



# IPIN 2024 PRESENTATION

## Exploring the Feasibility of Automated Data Standardization using Large Language Models for Seamless Positioning

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# Sensor Fusion?

*GSM/3/4/5G*

*Indoor GNSS*

*UWB*

*GNSS*

*Ultrasound*

*Image SLAM*

*Radio AM&FM*

*Accelerometer*

*BLE*

*Visual Positioning System (VPS)*

*Radar*

*NFC*

*WLAN*

*LiFi*

*WiFi*

*Theodolites*

*TV*

*Gyroscope*

*Imagemarkers*

*Contactless cards*

*LiDAR*

*Bar codes*

*Pressure*

*Cospas Sarsat, Argos*

*Magnetometer*

*Opportunity radio signals*



# Any Trouble?

## > Inconsistent Data Format

- Variety of **formats, units, or conventions**
  - UTC time or Local time?
  - UNIX or YYYY-MM-DDTHH:mm:ss.sssZ?
  - Degree or Radian?
  - Cartesian or Polar Coordinate?

## > Which can lead to

- Error during execution
- Incorrect state estimates

## > Current Solutions

- Sensor Calibration and Preprocessing Pipelines
- Manual Unit Conversions
- Manual Coordinate Transformations

## > Drawbacks

- High **complexity** and **maintenance cost**
- Manual **errors** -> error propagation
- Limited **flexibility & scalability**
- Compromised **real-time** performance



# Can LLMs Help?

## > LLMs as a Solution

- Contextual Understanding of Diverse Data
- Automatic Detection and Standardization
- Adaptability to New Sensors
- Reduction of Manual Effort and Error

**Complexity**

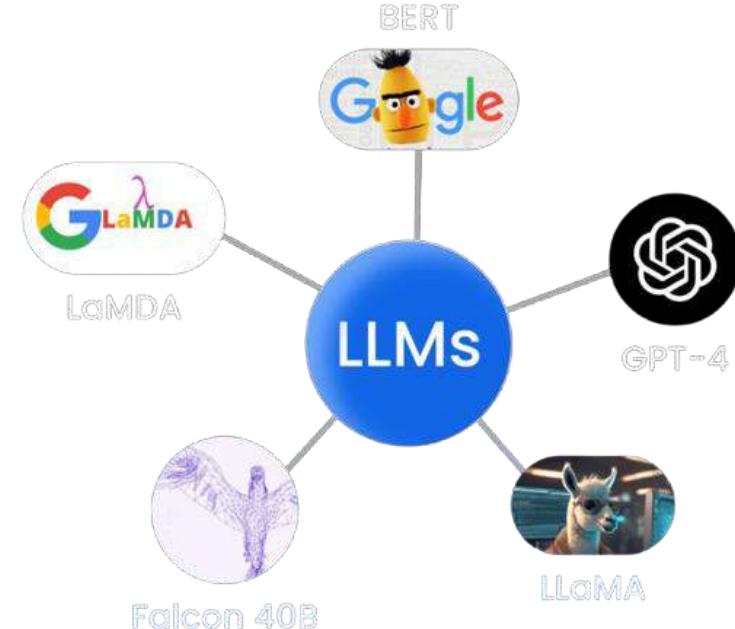
**Errors**

**Scalability**

**Real-time performance**

**Flexibility**

**Computational cost**





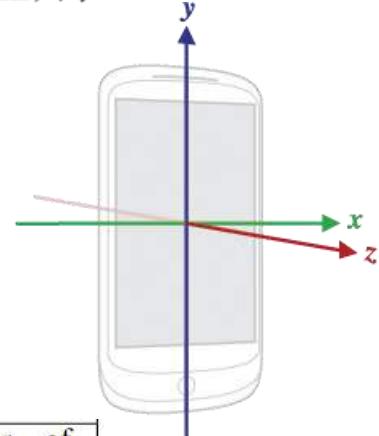
# Schema

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# The Pre-defined Schema

- The schema is based on common inputs to the Kalman filter for sensor fusion
- Assumption: Coordinate System is Android or WGS84/HK1980 format



Sensor Type	Required Fields	Values Object Properties	Description
Magneto-meter	name, time, values	x ( $\mu\text{T}$ ), y ( $\mu\text{T}$ ), z ( $\mu\text{T}$ )	Measures magnetic field strength along x, y, and z axes in microteslas ( $\mu\text{T}$ ).
Gyro-scope	name, time, values	x (rad/s), y (rad/s), z (rad/s)	Measures angular velocity along x, y, and z axes in radians per second (rad/s).
Accelerometer	name, time, values	x ( $\text{m/s}^2$ ), y ( $\text{m/s}^2$ ), z ( $\text{m/s}^2$ )	Measures acceleration along x, y, and z axes in meters per second squared ( $\text{m/s}^2$ ).
Gravity	name, time, values	x ( $\text{m/s}^2$ ), y ( $\text{m/s}^2$ ), z ( $\text{m/s}^2$ )	Measures gravity effects along x, y, and z axes in meters per second squared ( $\text{m/s}^2$ ).
Ultra-Wideband (UWB)	name, time, values	x (m), y (m), z (m)	Determines spatial position in meters (m).
Bluetooth	name, time, values	x (m), y (m), z (m)	Determines spatial position in meters (m).
Pedometer	name, time, steps	steps (count)	Tracks the number of steps taken (count).
Ori-entation	name, time, values	qx, qy, qz, qw	Provides orientation details in quaternion format.
Baro-meter	name, time, values	relative altitude (m), pressure (mBar)	Measures relative altitude in meters (m) and atmospheric pressure in millibars (mBar).
Location	name, time, values	latitude ( $^\circ$ ), longitude ( $^\circ$ ), altitude (m), speed (m/s), speed accuracy (m/s), horizontal accuracy (m), vertical accuracy (m)	Provides comprehensive location data including coordinates (degrees), speed (meters per second), altitude (meters), and accuracies (meters).
Image	name, time, image	image (data)	Provides image data in binary format.



# The Pre-defined Schema

Sensor Type	Required Fields	Values Object Properties	Description	Pedometer	name, time, steps	steps (count)	Tracks the number of steps taken (count).
Magneto-meter	name, time, values	x ( $\mu\text{T}$ ), y ( $\mu\text{T}$ ), z ( $\mu\text{T}$ )	Measures magnetic field strength along x, y, and z axes in microteslas ( $\mu\text{T}$ ).	Orientation	name, time, values	qx, qy, qz, qw	Provides orientation details in quaternion format.
Gyro-scope	name, time, values	x (rad/s), y (rad/s), z (rad/s)	Measures angular velocity along x, y, and z axes in radians per second (rad/s).	Baro-meter	name, time, values	relative altitude (m), pressure (mBar)	Measures relative altitude in meters (m) and atmospheric pressure in millibars (mBar).
Accelerometer	name, time, values	x ( $\text{m/s}^2$ ), y ( $\text{m/s}^2$ ), z ( $\text{m/s}^2$ )	Measures acceleration along x, y, and z axes in meters per second squared ( $\text{m/s}^2$ ).	Location	name, time, values	latitude ( $^\circ$ ), longitude ( $^\circ$ ), altitude (m), speed (m/s), speed accuracy (m/s), horizontal accuracy (m), vertical accuracy (m)	Provides comprehensive location data including coordinates (degrees), speed (meters per second), altitude (meters), and accuracies (meters).
Gravity	name, time, values	x ( $\text{m/s}^2$ ), y ( $\text{m/s}^2$ ), z ( $\text{m/s}^2$ )	Measures gravity effects along x, y, and z axes in meters per second squared ( $\text{m/s}^2$ ).	Image	name, time, image	image (data)	Provides image data in binary format.
Ultra-Wideband (UWB)	name, time, values	x (m), y (m), z (m)	Determines spatial position in meters (m).				
Bluetooth	name, time, values	x (m), y (m), z (m)	Determines spatial position in meters (m).				



