analytical chemistry

pubs.acs.org/ac

Perspective

Insights into Application of Metaverse and Virtual Platforms with Gas Chromatography: Communication, Concept Understanding, Instrumental Training, Optimization Skill Development, and Database Sharing

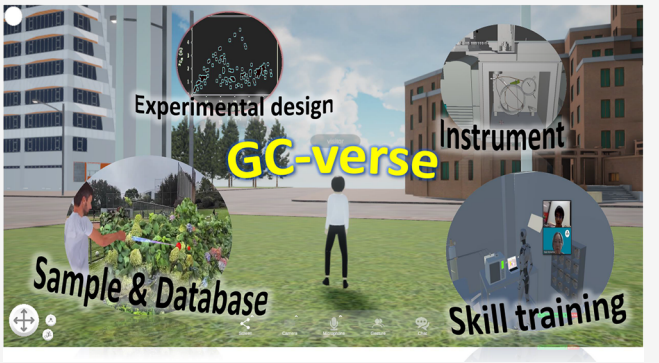
Friscilla Hermatasia, Lianrong Zhang, Ploy N. Pratanwanich, Nuttanee Tungkijanansin, Jirawat Thanatesiripong, Flavio A. Franchina, Yada Nolvachai, James J. Harynuk, Jan Leppert, Lunchakorn Wuttisittikulkij, Philip J. Marriott, and Chadin Kulsing*

Cite This: *Anal. Chem.* 2025, 97, 14867−14874

Read Online

ACCESS | Metrics & More | Article Recommendations | Supporting Information

ABSTRACT: Scientific collaboration traditionally relies on activities such as workshops, training programs, services, conferences, and personal meetings. In recent years, commercial-academic partnerships and global events such as pandemics have accelerated the development of online interaction platforms. A key challenge is to create immersive and interactive environments that extend beyond conventional search engines and video conferencing. This article introduces a novel 3D model platform compatible with the Metaverse of Academic Nexus for Global Opportunities (MANGOs), highlighting its potential applications in gas chromatography (GC) and comprehensive two-dimensional gas chromatography (GC×GC). The platform offers participants a virtual ecosystem for exploring fundamental concepts, practicing analytical skills, conducting experimental simulations, and sharing databases. Key features include virtual university settings, buildings, laboratories, instruments, a retention index (I) database, and immersive GC and GC×GC simulation environments for a variety of samples. Simulations of chromatograms and contour plots based on literature-reported experimental conditions are demonstrated. This new approach aims to enhance collaboration among gas chromatographers by enabling skill development, data exchange, and collective refinement of results obtained under diverse experimental setups.



Gas chromatography (GC) is recognized as a powerful separation technique for identifying and quantifying volatile and semivolatile compounds. The conventional one-dimensional (1D) separation approach often exhibits limited peak capacity and, for multicomponent samples, results in unresolved components.[1] The comprehensive two-dimensional GC (GC×GC) technique addresses this problem by utilizing two columns with different selectivity interfaced via a modulator. This modulator collects and focuses a small zone of compound(s) from the first-dimension (^{1}D) column and passes this to the second-dimension (^{2}D) column for further separation. Functionally, the modulation process is repeated at defined intervals within the modulation period (P_M).[2] This technique offers the advantage of enhanced analyte peak capacity[3,4] and improves confidence in untargeted compound identification with mass spectrometry (MS).[5,6] GC×GC has been used to analyze a wide range of biological, clinical, medical, geochemical, and environmental samples, among others.[4,7−9]

Chromatographers' communication may cover topics as diverse as separation/hyphenation/detection method development, experimental design, skills training, troubleshooting, data collection, data analysis, database searching, and validation. Onsite communication generally takes place through personal meetings, workshops, symposiums, or conferences, which often involve significant budgets and are limited by time constraints and collaboration opportunities. Online meetings could play a critical role overcoming these difficulties, albeit with limitations in detail, audience attention, hands-on experience, and visual interactions with data and instruments (although remote instrument operation can alleviate this[10]). Online meetings could be improved by the introduction of breakout sessions that simulate in-person conferences.[11] A recent GC×GC symposium

Received: January 15, 2025
Revised: June 17, 2025
Accepted: June 20, 2025
Published: July 10, 2025

https://doi.org/10.1021/acs.analchem.5c00362
Anal. Chem. 2025, 97, 14867−14874

used Gather, an interactive online meeting platform that allows participants to freely move around a virtual 2D space and engage in voice chats using microphones and cameras. Interestingly, the platform supported various environments, including general rooms and forest settings, as well as customization with conference and sponsor logos. However, the platform struggled to maintain participant engagement, probably due to a lack of GC-specific attractions.

In addition to the limitations mentioned above, the online sharing of GC−MS databases and the comparison of results across laboratories can be cumbersome and inefficient. Although retention index and MS databases are freely accessible through various sources, such as the NIST Chemistry WebBook,[12] they are often not effectively utilized for compound identification. Many researchers continue to report compound identities without referencing appropriate retention index databases, frequently resulting in questionable or incorrect identifications, as has been highlighted in recent discussions.[13,14] This presents a significant challenge when comparing GC or GC×GC results across different research groups. The process would be more straightforward if the positions of target compound peaks could be reliably aligned across varying experimental conditions, as reported in different studies.

A key challenge lies in establishing online communication and database-sharing platforms that are immersive, interactive, and globally accessible, while remaining affordable and offering unrestricted access. We present existing knowledge and methodologies with a perspective focused on integrating them into a unified Metaverse-based platform. This platform envisions a 3D virtual ecosystem designed to facilitate GC-related activities, including conceptual understanding, instrumental training, optimization skill development, and database sharing. In addition to integrating existing simulation approaches into this novel framework, the article also introduces, for the first time, a reliable retention index-based simulation method for generating GC chromatograms and GC×GC contour plots of samples under varying experimental conditions reported in the literature.

