

# Journal Club

Article

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# An automatic end-to-end chemical synthesis development platform powered by large language models

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## Content



- 1. Background for Research
- 2. LLM-RDF

3. Conclusion and Methods



# 1. Background for Research



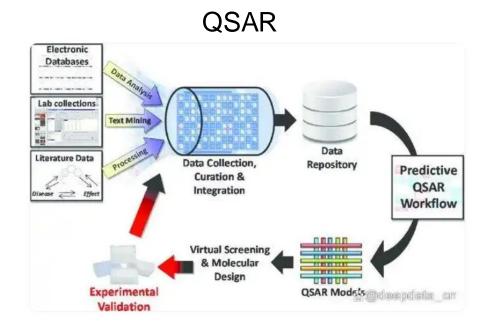
## **Importance**

#### synthesis reaction design for drug discovery and chemical process

relies on expert chemists, requires time and cost



#### machine learning accelerate the development

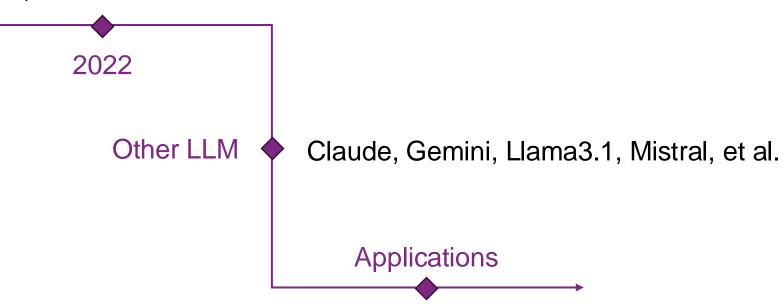


translation of multistep synthesis procedures from literature to experimental execution via natural language processing (NLP) models



#### Research Progress

OpenAl released the large language model (LLM) based ChatGPT



literature mining, molecule and material discovery, reaction condition recommendation, optimization and lab apparatus automation.



## Deficiencies and Challenges

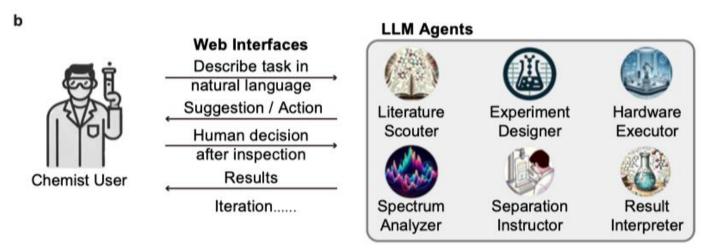
#### Fragmented coverage of the synthesis development stages

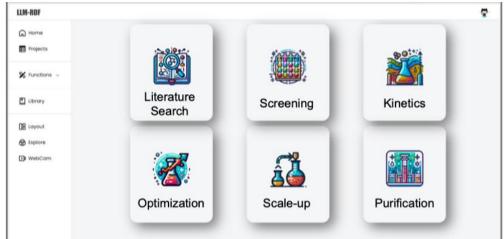
#### Fail to achieve fully autonomous end-to-end design

Task	Lit. Search	Screening	Kinetics	Optimization	Scale-up	Purification	Product
	LLMs Involved	I					
							Refs 26, 27
							Refs 40-41
							Refs 28, 29
							This Work



#### This Work





Cu/TEMPO catalyzed aerobic alcohol oxidation

# LLM-based reaction development framework

- GPT-4 based
- Pre-training
- No coding
- External tools available
- Human-machine cooperation



## 2. LLM-RDF

literature-oriented





#### Literature Search and Information Extraction!

#### Literature Search

**User:** Search for methods that can use air oxidation of primary alcohols into aldehydes and provide references.

Answer: Here are some notable methods (literatures):

- 1. Sustainable catalytic oxidation of alcohols over the interface between air and water<sup>49</sup>.
- 2. Highly practical copper(I)/TEMPO catalyst system for chemoselective aerobic oxidation of primary alcohols<sup>48</sup>.
- 3. Pd(II)-hydrotalcite-catalyzed oxidation of alcohols to aldehydes and ketones using atmospheric pressure of air<sup>50</sup>.
- 4. Photochemical oxidation of benzylic primary and secondary alcohols utilizing air as the oxidant<sup>51</sup>.

#### Results Analysis

**User:** Which method has the best potential for practical applications?

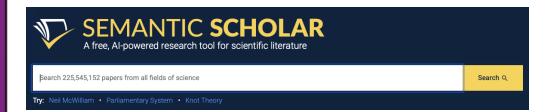
Answer: Among the methods discussed, method 2 stands out for ease of catalyst preparation, use of ambient air as oxidant, compatibility with various alcohols, operational simplicity, and chemoselectivity.