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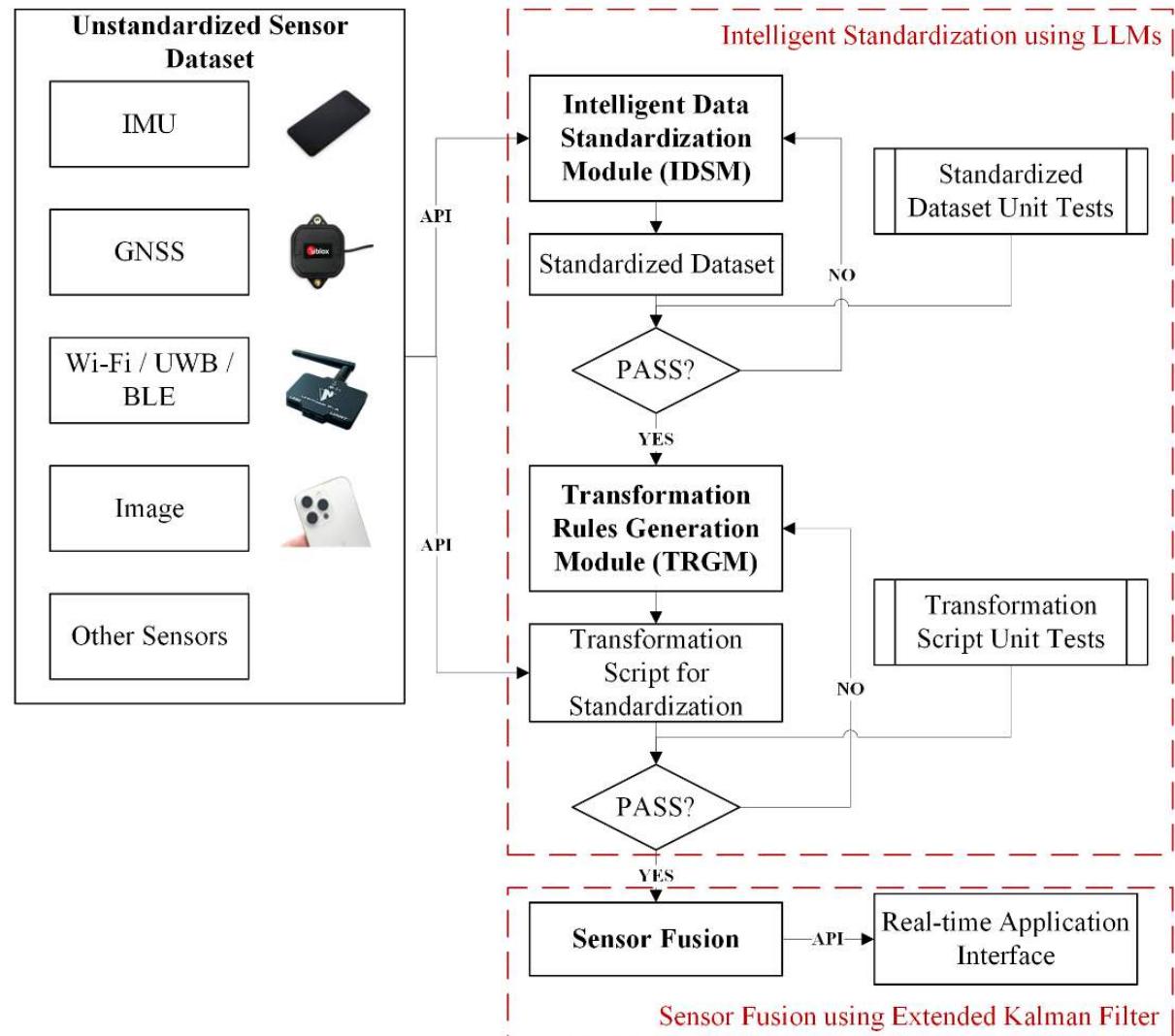
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# Framework

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# Proposed Framework





# Intelligent Data Standardization Module (IDSM)

## > Overview

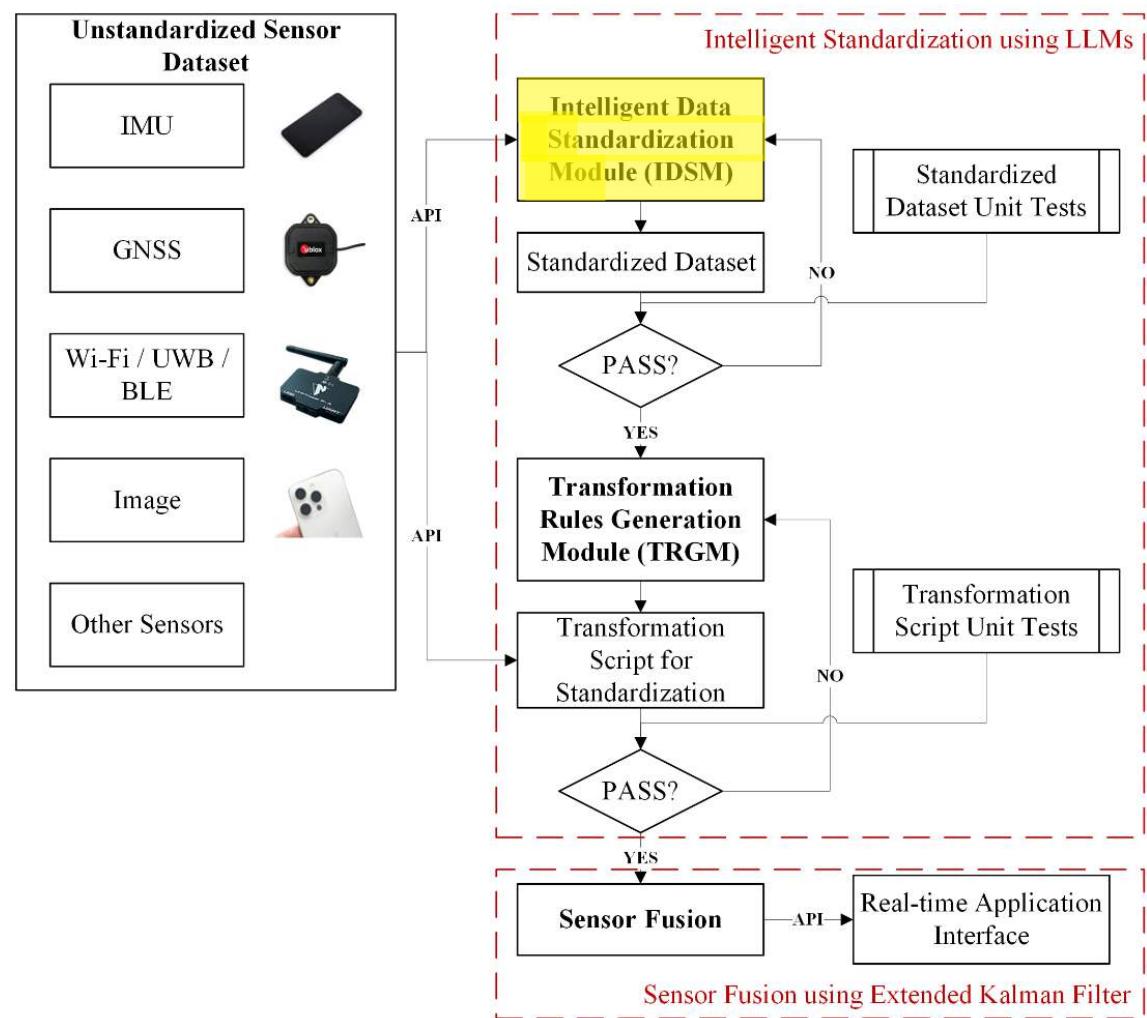
- IDSM leverages **GPT-4-0613** for standardizing sensor data.
- Trained Sensors: Pedometers, Magnetometers, Orientation Sensors, Gyroscopes, Accelerometers, Gravity Sensors, Barometers, GNSS Receivers, Bluetooth, and UWB

## > Data Standardization Process

- Input Data:  $\mathbf{D}_i = \{d_{i1}, d_{i2}, \dots, d_{in}\}$ .
- Standardized Data:  $\mathbf{S}_i = \text{IDSM}(\mathbf{D}_i)$

## > Fine-Tuning & Training

- Dataset: 100 training + 30 test pairs
- Structure: JSON-like format.