METAVERSE FOR GC: BEYOND ONLINE MEETING AND SEARCH ENGINES

The Metaverse can be conceptualized as a virtual environment in which users are represented by avatars and interact with others establishing social and economic connection.[15] Example components of the Metaverse include 3D virtual environments, communication platforms, and game-based activities. These elements could collectively form a robust ecosystem with engaging settings for GC communication, while also supporting integration with advanced technologies such as Artificial Intelligence (AI), Virtual Reality (VR), Augmented Reality (AR), and Extended Reality (XR). Such platform could provide a unique opportunity for beginners, students, educators, and researchers from both academia and industry to connect in real time, offering unlimited virtual space for GC conceptualization, instrumental training, optimization practice, skill development, and the sharing of databases and results. In order to demonstrate this capability, this perspective article utilizes the Metaverse of Academic Nexus for Global Opportunities (MANGOs), online at ref 16, a virtual educational platform designed to facilitate global academic collaboration. The platform seeks to address the limitations of traditional education, such as geographical barriers, resource constraints, and time limitations. MANGOs differs from existing online platforms by offering an immersive, interconnected academic environment rather than isolated virtual laboratories. It focuses on networking, interdisciplinary collaboration, and user-driven content creation. Unlike conventional virtual laboratories, users actively participate in building and sharing projects across diverse fields. MANGOs is also designed for continuous expansion, supporting future growth and evolving academic needs. This fosters an inclusive learning environment, guaranteeing that students, irrespective of their backgrounds or circumstances, have equitable opportunities to develop their skills, thereby contributing to their greater potential for advancement.[17] This platform, when combined with other components such as various 3D virtualizations and GC result simulations, could form an integrated ecosystem to create the GC-related opportunities outlined above, as summarized in Figure 1.

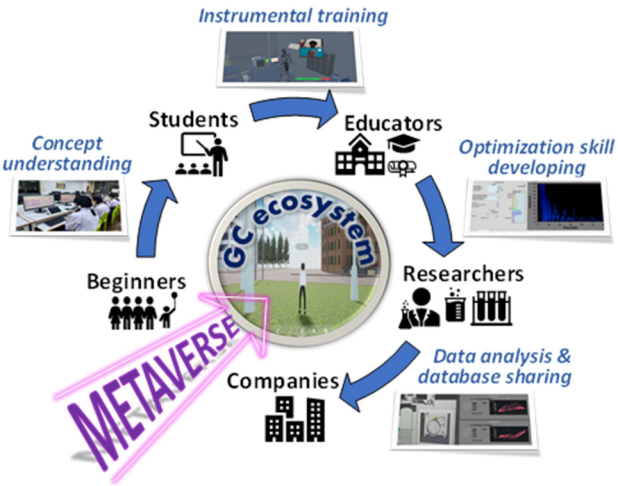


Figure 1. Diagram illustrating the potential integration of a GC-related ecosystem within the MANGOs platform.

METHODS

A virtual GC room could be constructed using a personal computer with relevant software, such as Blender (Blender Foundation, Netherlands) for model generation and Unity (Unity Software, Inc, San Francisco, US) for creating animations and interactions. This setup could fabricate 3D virtual spaces where users could communicate, interact, engage in social activities, analyze data, share databases, and conduct GC experiments through virtual reality. Blender, a renowned open-source visualization suite, is widely used in both entertainment and gaming, as well as for scientific visualization purposes. Through systematic tutorials, individuals can gain practical insights into Blender's functionalities, enabling them to create compelling visualizations and animations from their own data. The guide "3D Scientific Visualization with Blender" offers tailored instruction on 3D graphics and modeling, addressing various scenarios in the physical sciences. Instructional content includes navigation of the interface, 3D model generation, and mastery of lighting, animation, and camera control.[18] Subsequently, Unity is used to build interactions, leveraging its robust virtual reality (VR) development tools. Unity's widespread adoption and advanced features make it ideal for creating high-fidelity, real-time graphics for immersive user experiences. When integrated with a spreadsheet simulation system, this educational platform can compute chromatograms, further

https://doi.org/10.1021/acs.analchem.5c00362
Anal. Chem. 2025, 97, 14867−14874

enhancing its utility for scientific exploration and experimentation. A virtual GC laboratory could be simulated, with unlimited additional rooms and activities, incorporated within the MANGOs platform. Although the online integrated platform is under completion (https://www.mangosgo.com/mango33/), example case studies featuring related components are provided below.

COMMUNICATION, CONCEPT UNDERSTANDING, AND INSTRUMENTAL TRAINING

After logging into MANGOs, participants select avatars that they wish to represent their progress and perform operations through the virtual laboratory (Figure 2A). Starting at the central area, they can control their avatars to walk, run, jump, enter buildings, or simply sit outdoors. Avatars can also engage with outdoor monitors (Figure 2B,C) to receive updates or participate in online activities such as meetings, lectures, or presentations. These intuitive interactions serve two fundamental purposes: communication and conceptual understanding within the Metaverse. Participants can enter buildings, sit in a hall (Figure 2D), move between floors (Figure 2E), and explore different rooms (Figure 2F) until they locate the GC laboratory, where basic instrumental training or workshops may be conducted.

Figure 2. An example participant avatar engaged in various activities in MANGOs: (A) selecting a personalized avatar, (B, C) participating in outdoor activities, and (D−F) indoor activities.

The Blender/Unity software, along with Microsoft Excel, was used to simulate a GC laboratory featuring immersive and interactive environments, including sample preparation areas and GC and GC×GC instruments, with outputs such as a chromatogram and a contour plot, as illustrated in Figure 3.

An avatar in this virtual room can experience the various steps involved in sample analysis and learn to understand and operate GC analysis components. Instrumental skill training is facilitated through example demonstrations using GC−flame ionization detection (FID), as shown in Figure 4.

A participant can begin with column selection, choosing from 16 available options (Figure 4A). The name of the selected column is displayed in the top-right corner of the screen (e.g., HP-INNOWAX is shown as a case study). This column is then installed into the GC oven (Figure 4B). This step requires the participant to correctly insert the appropriate length of the column into both the inlet (top left) and the detector (top right). For example, ∼1 cm of the column could be inserted into the GC inlet chamber, and a few millimeters retracted after fully inserting the column outlet into the detector jet aperture. The connection shown in Figure 4B was only correct for the inlet part (marked with a check symbol), while the retraction length at the detector was incorrect (10 mm, as indicated by an × symbol). Note that participants cannot exit this window until all required lengths are correctly entered, reinforcing their understanding of dimensional accuracy.

