Modular Survey Framework for Human– Machine Interaction Research

Clark Borst

Delft University of Technology
Faculty of Aerospace Engineering
Department: Control & Operations
Section: Control and Simulation
2629 HS, Delft, The Netherlands
https://cs.lr.tudelft.nl

This repository provides validated **human factors and cognitive engineering surveys** for evaluating **human—machine interaction**, such as: decision-support systems, human-automation interaction, human-autonomy teaming, human-Al teaming, etc. Each survey is implemented as a **standalone HTML survey** that runs in your browser and can be embedded in Python or JavaScript applications using <iframe> elements.

Besides a set of validated surveys from literature, a customizable general-purpose survey is also available, enabling researchers to easily create custom HTML surveys.

All surveys send structured JSON results to the host via window, postMessage() for seamless data collection.

Alternatively, the survey can also be used standalone and automatically download a JSON file (see instructions in the section *Integration with Applications*).

Key benefits over cloud-based platforms

While cloud-based survey platforms are convenient for rapid data collection, they often rely on **remote data storage** and **closed architectures**. This HTML/JavaScript-based modular survey framework provides comparable flexibility and user experience, but with **full researcher control** over data, design, and integration.

1. Local Data Ownership & Privacy

- No external servers required all survey data are stored and processed locally in the participant's browser.
- Researchers can choose to download results as JSON or transmit them to their own secure local or institutional server.
- No third-party tracking, cookies, or cloud dependencies, ensuring compliance with GDPR and institutional ethics
 policies.

2. Modular, Transparent, and Extensible Design

- Surveys are defined in plain JavaScript configuration objects no hidden code, proprietary APIs, or vendor lock-in.
- Open a survey HTML file in your favourite editor (e.g., VSCode) and add your survey questions.

- Researchers can easily add new question types (e.g., Likert, sliders, dropdowns, open text, or matrix tables).
- Each survey (e.g., NASA-TLX, Trust, Understanding, SART, etc.) is a self-contained HTML module that can be
 embedded using an <iframe> or imported into larger experimental interfaces.

3. Full Offline Capability

- Surveys can run entirely offline, directly from a local file or USB drive.
- Perfect for lab studies, field experiments, or sensitive domains (e.g., aviation, defense, healthcare) where internet connectivity or external data transfer is restricted.

(i) 4. Researcher-Controlled Data Flow

- Output is structured in standardized JSON format for seamless import into Python, R, or MATLAB.
- Optional participant and condition IDs can be included in both the data file and filename for easy tracking across sessions.
- Results can be automatically downloaded, posted to a local server, or sent to a parent experiment controller via window.postMessage().

\$5. Integration with Experimental Software

- Embeddable via <iframe> in Python (Flask, PsychoPy, jsPsych) or JavaScript-based platforms.
- · Easy synchronization with human-in-the-loop experiments and simulators.
- The modular approach allows researchers to switch between instruments (e.g., from NASA-TLX to Trust) without re-coding the data pipeline.

6. Tailored to Human-Machine Interaction Research

- Designed for **Human–Machine Interaction research**.
- Supports calibration metrics, metacognitive confidence, and subjective ratings for trust, workload, understanding, and human—Al/autonomy teamwork.

License and Citation

This open-source survey framework and accompanying HTML templates are provided for **academic research and commercial use** under the **GPL-3** license.

You are free to download and/or fork the project and:

- Use the survey templates in research studies or teaching
- Modify or extend the code (e.g., add new question types, languages, or sections)
- Share adapted versions under the same license

You must:

- · Attribute the original authors of the surveys
- Cite this repository (see citation below)
- Distribute adaptations under the same license

Citation

If you use or adapt this survey framework in your research, please cite it as follows:

APA format

Borst, C. (2025). *Modular Open-Source Survey Framework for Human–Machine Interaction Research*. Al4REALNET Project. Available at: https://github.com/ai4realnet/survey-framework

BibTeX

Included Surveys

🗱 1a. Workload: NASA-TLX — Task Load Index

Purpose: Measures subjective workload across six dimensions:

Mental, Physical, Temporal Demand, Performance, Effort, and Frustration.