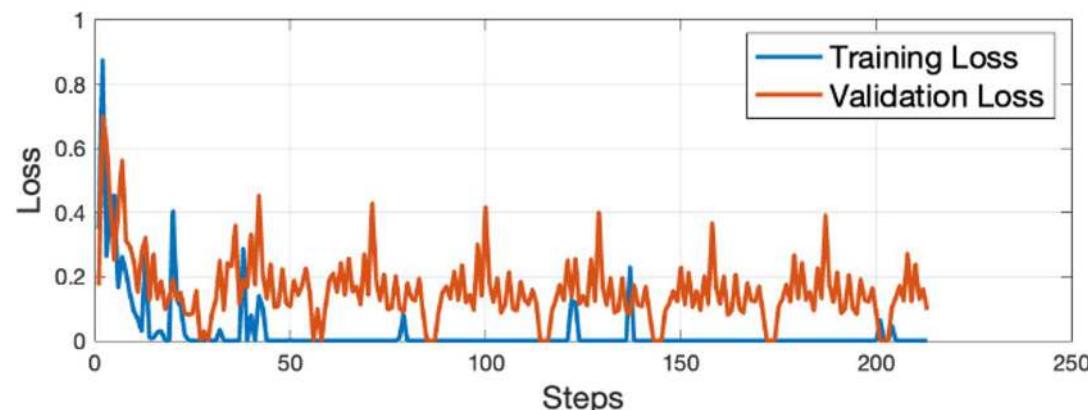




# Intelligent Data Standardization Module (IDSM)

## Data Input Issue Type

Issue Type	Description
Missing Values	Data entries were absent, requiring prediction or marking.
Irregular Data Formats	Sensor data appeared in non-uniform formats needing standardization.
Non-standard Unit Representations	Units of measurement varied, necessitating normalization.
Incomplete Information	Datasets were partially filled, reflecting real-world scenarios.



### > Training Loss

- Decreased from **0.3484** loss to near zero by step **27**.

### > Training Accuracy

- Increased from **93.38%** to **100%** by step **14**.

### > Validation Loss

- Started at **0.1724**, briefly increased to **0.6984** at step **2**, then declined to nearly zero by step **27**.

### > Validation Accuracy

- Increased from **96.14%** to near **100%** by step **27**.



# Intelligent Data Standardization Module (IDSM)

Unstandardized Data

```
{
  "time": {
    "time": "Saturday, 04
May 2024 14:00:00 GMT"
  },
  "acc": {
    "x": 0.456,
    "x": 0.123,
    "z": 0.789,
  },
  "mag": {
    "x": -24.321,
    "y": -12.849,
    "z": -0.233,
  },
  "gyro": {
    "x": -0.654,
    "y": 1.234,
    "z": 2.931,
  }
}
```

## Converted Data

- Timestamp Format
- Sensor Data Labels
- Data Structure
- Correction of Axis Labels
- Etc.

IDSM

Standardized Data

```
[
  {
    "name": "Accelerometer",
    "time": 1714831200000,
    "values": {
      "x": 0.456,
      "y": 0.123,
      "z": 0.789
    }
  },
  {
    "name": "Magnetometer",
    "time": 1714831200000,
    "values": {
      "x": -24.321,
      "y": -12.849,
      "z": -0.233
    }
  },
  {
    "name": "Gyroscope",
    "time": 1714831200000,
    "values": {
      "x": -0.654,
      "y": 1.234,
      "z": 2.931
    }
  }
]
```



# Standardized Dataset Unit Tests

## > Overview

- Validate compliance of sensor data with **predefined JSON schemas**.

## > Validation Function

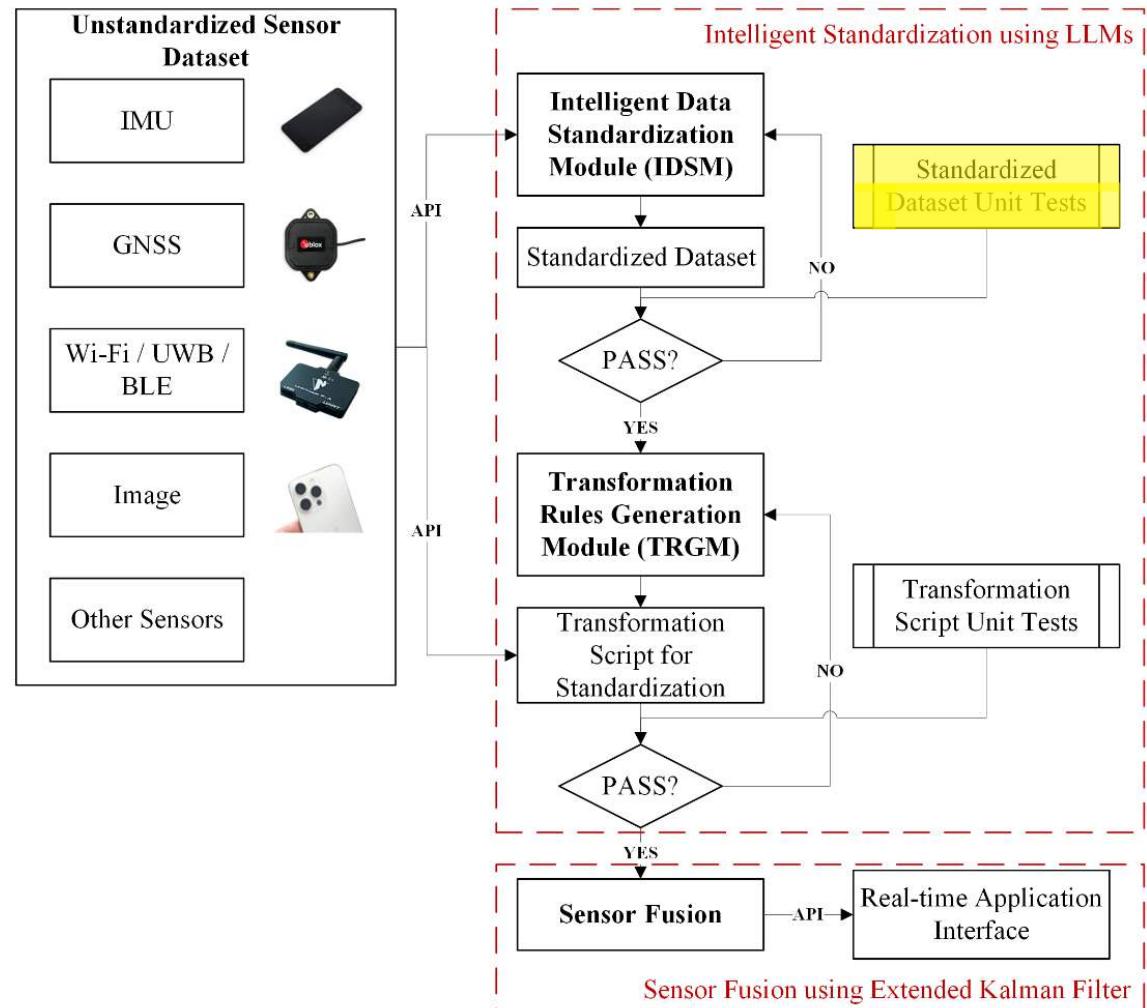
$$\cdot (v, e) = \mathcal{V}_{\text{IDSM}}(\mathcal{S}, \sigma)$$

## > Validation Process

- Library Used:
  - JSON Schema
- Checks Performed:
  - Correct Data Types
  - Required Fields

## > If fail

- Feed the error string back to LLMs to regenerate standardized JSON string



Most datasets (24 out of 30) required only **one iteration** for successful validation

The process typically completes in **5 iterations**; otherwise, it is regarded as a failure.