After this, the avatar must virtually close the GC oven, power on the instrument, and input the FID parameters. As with the previous step, incorrect inputs are not permitted. The example flow rate values for hydrogen, air, and nitrogen shown in Figure

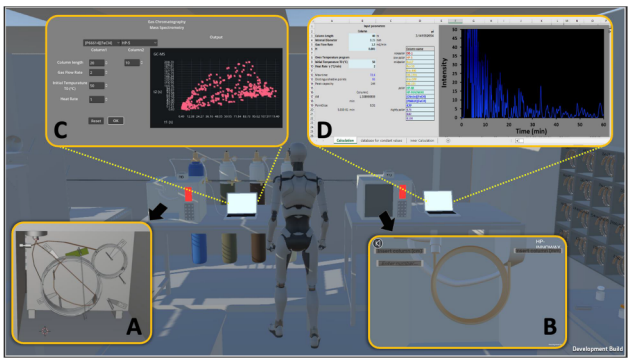


Figure 3. A 3D-rendered virtual laboratory featuring (A) GC×GC and (B) GC instruments, with the corresponding simulated kerosene analysis results shown in (C) and (D), respectively.

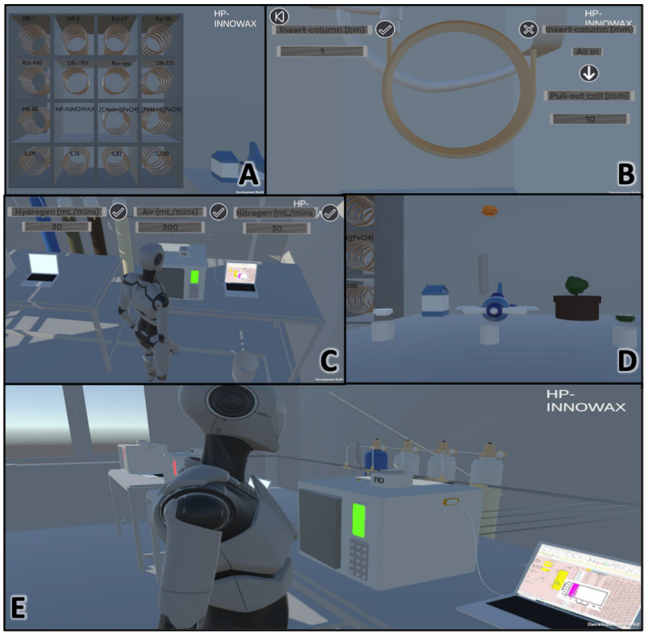


Figure 4. Instrument skill practice within the virtual GC laboratory. The platform simulates typical workflows and decision-making tasks encountered in a real GC lab, offering students a risk-free, authentic laboratory experience. (A) Participants learn to select appropriate GC columns for separating different sample types. (B, C) Participants then learn how to perform basic column maintenance and decide on operational parameters. (D) They control a virtual character to pick up a prepared sample (e.g., derivatized milk, jet fuel, or essential oil) from the sample bench. (E) The analysis is performed, with instant results displayed.

https://doi.org/10.1021/acs.analchem.5c00362
Anal. Chem. 2025, 97, 14867−14874

4C were within practical ranges and were therefore indicated with ✔. Next, the avatar selects a sample solution vial for liquid injection; Figure 4D shows, from left to right, vials containing derivatized milk, kerosene, and essential oil samples. In this case, the kerosene solution was selected. It is worth noting that additional sample preparation steps can be simulated and integrated into this 3D platform. The optimization and selection of sample preparation techniques can be simulated using experimental design parameters, enabling the extraction of a wide range of compounds through various literature-reported methods.[18] This may also involve the use of thermodynamic databases, data-driven training with chemometric models, or the application of machine learning to predict outcomes beyond the limitations of existing databases.[19,20] The sample is then injected into the GC inlet, and a simulated chromatogram is subsequently generated.

EXPERIMENTAL DESIGN AND OPTIMIZATION SKILL DEVELOPMENT

With our current 3D platform, users can investigate the effects of various GC and GC×GC parameters on simulated results (Figure 3C,D). This feature was included to facilitate the understanding of experimental design and optimization concepts, which are traditionally trial-and-error processes requiring numerous GC experiments.[21] This is impractical in laboratories due to lengthy analyses and high operational costs. As a result, it is difficult for beginning chromatographers to clearly understand the underlying concepts and develop the critical thinking skills needed to address practical challenges. At this point in the learning process, GC concepts can be effectively integrated to enhance understanding. To support this, computer simulation approaches have been developed and applied to facilitate the learning of optimization processes in GC for over a decade. These approaches rely on retention prediction databases, such as retention indices, molecular modeling, thermodynamics, or linear solvation energy relationship (LSER) constants.[2] The simulation approach exploring the concept of a continuum in multidimensional GC under constant carrier gas flow, using various column sets and experimental conditions, has been reported and can be implemented through either numerical[22] or analytical[23] simulations.

MORE ADVANCED FLOW PROGRAMMED/SYSTEM CONFIGURATION GC AND GC×GC SIMULATION

A modular simulation platform for complex GC systems[24] enables rapid evaluation of various configurations and settings, as well as their impacts on separation performance. The platform is based on a simulation model for one-dimensional GC separations,[25−27] with the option to (or not to) include a spatial thermal gradient. This model predicts retention times and peak widths based on thermodynamic parameters that describe the interaction of analytes with the stationary phase. The platform also supports the estimation of thermodynamic parameters from experimental data through simulation and optimization.[28] Furthermore, a database of thermodynamic parameters has been developed,[29] and the integration of additional databases, such as LSER,[30] for parameter estimation has been explored. Using these building blocks, the platform can simulate complex multicomponent GC systems, and also the GC×GC technique, with independent retentions in two individual columns. This is achieved by employing graph theory to represent the capillary network and simulating the separation processes in each segment individually. Accurate simulations require knowledge of pressure and flow distributions throughout the system under varying temperature and pressure programs. By leveraging graph theory principles, the platform automatically constructs and solves flow balance equations for arbitrary configurations of capillary networks.[31]