Method: Participants rate each dimension on a 0–100 scale and perform 15 pairwise comparisons to weight their importance.

Scientific Basis:

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Advances in Psychology, 52, 139–183.

Output: Weighted workload score (0–100) and per-dimension values.

Credits:

- Original version by Keith Vertanen https://www.keithv.com/software/nasatlx/
- Translated into modern Javascript for improved browser integration.

IMPORTANT: This survey should not be modified to maintain scientific validity.

NOTE: Both the original 2-part NASA-TLX and a simplified 1-part TLX (only scales) are available.

Tip: Radar box plots are a nice way to portray the TLX scales



C. Hamamura, "radarBoxplot: Implementation of the Radar-Boxplot." CRAN, Oct. 2021. doi: https://zenodo.org/doi/10.5281/zenodo.11373029

1b. Workload: Rating Scale Mental Effort (RSME)

Purpose:

The Rating Scale Mental Effort (RSME) measures the subjective mental effort a person perceives during task performance.

It is a one-dimensional rating scale with language-specific anchor/calibration points. RSME is a fast and easy-to-use alternative (for participants) compared to the two-dimensional NASA-TLX.

Scientific Basis:

- Zijlstra, F. R. H. & Van Doorn, L. (1985). The construction of a scale to measure perceived effort. Delft University of Technology, Department of Philosophy and Social Sciences.
- Zijlstra, F. R. H. (1993). Efficiency in work behaviour: A design approach for modern tools. Delft University Press.

Output Example:

· RSME score and text description

IMPORTANT: This survey should not be modified to maintain scientific validity.

NOTE: Both English and Dutch versions are available.

1c. Workload: Modified Cooper-Harper (MCH)

Purpose:

The Modified Cooper-Harper (MCH) measures the subjective mental effort a person perceives during task

It is a one-dimensional rating scale that follows a decision tree. MCH is a fast and easy-to-use alternative to the RSME and NASA-TLX.

Scientific Basis:

- Cooper, G. E., & Harper, R. P. (1969). The use of pilot rating in the evaluation of aircraft handling qualities (NASA TN D-5153). National Aeronautics and Space Administration (NASA)
- Wierwille, W. W., & Casali, J. G. (1983). A validated rating scale for global mental workload measurement applications. Proceedings of the Human Factors Society Twenty-Seventh Annual Meeting, 1983, 129-133.

Output:

MCH score

IMPORTANT: This survey should not be modified to maintain scientific validity.

NOTE: Other variants of MCH exist, for example, one for rating the *acceptance* of a display support tool. Those follow the exact same decision tree logic, but with different text descriptions.

Handling Qualities (original Cooper-Harper rating scale)

The original Cooper-Harper rating scale for pilot assessment of aircraft handling qualities is also included.

Scientific Basis:

 Cooper, G. E., & Harper, R. P. (1969). The use of pilot rating in the evaluation of aircraft handling qualities (NASA TN D-5153). National Aeronautics and Space Administration (NASA)

Output:

· CH score for handling qualities

IMPORTANT: This survey should not be modified to maintain scientific validity.

(SART) 2a. Situation Awareness Rating Technique (SART)

Purpose:

Measures **subjective situation awareness (SA)** — how effectively an operator perceives, comprehends, and anticipates the situation.

Based on **Taylor (1989, 1990)** and **Endsley (1995)**, SART captures workload balance and mental resource management through three meta-factors:

Category	Example Dimensions	Interpretation
Demand on Attentional Resources	Instability, Complexity, Variability	How dynamic or demanding the environment was
Supply of Attentional Resources	Arousal, Concentration, Spare Capacity, Division of Attention	How much attention and cognitive resource were available
Understanding of the Situation	Information Quantity, Information Quality, Familiarity	How well the situation was comprehended

Computation:

SART = (Understanding + Supply) - Demand

Higher scores indicate greater situation awareness (i.e., high understanding and attention, low demand).

Scientific Basis:

- Taylor, R. M. (1989). Situational Awareness Rating Technique (SART): The development of a tool for aircrew systems design. AGARD AMP Symposium on Situational Awareness in Aerospace Operations.
- Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. Human Factors, 37(1), 32-64.

