        | 6               | Robust emerging signal    |
| neural network               | 22    | 16        | 72.7%        | 6               | Robust emerging signal    |
| object detection             | 16    | 12        | 75.0%        | 6               | Robust emerging signal    |
| yolov8                       | 7     | 7         | 100.0%       | 6               | Robust emerging signal    |
| support vector machine       | 8     | 6         | 75.0%        | 6               | Robust emerging signal    |
| bayesian network             | 7     | 6         | 85.7%        | 6               | Robust emerging signal    |
| urban mobility               | 7     | 6         | 85.7%        | 6               | Robust emerging signal    |
| state of charge              | 6     | 6         | 100.0%       | 6               | Robust emerging signal    |
| attention mechanism          | 6     | 6         | 100.0%       | 6               | Robust emerging signal    |
| multi-objective optimization | 6     | 5         | 83.3%        | 6               | Robust emerging signal    |
| shared mobility              | 6     | 5         | 83.3%        | 6               | Robust emerging signal    |
| shared e-scooters            | 6     | 5         | 83.3%        | 6               | Robust emerging signal    |
| deep reinforcement learning  | 7     | 5         | 71.4%        | 4               | Candidate emerging signal |
| electric bicycle / e-bike    | 87    | 57        | 65.5%        | 3               | Candidate emerging signal |
| electric scooter / e-scooter | 58    | 40        | 69.0%        | 3               | Candidate emerging signal |
| convolutional neural network | 13    | 9         | 69.2%        | 3               | Candidate emerging signal |
| yolov5s                      | 5     | 5         | 100.0%       | 3               | Candidate emerging signal |
| travel behavior              | 5     | 5         | 100.0%       | 3               | Candidate emerging signal |
| shared micromobility         | 5     | 5         | 100.0%       | 3               | Candidate emerging signal |
| regenerative braking         | 5     | 4         | 80.0%        | 3               | Candidate emerging signal |
| health monitoring            | 4     | 4         | 100.0%       | 3               | Candidate emerging signal |
| electric bicycle detection   | 4     | 4         | 100.0%       | 3               | Candidate emerging signal |
| smart mobility               | 4     | 4         | 100.0%       | 3               | Candidate emerging signal |
| shared e-bike                | 4     | 4         | 100.0%       | 3               | Candidate emerging signal |
| deep neural network          | 4     | 4         | 100.0%       | 3               | Candidate emerging signal |
| artificial intelligence (ai) | 4     | 4         | 100.0%       | 3               | Candidate emerging signal |
| rebalancing                  | 4     | 4         | 100.0%       | 3               | Candidate emerging signal |
| decision tree                | 6     | 4         | 66.7%        | 2               | Candidate emerging signal |
| yolov5                       | 6     | 4         | 66.7%        | 2               | Candidate emerging signal |
| traffic safety               | 6     | 4         | 66.7%        | 2               | Candidate emerging signal |

## S11. Reproducibility and Audit-Artifact Inventory

This inventory distinguishes materials provided in the manuscript package from derived artifacts retained by the authors and source data that cannot be redistributed. It also documents the one known provenance limitation: the original record-

level rule-based label file was not retained, so the narrow-AI sensitivity analysis relies on a reconstructed implementation of the published coding definitions.

| Artifact                                                            | Status / location                                                                        | Reproducibility note                                                                                                                                                           |
|---------------------------------------------------------------------|------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Frozen Scopus V4-Revised search query                               | Provided in Appendix A of the main manuscript                                            | Exact search blocks, year window, document types, language, and final-stage restriction are reported.                                                                          |
| Focality screening rules and record-level decisions                 | Rules reported in Section 3.3; audit file retained by authors                            | Derived screening decisions can be shared on reasonable request, subject to Scopus licensing constraints.                                                                      |
| Keyword normalization and reference-canonicalization specifications | Procedures reported in Sections 3.4 and 3.7; detailed specifications retained by authors | Supports reconstruction of the normalized term and cited-reference layers.                                                                                                     |
| AI-family and application-domain coding dictionary                  | Provided in S7                                                                           | Operational inclusion/exclusion rules used for the revision-stage validation audit.                                                                                            |
| Human-validation sample and category-level metrics                  | Metrics provided in S8                                                                   | One mismatched Scopus record was excluded, leaving $n = 113$ evaluable records.                                                                                                |
| AI-definition and frontier-threshold sensitivity outputs            | Provided in S9–S10                                                                       | Documents the reconstructed narrow-AI analysis and the $3 \times 3$ frequency/recency threshold grid.                                                                          |
| Network node/edge files, derived tables, and Python scripts         | Retained by authors; available on reasonable request                                     | Derived artifacts may be shared subject to licensing restrictions on source bibliographic content.                                                                             |
| VOSviewer structural-check settings and outputs                     | Methods in Section 3.15; outputs summarized in S3–S4                                     | Used as cross-software structural checks rather than a replacement for the canonical Python workflow.                                                                          |
| Raw Scopus export                                                   | Not redistributed                                                                        | Scopus bibliographic content is licensed; the retrieval date and exact search strategy are reported instead.                                                                   |
| Original record-level rule-based label file                         | Not retained                                                                             | A reconstructed rule-based implementation of the published definitions was used for post-hoc sensitivity analysis; this limitation is disclosed in the main manuscript and S9. |