As online virtual simulation platforms, commercially available tools such as Gas Chromatography Simulation & Optimisation Software (GC-SOS)[32] and ACD/LABORATORIES LC and GC Simulator[33] have been reported. Participants might also refer to and familiarize themselves with other freeware optimization strategies for further understanding. They can be applied for a set of compounds, with the capability to simulate effects of different columns depending on experimental conditions. This was later extended into a Microsoft Excel-based spreadsheet, enabling the simulation of GC−MS results and the prediction of the number of separated peaks for a given sample and set of experimental conditions.[34] The application was reported for simulation of total ion and extracted ion chromatograms of a model kerosene sample containing 254 volatile compounds, as well as additional GC chromatograms simulated to support the optimization of separation of fatty acid methyl esters and hydrocarbons. In this context, participants were able to perform experimental design at home. The corresponding spreadsheets for performing GC and GC×GC separations of kerosene are provided as Supporting Information.

In order to further the understanding of GC—and GC×GC—on the part of the user, aspects of deeper interpretation of chromatographic quality such as efficiency, peak capacity, tailing phenomena, peak detection and integration, detector technology, column assessment and deterioration, and related criteria may be readily incorporated into this program. In particular, mass spectrometry as a key enabler of identification in GC and GC×GC could constitute a substantial module within the overall scope of Metaverse. Figure 5 presents example simulated GC−MS results obtained using total ion scan (TIC) and selected ion monitoring (SIM) modes under different acquisition rates and selection windows. Faster acquisition rates provide more detailed chromatograms (see the upper chromatograms in Figure 5A). With the same acquisition rate, a wider selection window during SIM operation results in

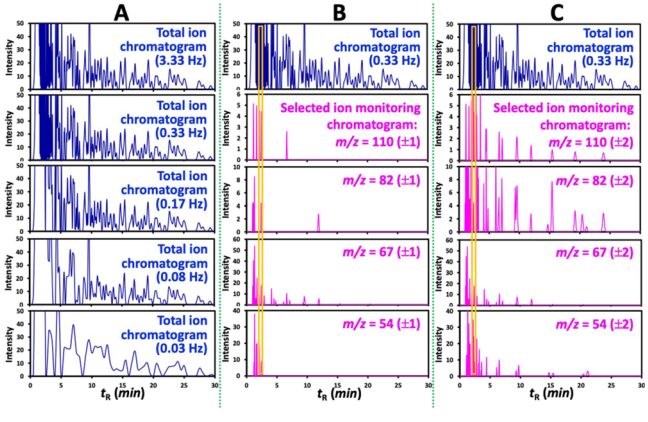


Figure 5. Simulated GC−MS results of kerosene, including (A) TIC obtained at different acquisition rates (Hz), and SIM chromatograms at 0.33 Hz focusing on m/z fragments of cyclooctene, using selection windows of (B) ±1 amu and (C) ±2 amu. The corresponding peaks are highlighted with rectangular regions at 2.4 min.

https://doi.org/10.1021/acs.analchem.5c00362
Anal. Chem. 2025, 97, 14867−14874

higher noise levels, as illustrated in Figure 5C, where the SIM chromatograms contain more peaks than those in Figure 5B.

The simulation also allows for adjustment of detector sensitivity by assigning different response factors to individual compounds. The ability to adjust these parameters enables the simulation to potentially represent a variety of detectors, including MS systems with different mass analyzers and detector technologies. For example, fast full-scan and exact-mass analysis using time-of-flight (TOF) MS can be simulated using higher frequency acquisition and narrower selection windows in extracted ion chromatogram analysis, in contrast to slower full-scan and nominal-mass analysis using a quadrupole mass analyzer.

However, the provided spreadsheet serves only as an illustrative tool for GC−MS analysis with 4 m/z fragments per compound. For a more practical approach, full mass spectral data should be used, such as those documented in the NIST WebBook database. In cases where compounds are not present in the library, chemometric or machine learning approaches can be applied to predict mass spectra for such compounds. This may involve using existing data as training sets to develop models that predict possible molecular fragments and, subsequently, the entire mass spectrum. A good example is the Competitive Fragmentation Modeling for Metabolite Identification (CFM-ID) 4.0 program.[35] This tool predicts possible mass fragments of a precursor ion or molecule, requiring InChI or SMILES input. It outputs fragment ions and their corresponding names, simulated based on bond connectivity and combinatorial fragmentation rules, applicable with experimental electron ionization (EI) MS data, such as those used in ref 36.

The quality of separation, based on the simulated TIC, can also be assessed using the spreadsheet, which shows 55 baseline-separated peaks and a total peak capacity of 69. It should be noted that the peak widths of compounds with known retention times were simulated using the theoretical plate height concept.[32] For more practical simulations, column aging effects can also be incorporated by inputting standard compound retention data obtained under well-defined experimental conditions. These data can then be used to determine aging constants, allowing for simulation of retention time shifts and peak broadening that fit the experimental data more accurately to the theoretical model.

Apart from the features described above, additional important capabilities could be incorporated into the simulation in the future such as data analysis strategies, including data interpretation, peak integration method selection, untargeted compound identification, and quantitative analyses. These functionalities could be enabled by integrating existing databases such as the NIST library, along with data analysis algorithms used in software such as GC Image or MassHunter. In addition, troubleshooting scenarios could be embedded into the simulation by modeling situations such as local temperature gradients, leakages, extra-column peak broadening due to system components (e.g., injectors, tubing, and detectors), column overloading, and adsorption isotherms. These scenarios could be explored using the modular simulation platform for complex GC systems described above.[22] Ultimately, practical case studies involving integrated sample preparation, separation, and detection method development could be simulated. All the elements described above could be seamlessly integrated into the virtual GC laboratory environment.