Output:

- Mean scores for Demand, Supply, and Understanding (1-7 scale)
- Composite SART Index = (Understanding + Supply) Demand

IMPORTANT: This survey should not be modified to maintain scientific validity.

2b. Situation Awareness (general)

Purpose:

Measures **subjective situation awareness (SA)** — how effectively an operator perceives, comprehends, and anticipates the situation.

Based on Taylor (1989, 1990) and Endsley (1995).

Category	Example Dimensions	
Perception	Perceiving the status, attributes, and dynamics of the relevant elements in a given environment	
Comprehension	Understanding the significance of the information in light of one's goals	
Projection	Anticipating future events and their likely consequences	

Scientific Basis:

• Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. Human Factors, 37(1), 32-64.

Output:

• Mean scores for Perception, Comprehension, and Projection (1–7 scale)

3. Trust (in Automation)

Purpose: Measures user trust toward automated systems, covering reliability, predictability, and faith.

Scientific Basis:

 Jian, J.-Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems., Int. J. Cognitive Ergonomics, 4 (1), 53–71.

Output: Mean trust rating (1–7) across subscales.

IMPORTANT: This survey should not be modified to maintain scientific validity.

4. Technology Acceptance (TAM / TAM2)

Purpose: Measures user acceptance and perceived usefulness/ease of use of automated systems.

Scientific Basis:

- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology.,
 MIS Quarterly, 13 (3), 319–340.
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: TAM2.,
 Management Science, 46 (2), 186–204.

Output: Composite acceptance (experimental!) score and subscale means (Usefulness, Ease of Use, Intention to Use).

🗱 5a. Understanding / Transparency

Purpose: Evaluates how well users understand a system's reasoning and internal logic.

This instrument combines two complementary subscales:

- Perceived Understanding the *subjective feeling* of comprehension.
- Factual / Conceptual Understanding objective correctness of the user's mental model, tested via factual or multiple-choice questions.

Why combine both?

According literature, understanding and explanations (in AI) serve both **epistemic** (truth-based) and **psychological** (comprehension-based) functions.

A system that is factually transparent but not perceived as understandable fails to foster calibrated trust, while perceived understanding without factual basis can lead to overconfidence.

By measuring both, one can assess how closely users' mental models align with the (AI) system's true behavior.

Scientific Basis:

- Miller, T. (2019). Explanation in Artificial Intelligence: Insights from the social sciences., Artificial Intelligence, 267, 1–38.
- Kulesza, T. et al. (2013). *Too much, too little, or just right? Ways explanations impact end users' mental models of intelligent systems.*, Conference: IEEE Symposium on Visual Languages and Human-Centric Computing.
- S. Mohseni, N. Zarei, E. D. Ragan (2021). *A multidisciplinary survey and framework for design and evaluation of explainable ai systems*. ACM Transactions on Interactive Intelligent Systems (TiiS) 11 (3-4) (2021) 1–45.
- B. McGuinness (2004). *Quantitative analysis of situational awareness (quasa): Applying signal detection theory to true/false probes and self-ratings*,1250 (48) in: Command and Control Research and Technology Symposium, pp. 15–17.

- Lopes, P., Silva, E., Braga, C., Oliveira, T., & Rosado, L. (2022). XAI Systems Evaluation: A Review of Human and Computer-Centred Methods. Applied Sciences, 12(19), 9423. https://doi.org/10.3390/app12199423
- Elizabeth R. Tenney, Barbara A. Spellman, Robert J. MacCoun (2008). *The benefits of knowing what you know (and what you don't): How calibration affects credibility*. Journal of Experimental Social Psychology, 44 (5), 1368-1375.

Output:

- Perceived Understanding Mean (1–7)
- Factual Accuracy (% correct)
- Experimental!! Composite Understanding Index (average of scaled perceived + factual)

Customizing the Understanding Scale

Researchers can easily modify or extend the question set in understanding.html .