#### Information Extraction

**User:** Extract the procedure and design space from the uploaded literature document.

Answer: Procedure: To a solution of alcohol in CH<sub>3</sub>CN in a tube was added (1) CuOTf, (2) bpy, (3) TEMPO, and (4) NMI. Design Space: Cu Salts: Cu(OTf), CuBr, Cu(OTf)<sub>2</sub>, CuBr<sub>2</sub>, Bases:

NMI, DBU, Time:1, 6, 24 hours.



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## Substrate Scope and Condition Screening

First-principle theories hard to predict yield

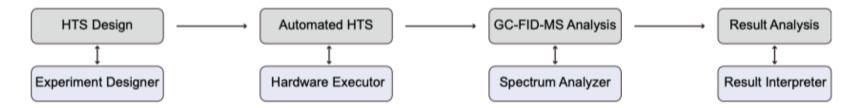
Machine learning based methods need amount of experimental data

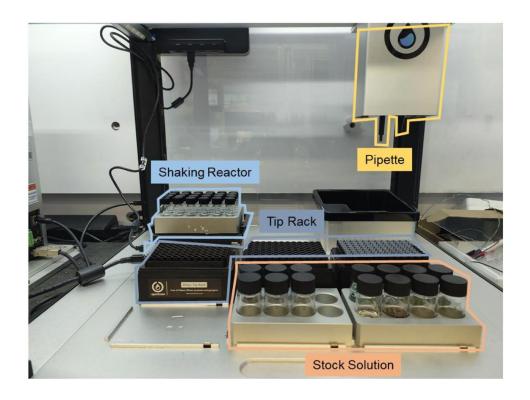
High-throughput screening need programming, manual analysis and expensive

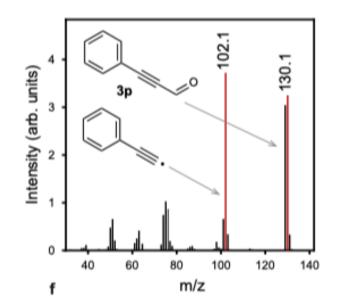
It uses **microplates** as the carrier for experimental tools, an **automated operating system** to execute the experimental process, a sensitive and rapid **detection instrument** to collect experimental result data, and a **computer to analyze** and process the experimental data.