RESULT COMPARISON AND DATABASE SHARING

When GC data and results are shared, individual compounds are likely to have different retention positions arising from different experimental conditions to literature results, and hence making direct comparison difficult. This could be achievable using the simulation approaches described above. However, the underlying data are derived from temperature- and flow-dependent equations and rely on thermodynamic/chemometric databases of compounds with stationary phases depending on experimental conditions. Unfortunately, these databases were documented with a limited set of data, such as <10,000 compounds. They are thus more suitable for investigation and optimization of experimental parameters, as well as understanding the effect of each parameter on the chromatographic outcomes.

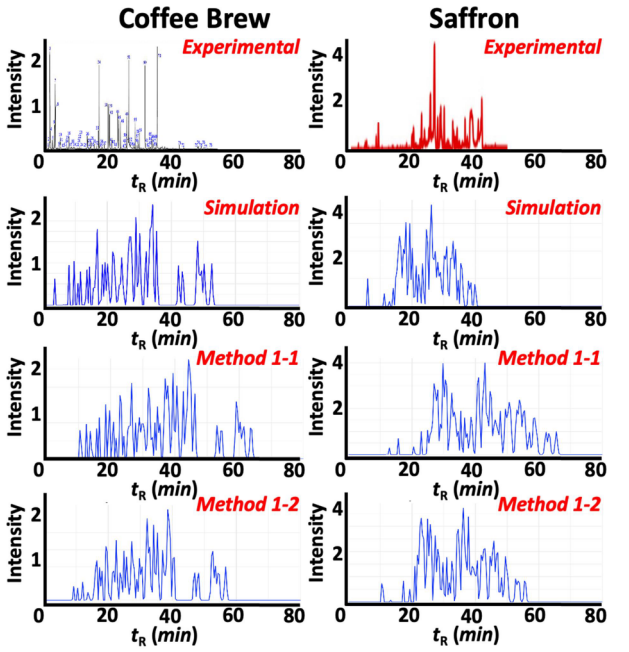


Figure 6. Simulation of chromatograms of *Coffee Brew*[37] and *Saffron*[38] in 1D separation compared with the experimental chromatograms, and their simulated chromatograms using other experimental conditions (*Methods 1−1* and *1−2*) that were reported from refs 39 and 14, respectively, using the RI-based curve fitting approach with the database taken from NIST20. All the compound amounts were assumed to be identical in the simulation resulting in intensity profiles that differed from the experimental results. However, the peak positions were almost the same. Adapted with permissions from Thammarat, P.; Kulsing, C.; Wongravee, K.; Leepipatpiboon, N.; Nhujak, T. Identification of Volatile Compounds and Selection of Discriminant Markers for Elephant Dung Coffee Using Static Headspace Gas Chromatography—Mass Spectrometry and Chemometrics. *Molecules* 2018, 23, 1910;[37] Jiang, M.; Kulsing, C.; Nolvachai, Y.; Marriott, P. J. Two-Dimensional Retention Indices Improve Component Identification in Comprehensive Two-Dimensional Gas Chromatography of Saffron. *Analytical Chemistry* 2015, 87, 5753−5761.[38] Copyright 2018 Creative Commons Attribution (CC BY) licensed by MDPI. Copyright 2015 American Chemical Society.

Alternatively, simulations can be performed under specific experimental conditions using reported peak retention data and retention index (RI) libraries.[14] This relies on curve fitting, which leads to a specific set of fitting constants that can be used to predict retention times under consistent experimental