Locate the configuration block:

```
const questions = [
   // Subjective (Likert)
   { type: "likert", text: "I understood what the system was doing.", scale: "Perceived Understanding" },
   { type: "likert", text: "The system's predictions were confusing or unpredictable.", scale: "Perceived Unders
   // Factual (True/False)
   { type: "factual", text: "The system used a distance threshold of 5 nautical miles to predict conflicts.", sc
   // Conceptual (Multiple Choice)
   { type: "conceptual",
        text: "What factor does the system prioritize when ranking conflicts?",
        options: ["Distance between aircraft", "Time-to-conflict", "Altitude difference", "Random selection"],
        correctIndex: 1 }
];
```

You can:

- · Add or remove items by editing the array.
- · Change type to "likert", "factual", or "conceptual".
- Provide correct or correctIndex for factual/conceptual items.
- Adjust question text to match your system (e.g., thresholds, decision rules).
- Optionally weight the components differently in the final composite score.

This enables each research group to tailor the survey to their specific support system while keeping a consistent structure and JSON output format.

\$5 5b. Understanding + Metacognitive Confidence

Purpose:

This survey assesses factual and conceptual understanding of how an automated system works, together with

metacognitive self-confidence for each response. It measures not only *what users know* but also *how accurately they know that they know it* — capturing **calibrated understanding**.

What It Measures:

Category	Description	Example Item	Response Type
Factual Understanding	Objective comprehension of system parameters, thresholds, or rules	"The system uses a 5 nm distance threshold to predict conflicts."	True/False (radio buttons)
Conceptual Understanding	Understanding of principles and reasoning behind system behavior	"The system's conflict- detection logic depends primarily on"	Multiple-choice (dropdown)
Metacognitive Confidence	Self-rated confidence for each response (0–10)	"How confident are you in your answer?"	Slider (0-10)

This survey quantifies **how well confidence aligns with correctness** — a key concept in metacognition research. An *ideal calibration* pattern is:

- High confidence for correct answers
- Low confidence for incorrect answers

The survey computes an experimental **Calibration Index** that penalizes overconfidence in wrong answers and underconfidence in correct ones.

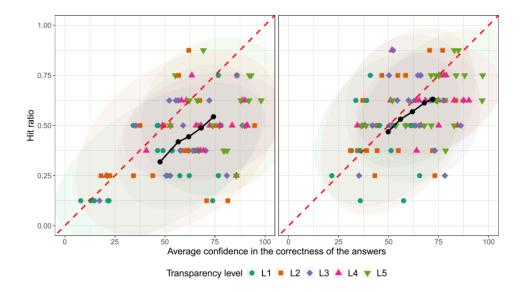
Lower calibration scores indicate better self-awareness and understanding accuracy.

Calibration index

The calibration index is computed as the mean difference between scaled correctness (0–10) and confidence ratings (0–10). Values near zero indicate good calibration, while negative (< 0) and positive (> 0) values reflect overconfidence and underconfidence, respectively.

Tip: Patterns in calibrated understanding can be portrayed in a scatter plot, with correct percentages on the y-axis and confidence percentages on the x-axis. Data points on or close to the diagonal indicate good calibration. This has been applied in:

Zou, Y., & Borst, C. (2025). Algorithmic transparency in path planning: A visual approach to enhancing human understanding. International Journal of Human-Computer Studies, 203(103573), 1–27.
 https://doi.org/10.1016/j.ijhcs.2025.103573



Scientific Foundations:

This instrument integrates research from cognitive psychology, Al explainability, and trust calibration:

- Miller, T. (2019). *Explanation in Artificial Intelligence: Insights from the social sciences.*, Artificial Intelligence, 267, 1–38.
- Kulesza, T. et al. (2013). *Too much, too little, or just right? Ways explanations impact end users' mental models of intelligent systems.*, Conference: IEEE Symposium on Visual Languages and Human-Centric Computing.
- S. Mohseni, N. Zarei, E. D. Ragan (2021). A multidisciplinary survey and framework for design and evaluation of explainable ai systems. ACM Transactions on Interactive Intelligent Systems (TiiS) 11 (3-4) (2021) 1–45.
- B. McGuinness (2004). *Quantitative analysis of situational awareness (quasa): Applying signal detection theory to true/false probes and self-ratings*,1250 (48) in: Command and Control Research and Technology Symposium, pp. 15–17.
- Lopes, P., Silva, E., Braga, C., Oliveira, T., & Rosado, L. (2022). XAI Systems Evaluation: A Review of Human and Computer-Centred Methods. Applied Sciences, 12(19), 9423. https://doi.org/10.3390/app12199423
- Elizabeth R. Tenney, Barbara A. Spellman, Robert J. MacCoun (2008). *The benefits of knowing what you know (and what you don't): How calibration affects credibility*. Journal of Experimental Social Psychology, 44 (5), 1368-1375.

