Human-in-the-Loop Digital-Twin Continuous-Improvement Framework Integrating Virtual Reality, Human Performance Models, and Dynamic Scheduling

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ULSAN NATIONAL INSTITUTE OF SCIENCE AND TECHNOLOGY 2007

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Photo by Stefan Els

Human-in-the-Loop Digital-Twin Continuous-Improvement Framework Integrating Virtual Reality, Human Performance Models, and Dynamic Scheduling – Validation, Sample Efficiency, and Practical Application

Clint Alex Steed

Department of Mechanical Engineering

Dissertation Defence Exam

December 13/14, 2023

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Content

- Background
- Overview
- Methodology
- Part 1: Complex simulation of human performance models
- Part 2: Sample efficient HITL simulation
- Part 3: Design for assembly decision framework
- Summary: System statements

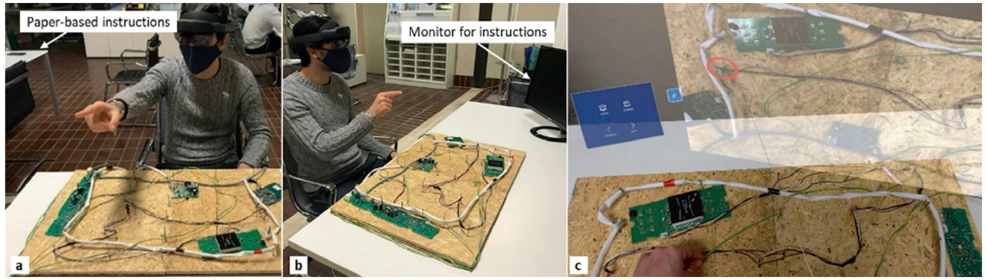
Background: Humans are essential in manufacturing assembly

- Manufacturing assembly link to economics
  - Made-in-china 2025 (8/10 industries) [1]
  - Industry 5.0 (human-centric) [2]
- Automation fallacy
  - Remove the need for humans [3]
  - Cost of automation [4]

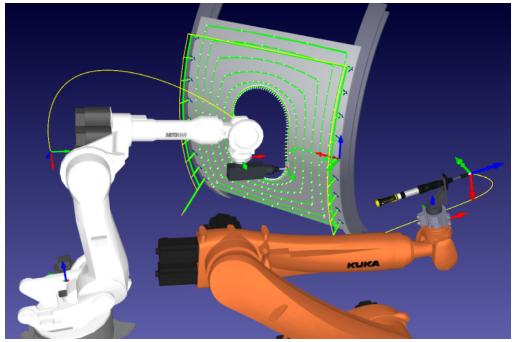
[1] L. Li, ‘China’s manufacturing locus in 2025: With a comparison of “Made-in-China 2025” and “Industry 4.0”’, Technological Forecasting and Social Change, vol. 135, pp. 66–74, Oct. 2018, doi: 10.1016/J.TECHFORE.2017.05.028.
[2] ‘Industry 5.0: Towards more sustainable, resilient and human-centric industry’. Accessed: Sep. 19, 2022. [Online]. Available: https://research-and-innovation.ec.europa.eu/news/all-research-and-innovation-news/industry-50-towards-more-sustainable-resilient-and-human-centric-industry-2021-01-07_en
[3] S. Gibbs, ‘Elon Musk drafts in humans after robots slow down Tesla Model 3 production’, The Guardian, Apr. 16, 2018. Accessed: Nov. 06, 2023. [Online]. Available: https://www.theguardian.com/technology/2018/apr/16/elon-musk-humans-robots-slow-down-tesla-model-3-production
[4] G. Boothroyd, ‘Product design for manufacture and assembly’, Computer-Aided Design, vol. 26, no. 7, pp. 505–520, 1994, doi: 10.1016/0010-4485(94)90082-5.

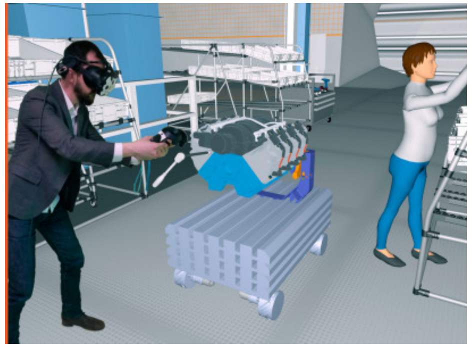
Background: Human-centricity as conflicting forces

- Operator 4.0 (wearables) [1]
  - Cost of sensors, not acknowledge
- VR example [2]
  - LCD<{AR & VR & paper}
- Techno-centric vs human-centric [3]
  - Re-purpose I4.0 technologies
  - Digital twin -> Virtual reality



LCD instructions: most comfort & least error





Simulation based development of robotic systems -> VR based development of human

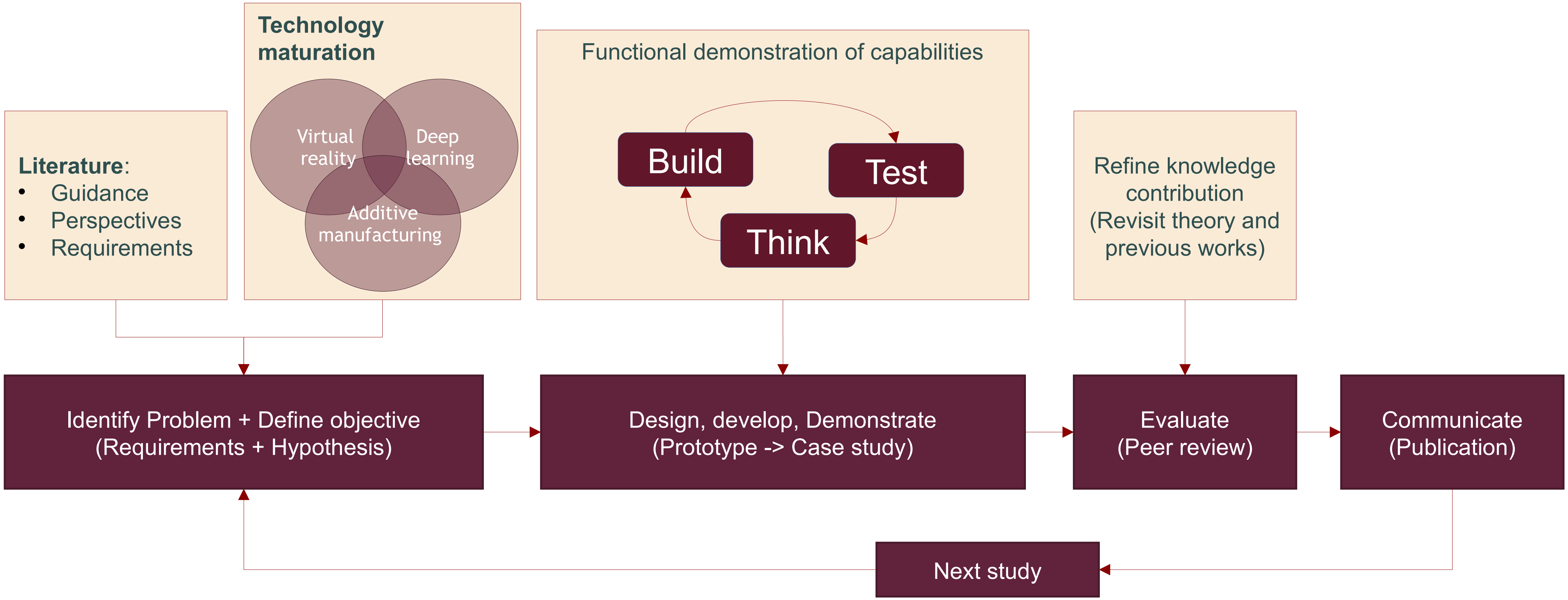
[1] D. Romero, J. Stahre, and M. Taisch, 'The Operator 4.0: Towards socially sustainable factories of the future', Computers & Industrial Engineering 2020
[2] A. Papetti, M. Ciccarelli, M. Palpacelli, and M. Germani, 'How to provide work instructions to reduce the workers' physical and mental workload', presented at the Conference of manufacturing systems, 2023.
[3] B. Wang, P. Zheng, Y. Yin, A. Shih, and L. Wang, 'Toward human-centric smart manufacturing: A human-cyber-physical systems (HCPS) perspective', Journal of Manufacturing Systems, 2022

Research study objectives: Development of human-centric assembly systems

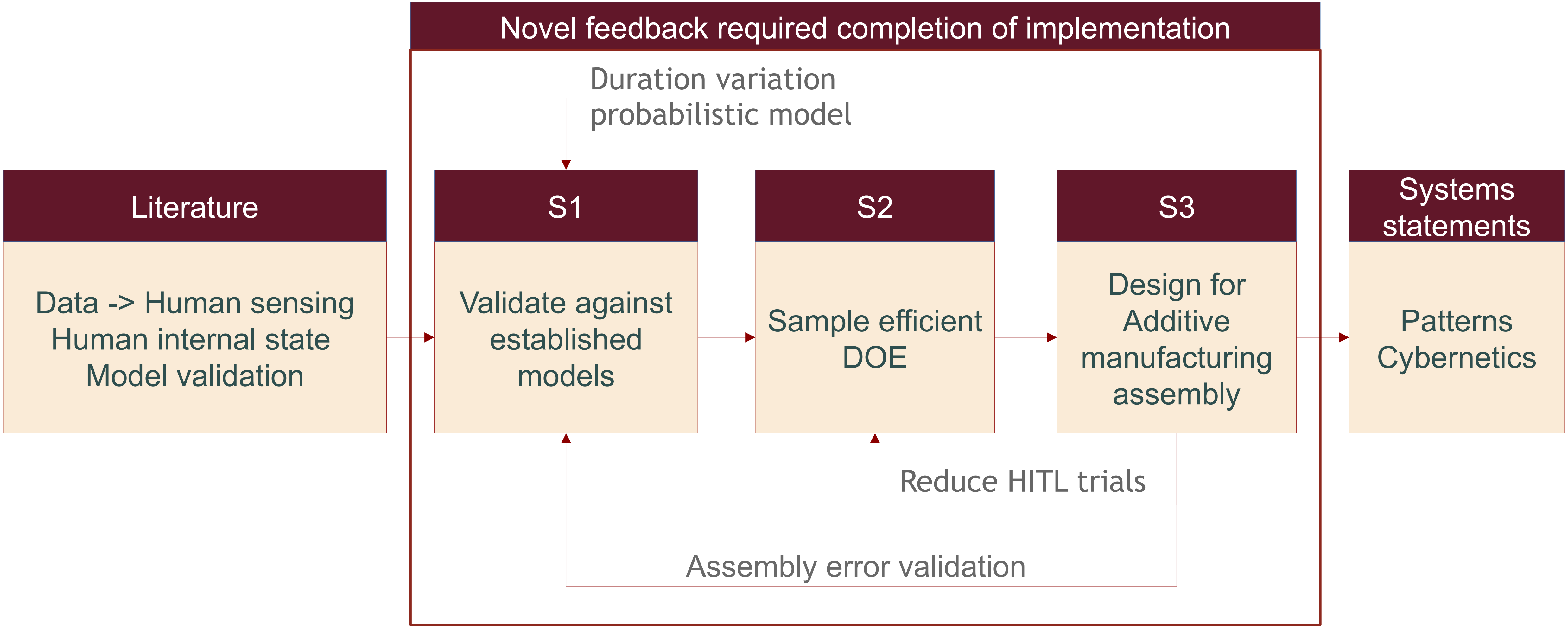
- Development as flexibility strategy
  - Constant changes or maintenance
- Human-centric
  - Challenging to model and predict behaviour
  - Validate easily and often
- Modern
  - Virtual reality as immersive digital twin

Methodology

- Design Science Research
- Systems engineering



Methodology: novel feedback



Overview of contributions 1

Part 1: Complex simulation of human performance models

Proposes a virtual reality workstation as a digital twin used for data-based validation and performance modelling, confirmed through:

- Various assembly task complexities
- Established quality risk and task duration
- Novel assembly error and probabilistic task duration

[1] C. A. Steed and N. Kim, ‘Complex human performance data acquisition from virtual manufacturing assembly simulations’, Advanced Engineering Informatics, **Under-review**

Overview of contributions 2

Part 2: Sample efficient HITL simulation

Demonstrated the value of sample efficient DoE:

- Demonstrated reduce HITL trials using active DoE
- Emphasized dynamic schedulers ethical role in preserving operators' autonomy
- Addresses limitation in prior experimental frameworks with Online DoE increasing scale of data

[1] C. A. Steed and N. Kim, 'Deep active-learning based model-synchronization of digital manufacturing stations using human-in-the-loop simulation', Journal of Manufacturing Systems, 2023.

Overview of contributions 3

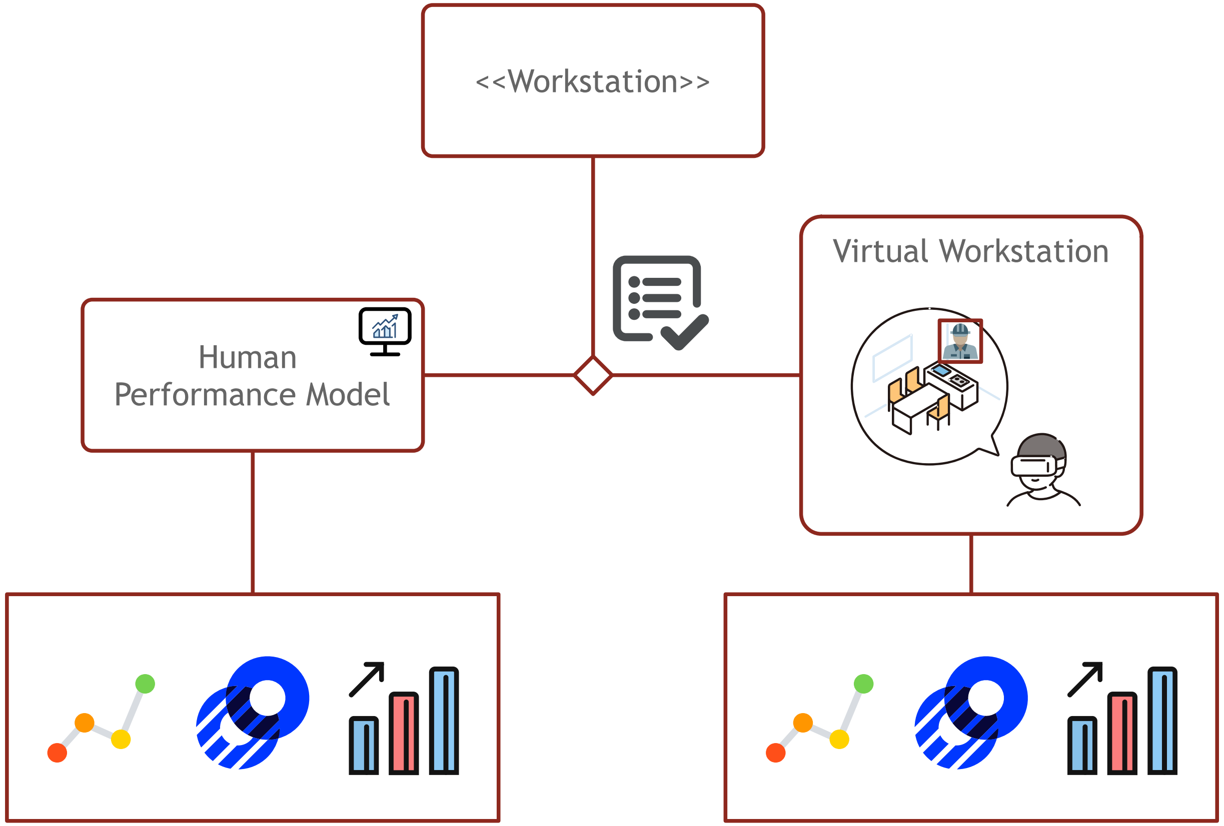
Part 3: Design for assembly decision framework

Design for manufacturing assembly demonstrative case study:

- Combine design by considering the assembly costs and printing costs
- Streamlines validating frameworks correlation between assembly time and assembly error
- Demonstrates practical application of the system to address modern challenges in assembly

[1] U. Auyeskhan, C. S. Alex, S. Park, D.-H. Kim, I. D. Jung, and N. Kim, 'Virtual reality based assembly-level design for additive manufacturing decision framework involving human aspects of design', Journal of Computational Design and Engineering, 2023

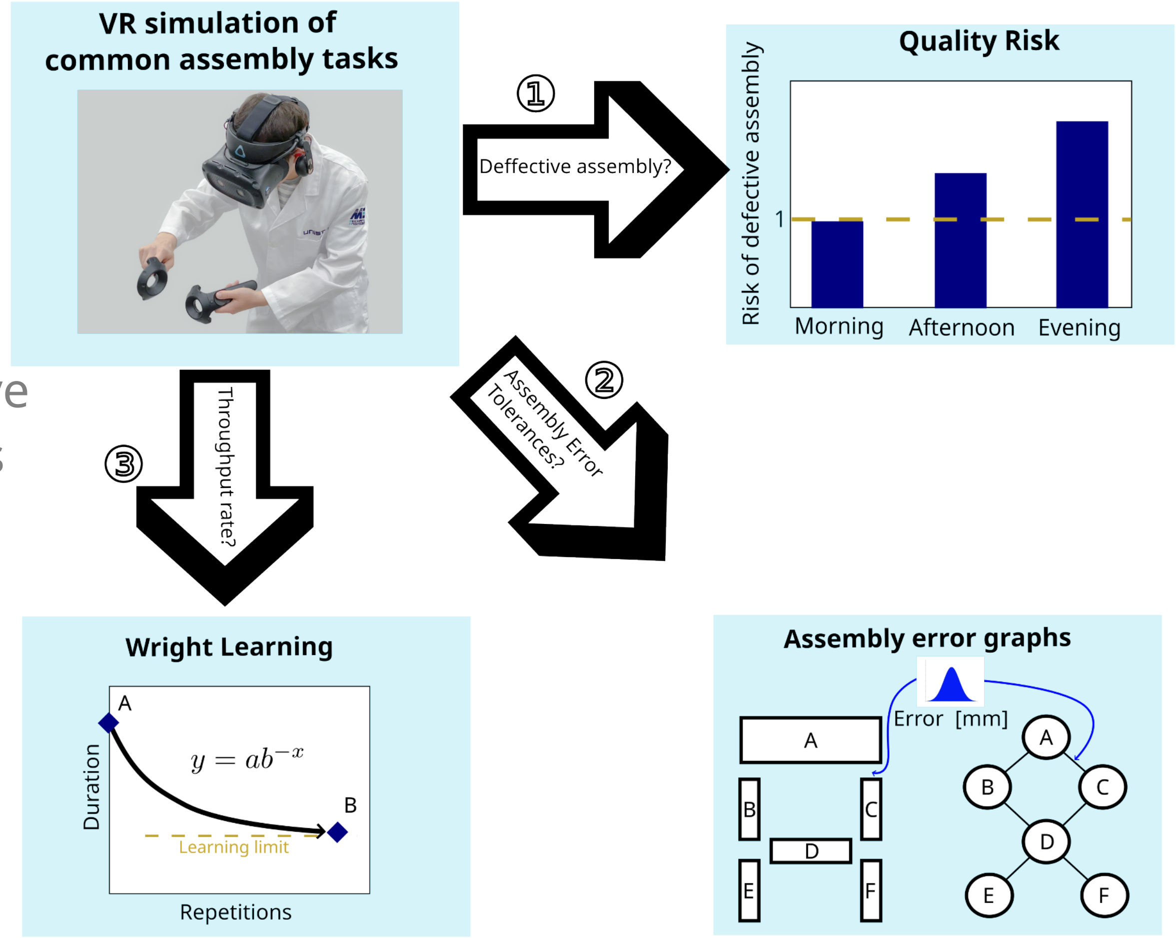
1 Objectives

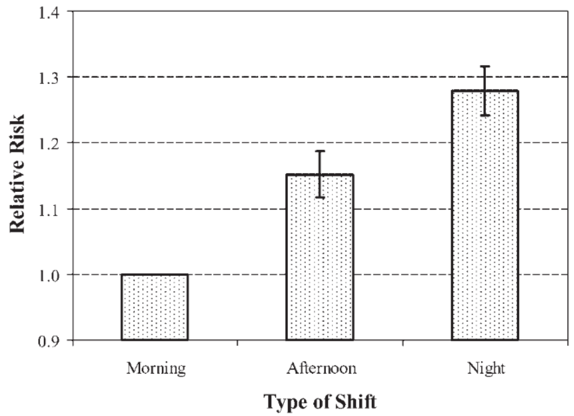


Can we substitute the virtual workstation for the physical one?

Can we use the virtual workstation to study human performance?