# Transformation Rules Generation Module (TRGM)

## > Overview

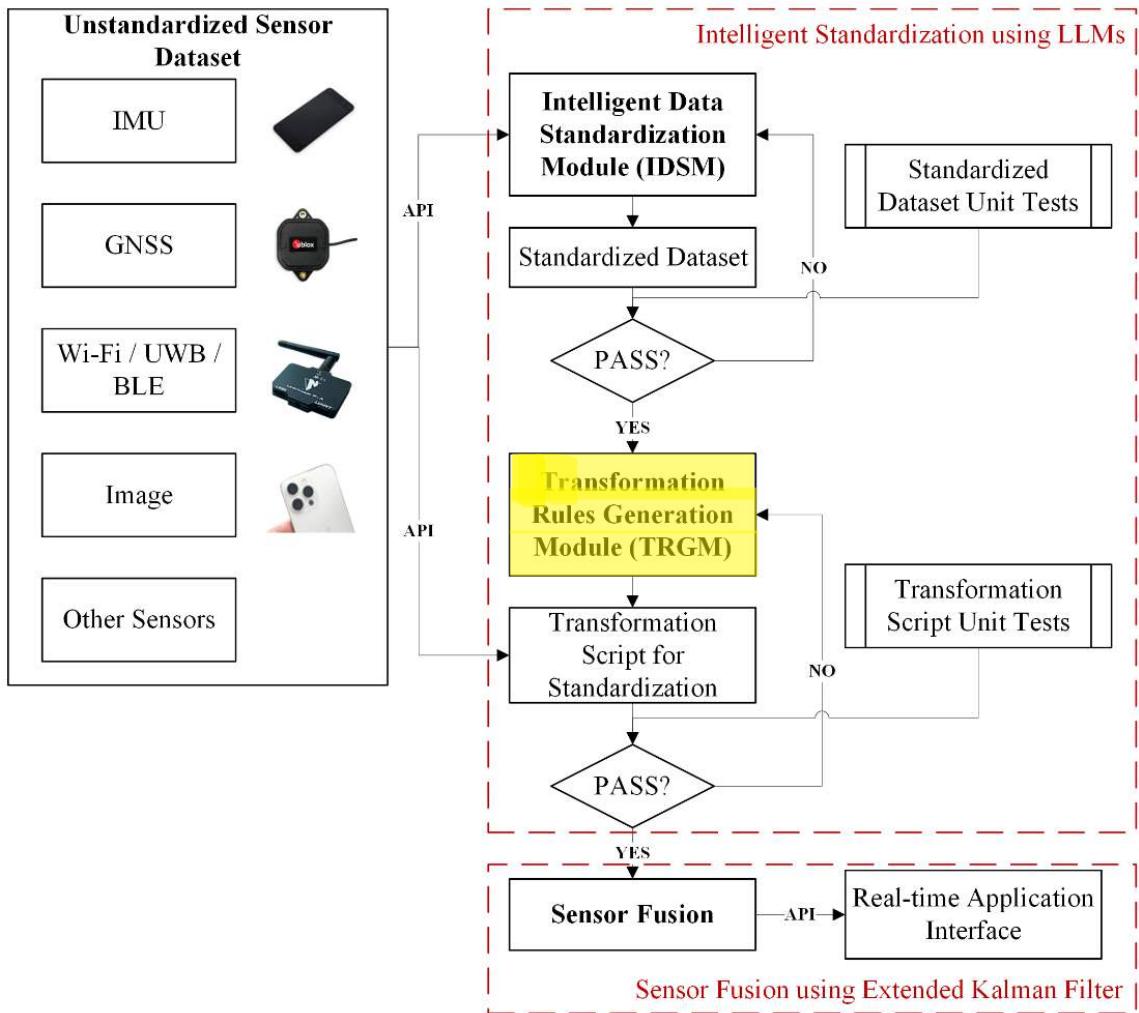
- TRGM leverages **GPT-4-0613** to generate transformation script for standardization

## > Transformation Process

- $(v, e) = \mathcal{V}_{\text{TRGM}}(\mathcal{T}, \mathcal{S})$

## > Transformation Rules

Field Name	Data Type	Description
inputPath	String	JSONPath expression pointing to the source field in the input JSON structure.
outputPath	String	JSONPath expression pointing to the target field in the output JSON structure.
transformation	Function	A function or expression used to transform the input data before mapping it to the output path.
<b>Example</b>		
inputPath	String	<code>\$.sensor_data.Accelerometer.timestamp</code>
outputPath	String	<code>\$[?(@.name == 'Accelerometer')].time</code>
transformation	Function	<code>float(re.search(r'[-]+]?*?+', value).group(0))</code>





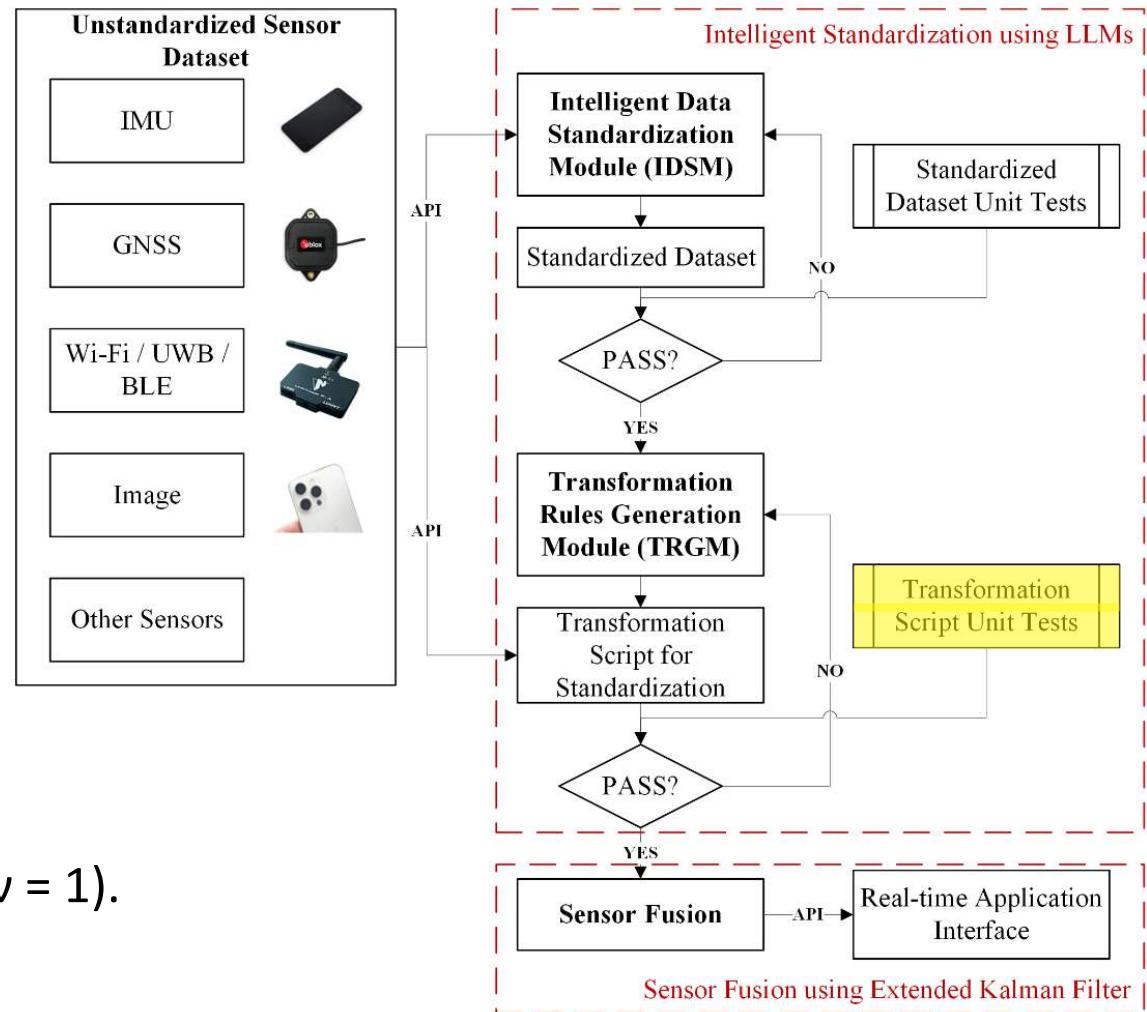
# Transformation Script Unit Tests

## > Overview

- Ensure accuracy and functionality of transformation scripts generated by LLMs.
- Scripts convert input JSON data ( $I$ ) into the standardized format ( $S$ ).