Together, these works highlight that **true understanding** requires both accurate mental models and **appropriate confidence calibration**, enabling trustworthy human–machine interaction.

Output Metrics:

Metric	Meaning	Example
Factual Accuracy	% of correct factual items	80%
Conceptual Accuracy	% of correct conceptual items	75%
Mean Confidence	Average self-rated confidence (0–10)	7.2

Metric	Meaning	Example
Calibration Index	(Experimental!!) Difference between confidence and correctness (closer to zero = better)	1.4

Example:

Item	Correct (s)	Confidence (c) (0-10)	Contribution (10·s - c)
1	1	9	+1
2	0	6	-6
3	1	7	+3

Calibration Index: CI = (1 + (-6) + 3) / 3 = -0.67

Interpretation: slightly negative, indicating mild overconfidence



6. Human–Autonomy Teaming (HAT)

Purpose:

Assesses the perceived quality and effectiveness of human-Autonomy Teamwork during a collaborative task. The survey may measure how well humans and autonomous (AI) systems align, coordinate, trust, complement, and share awareness.

Solution Conceptual Dimensions

Category	Description	Example Item
Shared Goals & Alignment	Measures goal congruence and alignment of objectives between human and automation.	"The automation and I were working toward the same objectives."
Communication & Coordination	Evaluates clarity of communication, anticipatory coordination, and information exchange.	"The automation communicated its intentions clearly."
Mutual Trust & Dependability	Reflects confidence in reliability, dependability, and predictability of Al actions.	"I could rely on the automation to perform its assigned functions."
Complementarity & Role Clarity	Assesses clarity of roles and the automation's ability to complement human strengths.	"The automation complemented my skills and compensated for my weaknesses."
Shared Situation Awareness	Gauges the extent to which the human and automation maintain a common understanding of the situation.	"The automation helped me maintain awareness of the situation."

Computation:

Each item is rated on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree).

A per-dimension mean is computed, and an experimental(!!) overall Team Effectiveness Index is derived as:

Team Effectiveness Index = Mean of all dimension means (experimental!! not validated!)

Scientific Foundations

The HAT structure is based on research on team cognition, trust in automation, and human-automation collaboration:

- Cooke, N. J., Gorman, J. C., Myers, C. W., & Duran, J. L. (2013). Interactive team cognition. Cognitive Science, 37(2), 255–285.
- O'Neill, T. A., McNeese, N. J., Barron, A., & Schelble, B. G. (2020). *Human–autonomy teaming: A review and analysis of the empirical literature*. Human Factors, 62(7), 1020–1045.
- Lyons, J. B., Sycara, K., Lewis, M., & Capiola, A. (2021). Human–Autonomy Teaming: Definitions, Debates, and Directions. Frontiers in Psychology, 12(May), 1–15. https://doi.org/10.3389/fpsyg.2021.589585
- Endsley, M. R. (2017). From Here to Autonomy: Lessons Learned from Human-Automation Research. Human Factors, 59(1), 5–27. https://doi.org/10.1177/0018720816681350

Output

- Mean score per dimension (1–7 scale)
- Overall Team Effectiveness Index (experimental!!)
- · Optional raw response data for analysis

■ 7. UAV Displays (MCH-UVD)

Purpose:

A quasi-subjective **display evaluation tool** called the Modified Cooper-Harper for Unmanned Vehicle Displays (MCH-UVD). This tool, adapted from the Cooper-Harper aircraft handling scale, allows operators to assess a display, translating their judgments on potential display shortcomings into a number corresponding to a particular deficiency in operator support.

Scientific Foundations

 B. Donmez, M. L. Cummings, H. D. Graham, A. S. Brzezinski (2010). Modified cooper harper scales for assessing unmanned vehicle displays, in: Proceedings of the 10th Performance Metrics for Intelligent Systems Workshop, 2010, pp. 235–242.