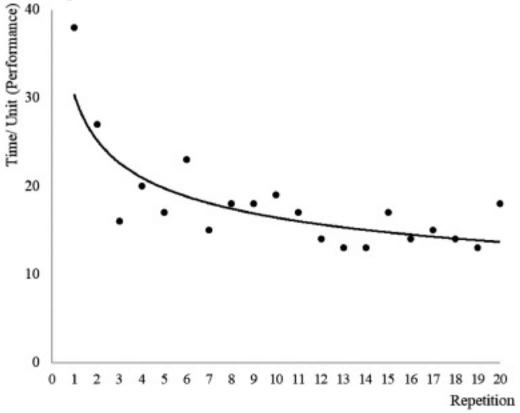
1 Background: Established human performance models





[1] Risk of injury is a function of Time-of-day -> risk of defect

[2] Wright learning curve Models task duration vs Repetitions



Few works investigate this assembly error:

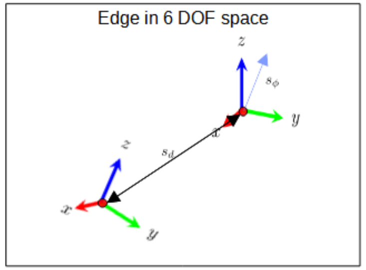
- Difficult to measure/validate

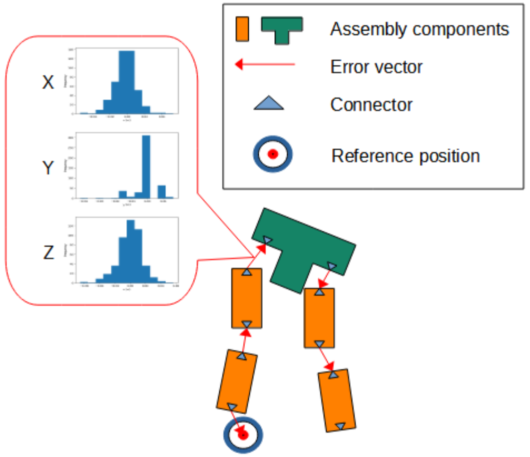
[1] S. Folkard and D. A. Lombardi, ‘Modeling the impact of the components of long work hours on injuries and “accidents”’, American Journal of Industrial Medicine, vol. 49, no. 11, pp. 953-963, 2006
[2] N. Asadayoobi, M. Y. Jaber, and S. Taghipour, ‘A new learning curve with fatigue-dependent learning rate’, Applied Mathematical Modelling, vol. 93, pp. 644-656, May 2021,

1 Additional theory: Assembly errors

Joint name	Illustration	Task(joints)
Radial occluded alignment		1(1-6);3(1-4);4(1);3(1)
Biased occluded alignment		4(3,4)
Radial alignment		3(2-3);4(2,5)

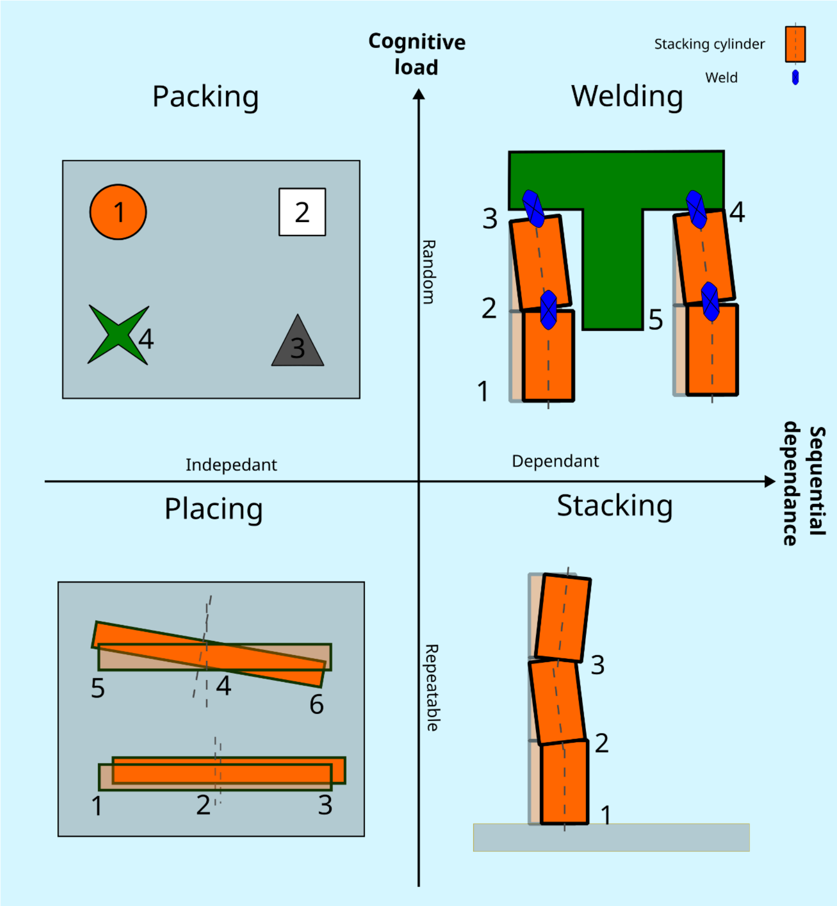
Similar joints should present similar errors





Assembly error represents poor quality products

1 Experiment design: Task complexity



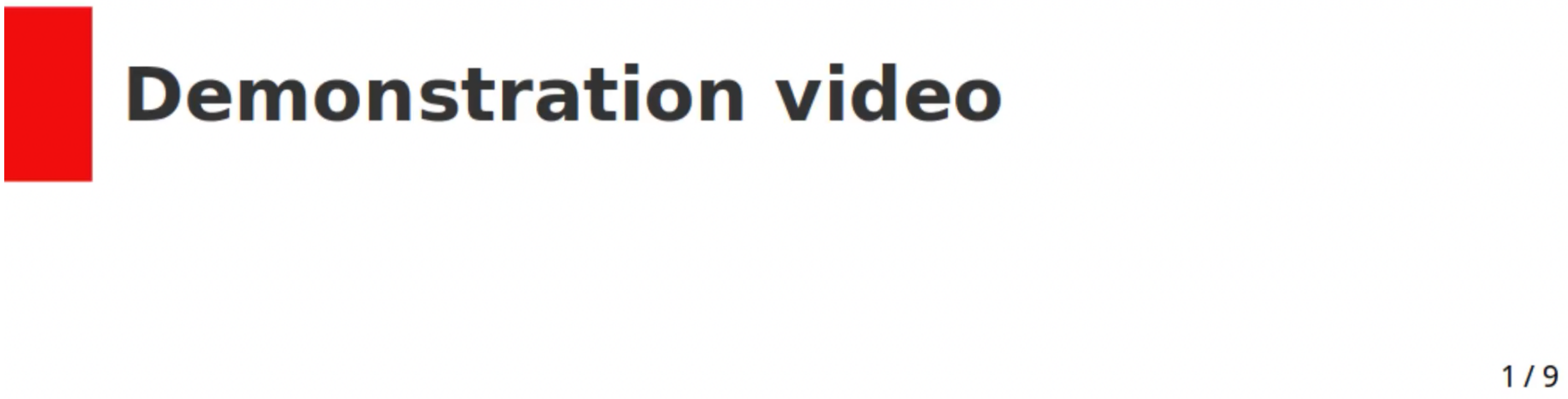
Four common assembly task simulations separated by task complexity

Task complexity:

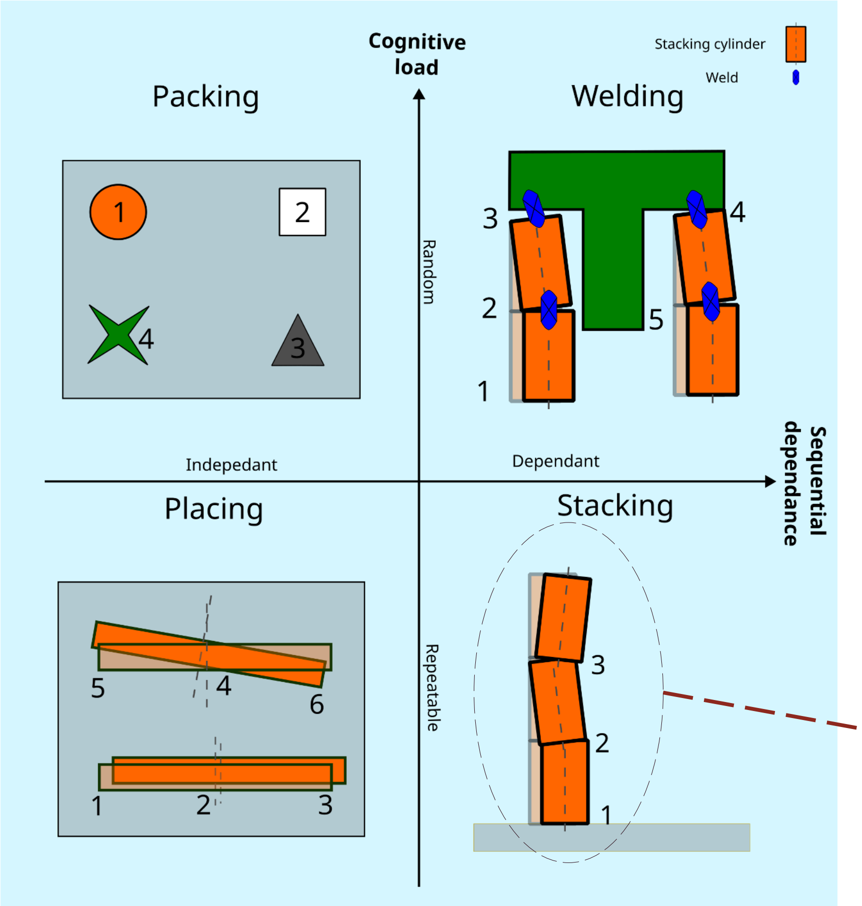
Cognitive load (recognition)
- Repeatable vs random

Motor patterns
- Sequentially independent

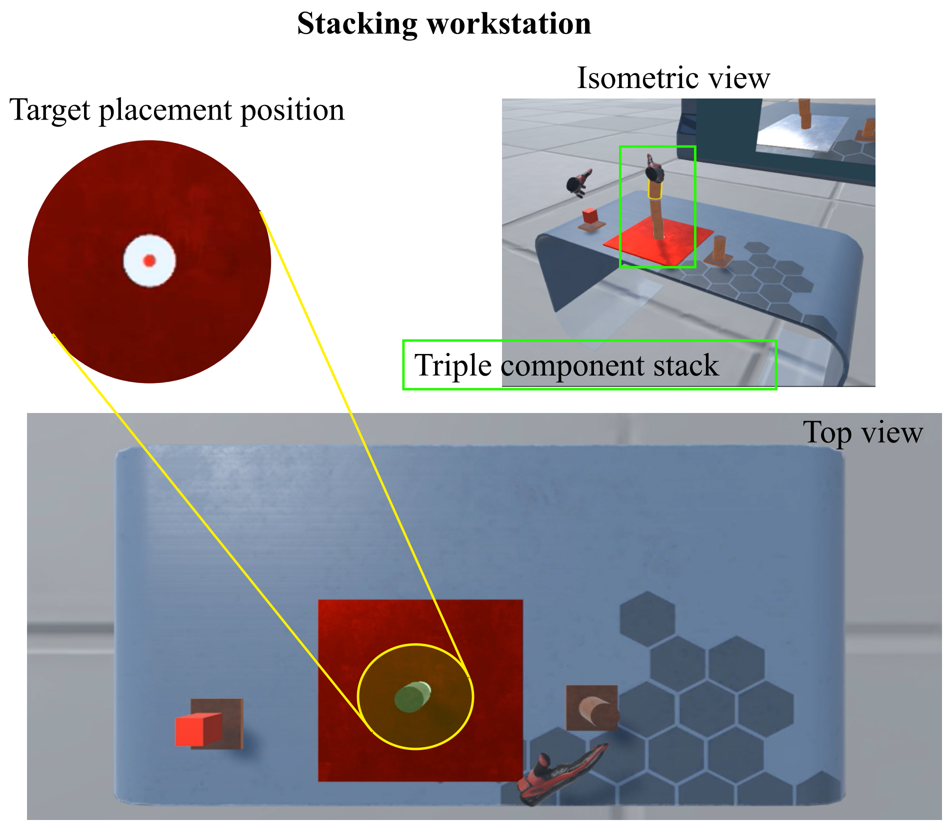
1 Experiment design: Video demonstration