## > Validation Function

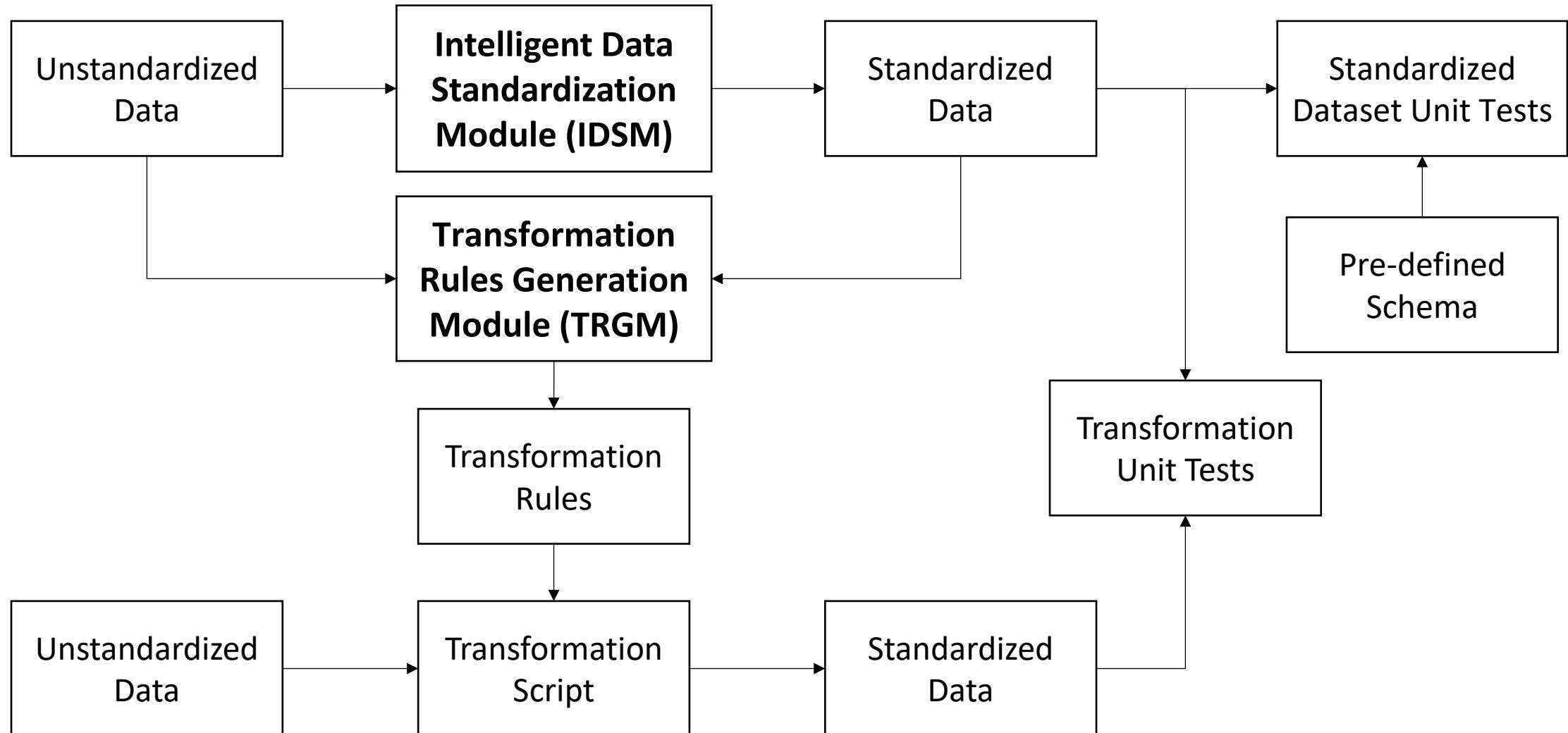
- $(v, e) = \mathcal{V}_{TRGM}(\mathcal{T}(I), S)$
- $\mathcal{T} = F_{TRGM}(S, I, e)$



Process repeats until no errors are detected ( $v = 1$ ).



# Proposed Framework





## Unstandardized Data

```
{
  "sensor_data": {
    "Accelerometer": {
      "timestamp": 1683302400000,
      "readings": {
        "x": 9.81,
        "y": 0.02,
        "z": -0.03
      }
    },
    "Magnetometer": {
      "timestamp": 1683302400000,
      "accuracy_level": 2,
      "coordinates": {
        "x": 0.012,
        "y": -0.030,
        "z": 0.022
      }
    },
    "Gyroscope": {
      "timestamp": 1683302400000,
      "axis": {
        "x": 1.23,
        "y": 0.45,
        "z": -0.67
      }
    }
  }
}
```

**IDSM**

## Standardized Data

```
[
  [
    {
      "name": "Accelerometer",
      "time": 1683302400000,
      "values": {
        "x": 9.81,
        "y": 0.02,
        "z": -0.03
      }
    },
    {
      "name": "Magnetometer",
      "time": 1683302400000,
      "accuracy": 2,
      "values": {
        "x": 0.012,
        "y": -0.030,
        "z": 0.022
      }
    },
    {
      "name": "Gyroscope",
      "time": 1683302400000,
      "values": {
        "x": 1.23,
        "y": 0.45,
        "z": -0.67
      }
    }
  ]
]
```

## Transformation Rules

```
{
  "rules": [
    {
      "inputPath": "$.sensor_data.Accelerometer.timestamp",
      "outputPath": "$[?(@.name == 'Accelerometer')].time"
    },
    {
      "inputPath": "$.sensor_data.Accelerometer.readings.x",
      "outputPath": "$[?(@.name == 'Accelerometer')].values.x"
    },
    {
      "inputPath": "$.sensor_data.Magnetometer.timestamp",
      "outputPath": "$[?(@.name == 'Magnetometer')].time"
    },
    {
      "inputPath": "$.sensor_data.Magnetometer.coordinates.x",
      "outputPath": "$[?(@.name == 'Magnetometer')].values.x"
    },
    {
      "inputPath": "$.sensor_data.Gyroscope.timestamp",
      "outputPath": "$[?(@.name == 'Gyroscope')].time"
    },
    {
      "inputPath": "$.sensor_data.Gyroscope.axis.x",
      "outputPath": "$[?(@.name == 'Gyroscope')].values.x"
    }
  ]
}
```

**TRGM**



# Transformation Rules

## Generic Transformation Script

```
def apply_transformation(input_JSON, transformation_rules):
    """Applies transformation rules to input JSON and produces output JSON."""
    output_JSON = {}

    for rule in transformation_rules["rules"]:
        # Convert inputPath to list of keys for dictionary access
        input_keys = rule['inputPath'].replace('.', '').split('.')
        value = get_from_dict(input_JSON, input_keys)

        # Check if a transformation is needed and apply it
        if "transformation" in rule:
            transformation_code = rule["transformation"]
            value = eval(transformation_code)

        # Convert outputPath to list of keys and set value in output JSON
        output_keys = rule['outputPath'].replace('.', '').split('.')
        set_in_dict(output_JSON, output_keys, value)

    return output_JSON
```

"speed": "1.5 m/s"

**Change in Location**

**Change in Value**

## Transformation Rules

```
{
  "rules": [
    {"inputPath": "$.name", "outputPath": "$.name"},  

    {"inputPath": "$.time", "outputPath": "$.time"},  

    {"inputPath": "$.values.latitude", "outputPath": "$.values.latitude"},  

    {"inputPath": "$.values.longitude", "outputPath": "$.values.longitude"},  

    {"inputPath": "$.values.altitude", "outputPath": "$.values.altitude"},  

    {  

      "inputPath": "$.values.speed",  

      "outputPath": "$.values.speed",  

      "transformation": "float(re.search(r'[-]?\d*\.\d+', value).group(0))"  

    },  

    {"inputPath": "$.values.speedAccuracy", "outputPath": "$.values.speedAccuracy"},  

    {"inputPath": "$.values.bearingAccuracy", "outputPath": "$.values.bearingAccuracy"},  

    {"inputPath": "$.values.horizontalAccuracy", "outputPath": "$.values.horizontalAccuracy"},  

    {"inputPath": "$.values.verticalAccuracy", "outputPath": "$.values.verticalAccuracy"},  

    {"inputPath": "$.values.bearing", "outputPath": "$.values.bearing"}  

  ]
}
```



# Extended Kalman Filter (EKF)

## > Method:

- The standardized data is passed to the Extended Kalman Filter (EKF) for sensor fusion.

## > Outcome:

- The EKF integrates data from multiple sensors (GNSS, UWB, IMU, BLE...) to provide real-time positional and velocity estimates.