Output:

MCH-UVD rating (10 is worst, 1 is best)

IMPORTANT: This survey should not be modified to maintain scientific validity.

■ General Purpose Configurable Survey

Purpose:

This HTML-based survey framework provides researchers with a **ready-to-use**, **customizable template** for creating questionnaires with multiple sections, flexible question types, and automatic results reporting. It is ideal for studies on **human–Al interaction**, **usability**, **human factors**, or any domain requiring structured subjective data collection.

Key Features

Feature	Description
Configurable Sections	Define any number of survey sections (e.g., "Trust in AI", "Workload", "Understanding").
Flexible Question Types	Supports Likert (tables) (5- or 7-point), True/False, Drop-down, Slider, Ranking, Multiple Selection, and Text Input questions.
5 or 7-Point Likert Scales	Select per item using scaleType: 5 or scaleType: 7 in the configuration.
Copen Text Fields	Participants can type qualitative responses; these are included in results output.
Results per Section	Displays responses grouped by section on a clean, separate results page.
JSON Data Export	Results automatically structured for easy integration or data analysis.
iframe-Ready Integration	Returns results via window.postMessage() for embedding in Python or JS-based experiments.

Configuration Overview

The survey is defined entirely by a single JavaScript object called surveyConfig at the top of the file.

Example:

```
items: [
      {
        id: "trust_table",
        type: "likert-table",
        scaleType: 7,
        statements: [
          { text: "The system is dependable.", reverse: false },
          { text: "The system behaves in a consistent manner.", reverse: false },
          { text: "I can trust the system.", reverse: false },
          { text: "The system is deceptive.", reverse: true },
          { text: "The system behaves unexpectedly.", reverse: true },
          { text: "I am suspicious of the system's output.", reverse: true }
    ]
  },
    section: "Misc Question Types",
    description: "This section demonstrates ranking and multiple selection.",
    items: [
        id: "rank1",
        type: "rank",
        text: "Rank the following automation features in order of usefulness:",
        options: ["Conflict detection", "Trajectory prediction", "Alert management", "Workload balancing"]
      },
      {
        id: "multi1",
        type: "multi",
        text: "Which of the following features did you actively use? (Select all that apply)",
        options: ["Conflict resolution", "Traffic filtering", "AI recommendations", "Map zooming"]
    ]
  }
1;
```

Integration with Applications

Each survey is self-contained and communicates via:

```
window.top.postMessage(resultObj, "*");
```

Javascript, HTML and Python applications can catch these events and message contents, allowing for saving and/or further processing.

Alternatively, you can also use the surveys completely standalone and automatically download to a local JSON file. Open the HTML survey in an editor (e.g., VSCode) and locate this section:

```
<script>
```

Setting these booleans to true enables you to use the HTML surveys completely as standalone instruments that run in your browser and don't require any Javascript or Python applications. Just open the surveys in your browser and start collecting data!

Catching message event

Using Python (Flask Example)

```
from flask import Flask, render_template, request, jsonify
app = Flask(__name__)

@app.route('/')
def index(): return render_template('main.html')

@app.route('/understanding')
def understanding(): return render_template('understanding.html')

@app.route('/save_results', methods=['POST'])
def save_results():
    data = request.get_json()
    print("Survey results:", data)
    return jsonify(success=True)

if __name__ == '__main__':
    app.run(debug=True)
```

Main.html:

```
<iframe id="surveyFrame" src="/understanding" width="100%" height="800" frameborder="0"></iframe>
<script>
window.addEventListener("message", e => {
  if (e.data && e.data.success)
    fetch("/save_results", {
      method: "POST",
      headers: {"Content-Type": "application/json"},
      body: JSON.stringify(e.data)
    });
});
</script>
```

Acknowledgements

Part of this work has been conducted within the AI4REALNET (AI for REAL-world NETwork operation) project (https://ai4realnet.eu/), which received funding from the European Union's Horizon Europe Research and Innovation programme under the Grant Agreement No 101119527, and from the Swiss State Secretariat for Education, Research and Innovation (SERI). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union and SERI. Neither the European Union nor the granting authority can be held responsible for them.