1 Experiment design: Virtual stacking

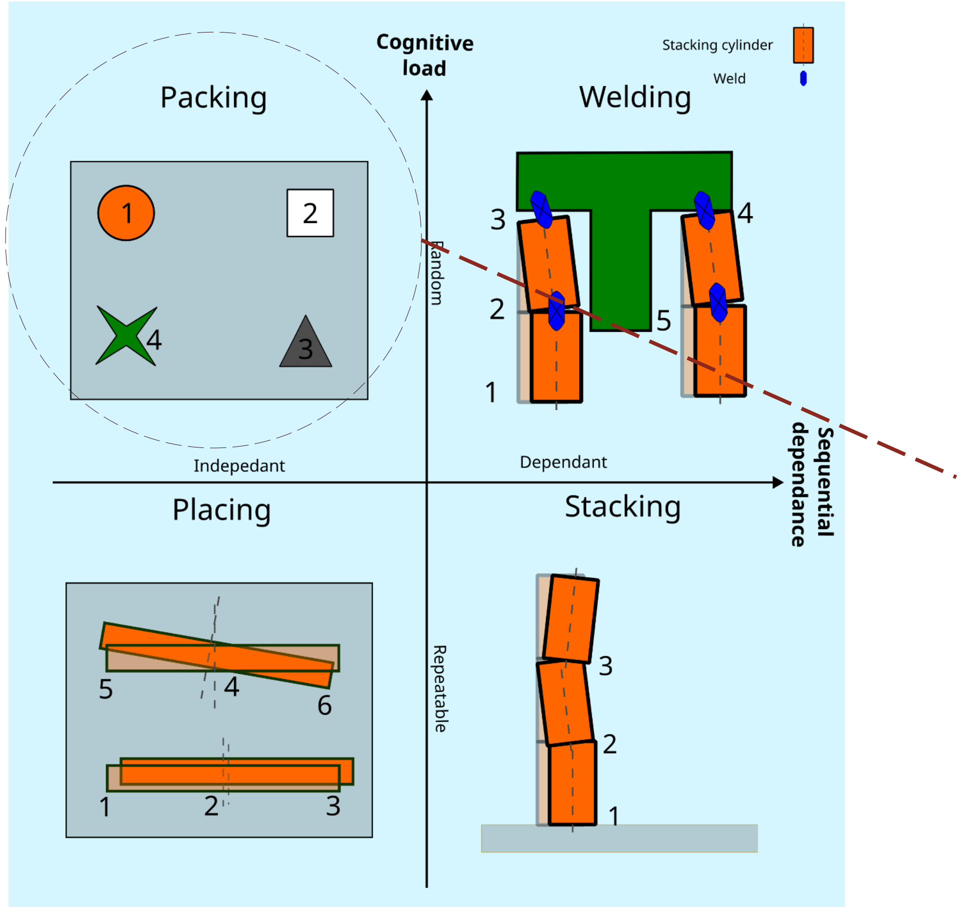


Four common assembly task simulations separated by task complexity

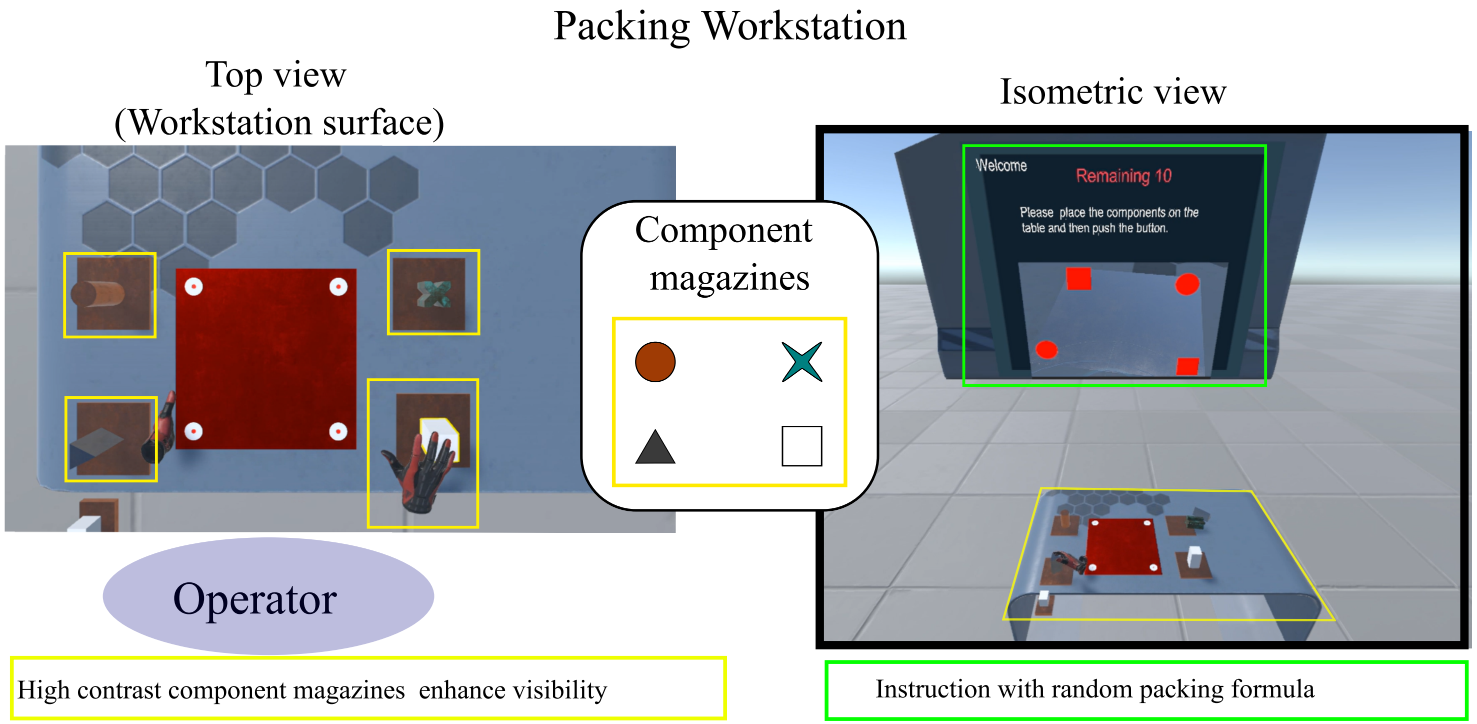


Stacking: Repeatable and sequentially dependent

1 Experiment design: Virtual packing

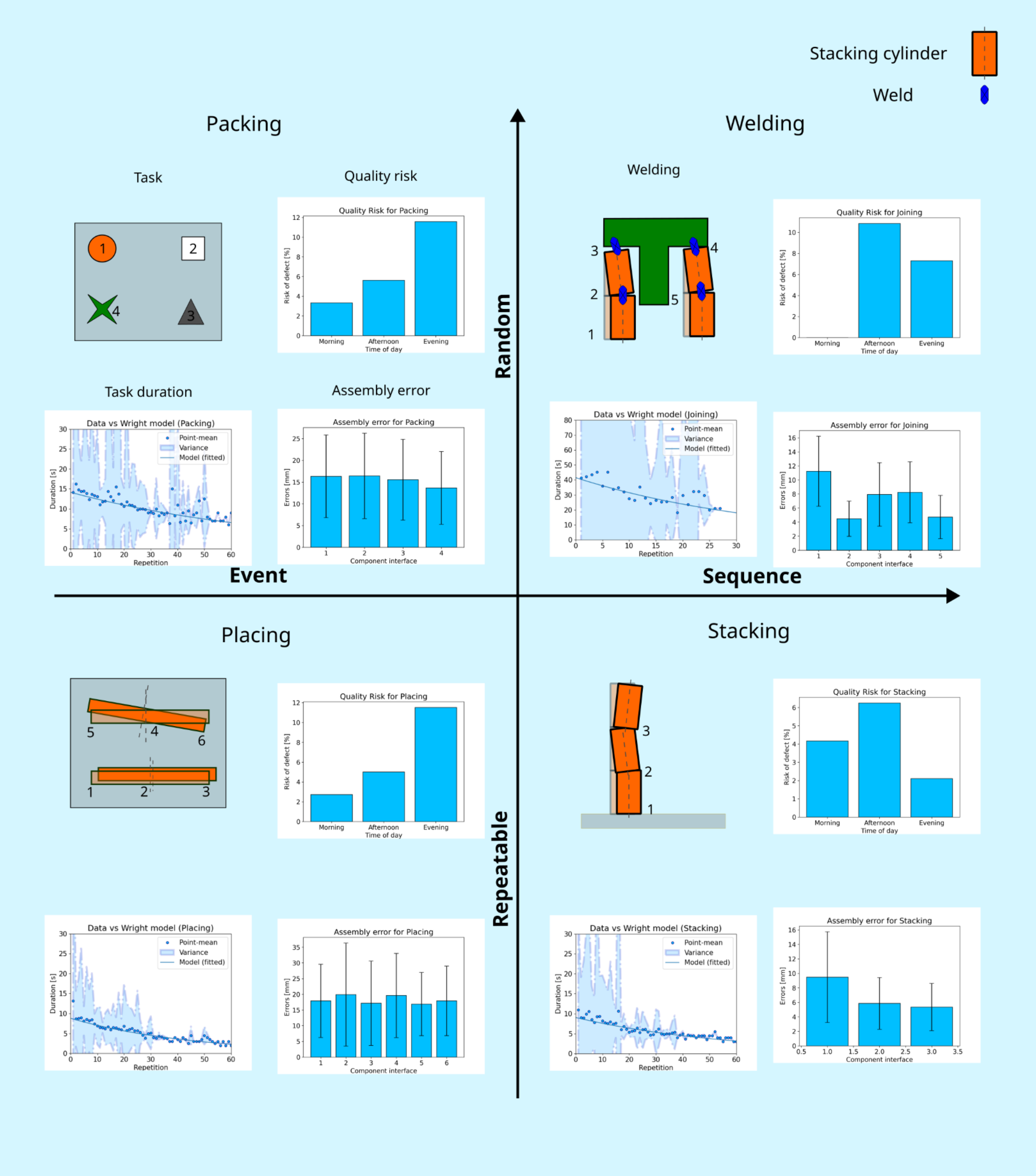


Four common assembly task simulations separated by task complexity



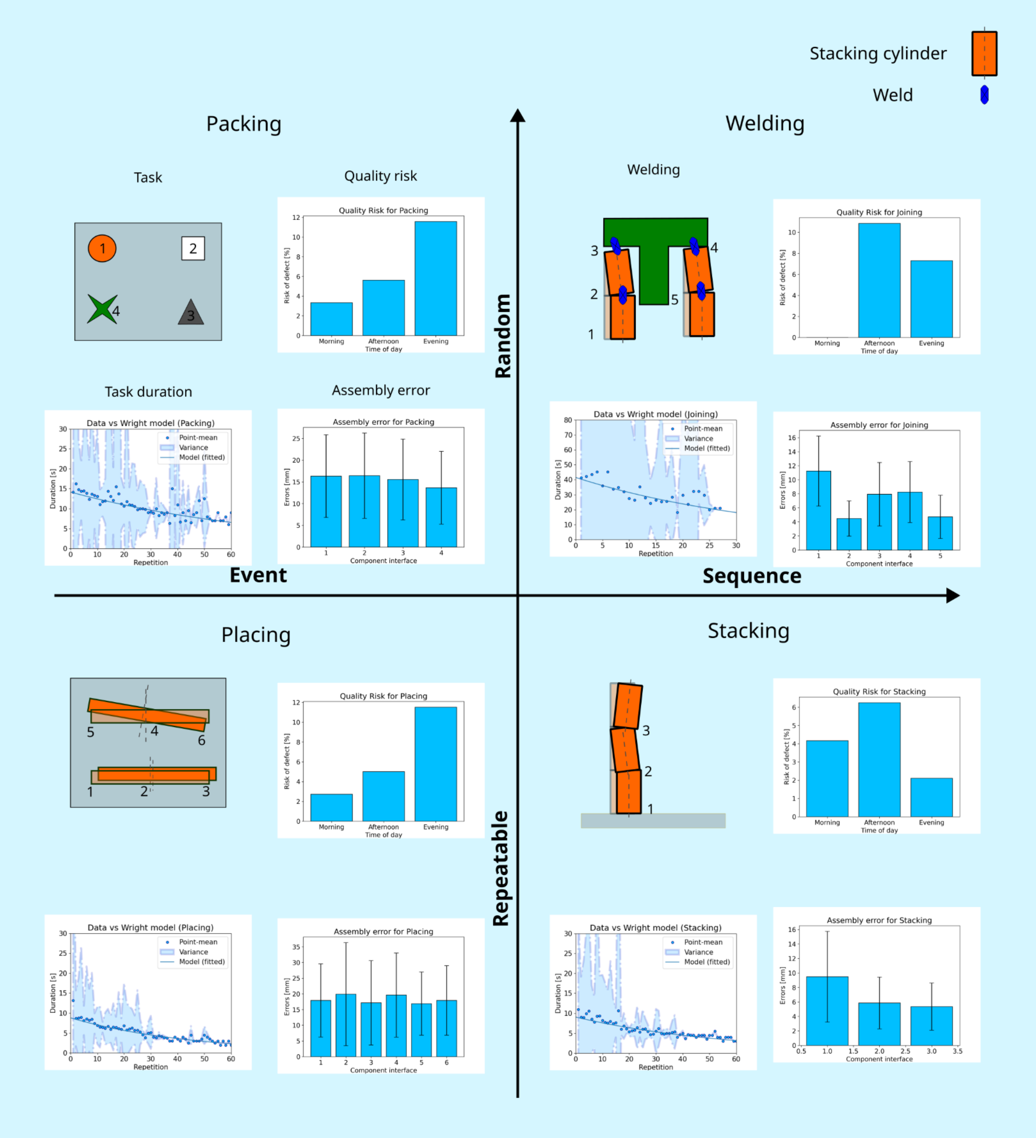
Packing: Random and sequentially independent

1 Results: Overview

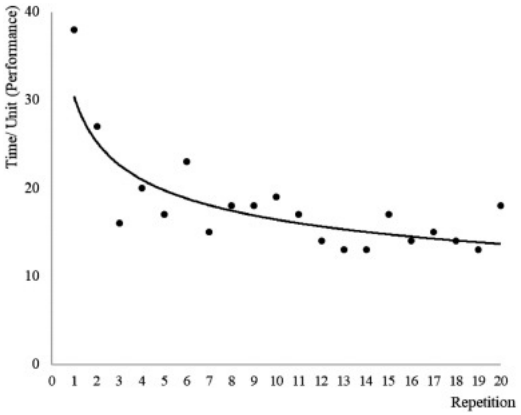


- Wright learning ✔ task duration
- Quality risk ✔ sequentially independent
- Assembly error ✔ similar joints

1 Results: Wright learning

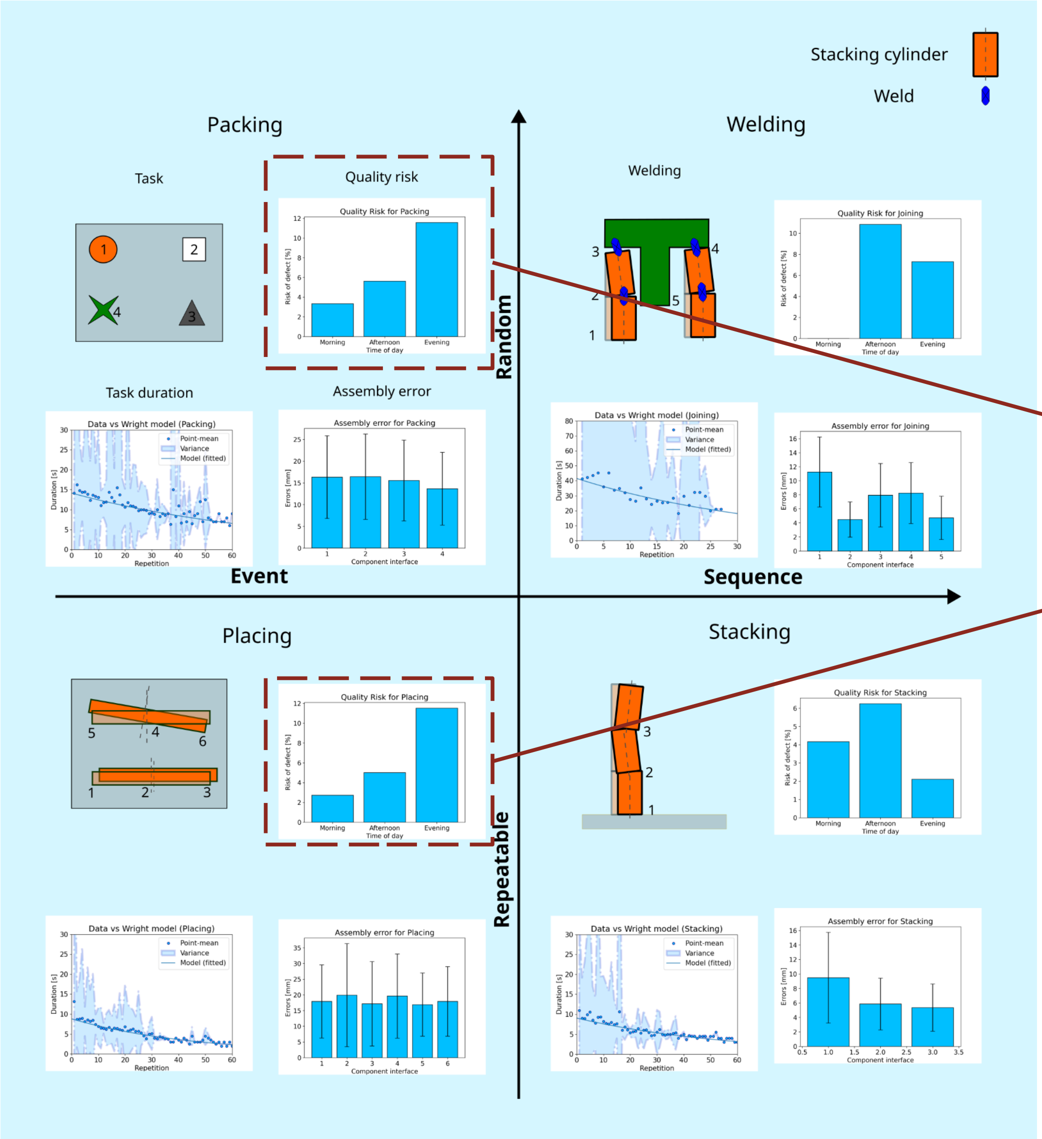


Wright learning ✔ task duration

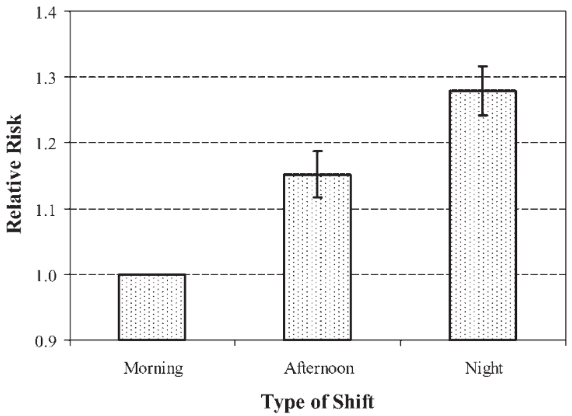


- All task durations adhere to Wright learning curve (model)
- Variance may be predictable?

1 Results: Quality risk

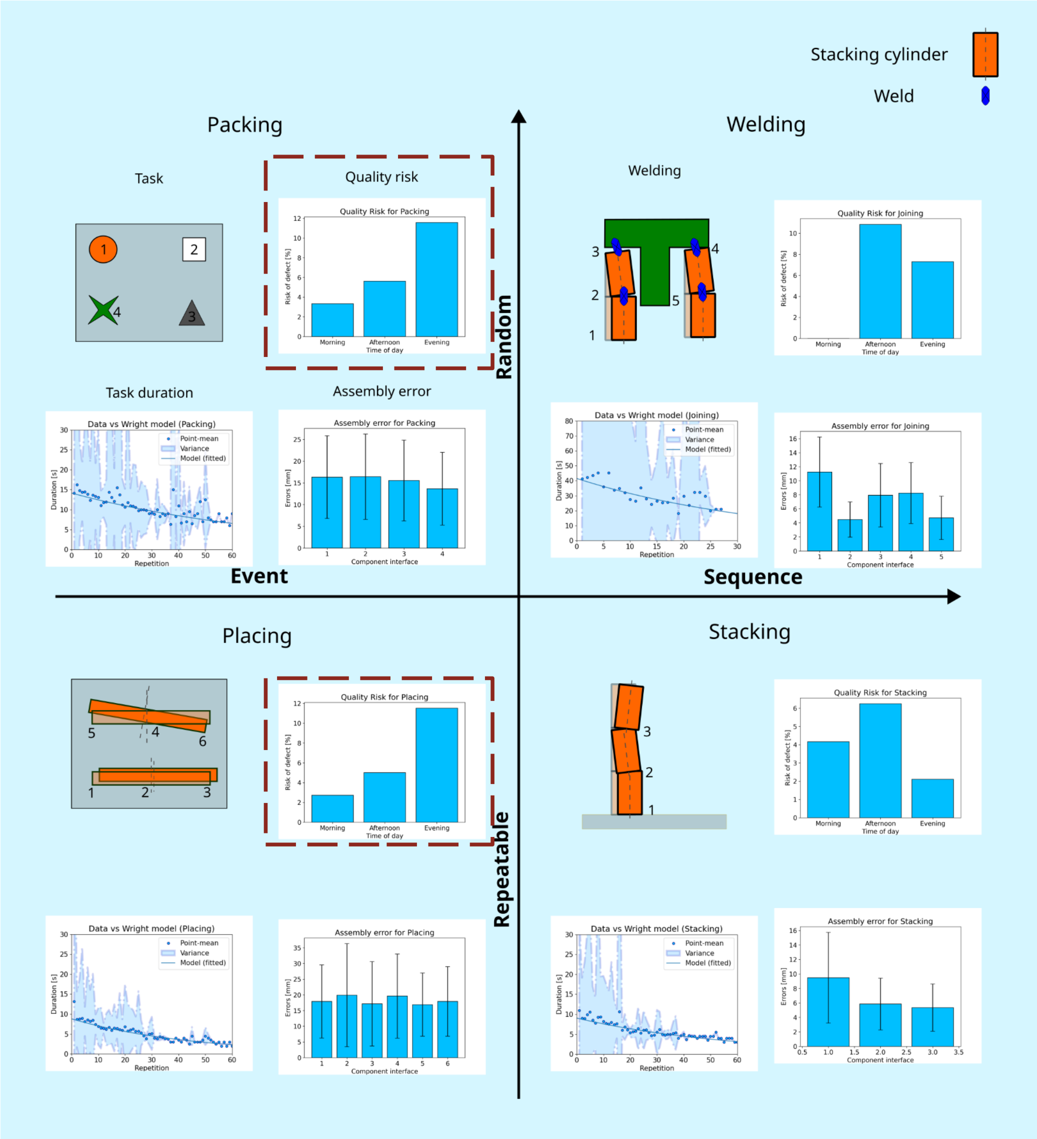


Quality risk ✔ sequentially independent



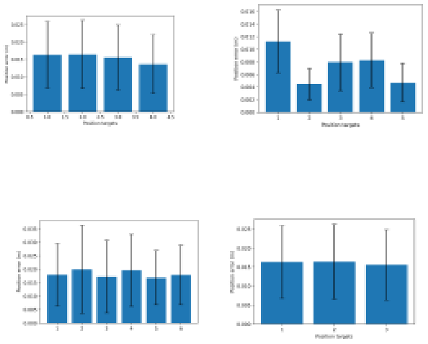
Similar profile
(Morning<afternoon<night)
Similar values (5%).

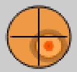
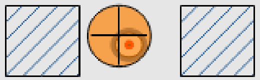
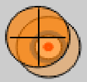
1 Results 1: Assembly error



Assembly displacement error ✔ similar joints

Assembly displacement

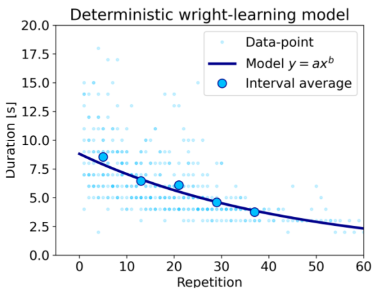


Joint name	Illustration	Task(joints)
Radial occluded alignment		1(1-6);3(1-4);4(1);3(1)
Biased occluded alignment		4(3,4)
Radial alignment		3(2-3);4(2,5)

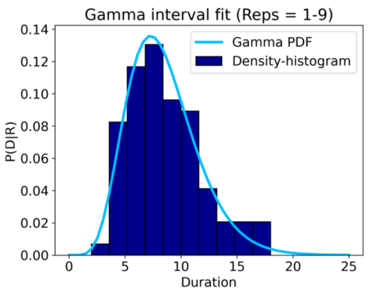
Similar joint classes presented similar errors

1 Results 2: Dynamic wright learning

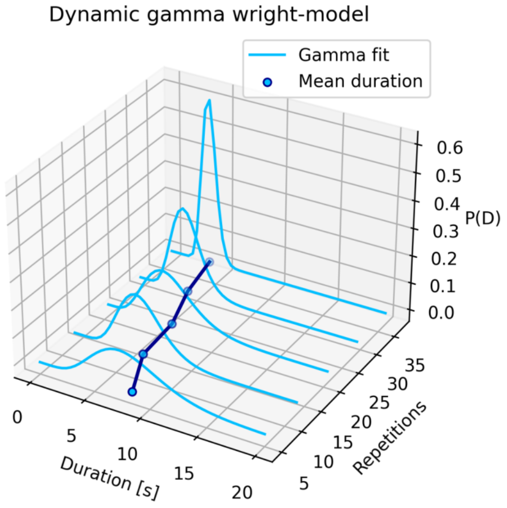
[A]



[B]



[C]



[D]

Interval	shape	scale	μ	χ^2	#points	low-Rep	high-Rep
1.0	7.32	1.15	8.44	1.0	91.0	1.0	9.0
2.0	10.32	0.62	6.35	1.0	77.0	9.0	17.0
3.0	6.92	0.87	5.99	0.56	77.0	17.0	25.0
4.0	10.87	0.41	4.5	0.0	50.0	25.0	33.0
5.0	30.81	0.12	3.65	0.0	24.0	33.0	41.0

- Dynamic wright fits well initially,
- Drops of quick
  - Chi-square low-data sensitivity

Novel finding

1 Implications

- VR quantified human performance → substitute for physical system
  - Wright learning ✔task duration
  - Quality risk ✔sequentially independent
- VR observed new phenomena → study (novel) human behavior
  - Assembly error ✔similar joints
  - Dynamic wright learning curve

VR can be used to study and simulate human performance for manual assembly tasks.

1 Conclusion

Part 1: Complex simulation of human performance models

Proposes a virtual reality workstation as a digital twin used for data-based validation and performance modelling, confirmed through:

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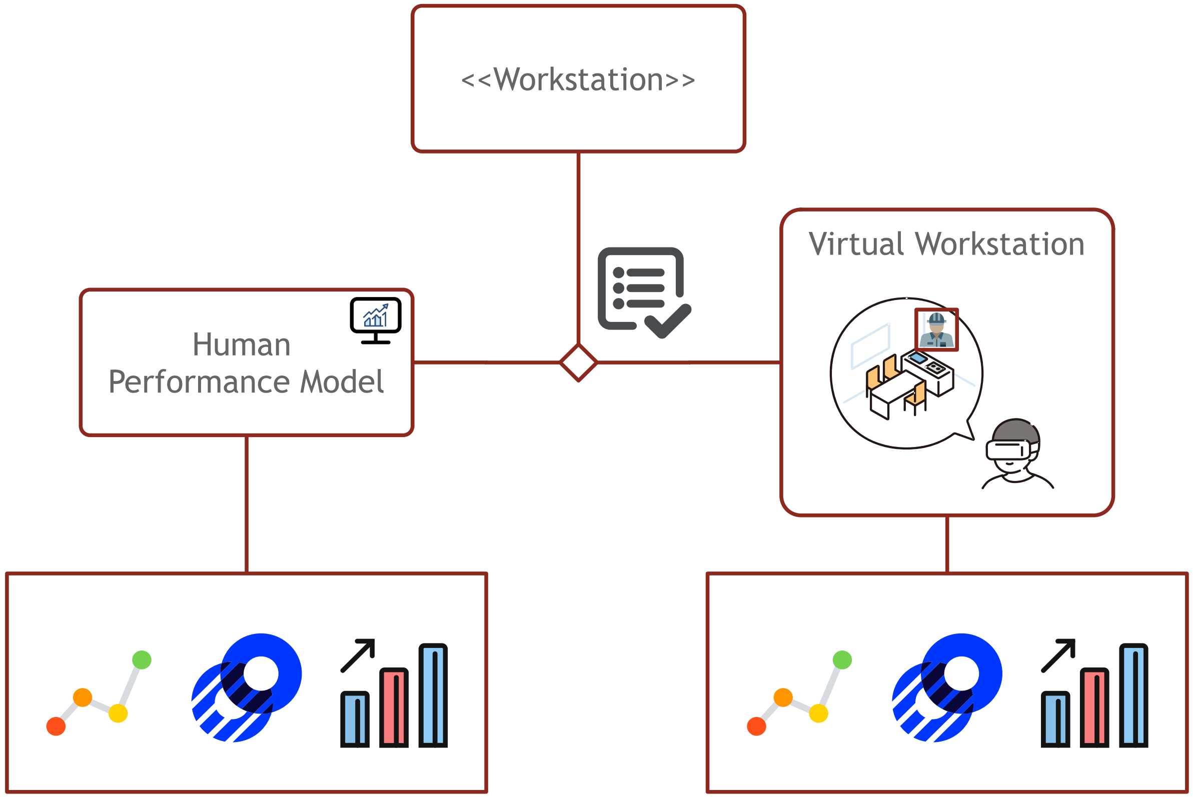


VR can be substituted for physical system.