## > State Transition Matrix & State Vector

$$\mathbf{F}_k = \begin{bmatrix} \mathbf{I}_{3 \times 3} & \Delta t \mathbf{I}_{3 \times 3} \\ \mathbf{0}_{3 \times 3} & \mathbf{I}_{3 \times 3} \end{bmatrix} \quad \mathbf{x} = \begin{bmatrix} x \\ y \\ z \\ v_x \\ v_y \\ v_z \end{bmatrix}$$

Sensor Type	Measurement Vector	Measurement Covariance Matrix
GNSS Receiver	$\mathbf{z}_{\text{GNSS}} = \begin{bmatrix} \phi_{\text{GNSS}} \\ \lambda_{\text{GNSS}} \\ h_{\text{GNSS}} \end{bmatrix}$	$\mathbf{R}_{\text{GNSS}} = \begin{bmatrix} 655.00 & 0 & 0 \\ 0 & 655.00 & 0 \\ 0 & 0 & 655.00 \end{bmatrix}$
UWB Sensor	$\mathbf{z}_{\text{UWB}} = \begin{bmatrix} x_{\text{UWB}} \\ y_{\text{UWB}} \\ z_{\text{UWB}} \end{bmatrix}$	$\mathbf{R}_{\text{UWB}} = \begin{bmatrix} 1.00 & 0 & 0 \\ 0 & 1.00 & 0 \\ 0 & 0 & 1.00 \end{bmatrix}$
Camera	$\mathbf{z}_{\text{cam}} = img_{\text{cam}}$	$\mathbf{R}_{\text{cam}} = \begin{bmatrix} 0.15 & 0 & 0 \\ 0 & 0.15 & 0 \\ 0 & 0 & 0.15 \end{bmatrix}$

Sensor Type	Control Input Vector	Control Input Matrix	Process Noise Covariance
IMU	$\mathbf{u}_{\text{IMU}} = \begin{bmatrix} a_x \\ a_y \\ a_z \\ \omega_x \\ \omega_y \\ \omega_z \\ m_x \\ m_y \\ m_z \end{bmatrix}$	$\mathbf{B}_{\text{IMU}} = \begin{bmatrix} \frac{\Delta t^2}{2} \mathbf{I}_{3 \times 3} \\ \Delta t \mathbf{I}_{3 \times 3} \end{bmatrix}$	$\mathbf{Q} = \begin{bmatrix} \frac{\sigma_a^2 \Delta t^4}{4} \mathbf{I}_{3 \times 3} & \frac{\sigma_a^2 \Delta t^3}{2} \mathbf{I}_{3 \times 3} \\ \frac{\sigma_a^2 \Delta t^3}{2} \mathbf{I}_{3 \times 3} & \sigma_a^2 \Delta t^2 \mathbf{I}_{3 \times 3} \end{bmatrix}$

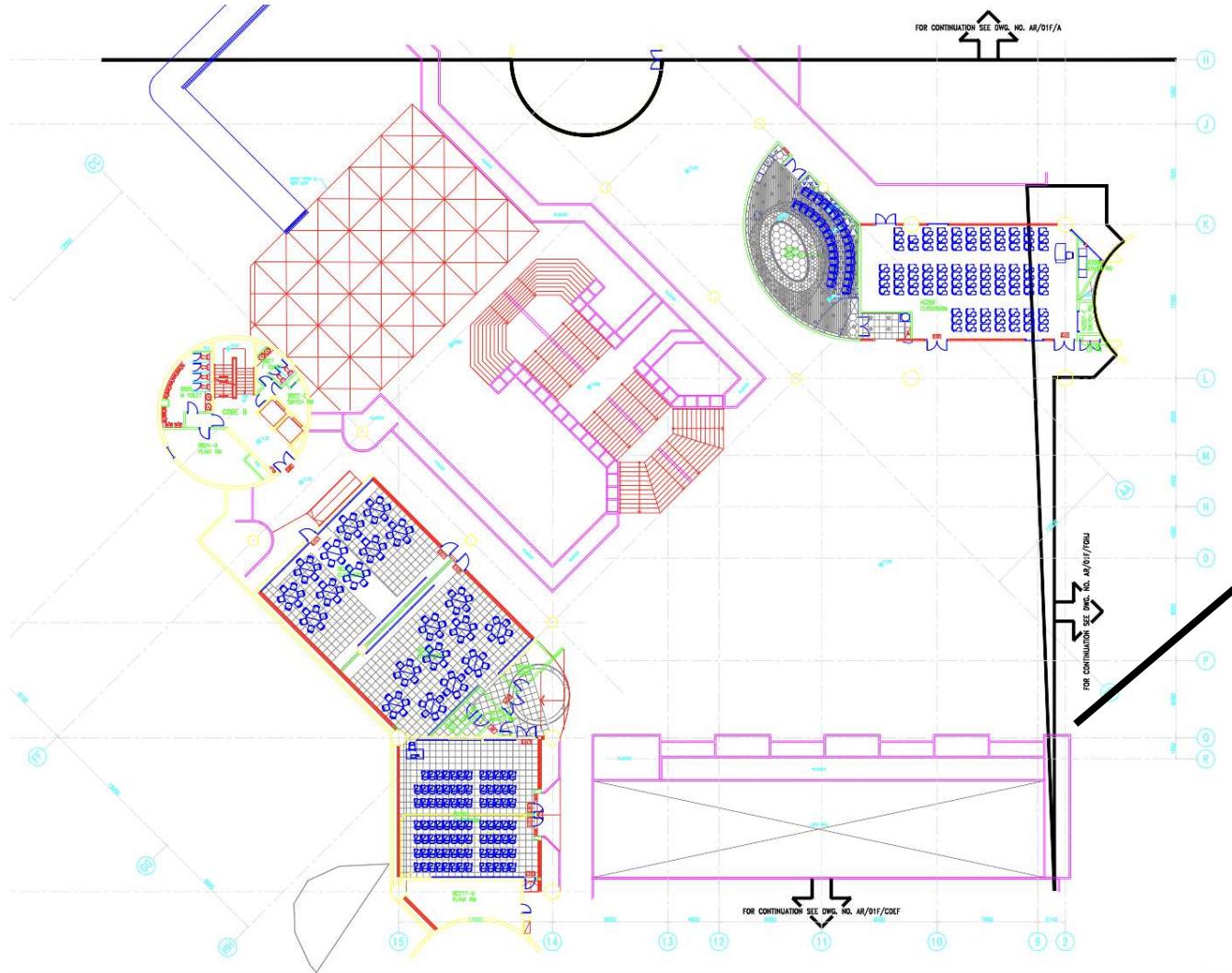


# Experiment

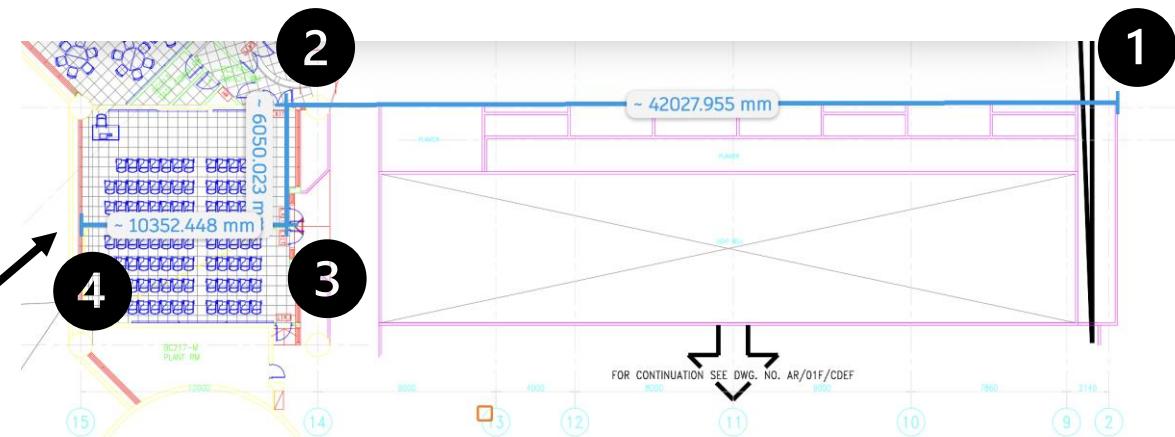
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# Experiment Setup



The experiment took place in a  
seamless 60-meter environment





# Experiment Setup

## > Streaming Sensors:

- GNSS [11]
  - U-blox F9P
  - iPhone 14 Pro
- UWB [12]
  - Nooploop LinkTrack P-A Series
- VPS [13 – 14]
  - Samsung Galaxy Note 20 Ultra
- IMU [15]
  - iPhone 14 Pro

## > Location

- Tang Ping Yuen Square + BC203



[11] "ZED-F9P module," U-blox. <https://www.u-blox.com/en/product/zed-f9p-module> (accessed May 21, 2024).

[12] "UWB High-Precision Positioning: LinkTrack P-A Series," Nooploop. <https://www.nooploop.com/en/linktrack/> (accessed May 21, 2024).

[13] P.-E. Sarlin, C. Cadena, R. Siegwart and M. Dymczyk, "FromCoarse to Fine: Robust Hierarchical Localization at Large Scale," 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA, 2019, pp. 12708-12717, doi:10.1109/CVPR.2019.01300.