https://doi.org/10.1021/acs.analchem.5c00362
Anal. Chem. 2025, 97, 14867−14874

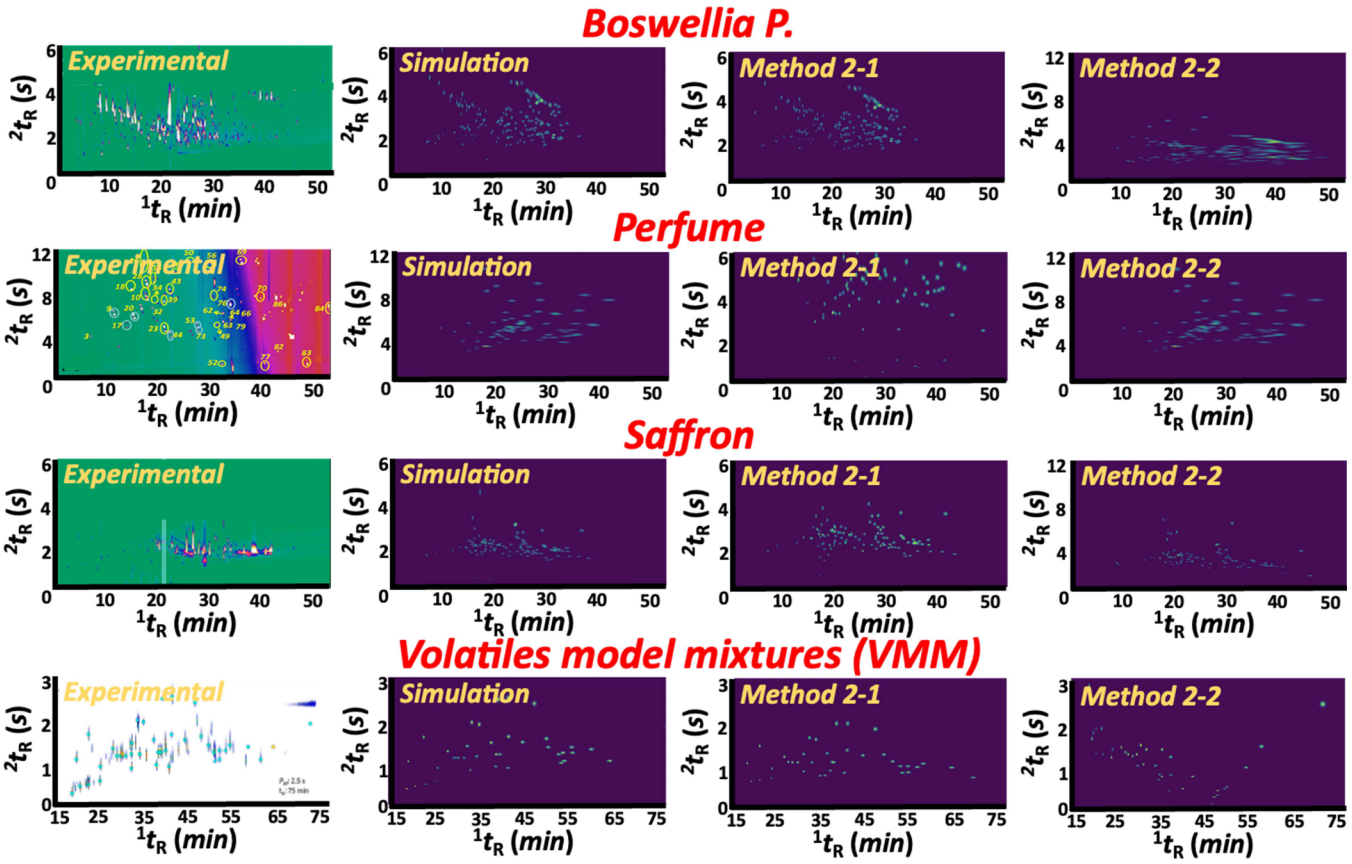


Figure 7. Simulation of GC×GC contour plots of *Boswellia P.*,[40] *perfume*,[14] *Saffron*,[38] and *Volatiles model mixtures (VMM)*,[39] compared with the experimental contour plots, and their simulated contour plots using other experimental conditions (*Methods 2−1* and *2−2*) that were reported from refs 41 and 14, respectively, using the *I*-based curve fitting approach with the database taken from NIST20. All the compound amounts were assumed to be identical in the simulation resulting in intensity profiles that differed from the experimental results. However, the peak positions were almost the same. Adapted with permissions from Jiang, M., Kulsing, C. & Marriott, P.J. Comprehensive 2D gas chromatography−time-of-flight mass spectrometry with 2D retention indices for analysis of volatile compounds in frankincense (*Boswellia papyrifera*). *Anal. Bioanal Chem* 2018, 410, 3185−3196;[40] Kakanopas, P., Janta, P., Vimolmangkang, S., Hermatasia, F., Kulsing, C. Retention index-based approach for simulation of results and application for validation of compound identification in comprehensive two-dimensional gas chromatography. *Journal of Chromatography A* 2022, 1679, 463394;[14] Jiang, M.; Kulsing, C.; Nolvachai, Y.; Marriott, P. J. Two-Dimensional Retention Indices Improve Component Identification in Comprehensive Two-Dimensional Gas Chromatography of Saffron. *Analytical Chemistry* 2015, 87, 5753−5761.[38] Cordero, C., Rubiolo, P., Cobelli, L., Stani, G., Miliazza, A., Giardina, M., Firor, R., Bicchi, C. Potential of the reversed-inject differential flow modulator for comprehensive two-dimensional gas chromatography in the quantitative profiling and fingerprinting of essential oils of different complexity, *Journal of Chromatography A* 2015, 1417, 79−95.[39] Copyright 2015 and 2022 Elsevier. Copyright 2015 American Chemical Society. Copyright 2018 Springer-Verlag.

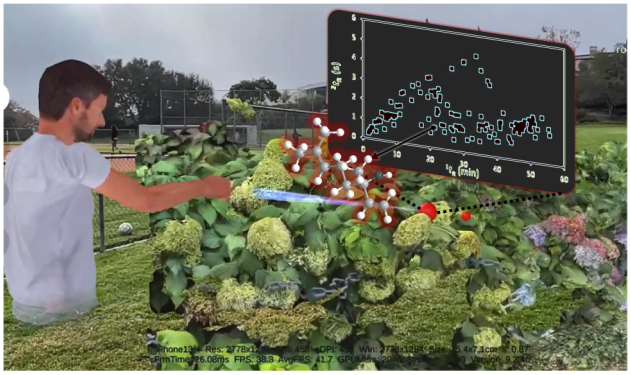


Figure 8. Database sharing platform: a Metaverse garden where a participant selects a plant with a GC×GC contour plot and a terpene molecule, adapted from ref 43. Courtesy of EON Reality.

conditions, without the need for alkane reference data (RI-based curve fitting approach). To achieve this, first- and second-dimensional retention index values (^1I and ^2I) are used to simulate peak retention times (^1t_R and ^2t_R) for samples containing known sets of volatile compounds in GC or GC×GC analyses. This method was initially applied to simulate results for 542 compounds found in herb, acacia honey, incense, perfume, and cannabis samples under various experimental conditions. Compared with the experimental results, the simulation showed correlations, with R^2 values ranging from 0.98 to 1.00 for ^1t_R and from 0.80 to 0.97 for ^2t_R. The approach has been simplified and applied to a larger set of compounds and samples (currently covering 7424 compounds across 85 GC×GC−MS data sets reported in the literature [under revision]). Note that this approach can only simulate GC or GC×GC retention times under a single experimental condition and is not applicable when experimental parameters vary. However, the use of RI enables linkage to a much larger data set, e.g., >200,000 compounds in the NIST library. This makes the approach more suitable for prediction of compound retention times of various samples under a fixed experimental condition. While the method is limited to compounds with available RI data on the selected column phases, it holds significant value

https://doi.org/10.1021/acs.analchem.5c00362
Anal. Chem. 2025, 97, 14867−14874

both experimentally and theoretically. It is worth noting that different chemometric or machine learning models could be applied to predict RI data for new compounds that are not present in the database. This could involve using the existing data as training sets to build models for the prediction of RI values of new compounds. These predicted data have already been documented in the NIST library. Also note that a Metaverse platform facilitating RI data communication could ultimately enhance participation within a wider group of researchers, leading to increased experimental data contributions. This would improve the accuracy of retention index prediction using machine learning-based approaches.