Overview of contributions 2

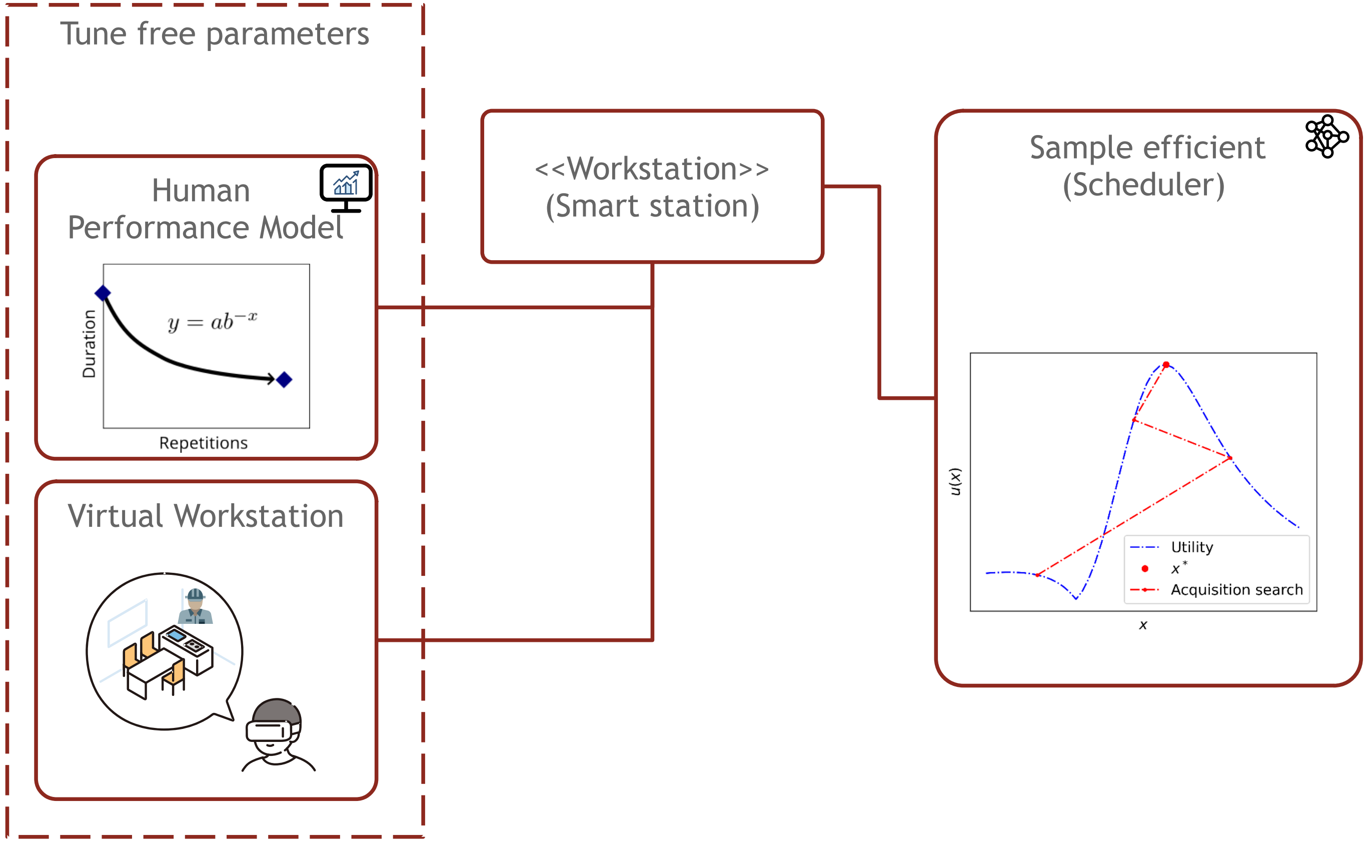
Part 2: Sample efficient HITL simulation

Demonstrated the value of sample efficient DoE:

- Demonstrated reduce HITL trials using active DoE
- Emphasized dynamic schedulers ethical role in preserving operators' autonomy
- Addresses limitation in prior experimental frameworks with Online DoE increasing scale of data

[1] C. A. Steed and N. Kim, 'Deep active-learning based model-synchronization of digital manufacturing stations using human-in-the-loop simulation', Journal of Manufacturing Systems, 2023.

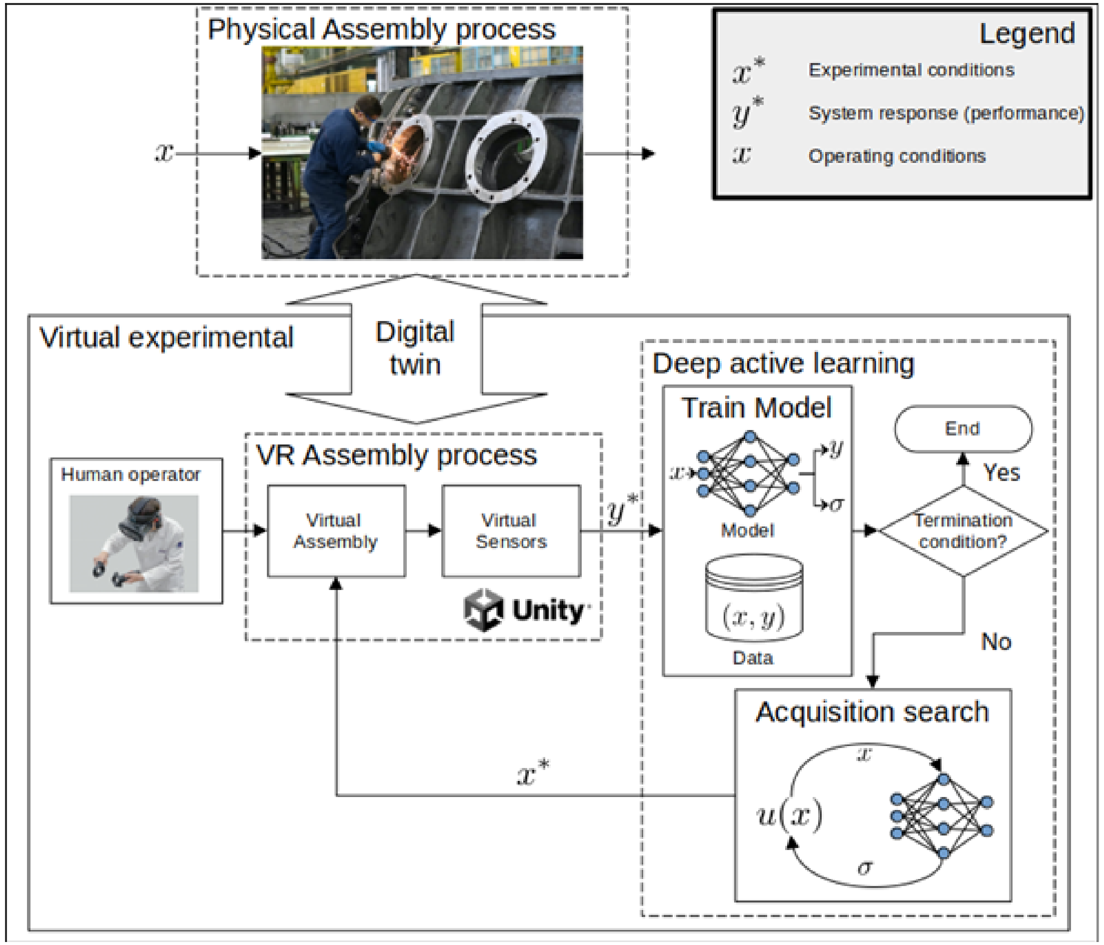
2 Objectives



Can we use an intelligent scheduler as online Design of Experiments?

Can we reduce number of experimental trials required to model task duration?

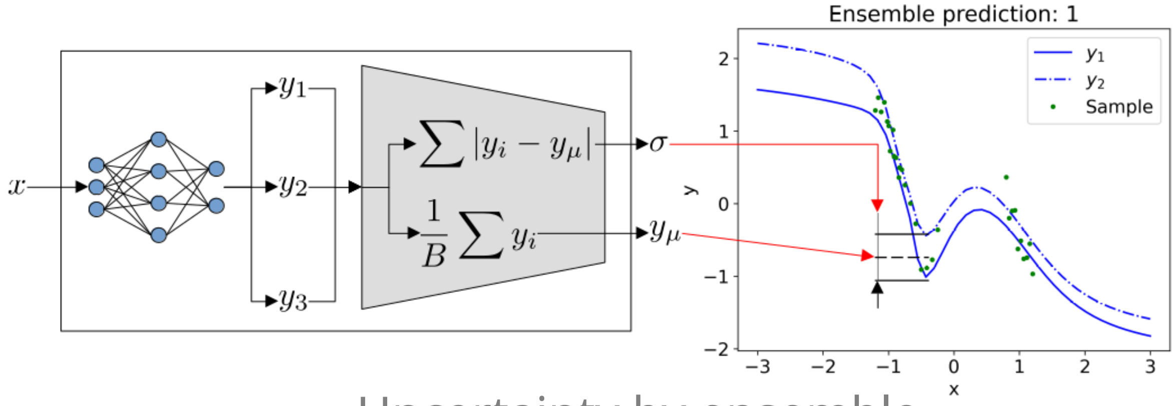
2 Background: Virtual smart stations



- Virtual workstation as digital twin
- Online Design of Experiments (DoE)
  - Sample efficiency as uncertainty sampling
- VR experimental frameworks
  - Offline [1-2]

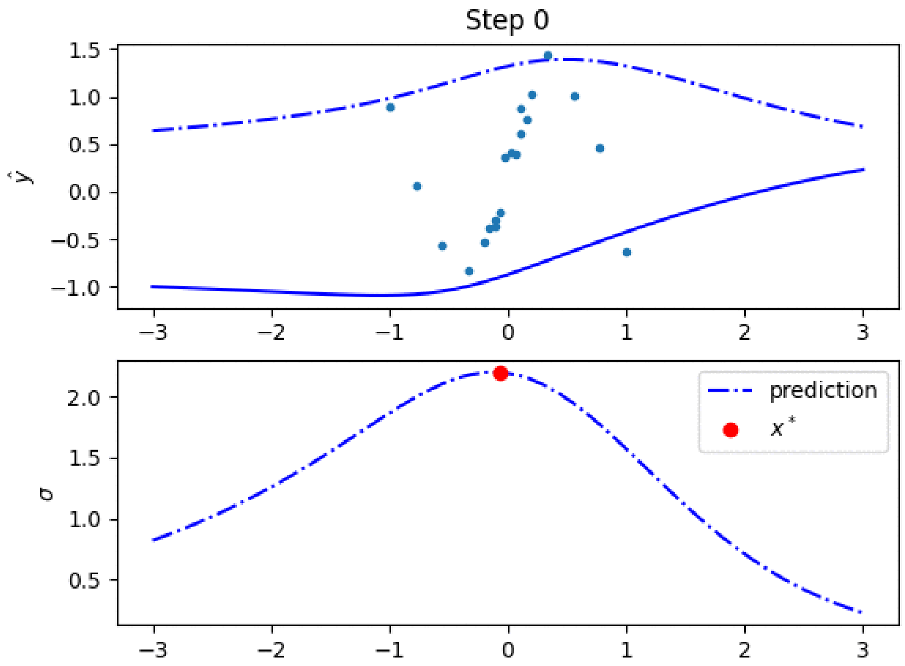
[1] J. Brookes, M. Warburton, M. Alghadier, M. Mon-Williams, and F. Mushtaq, 'Studying human behavior with virtual reality: The Unity Experiment Framework', Behavior Research Methods, 2020
[2] J. Grübel, R. Weibel, M. H. Jiang, C. Hölscher, D. A. Hackman, and V. R. Schinazi, 'EVE: A Framework for Experiments in Virtual Environments', Lecture Notes in Computer Science, 2017

2 Theory: Uncertainty sampling



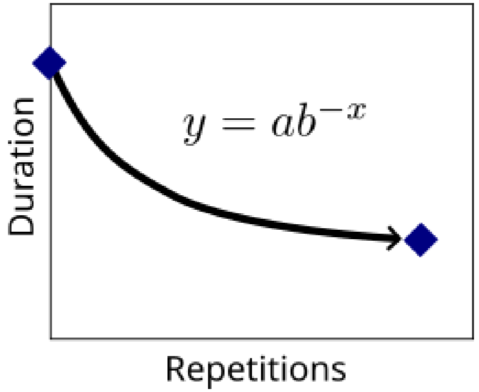
Uncertainty by ensemble

- Sample at highest uncertainty
- Uncertainty as Query by committee
    - If multiple models agree, low uncertainty



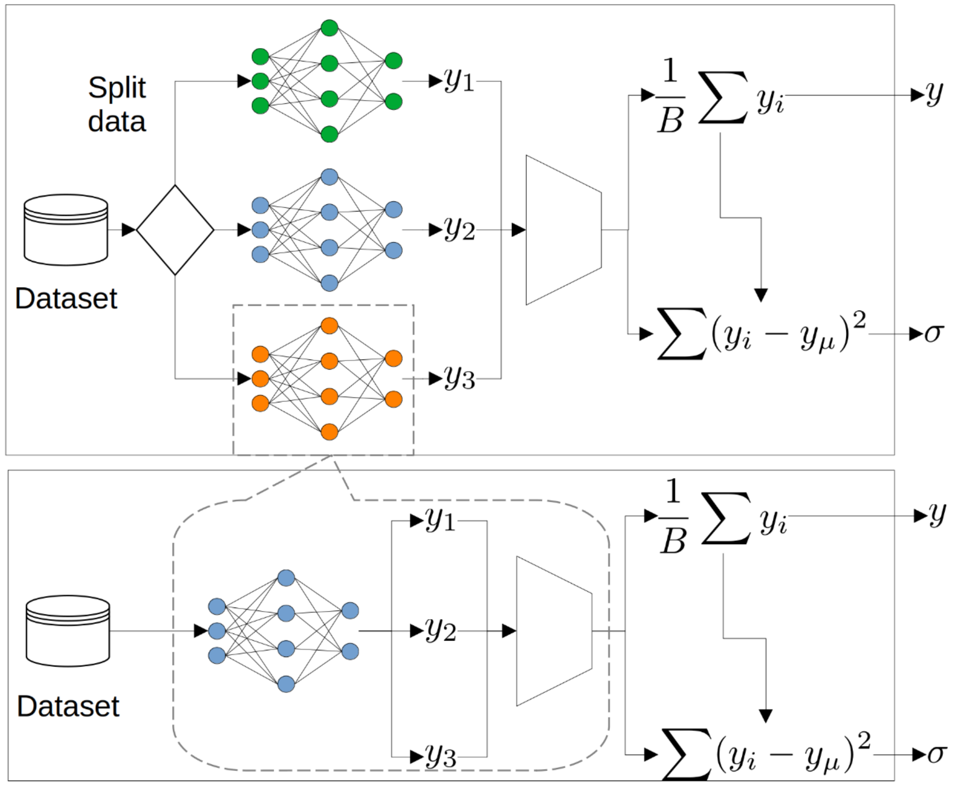
Simple example: Sample at highest uncertainty

2 Theory: Deep HPM



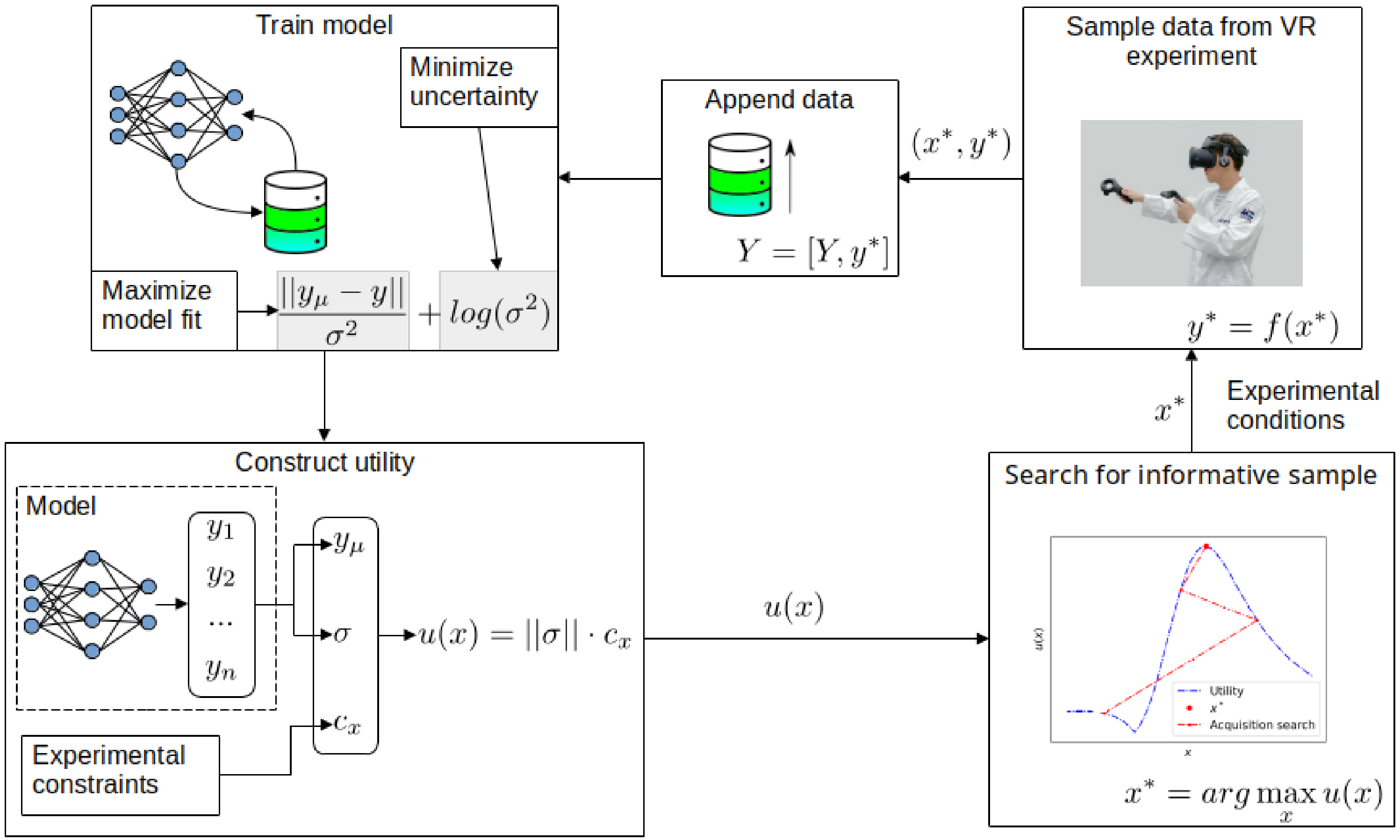
Wright learning as HPM, free parameters (a,b)

- Human performance models are simple
  - Free parameter tuned from data
- Deep HPM as low complexity Neural-nets
  - low(er) training times
  - behavior inference



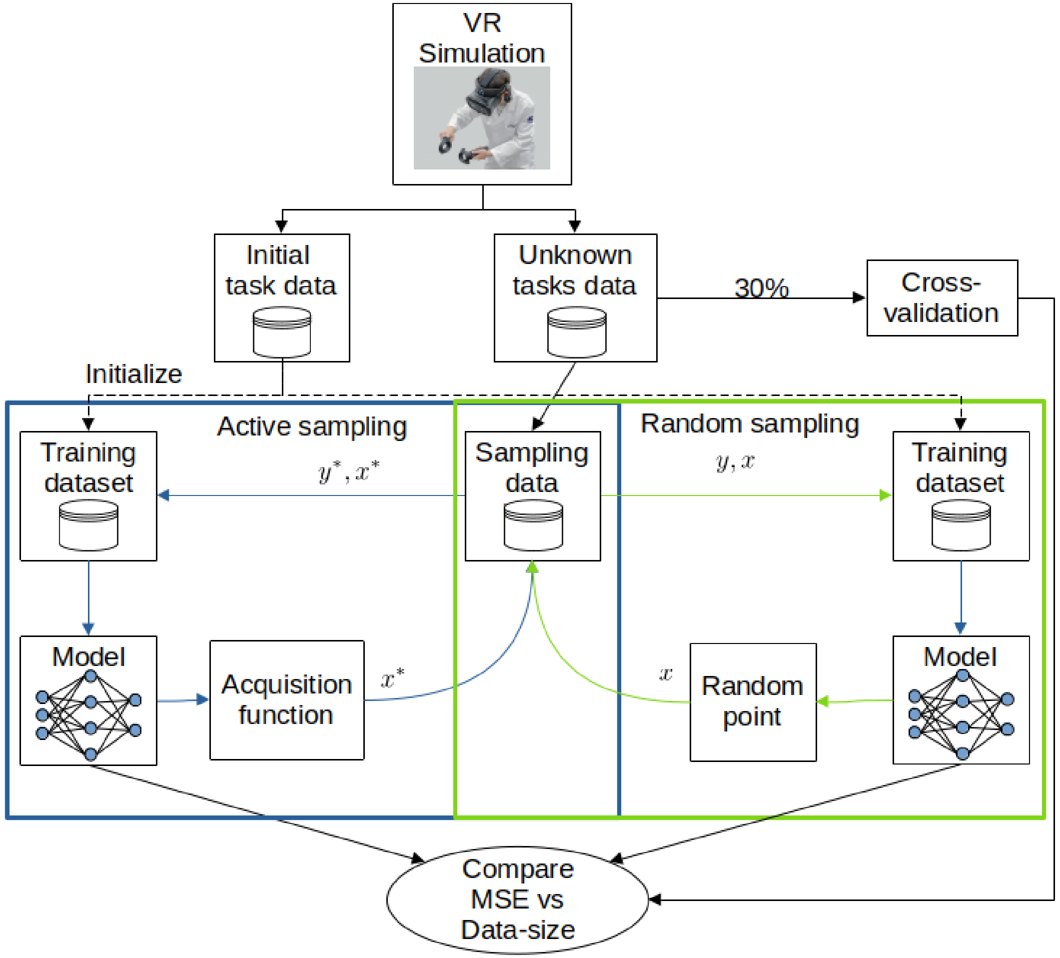
Proposed low-complexity deep ensemble method (bottom) estimates uncertainty