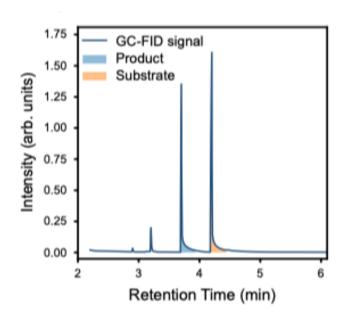


## Substrate Scope and Condition Screening



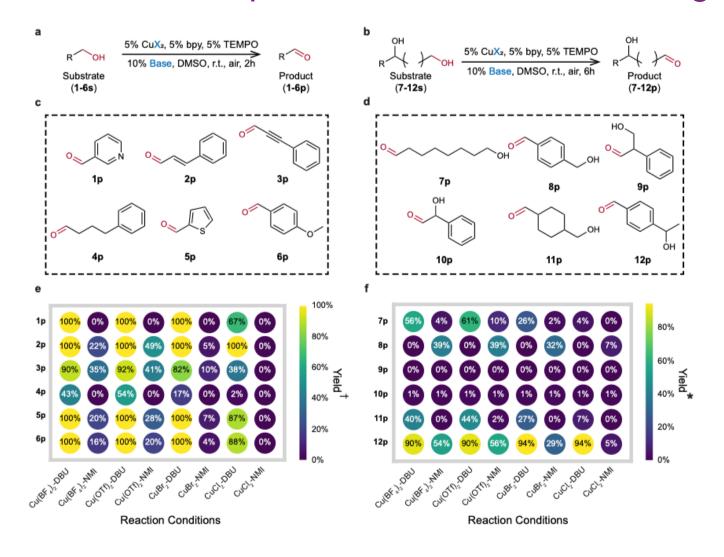






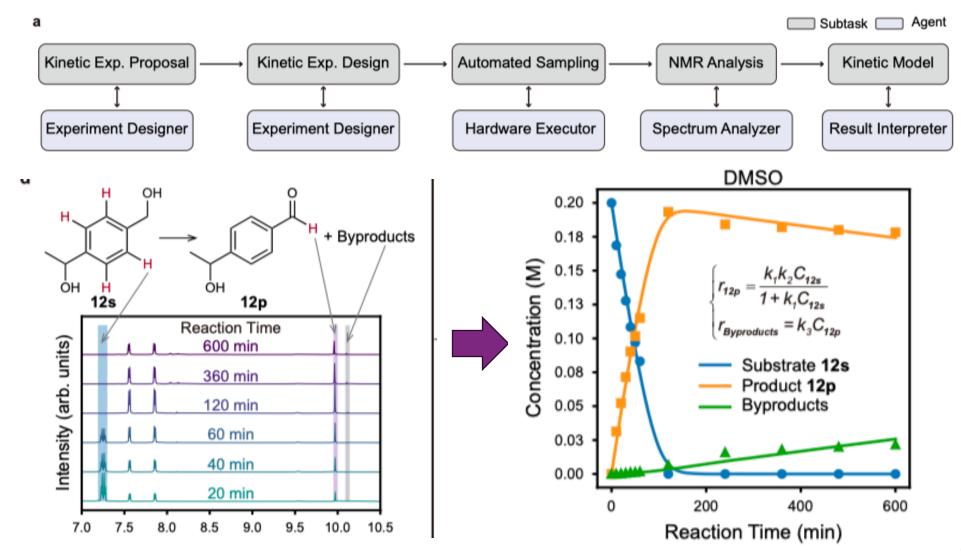


### Substrate Scope and Condition Screening





#### Reaction Kinetics Study







Iteration

## Reaction Condition Optimization!

#### **Bayesian Optimization**

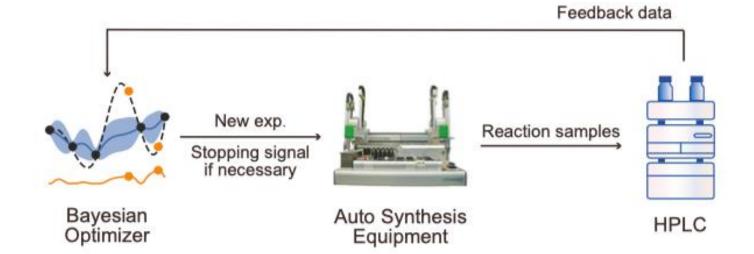
- An efficient global optimization algorithm
- Suitable for the "black-box function"

Surrogate Model - eg. Gaussian process

fit experimental data
predict the results

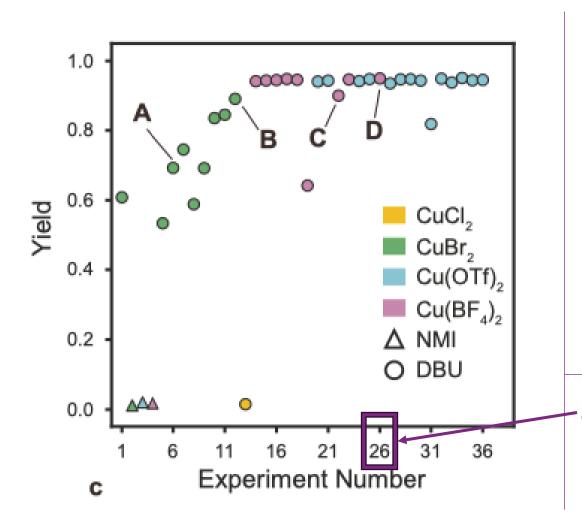
Acquisition Function — eg. expected improvement

select most worthy condition to be tested

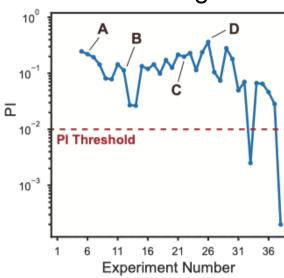




#### **Reaction Condition Optimization**



Use probability of improvement and LLM to terminate the BO algorithm.



D: 26th Experiment

The recommendation is to terminate optimization because high yields have been achieved, and a wide range of conditional spaces have been explored.





#### Reaction Scale-up and Product Purification

#### **Scale-up reaction**

#### **Choose Condition**

**User:** Select the best condition, considering cost, efficiency for large-scale production.

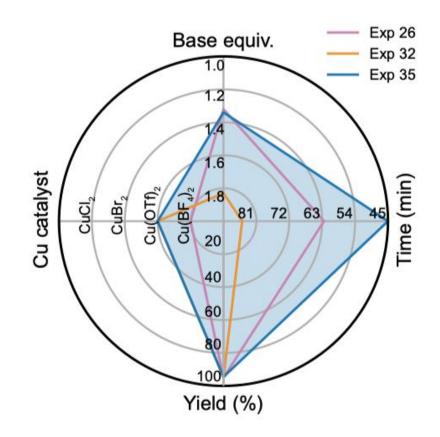
**Answer:** To select the optimal experimental condition, numerical scoring was applied to reaction time, base equivalence, and catalyst cost (CuCl<sub>2</sub> < CuBr<sub>2</sub> < Cu(OTf)<sub>2</sub> < Cu(BF<sub>4</sub>)<sub>2</sub>), with lower values preferred. Each parameter was normalized to a 0-1 scale. The 35th experiment was chosen from among those with high yields, as it had the highest average score across the evaluated parameters. The right radar chart highlighted that the experiment 35 had the largest area, reflecting superior performance across the evaluated criteria.