Examples involve simulation of GC chromatograms (Figure 6) and GC×GC contour plots (Figure 7) of different samples using experimental conditions reported in literature. The detailed algorithmic description of the process is provided in Supporting Information. Note that the RI-based curve fitting approach was applied to obtain the fitting constants of all methods followed by prediction of t_R (1D GC) or ^1t_R and ^2t_R (GC×GC) of all the compounds in each sample separated using each method. 1D and 2D Gaussian equations were then applied to generate 1D[34] and 2D[42] separation profiles prior to contour plot generation herein using R software. Wraparound effects were also taken into account in the simulation of GC×GC contour plots for any compounds with ^2t_R longer than P_M. With these approaches, one could simulate chromatograms of samples and compare them with others, as well as locate their target compound peaks, under the same experimental conditions reported in literature. This fulfills the desirable feature for result comparison, as mentioned above.

Another application of this RI-based curve fitting approach includes validation of 7466 peak annotations solely focusing on the compounds with available ^1I and ^2I data in 85 GC×GC results from the literature. This could identify 1283 suspected compound identities (with ^1I or ^2I mismatches when comparing the reported and literature data) [under revision]. This capability enables users to input their GC×GC−MS identification results into the Metaverse, which will be validated with the output of suspected compound sets.

Furthermore, the 3D virtual platform could be used to promote database sharing activities. An example is provided in Figure 8 with a simulated garden where a user could select plants of interest. These 3D plants could be encoded with chemical fingerprints, represented by GC chromatograms or GC×GC contour plots. Each peak in the contour plot could then be selected, and the identity could be obtained along with properties such as a characteristic odor, taste, or health-related effect. It could also be possible for users to add new sample data into the central library of the Metaverse.

CONCLUSIONS

The integration of GC methodologies within a Metaverse framework promises to be a novel avenue for enhancing analytical practices. By simulating virtual environments that encompass sample preparation, instrumentation, and data analysis, this approach could significantly advance education, research collaboration, and database sharing. AI could further enhance this potential by tailoring training programs, streamlining workflows, and forecasting GC outcomes beyond the scope of existing databases. In addition, the future application of AR could improve real-world laboratory operations by overlaying real-time guidance and troubleshooting instructions, while VR could provide fully immersive simulations for safe, repeatable training in complex tasks. Together, the integration of AI, AR, and VR within Metaverse platforms promises to standardize chromatographic practices, accelerate skill development, and broaden access to advanced analytical tools, ultimately reshaping the future of GC education and practice.

While the integrated Metaverse platform could offer substantial advantages, several potential limitations should be considered. Technological accessibility remains a major concern, as advanced hardware and stable high-speed Internet connections may not be universally available, particularly in resource-limited settings. User adaptability is another challenge, as effective use of virtual environments requires a level of digital literacy and openness to new learning modalities, which may vary across users. Furthermore, maintaining up-to-date virtual simulations and comprehensive, high-quality chromatographic databases demands continuous resource investment, interdisciplinary collaboration, and rigorous validation to ensure scientific accuracy. These factors highlight the need for strategic planning and inclusive design to fully realize the transformative potential of these emerging technologies in gas chromatography.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.analchem.5c00362.

Simulation of compound retention indices in one-dimensional (1D) and two-dimensional (2D) gas chromatography (GC) results; platform and workflow of simulation and validation process for GC and GC × GC results; and list of method in experimental GC and GC×GC analysis for simulation and validation compound peaks in the GC−MS and GC×GC−MS results (PDF)

GC kerosene simulation (XLS)

GC×GC kerosene simulation (XLS)

AUTHOR INFORMATION

Corresponding Author

Chadin Kulsing − *Department of Chemistry, Faculty of Science and Electrochemistry and Optical Spectroscopy Centre of Excellence (EOSCE), Department of Chemistry, Faculty of Science, Chulalongkorn University, Bangkok 10330, Thailand*; orcid.org/0000-0003-0348-1746; Email: chadin.k@chula.ac.th

Authors

Friscilla Hermatasia − *Department of Chemistry, Faculty of Science, Chulalongkorn University, Bangkok 10330, Thailand*

Lianrong Zhang − *Department of Chemistry, Faculty of Science, Chulalongkorn University, Bangkok 10330, Thailand*

Ploy N. Pratanwanich − *Department of Mathematics and Computer Science, Faculty of Science and Chula Intelligent and Complex Systems Research Unit, Chulalongkorn University, Bangkok 10330, Thailand*

Nuttanee Tungkijanansin − *Department of Chemistry, Faculty of Science, Chulalongkorn University, Bangkok 10330, Thailand*

Jirawat Thanatesiripong − *Department of Chemistry, Faculty of Science, Chulalongkorn University, Bangkok 10330, Thailand*

Flavio A. Franchina − *Department of Chemical, Pharmaceutical, and Agricultural Sciences, University of Ferrara, Ferrara 44121, Italy*

https://doi.org/10.1021/acs.analchem.5c00362
Anal. Chem. 2025, 97, 14867−14874

Yada Nolvachai − *ARC Training Centre for Hyphenated Analytical Separation Technologies (HyTECH) and CASS Food Research Centre, School of Exercise and Nutrition Sciences, Deakin University, Burwood, VIC 3125, Australia;* orcid.org/0000-0002-8436-1836

James J. Harynuk − *Department of Chemistry and The Metabolomics Innovation Centre, University of Alberta, Edmonton, Alberta T6C 2X4, Canada;* orcid.org/0000-0002-9627-5206

Jan Leppert − *Independent Researcher, Bonn 53225, Germany;* orcid.org/0000-0001-8857-8103

Lunchakorn Wuttisittikulkij − *Department of Electrical Engineering, Faculty of Engineering, Chulalongkorn University, Bangkok 10330, Thailand*

Philip J. Marriott − *Australian Centre for Research on Separation Science, School of Chemistry, Monash University, Melbourne, VIC 3800, Australia;* orcid.org/0000-0001-5180-1041

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.analchem.5c00362

Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

This research is supported by the Second Century Fund (C2F) Scholarship, Chulalongkorn University. This research is supported by the 90th Anniversary of the Chulalongkorn University Scholarship under Ratchadapisek Sompoch Endowment Fund. Y.N. is funded by the Australian Research Council (ARC) Training Centre for Hyphenated Analytical Separation Technologies (HyTECH, project number IC220100035).