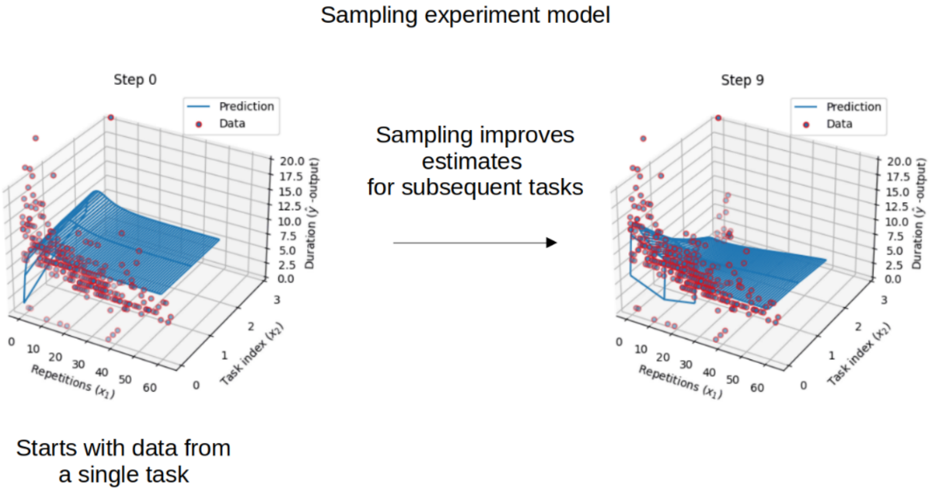
2 Theory: Active loop



1) Sample from VR experiment
2) Train model
3) Construct utility with uncertainty
4) Search utility

2 Sampling experiment: Active loop

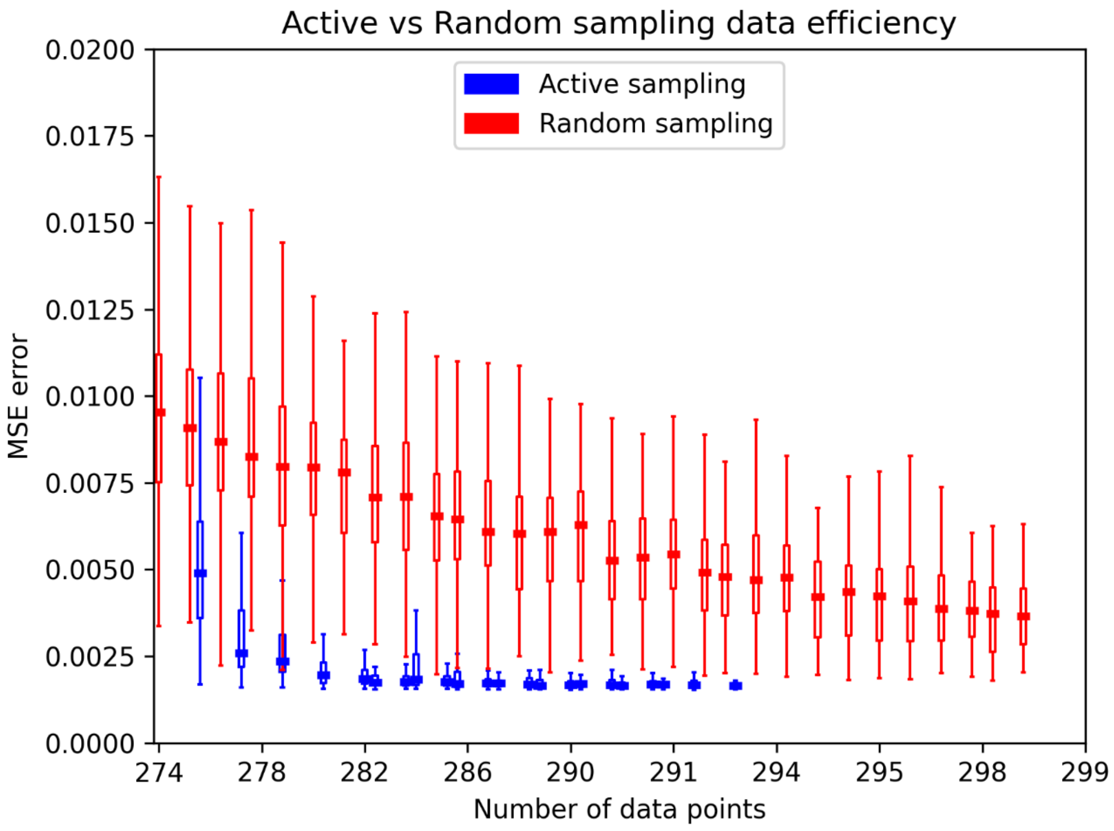




Sample enriched to fit other tasks

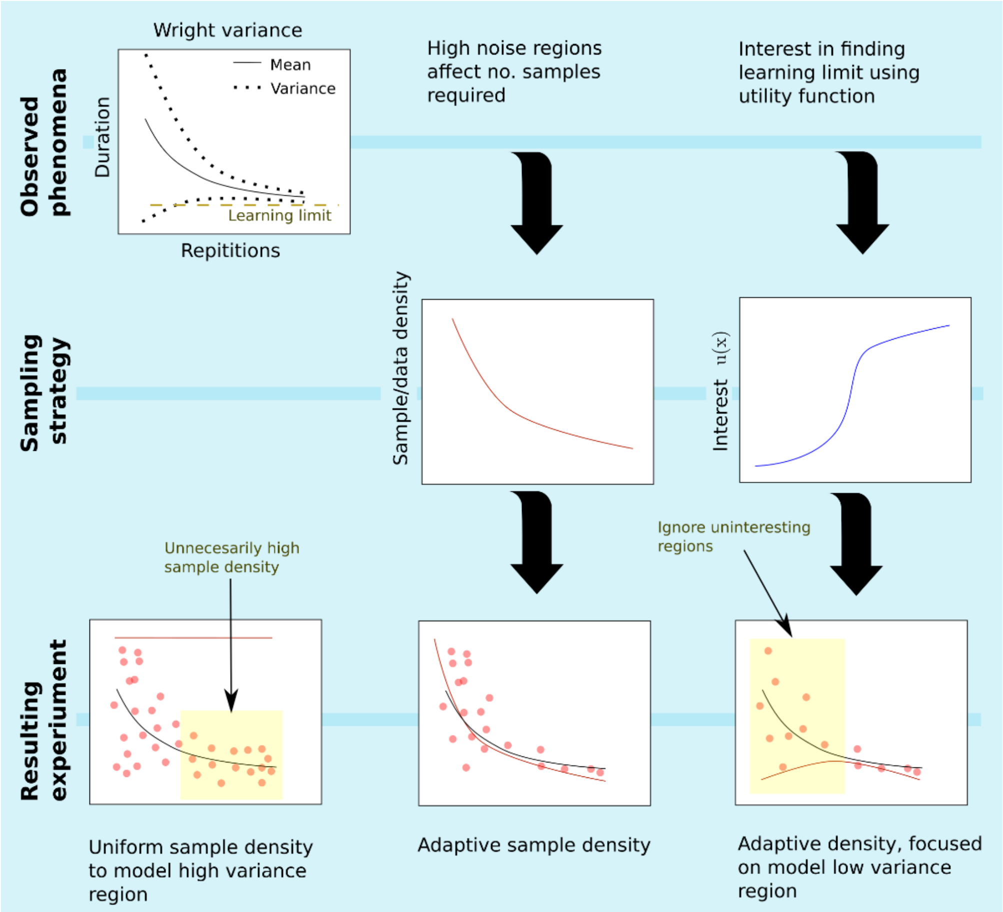
Active vs random sampling, uses one task as initial data and samples from similar tasks

2 Results: Sample efficiency



- Significantly less data required

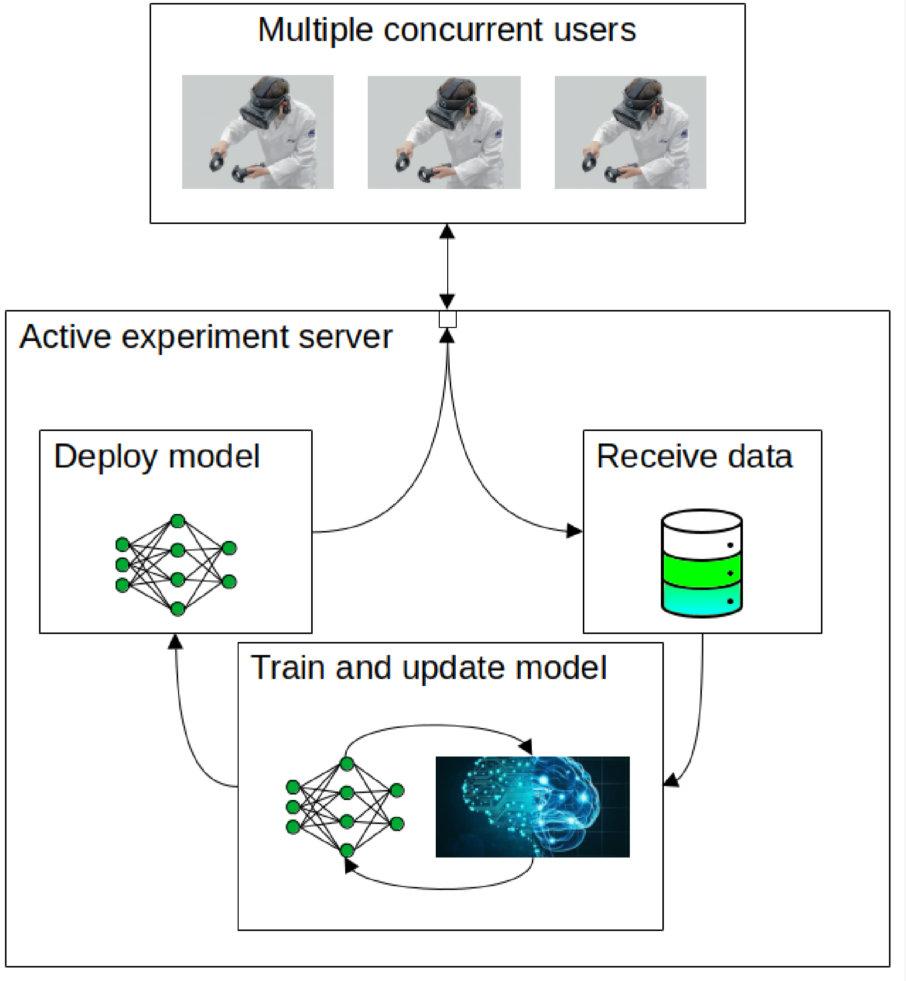
2 Applications: Adaptive sampling



Active sampling strategies for Wright learning

- Active experimental design for Wright learning
  - Simple strategies over-sample (left)
  - Uncertainty strategy adapts sampling (center)
  - Utility sampling reaches task learning limits (right)

2 Applications: Online experimental design

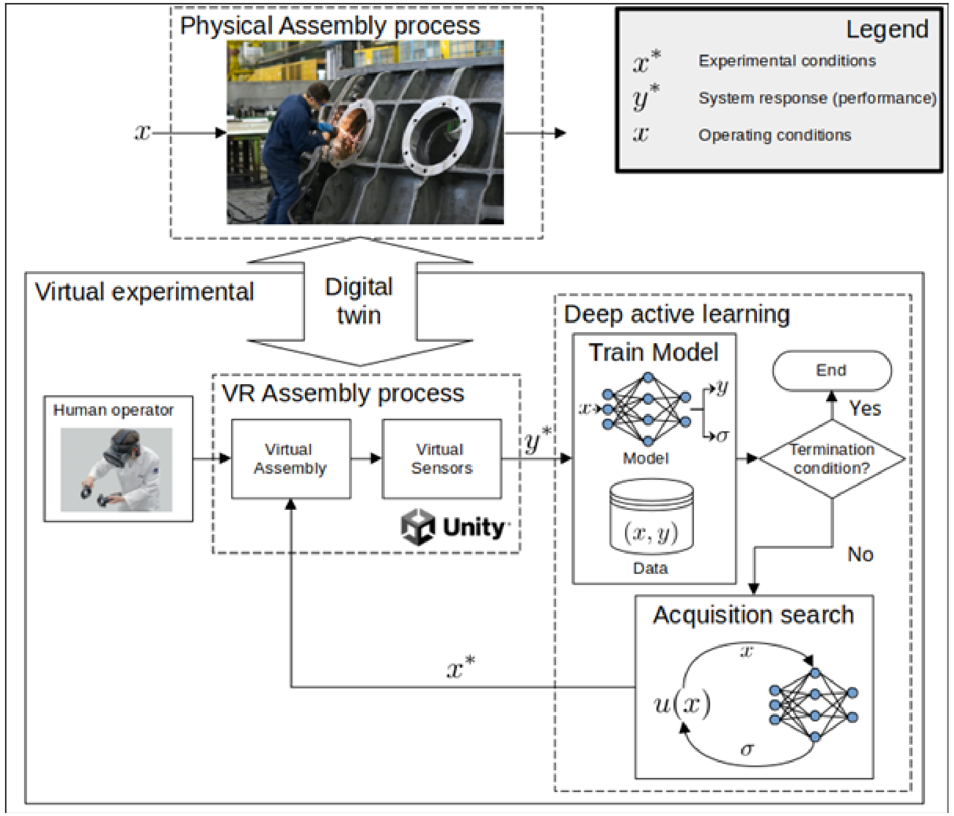


Online DoE enables remote, concurrent experiments

- Scalable human experiments
  - Online DoE=sample efficient
  - Distributed and portable
  - Complex model (deep HPM)
- Numerous applications

2 Implications

- Sample efficient experiments
- Scale of experiments means more data
- Virtually prototype smart workstations
  - DAQ
  - Intelligence/adaption



Sample efficient VR can simulate human performance for manual assembly tasks.

2 Conclusion

Part 2: Sample efficient HITL simulation

Demonstrated the value of sample efficient DoE:

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- Emphasized dynamic schedulers ethical role in preserving operators' autonomy
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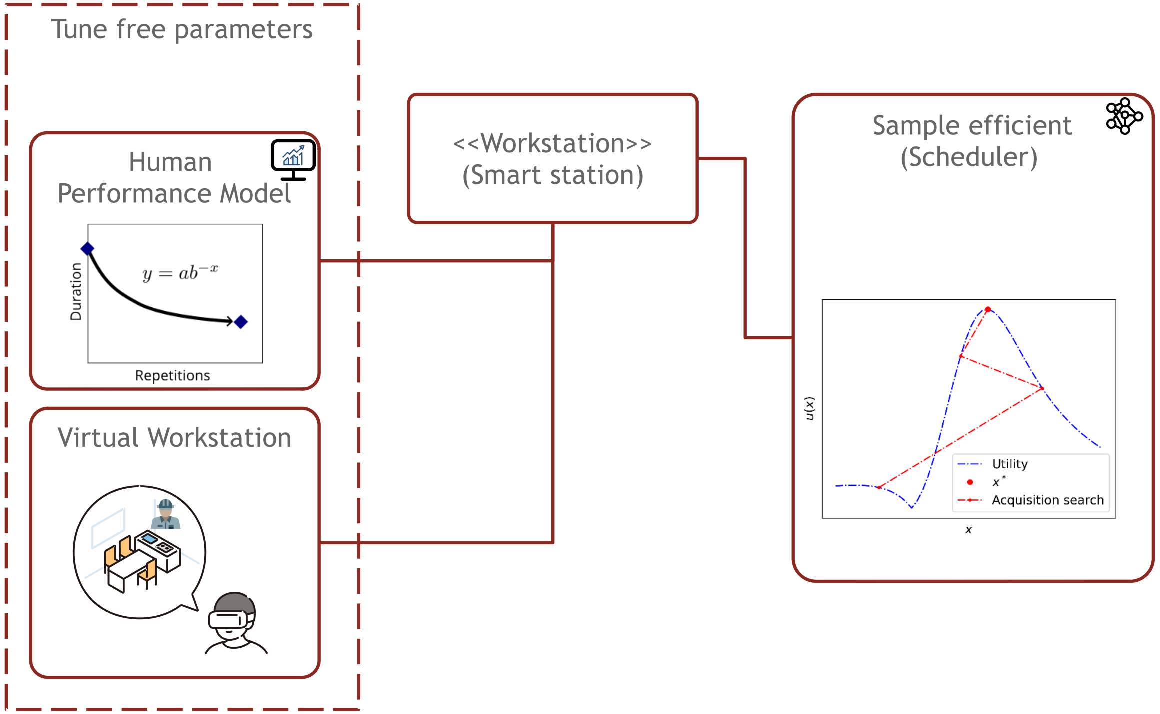


VR as efficient scalable experimental platform.

Overview of contributions 3

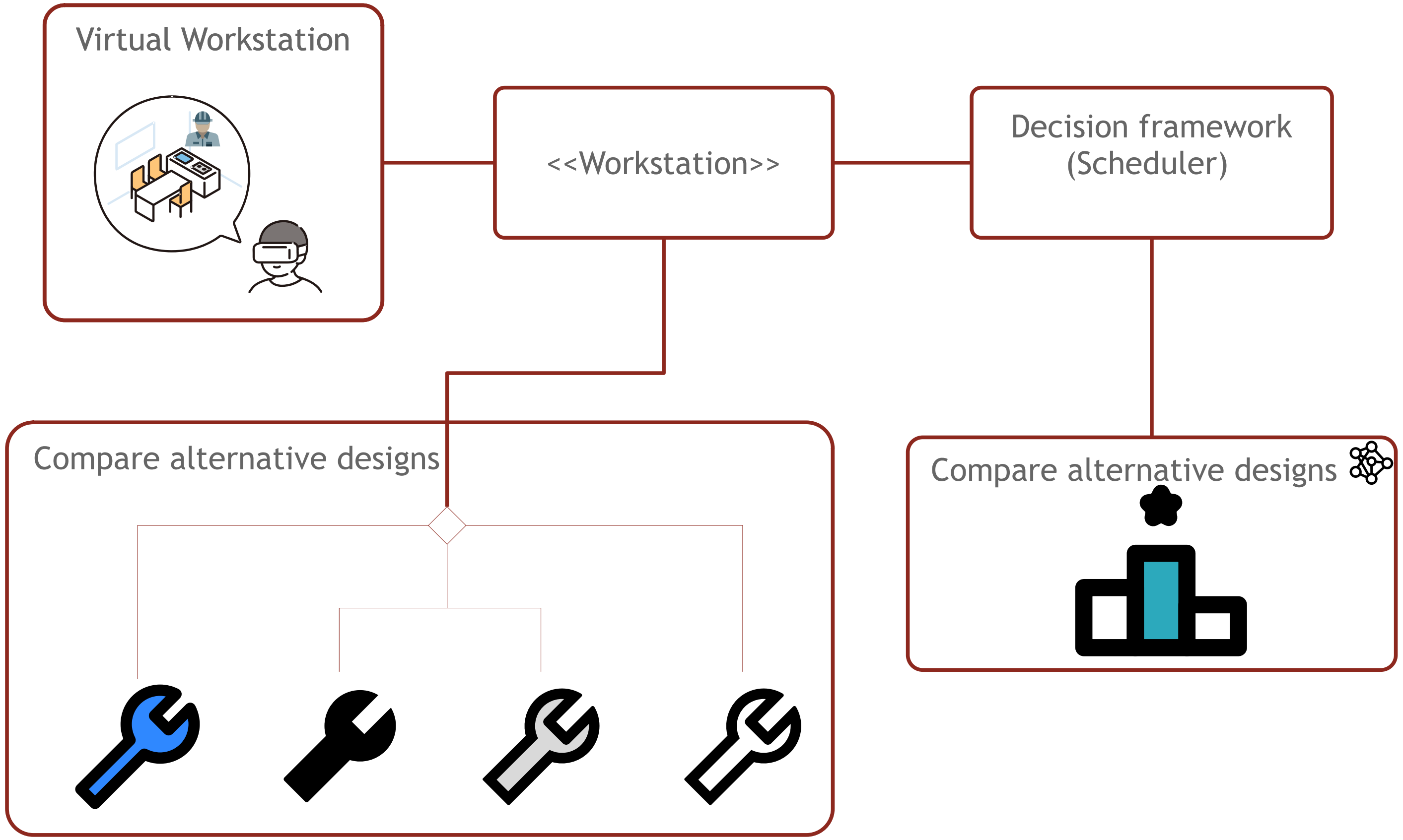
Part 3: Design for assembly decision framework