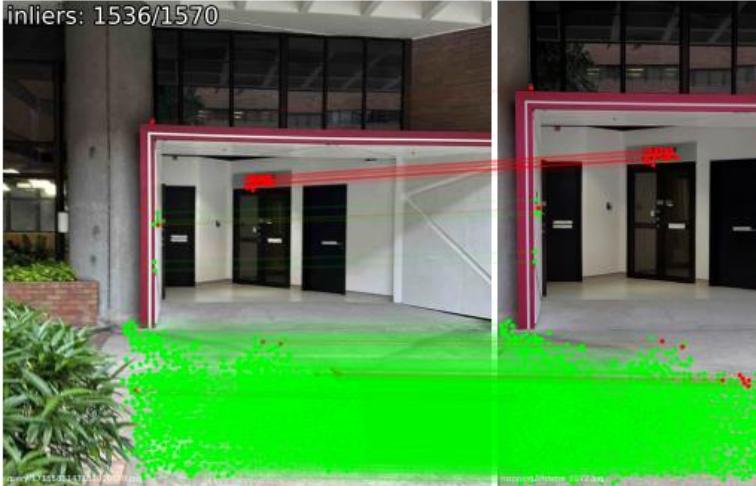
[14] P.-E. Sarlin, D. DeTone, T. Malisiewicz and A. Rabinovich, "SuperGlue: Learning Feature Matching With Graph Neural Networks," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, USA, 2020, pp. 4937-4946, doi:10.1109/CVPR42600.2020.00499.

[15] K. T. H. Choi, "tszheichoi / awesome-sensor-logger," GitHub. <https://github.com/tszheichoi/awesome-sensor-logger/>.



# Experiment Setup

## Visual Positioning System\*



5x Real-Time Speed

\*Compromised performance in indoor environments.

### Ultra-wideband





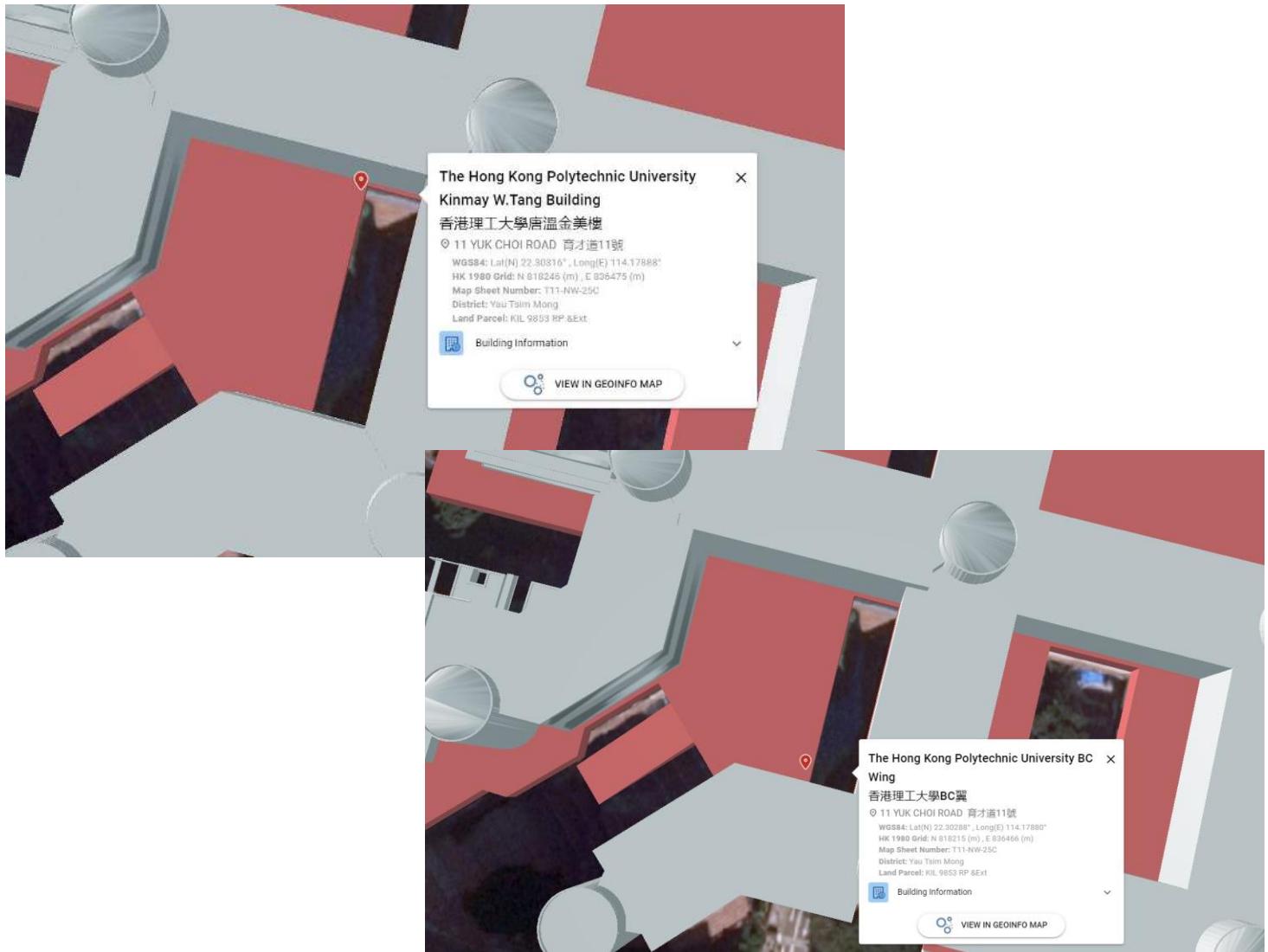
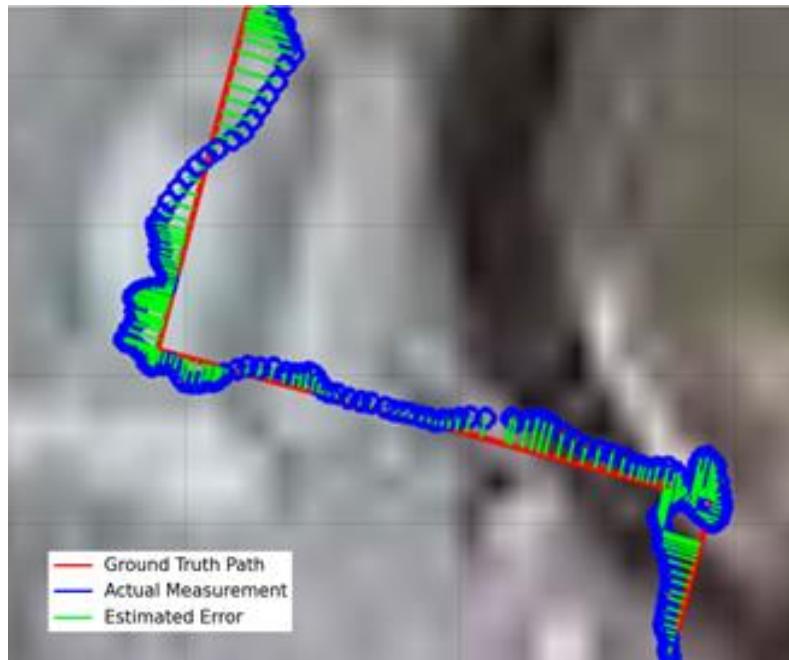
# Experiment Setup