#### Scale-up Design\*

User: Design a scale-up strategy for the gas-liquid biphasic aerobic alcohol oxidation reaction, currently at 7.5 mg in 1.25 mL reaction mixture.

Answer: The core of scaling up this reaction is ensuring efficient gas-liquid contact for effective oxygen transfer. Propose a two-stage scale-up:

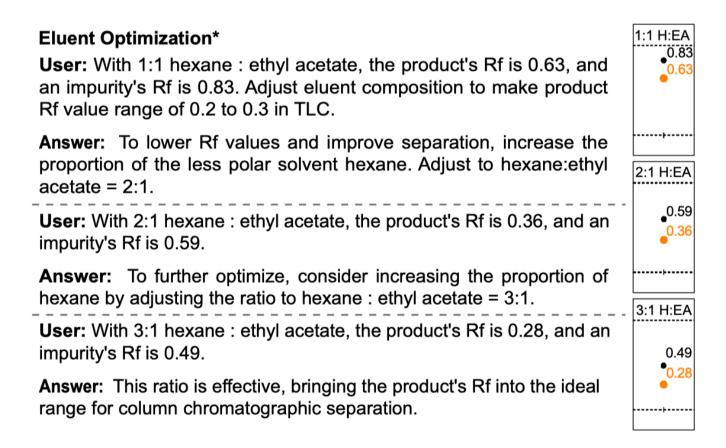
- 1 g scale to validate reproducibility: Reactor: 250 mL round-bottom flask; Mass transfer: Mechanical stirring; Oxygen source: Ambient air.
- •100 g scale to assess industrial production feasibility: Reactor: > 20 L glass or stainless steel reactor; Mass transfer: bubbling device or gas distributor; Oxygen source: Air or oxygen introduced through gas distributor or bubbling device.





#### Reaction Scale-up and Product Purification

#### **Purification**





## 3. Conclusion and Methods



#### Conclusion

LLM-RDF demonstrates a transformative approach to chemical synthesis that integrates chemist users, LLM-based agents, and automated experimental platforms, significantly streamlining the traditional expertdriven and labor-intensive workflow of reaction development.

#### **Limitations**

- LLM-based agents may provide incorrect responses ← Introducing another LLM to double-check
- Lack of domain knowledge
- Mathematical operations (recognized limitations) ← Equip
- Reproducibility and transparency
- Communication among LLM-based agents

- Retrieval-augmented generation
- Equip with integrated tools
- More training
- People can only do critical decisions



#### Methods

Web application Frontend: Vue.js, Node.js

Backend: Python FastAPI

GPT-4 APIs hosted on Azure



#### Methods

#### **JSON**

A lightweight data-interchange format

Easy for humans to read and write

Convenient for machines to parse and generate

Adopts an independent text format

Array (in square brackets)

Each object is enclosed in curly braces Including key - value pairs

```
1. [
            "reagent": "alcohol",
            "parameter": 0.25,
            "unit": "ml"
        },
6.
            "reagent": "Cu catalyst",
8.
            "parameter": 0.25,
            "unit": "ml"
10.
11.
        },
12.
13.
            "reagent": "bpy",
            "parameter": 0.25,
15.
            "unit": "ml"
16.
        },
```



#### Methods

#### **Bayesian Algorithm**

$$\begin{aligned} \left\{ \mathbf{x}_{new}^{(k)} \right\}_{k=1}^{q} &= \operatorname{argmaxqEI} \left( \left\{ \mathbf{x}^{(k)} \right\}_{k=1}^{q} \right) \\ &= \operatorname{argmax} \mathbb{E}_{n} \left( \operatorname{ReLu} \left( \max_{i=1,..,q} f \left( \mathbf{x}_{i} \right) - f_{n} \left( \mathbf{x}^{+} \right) \right) \right) \end{aligned}$$
 (3)

where  $\{\mathbf{x}_{new}^{(k)}\}_{k=1}^q$  is the q newly proposed reaction conditions,  $\mathbf{x}^+$  is the current optimal condition, and  $\mathbb{E}_n$  indicates that the expectation is taken under the posterior distribution at time n.

#### **PI Algorithm**

$$PI(\mathbf{x}) = \mathbb{P}\left(f(\mathbf{x}) \ge f(\mathbf{x}^+) + \xi\right) = \Phi\left(\frac{\mu(\mathbf{x}) - f(\mathbf{x}^+) - \xi}{\sigma(\mathbf{x})}\right) \tag{4}$$

where  $\mu(\cdot)$  is GP's mean,  $\sigma(\cdot)$  is GP's standard deviation,  $\Phi(\cdot)$  is the normal cumulative distribution function, and  $\xi$  is the trade-off parameter of exploitation and exploration.

# Thank You