Design for manufacturing assembly demonstrative case study:

- Combine design by considering the assembly costs and printing costs
- Streamlines validating frameworks correlation between assembly time and assembly error
- Demonstrates practical application of the system to address modern challenges in assembly

[1] U. Auyeskhan, C. S. Alex, S. Park, D.-H. Kim, I. D. Jung, and N. Kim, ‘Virtual reality based assembly-level design for additive manufacturing decision framework involving human aspects of design’, Journal of Computational Design and Engineering, 2023

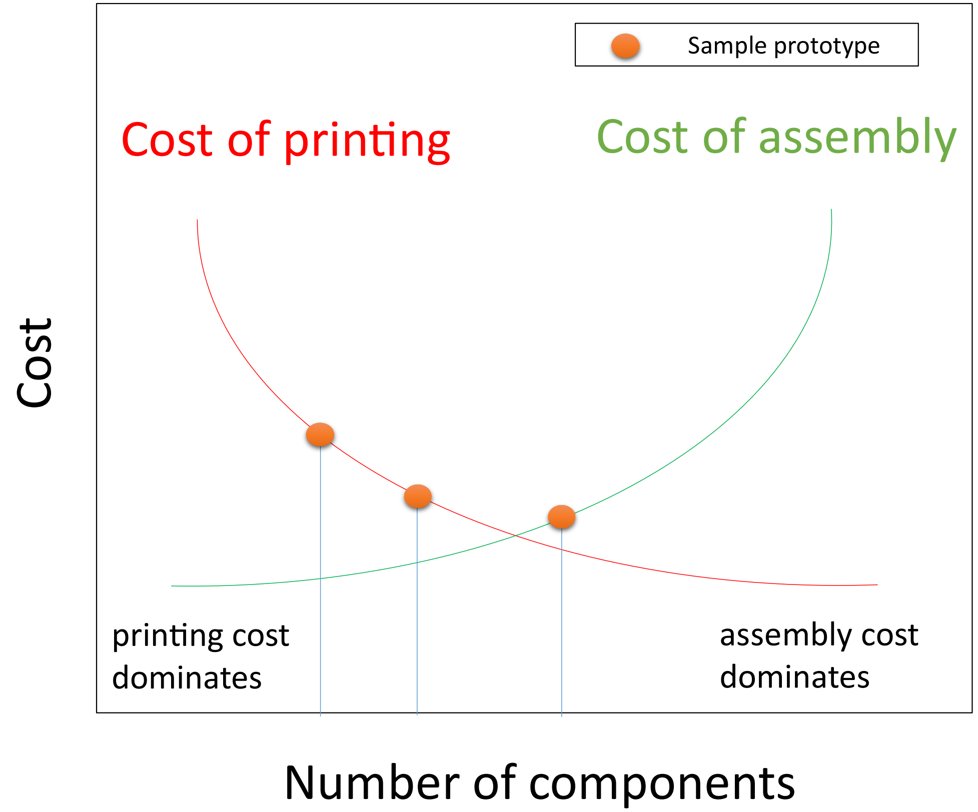
3 Objectives

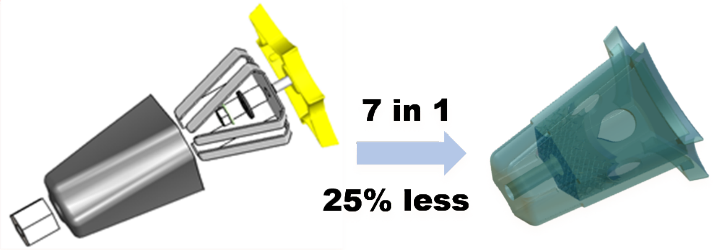


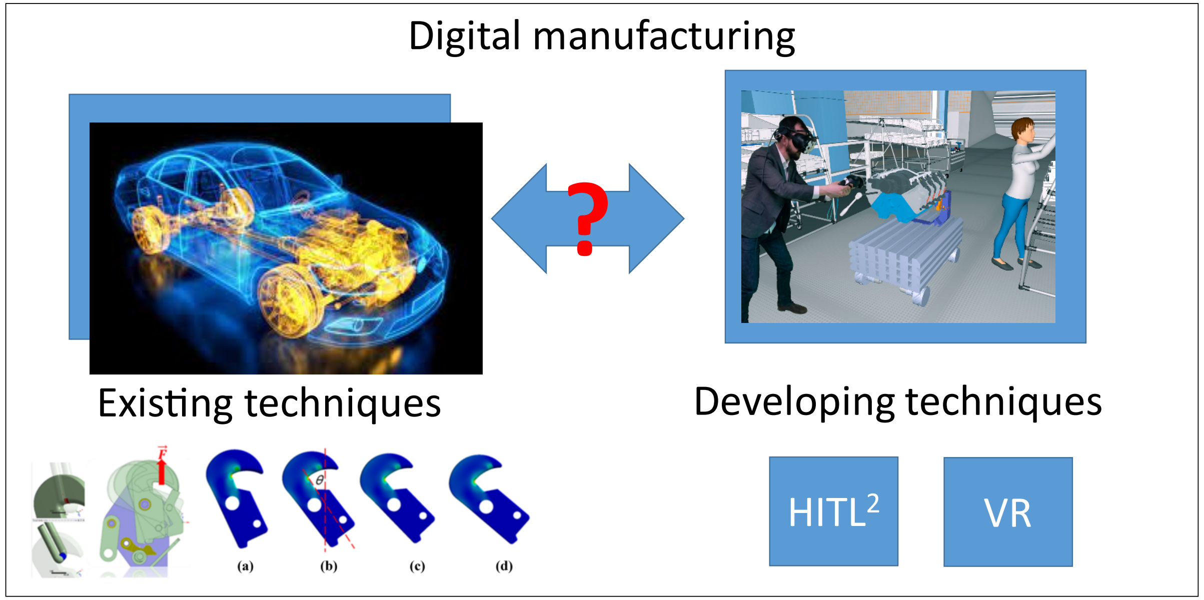
Can we use virtual workstations to compare assembly designs?

3 Background: Assembly vs printing and digital prototyping

As the number of consolidations increase, the assembly costs[1] decrease and the printing costs increase.



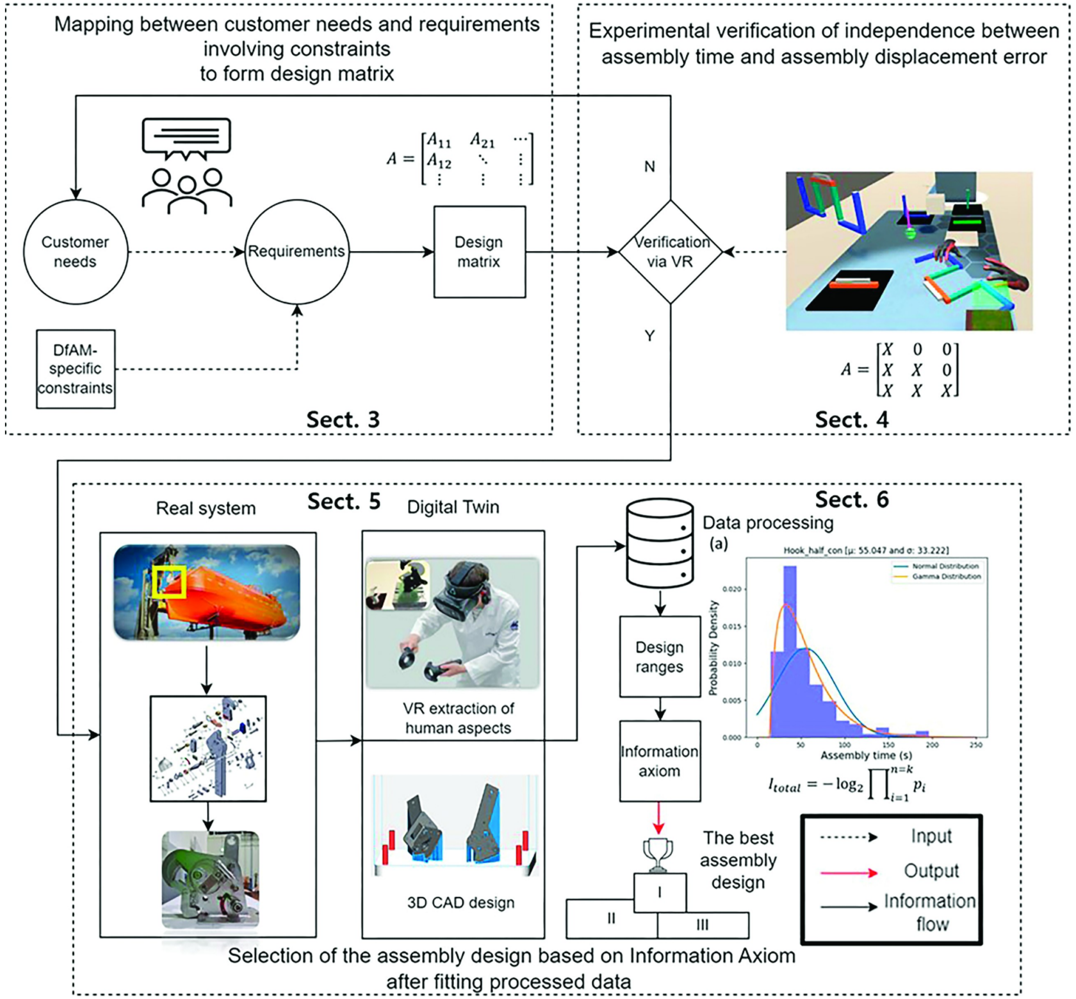




Law of part consolidation, balancing printing and assembly cost

Virtual assembly extends existing digital prototyping of product (and workstation)

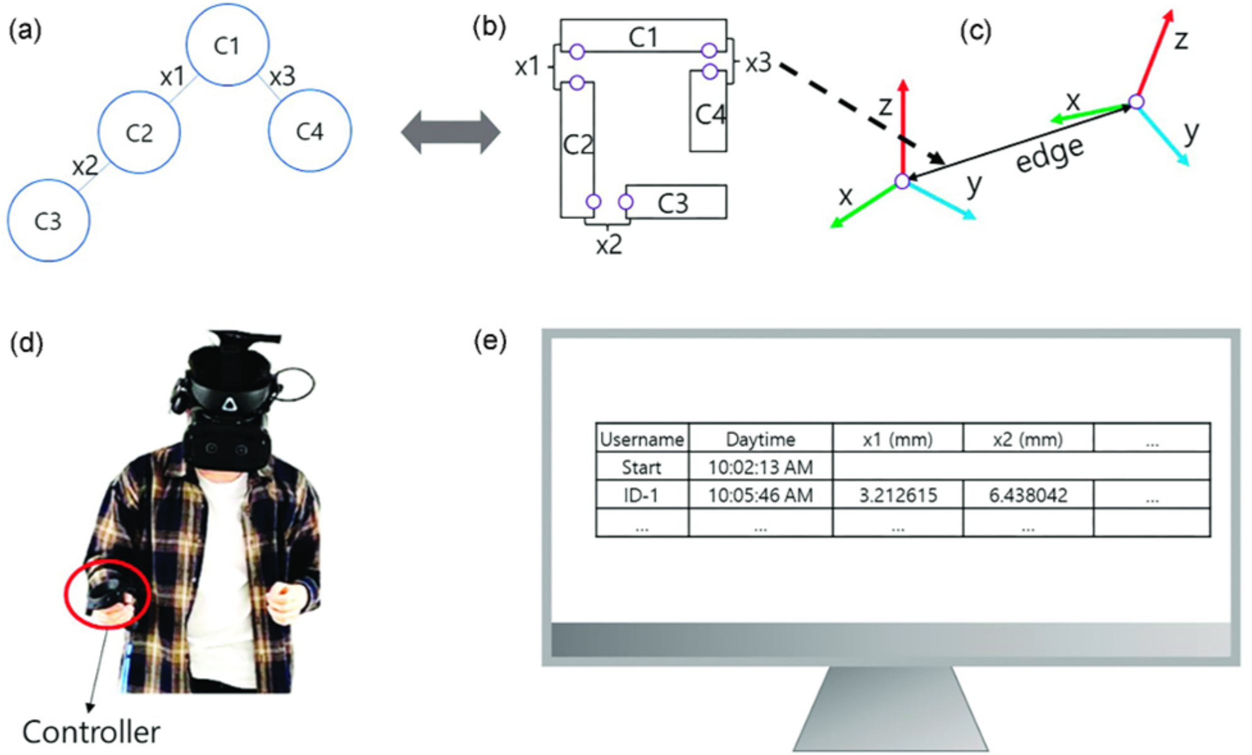
3 Background: Decision support problem



- Design methods for additive manufacturing [1-3]
  - Typically using expert intuition
  - Do not include manual assembly factors
- This work:
  - Simulates with virtual assembly
  - Quantified through simulation data
  - Real world lifeboat hook
  - Combine assembly and printing data
- Requirements, Verification, Virtual prototyping, Rank design

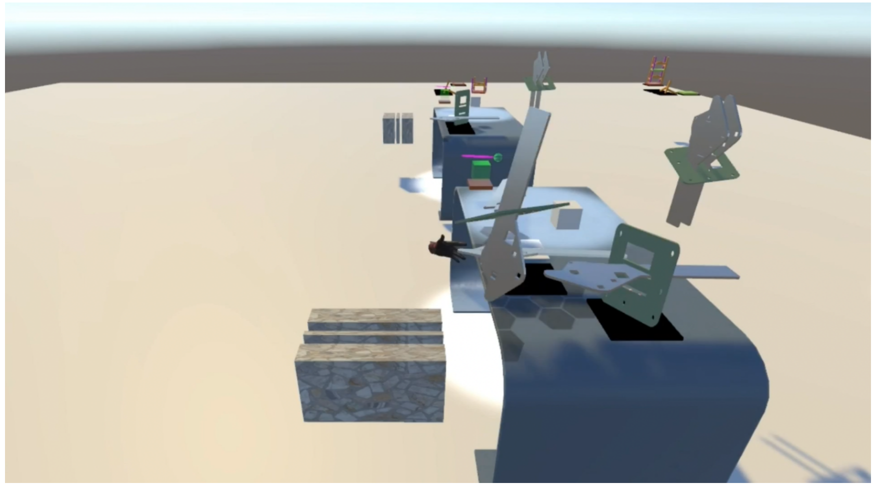
[1] P. Pradel, Z. Zhu, R. Bibb, and J. Moultrie, 'A framework for mapping design for additive manufacturing knowledge for industrial and product design', *Journal of Engineering Design,2018*
[2] K. Renjith, G. E. Okudan Kremer, and K. Park, 'A design framework for additive manufacturing through the synergistic use of axiomatic design theory and TRIZ', *IISE Annual Conference* , 2018
[3] K. Salonitis, 'Design for additive manufacturing based on the axiomatic design method', *Int J Adv Manuf Technol, 2016*

3 Theory: Independent error and time



Username	Daytime	x1 (mm)	x2 (mm)	...
Start	10:02:13 AM			
ID-1	10:05:46 AM	3.212615	6.438042	...
...	...	...	...	

Quantify assembly error through virtual assembly

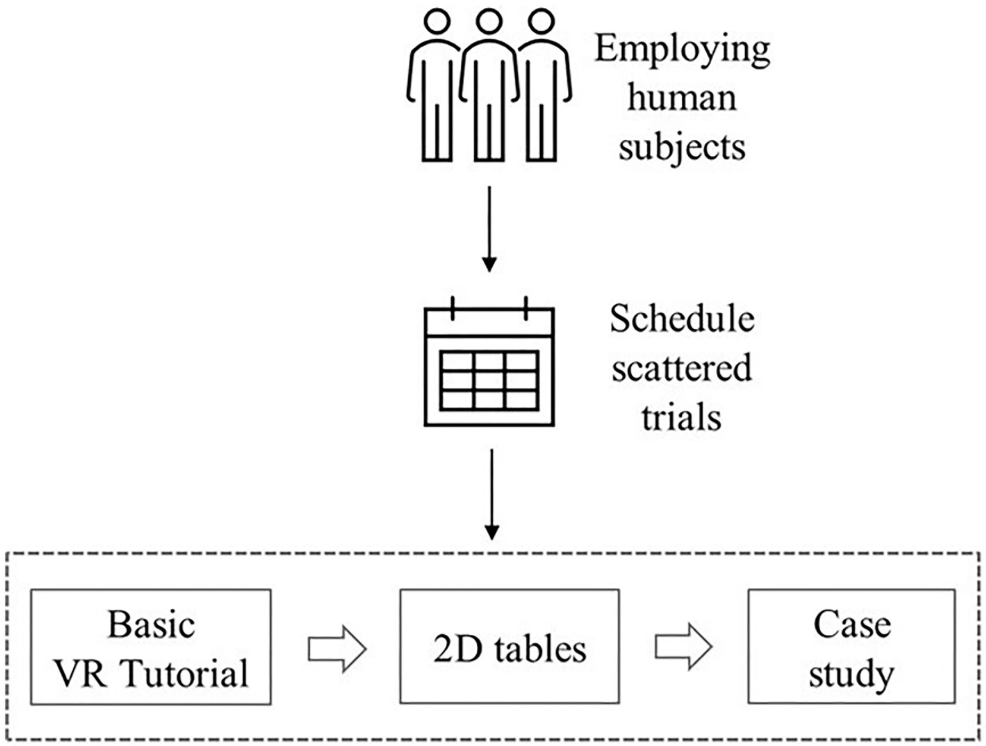


Assembly duration from VR

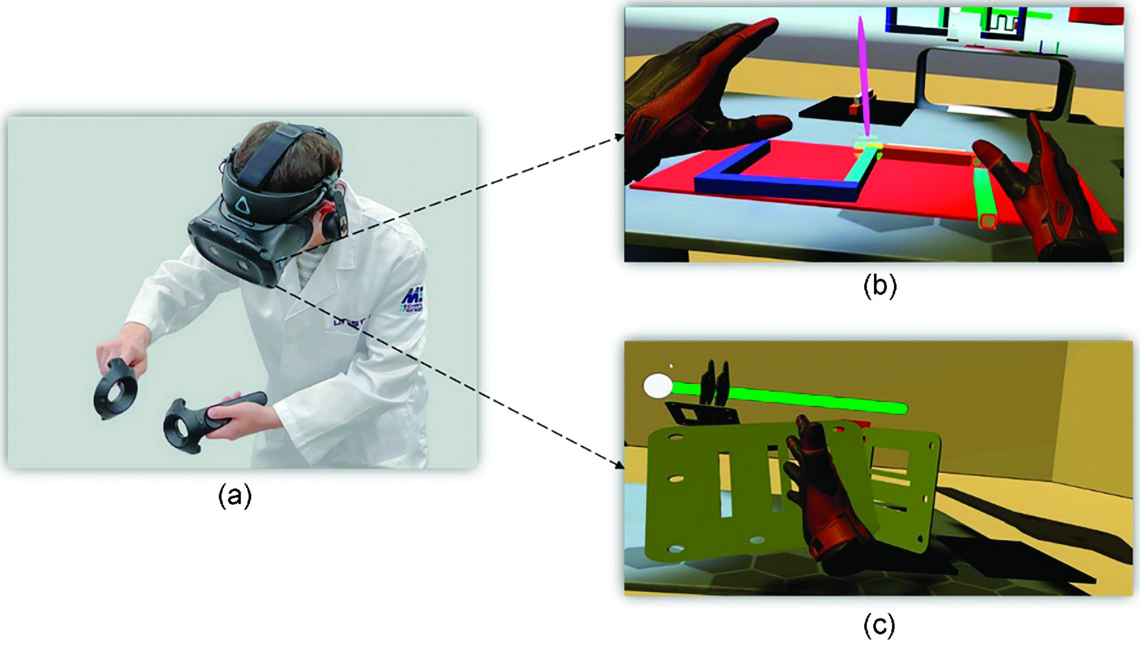
$$\mathrm{A} = \begin{bmatrix} X & 0 & 0 \\ X & X & 0 \\ X & X & X \end{bmatrix}$$