## > Ground Truth

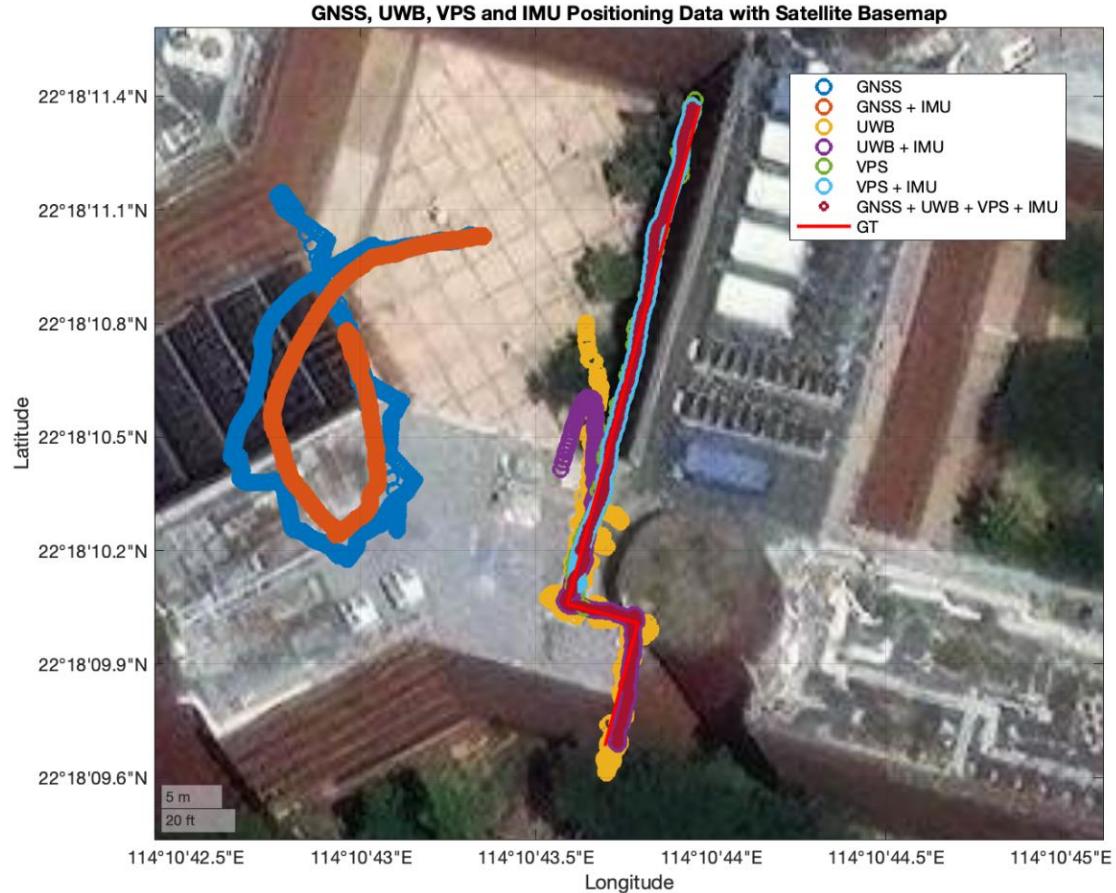
- HKSAR Gov's GeoInfo Map
- Detailed Floor Plan

## > Absolute Trajectory Error (ATE)

$$E = \sqrt{(x_m - x_t)^2 + (y_m - y_t)^2}$$

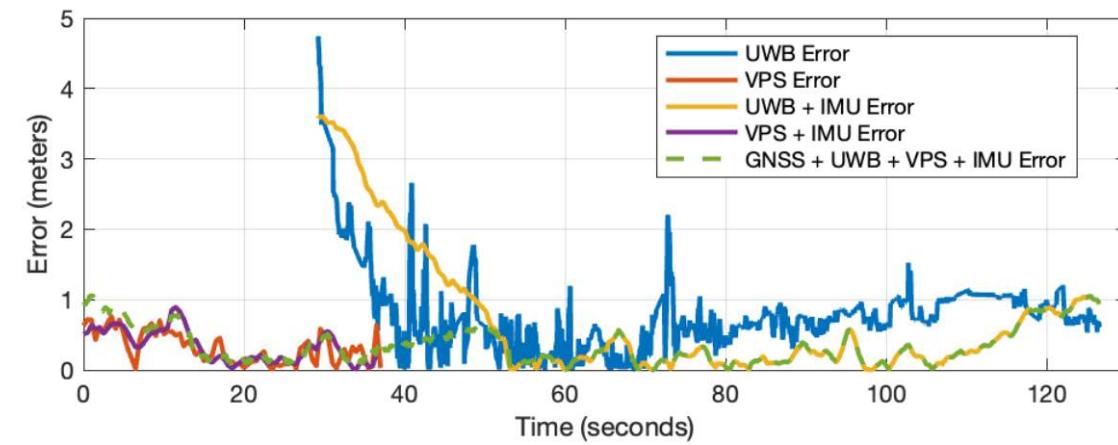


# Experiment Results



Sensor data from multiple devices can be seamlessly fused under our proposed framework to achieve optimized positioning results.

Method	Mean Error (m)	Std. Dev. (m)	RMSE (m)	Median Error (m)	Max Error (m)
GNSS	25.02	5.47	25.61	25.21	33.75
GNSS + IMU	23.24	4.22	23.62	23.38	29.40
UWB	0.79	0.62	1.00	0.71	4.75
UWB + IMU	0.69	0.89	1.13	0.31	3.92
VPS	0.32	0.23	0.39	0.30	0.76
VPS + IMU	0.33	0.23	0.41	0.31	0.91
<b>GNSS + VPS + UWB + IMU</b>	<b>0.33</b>	<b>0.24</b>	<b>0.41</b>	<b>0.27</b>	<b>0.95</b>





# Conclusion

## > Automated Data Standardization

- Demonstrated the feasibility of real-time standardization with large language models.

## > IDSM Performance

- Achieved near-zero loss and nearly full accuracy in training/validation.
- Standardized data across diverse sensor inputs.

## > TRGM Efficiency

- Significantly reduced manual effort in script generation.
- Enhanced productivity, minimized human intervention.

## > Limitations

- Reliant on predefined schemas and manual covariance matrices.
- Controlled settings may not fully reflect real-world complexities.



# Future Vision

## > Broad Future & Spectrum of Application

- **Expanding Potential:** LLMs demonstrate vast potential across diverse fields.
- **Sensor Integration:** LLMs can be integrated with various sensor technologies, opening new possibilities for real-time applications in seamless positioning.
- **Contextual Capabilities:** LLMs enhance the understanding of their environment, unlocking new possibilities for interaction and application.

## > Rising Performance of Large Language Models.

- **Latency Optimization:** Efforts are ongoing to reduce response times, enhancing the efficiency of LLMs in real-world applications.
- **Improved Accuracy:** LLMs are becoming more precise, providing increasingly reliable outputs in various use cases.



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**Thank you for your attention!**  
Questions, Comments and Collaboration are welcome.

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# Appendix - Intelligent Data Standardization Module

## > Data Standardization Process

- The IDSM's primary objective is to transform heterogeneous sensor data D into a standardized format S. The raw data collected from various sensors is represented as
  - Input Data:  $\mathbf{D}_i = \{d_{i1}, d_{i2}, \dots, d_{in}\}$ .
- where  $d_i$  denotes the data from the i-th sensor. The standardization process is expressed as:
  - Standardized Data:  $\mathbf{S}_i = \text{IDSM}(\mathbf{D}_i)$

## > Unit Tests Validation Function

- The unit tests validate the standardized dataset S against predefined JSON schemas for various sensor types. The validation function is expressed as:
  - $(v, e) = \mathcal{V}_{\text{IDSM}}(S, \sigma)$
- where  $v$  indicates whether  $S$  conforms to schema  $\sigma$ , and  $e$  contains details of validation errors. The iterative process ensures  $S$  conforms to the schema through multiple cycles if necessary, up to a maximum of five iterations, based on empirical evidence and practical considerations.



# Appendix - Transformation Rules Generation Module

## > Transformation Process

- It converts input JSON files into a specified output format, reducing manual intervention. The process is represented as:
  - $(v, e) = \mathcal{V}_{TRGM}(\mathcal{T}, \mathcal{S})$
- where S is the standardized data, and I is the input JSON structure. The transformation rules are then used to create a "Transformation Script for Standardization" T , ensuring consistency in data transformation tasks.

## > Unit Tests Validation Function

- The unit tests validate the accuracy and functionality of the transformation scripts generated by the LLM. These scripts are essential for converting the input JSON data (I) into the desired standardized format (S). The validation function, which assesses whether the transformation scripts perform as expected, is formally expressed as:
  - $(v, e) = \mathcal{V}_{TRGM}(\mathcal{T}(I), \mathcal{S})$
- Here,  $\mathcal{T}(I)$  represents the output generated by applying the transformation script  $\mathcal{T}$  to the input JSON structure I, v indicates the success of the transformation in matching the standardized data schema S, and e details any errors encountered during the process. If discrepancies or errors ( $e \neq 0$ ) are identified, these errors are fed back into the transformation function:
  - $\mathcal{T} = \mathcal{F}_{TRGM}(S, I, e)$