Independence between error and time

3 Experiment: Overview

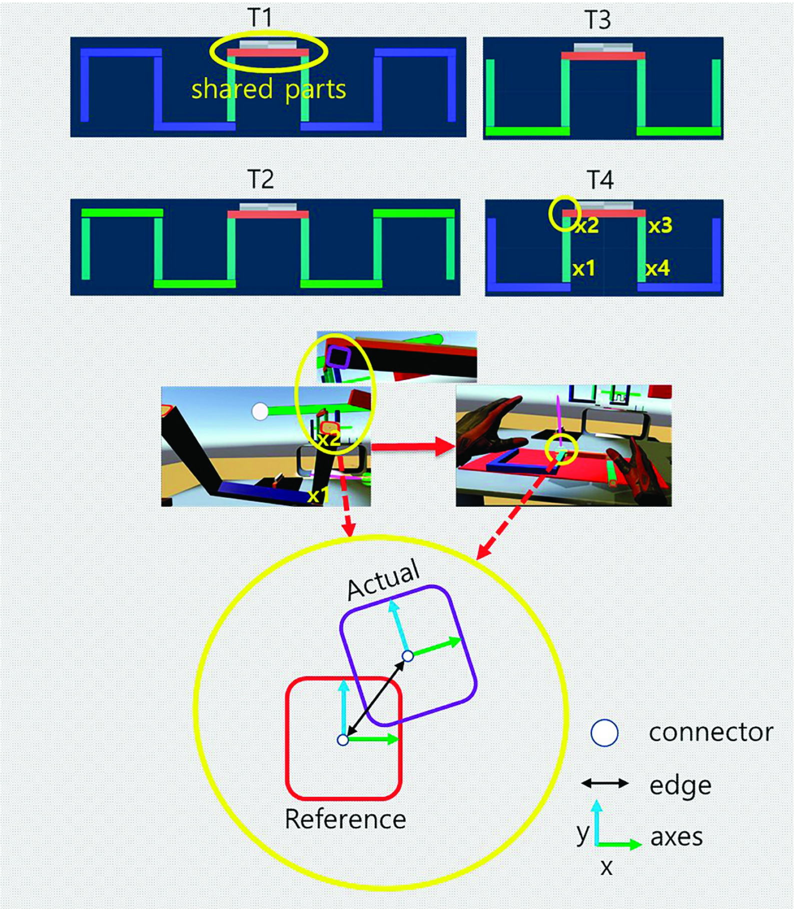


Two assembly simulations:
Simplified and case study



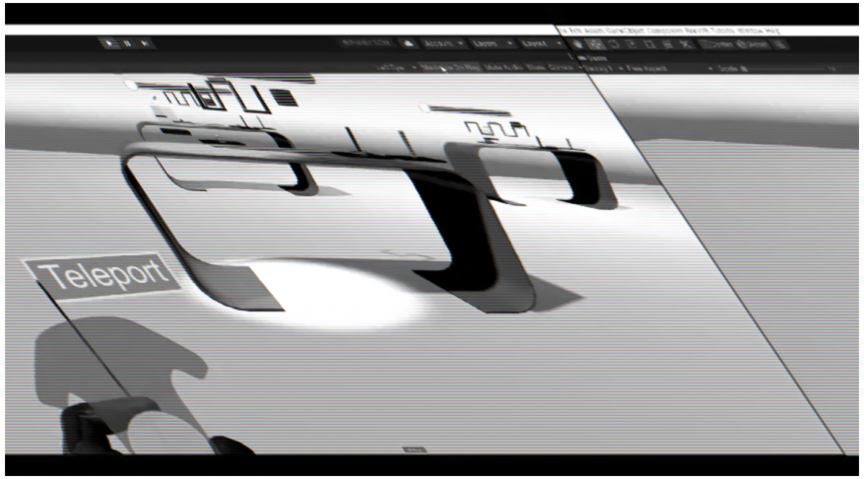
Simplified =decorrelation (b)
Case study = rank (c)

3 Experiment: Simplified 2D model

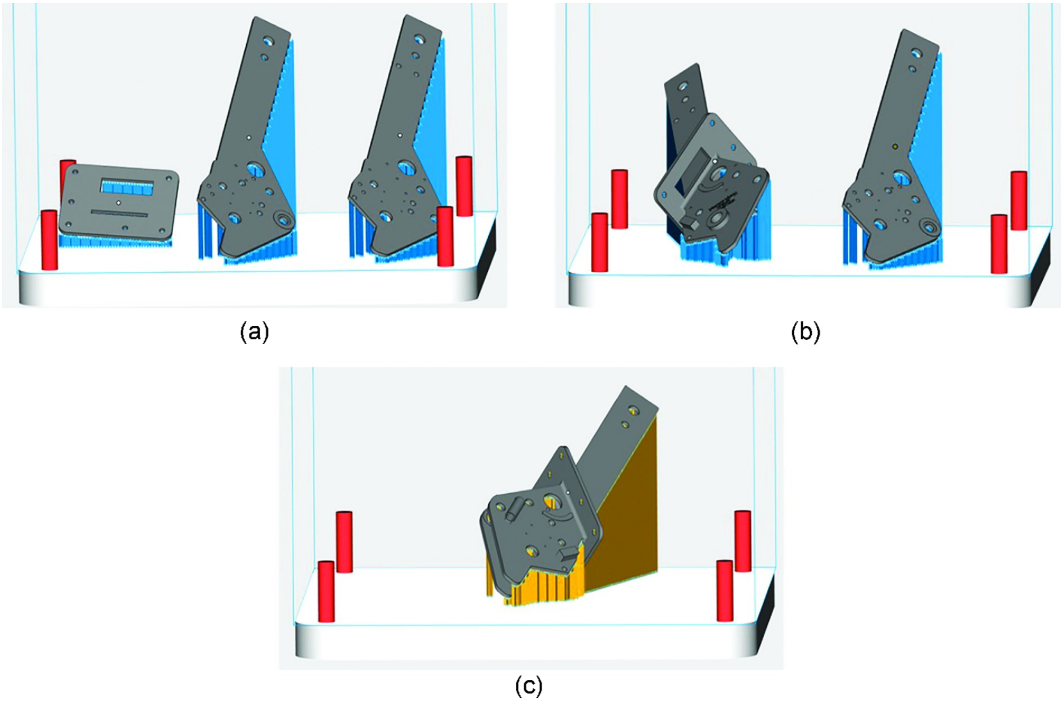


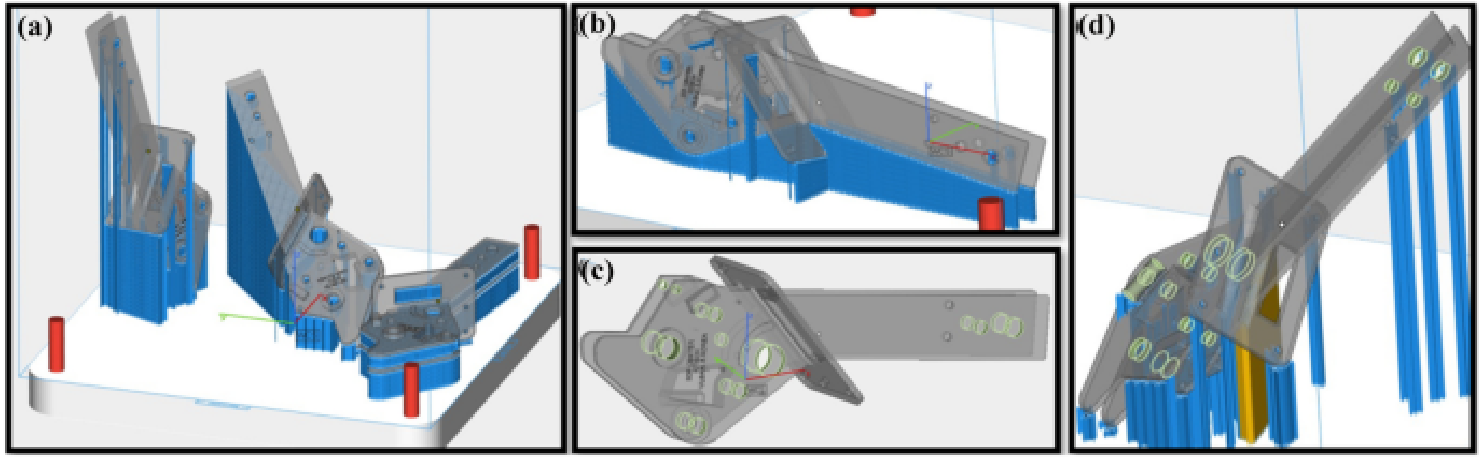
Simplified assembly simulation
with 4 variants (T1,T2,T3,T4)

- More data
  - More components
  - More variations
  - More Repetitions (less cognitive load)



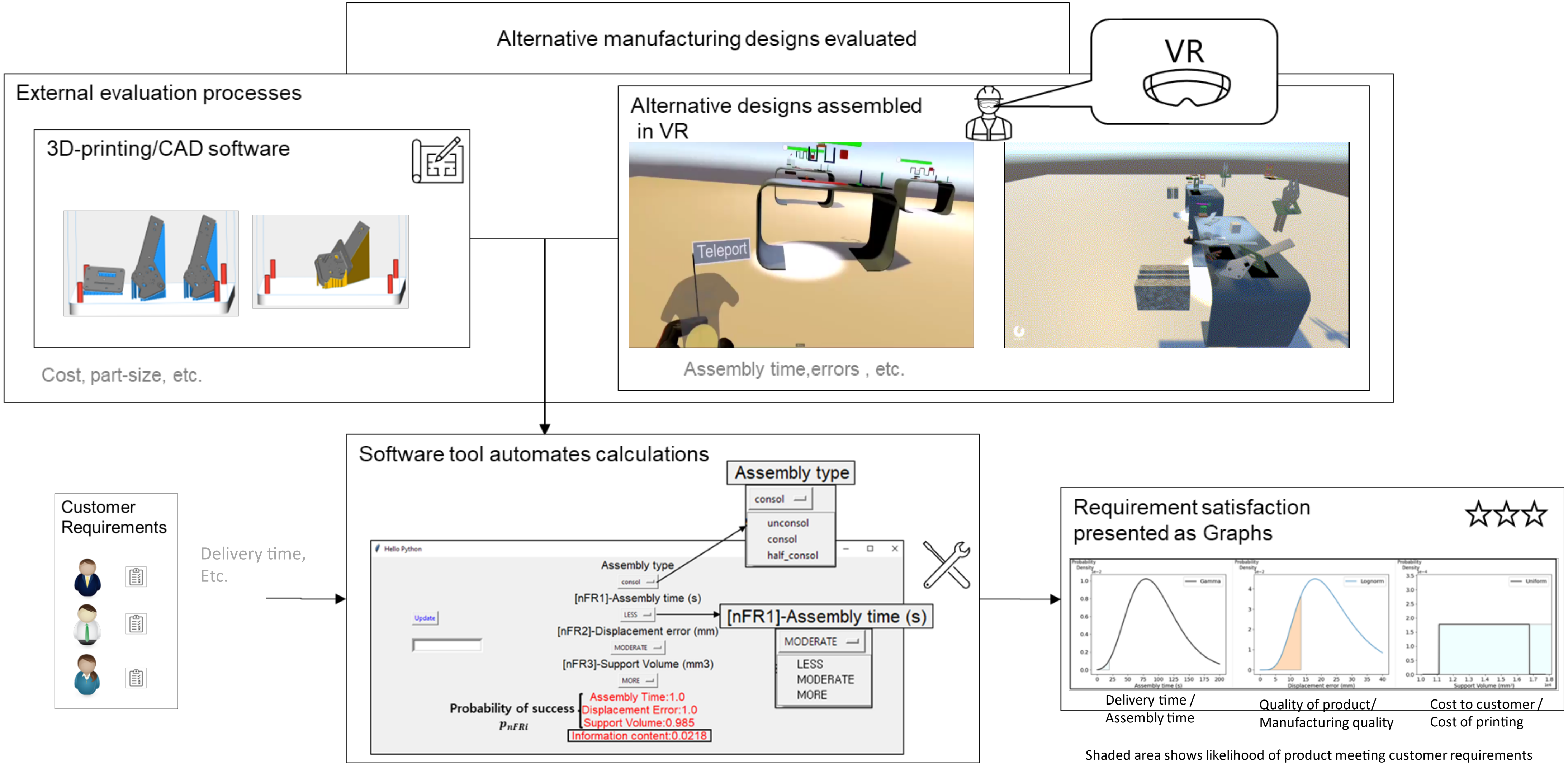
3 Experiment: Case study





- Simulate hook assembly
  - Three variants
    - a) unconsolidated
    - b) half-consolidated
    - c) consolidated
  - More components
- Simulate hook print
  - Support material

3 Demonstration: Design selection

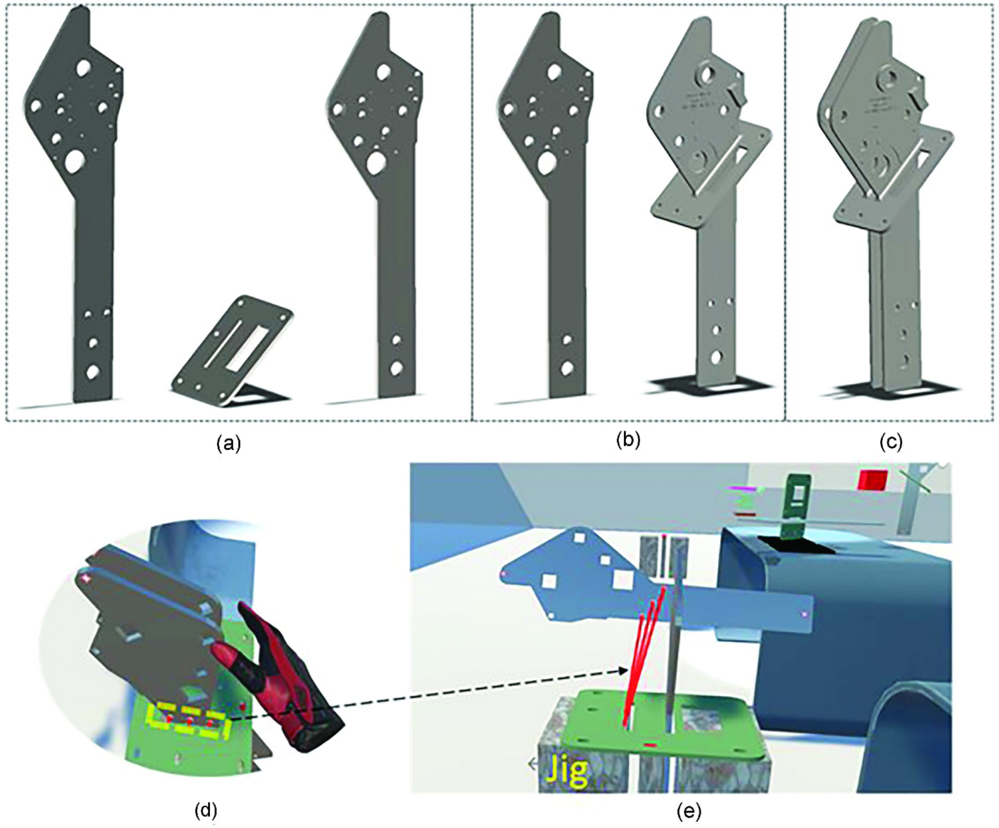


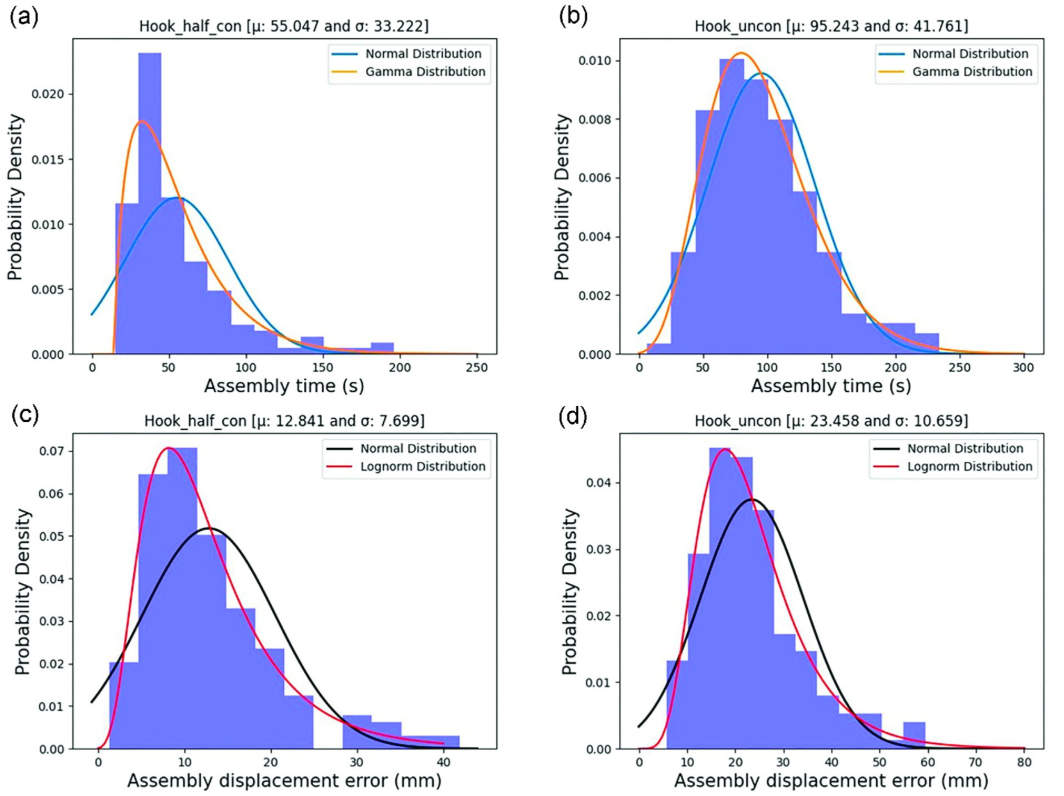
3 Results: Independence simulation

- Weak correlation
  - >0.12
  - Axiomatic assumption holds
  - Framework valid for this problem

2D tables	Assembly displacement errors (nFR2)										L1-norm of nFR2 versus nFR1
Assembly time (nFR1)	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	
T-1	−0.191	−0.120	0.134	−0.131	−0.061	−0.219					**−0.113**
T-2	−0.101	−0.143	−0.159	−0.0797	−0.016	−0.004	0.010	0.008	0.061	−0.067	**−0.042**
T-3	−0.149	−0.106	−0.2235	−0.075	−0.034	0.014					**−0.117**
T-4	−0.0957	−0.137	−0.075	−0.0398							**−0.109**

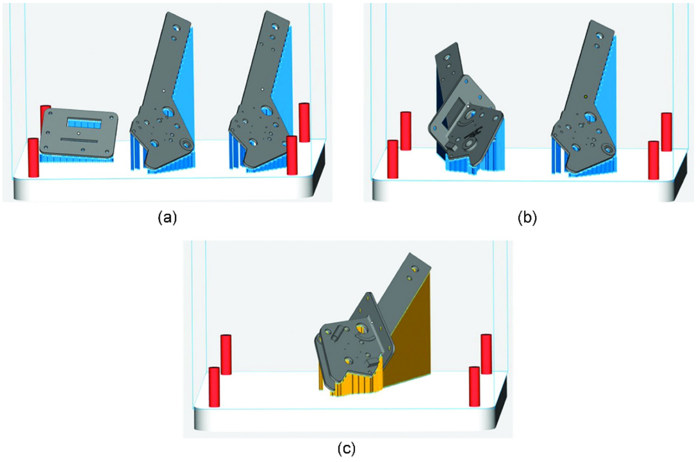
3 Results: Case study simulation



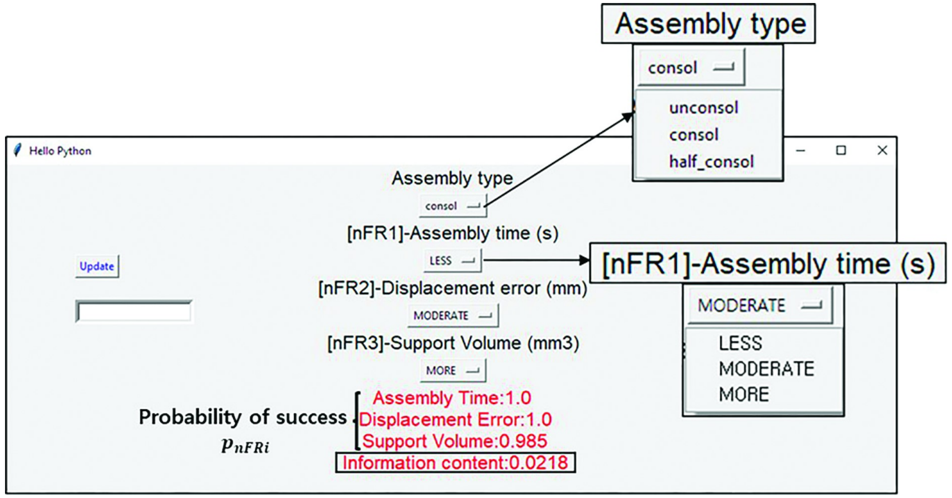


Statistical tests confirm error fits well, Duration less so

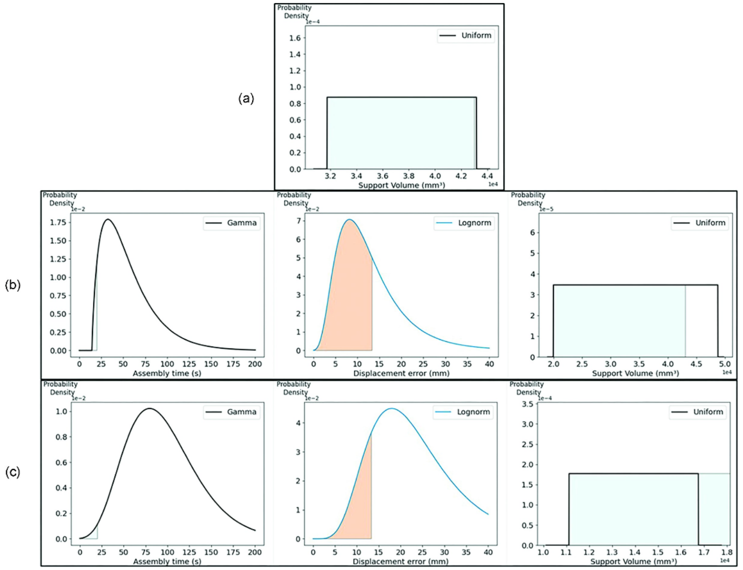
3 Results: Decision framework



Virtual prototyping



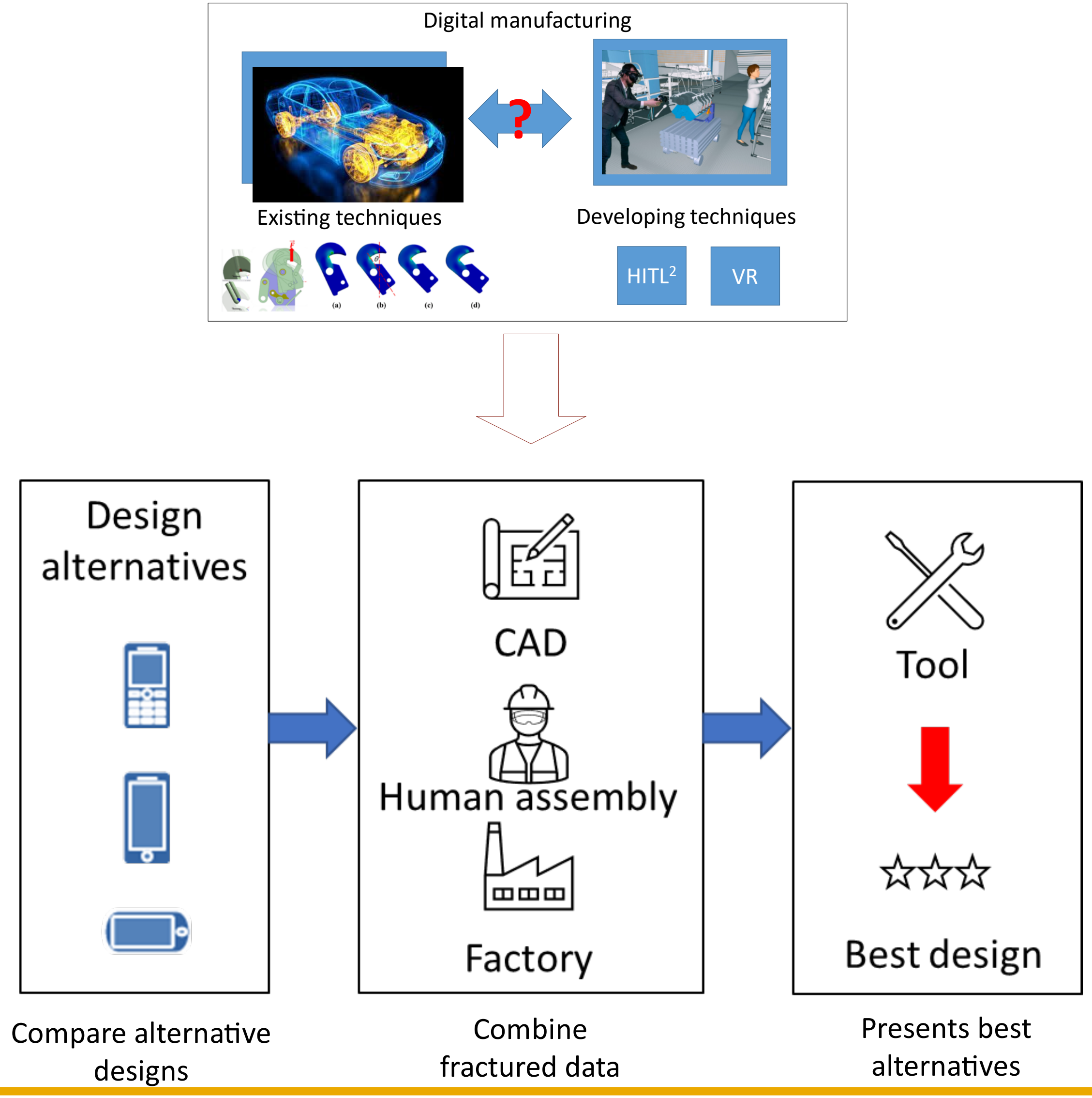
GUI Decision framework



Results where shaded area is likelihood of design meeting requirements

	Unconsol	Half-consol	Consol
***pnFR*1**	0.0078	0.0409	1
***pnFR*2**	0.15	0.6257	1
***pnFR*3**	1.0	0.8001	0.985
Itotal	9.7312	5.6104	0.0218

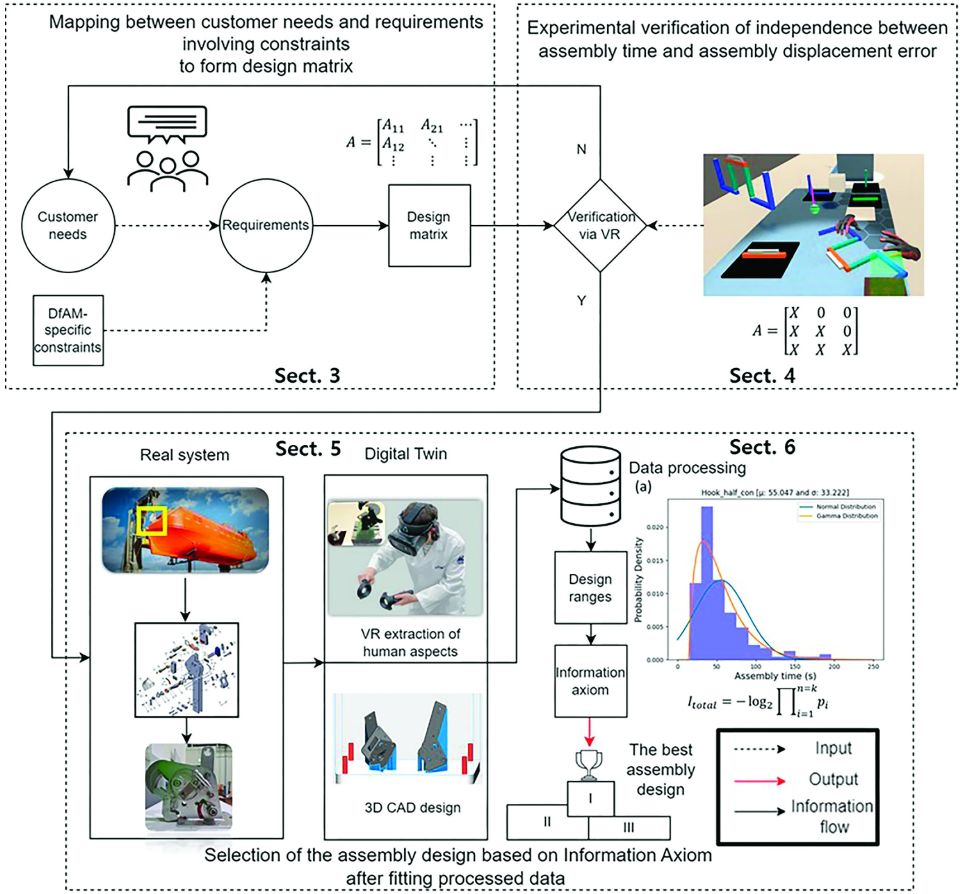
3 Application: Digital Decision framework



- Digital prototype
  - Additive design & assembly
  - Product and (human) process
- Comparison in other domains
  - This: Part consolidation for AM
  - New tool, technology, process
- Human-centric (manufacturing)?
  - Independence verification

3 Implications

- Demonstration on modern problem
- Holistic Digital prototyping
  - Workstation
  - Design alternative (product)
  - Human operator



VR manufacturing simulation incorporates environment, product, and operator.

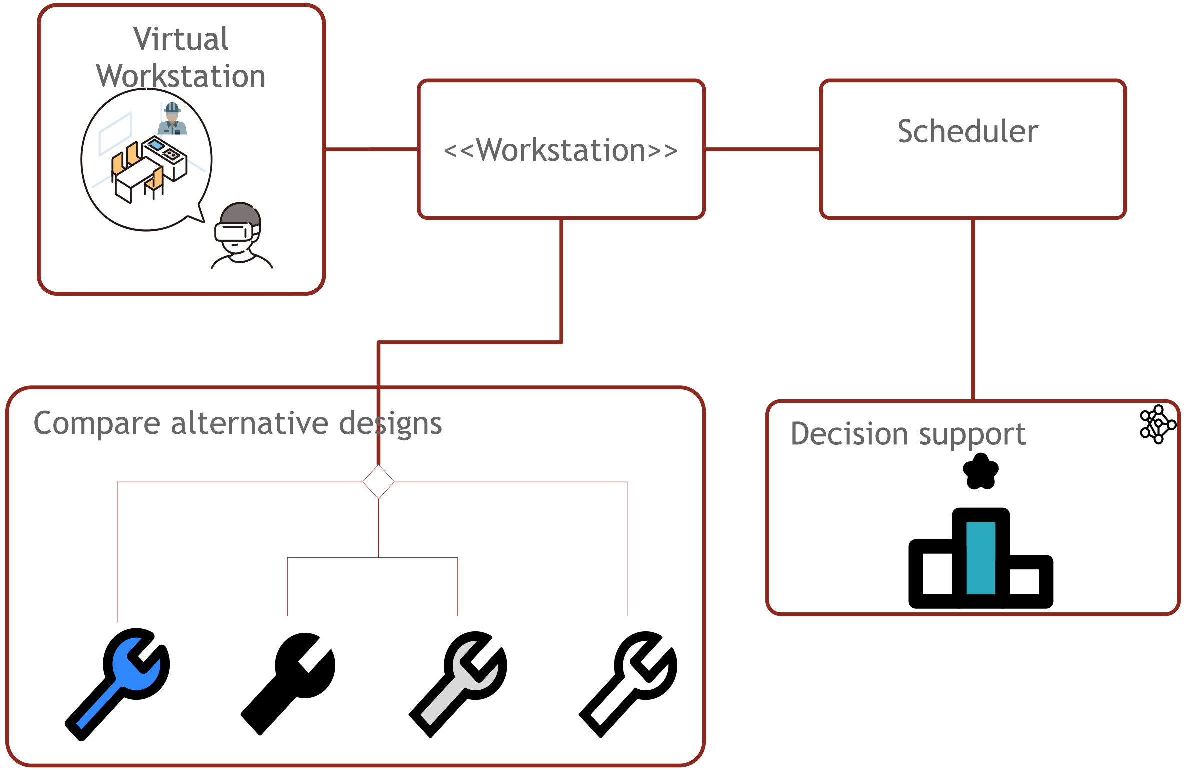
Overview of contributions 3

Part 3: Design for assembly decision framework

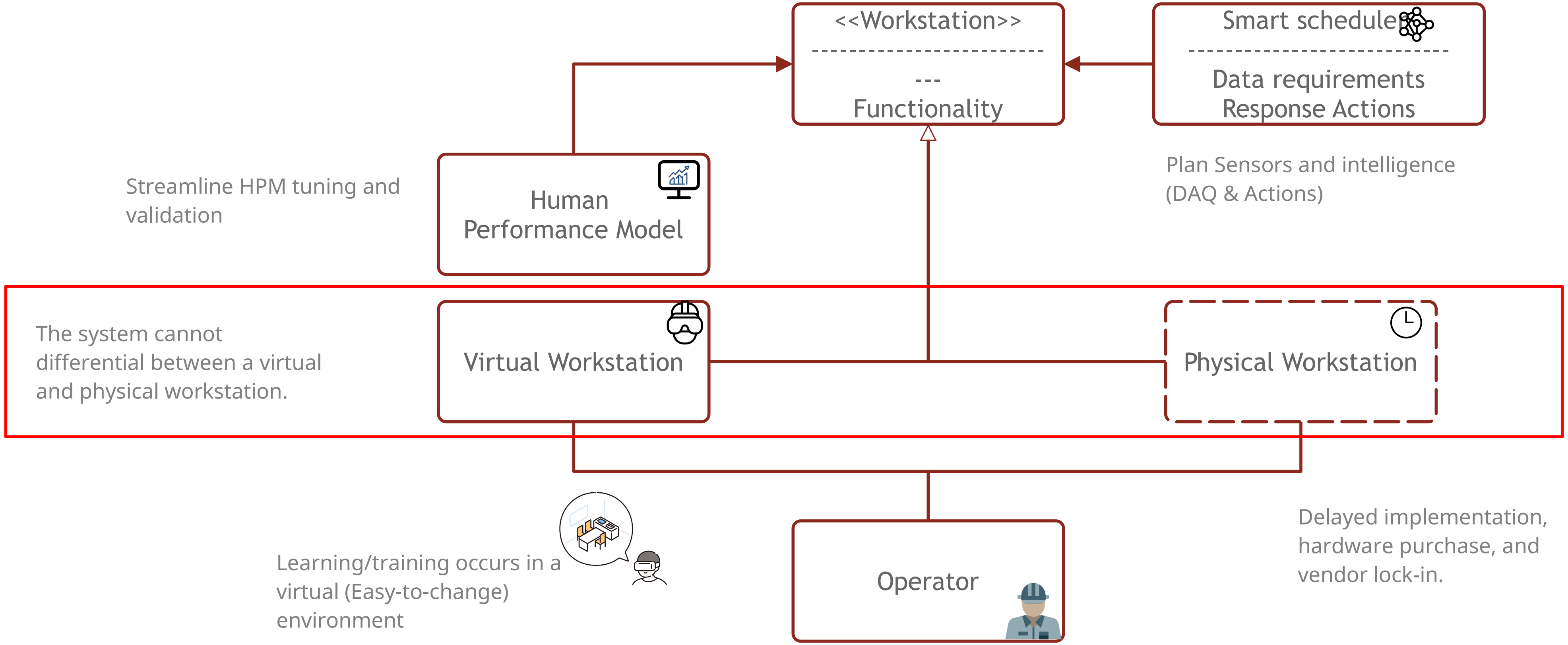
Design for manufacturing assembly demonstrative case study:

- Combine design by considering the assembly costs and printing costs
- Streamlines validating frameworks correlation between assembly time and assembly error
- Demonstrates practical application of the system to address modern challenges in assembly

[1] U. Auyeskhan, C. S. Alex, S. Park, D.-H. Kim, I. D. Jung, and N. Kim, ‘Virtual reality based assembly-level design for additive manufacturing decision framework involving human aspects of design’, Journal of Computational Design and Engineering, 2023



4 Digital mocking design pattern



VR enables a human-centric digital twin.

4 Future work:Empathetic control

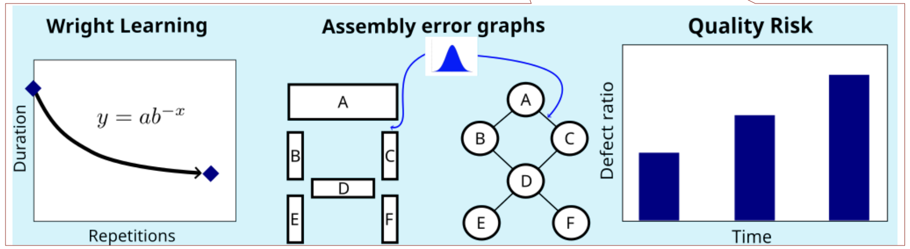
1) HP non-invasive sensors
2) Emotion state from HPM
3) Scheduler control
4) Workstation performance

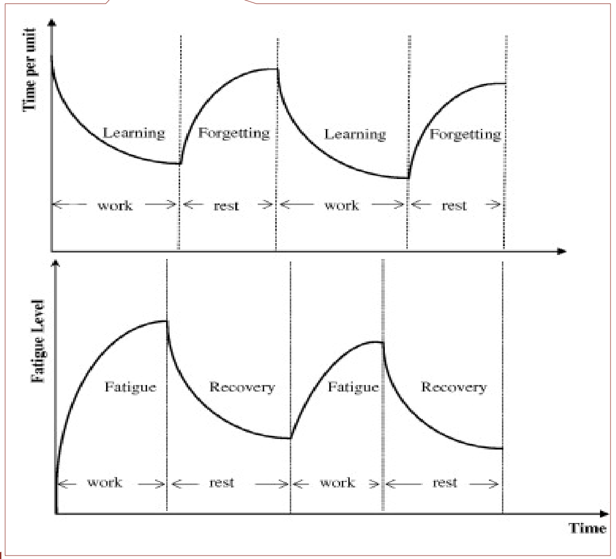
Sensor as workstation performance

Observer (Human internal state)

Observe human internal state:
- Fatigue
- Learning

Scheduler as controller

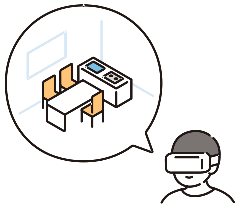




Scheduler actions:
- Work,
- Rest,
- End

HPM as non-invasive sensors:
- Task duration
- Quality risk
- Assembly error

System as workstation



Cybernetic control of human internal state via dynamic scheduling.

Summary: Virtual validation

- Objective: Validate virtual workstation as a **substitute for physical workstation**.
- Methodology: Tested through various **assembly tasks of different complexities**.
- Findings: Confirmed ability to simulate existing models and quantify measures practically unmeasurable in the physical world.
- Significance: Demonstrates potential for studying **existing and** uncovering **novel** insights.

Summary: Sample Efficient Human in the Loop Simulation

- Importance of Scheduler: Highlights the role of an **intelligent scheduler** in the context of Wright learning model.
- Development: Introduces a **sample-efficient scheduler** as a Design of Experiments (DoE) module.
- Autonomy and Empathy: Emphasizes preserving operators' autonomy and considering emotional states for empathetic HITL labor.
- Scale Increase: Addresses a limitation by significantly increasing the **scale of** acquired experimental **data** for enhanced HITL model tuning feasibility.

Summary: Assembly Design Decision Support Framework

- Practical Application: **Demonstrates** the application of the system for contemporary **challenges** in assembly design.
- Streamlining: Streamlines assembly design selection considering both **printing costs** and **manual assembly** expenses.
- Integration: Integrates Human Performance Model (HPM), scheduler, and Axiomatic design for comprehensive analysis.
- Validation: **Validates** assumptions regarding the correlation between **assembly time and error**, modeling them as gamma and log-normal distributions.

Summary: Overall Contributions

- Feasibility of Continuous Improvement: Shows the feasibility of **continuous improvement** of workstations through **digital prototyping**.
- Challenges in Additive Manufacturing: Addresses challenges in **additive manufacturing** design decisions through HITL simulation and **decision support**.
- Human-Centric Workstation: Underscores the importance of a human-centric workstation **component** for **validating assumptions, tuning models, incorporating external information, and simulating changes** for enhanced decision-making.

Summary: Conclusion

- Summary: Contributions encompass advancements in virtual validation, efficient human-in-the-loop simulation, and a practical decision support framework for assembly design.
- Pattern's Potential: Showcases the potential of the proposed pattern in addressing real-world challenges in human-centric systems.

Outputs: Conference

- C. A. Steed and N. Kim, ‘Investigating the relationship between production quality and human fatigue’, in International Federation of Operational Research Societies (IFORS 2021), 2021.
- C. A. Steed and N. Kim, ‘Unsupervised hidden state estimation as blind source separation using Auto-encoder RNN filter’, in 15th International Conference on Advanced Computational Intelligence, 2023.

Outputs: Journal

- C. A. Steed and N. Kim, ‘Complex human performance data acquisition from virtual manufacturing assembly simulations’, Advanced Engineering Informatics, **Under-review**
- C. A. Steed and N. Kim, ‘Deep active-learning based model-synchronization of digital manufacturing stations using human-in-the-loop simulation’, Journal of Manufacturing Systems, 2023.
- U. Auyeskhan, C. S. Alex, S. Park, D.-H. Kim, I. D. Jung, and N. Kim, ‘Virtual reality based assembly-level design for additive manufacturing decision framework involving human aspects of design’, Journal of Computational Design and Engineering, 2023

Outputs: Patent

- N. Kim, C. A. Steed, S. Park, and Y. H. Park, 'A Simulation Method and System Using A Real-Time Agent Status Linkage', KR 10-2022-0035101 → PCT
- N. Kim, C. A. Steed, A. Ulanbek, S. Park, and Y. H. Park, 'Decision-making System for Manufacturing Design', KR 10-2022-0089360 → PCT

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Thank you
Enkosi
Dankie

Photo by Stefan Els