■ REFERENCES

(1) Lubes, G.; Goodarzi, M. *Chem. Rev.* **2017**, *117* (9), 6399−6422.
(2) Kulsing, C.; Nolvachai, Y.; Marriott, P. J. *TrAC Trends Anal. Chem.* **2020**, *130*, No. 115995.
(3) Marriott, P. J.; Chin, S.-T.; Maikhunthod, B.; Schmarr, H.-G.; Bieri, S. *TrAC Trends Anal. Chem.* **2012**, *34*, 1−21.
(4) Marriott, J. P.; Shellie, R. *TrAC Trends Anal. Chem.* **2002**, *21* (9), 573−583.
(5) Nolvachai, Y.; Kulsing, C.; Marriott, P. J. *TrAC Trends Anal. Chem.* **2017**, *96*, 124−137.
(6) Tranchida, P. Q.; Franchina, F. A.; Dugo, P.; Mondello, L. *Mass Spectrom. Rev.* **2016**, *35* (4), 524−34.
(7) Coon, A. M.; Dane, A. J.; Setzen, G.; Cody, R. B.; Musah, R. A. *ACS Omega* **2022**, *7*, 230−239.
(8) Qian, K.; Wang, F. C. *J. Am. Soc. Mass Spectrom.* **2019**, *30* (12), 2785−2794.
(9) Dymerski, T. *Crit. Rev. Anal. Chem.* **2018**, *48* (4), 252−278.
(10) Nolvachai, Y.; Zavahir, J. S.; Herron, R.; Marriott, P. J. *J. Chem. Educ.* **2023**, *100*, 1100.
(11) Sarabipour, S.; Khan, A.; Seah, Y. F. S.; Mwakilili, A. D.; Mumoki, F. N.; Sáez, P. J.; Schwessinger, B.; Debat, H. J.; Mestrovic, T. *Nature Human Behaviour* **2021**, *5* (3), 296−300.
(12) National Institute of Standards and Technology (NIST): *NIST Chemistry WebBook*, p https://webbook.nist.gov/.
(13) Bizzo, H. R.; Brilhante, N. S.; Nolvachai, Y.; Marriott, P. J. *J. Chromatogr. A* **2023**, *1708*, No. 464376.
(14) Kakanopas, P.; Janta, P.; Vimolmangkang, S.; Hermatasia, F.; Kulsing, C. *J. Chromatogr. A* **2022**, *1679*, No. 463394.
(15) Ritterbusch, G. D.; Teichmann, M. R. *IEEE Access* **2023**, 12368.
(16) Chulalongkorn University: *MANGOs (Metaverse of Academic Nexus for Global Opportunities)*, p https://www.mangosgo.com/.
(17) Bucea-Manea-Ţoniş, R.; Bucea-Manea-Ţoniş, R.; Simion, V. E.; Ilic, D.; Braicu, C.; Manea, N. *Sustainability* **2020**, *12* (14), 5872.
(18) Rezaee, M.; Khalilian, F.; Pourjavid, M. R.; Seidi, S.; Chisvert, A.; Abdel-Rehim, M. *Int. J. Anal. Chem.* **2015**, *2015* (1), 1.
(19) Winter, B.; Winter, C.; Esper, T.; Schilling, J.; Bardow, A. *Fluid Phase Equilib.* **2023**, *568*, No. 113731.
(20) Kent, R.; Birt, J. *Rev. Acc. Stud.* **2021**, *26* (4), 1532−1586.
(21) Nolvachai, Y.; Kulsing, C.; Marriott, P. J. *Anal. Chem.* **2016**, *88* (4), 2125−2131.
(22) Kulsing, C.; Nolvachai, Y.; Rawson, P.; Evans, D. J.; Marriott, P. J. *Anal. Chem.* **2016**, *88* (7), 3529−3538.
(23) Siriviboon, P.; Tungkaburee, C.; Weerawongphrom, N.; Kulsing, C. *J. Chromatogr. A* **2019**, *1602*, 425−431.
(24) Leppert, J. *GasChromatographyToolbox*. GasChromatography-Toolbox, p https://gaschromatographytoolbox.org/.
(25) Leppert, J.; Blumberg, L. M.; Boeker, P. *J. Chromatogr. A* **2020**, *1612*, No. 460645.
(26) Leppert, J.; Müller, P. J.; Chopra, M. D.; Blumberg, L. M.; Boeker, P. *J. Chromatogr.. A* **2020**, *1620*, No. 460985.
(27) Leppert, J. *J. Open Source Softw.* **2022**, *7*, 4565.
(28) Leppert, J.; Brehmer, T.; Wüst, M.; Boeker, P. *J. Chromatogr. A* **2023**, *1699*, No. 464008.
(29) Brehmer, T.; Duong, B.; Marquart, M.; Friedemann, L.; Faust, P. J.; Boeker, P.; Wüst, M.; Leppert, J. *ACS Omega* **2023**, *8* (22), 19708−19718.
(30) Brehmer, T.; Duong, B.; Boeker, P.; Wüst, M.; Leppert, J. *J. Chromatogr. A* **2024**, *1717*, No. 464665.
(31) Leppert, J.; Brehmer, T.; Boeker, P.; Wüst, M. *J. Sep. Sci.* **2024**, *47* (16), No. e2400419.
(32) *4S Company: GC-SOS Gas Chromatography Simulation & Optimization Software*, pp https://www.gc-sos.com.
(33) Develop Chromatographic Methods Faster with Prediction and Optimization Software. *ACD/LABS: Develop Chromatographic Methods Faster with Prediction and Optimization Software*, pp https://www.acdlabs.com/products/spectrus-platform/method-selection-suite/.
(34) Thaveesangsakulthai, I.; Kulsing, C. *J. Chem. Educ.* **2021**, *98* (8), 2714−2719.
(35) Wang, F.; Liigand, J.; Tian, S.; Arndt, D.; Greiner, R.; Wishart, D. S. *Anal. Chem.* **2021**, *93* (34), 11692−11700.
(36) Karapakdee, P.; Wilairat, P.; Kokpol, S.; Nolvachai, Y.; Kulsing, C. *J. Chromatogr. A* **2024**, *1714*, No. 464527.
(37) Thammarat, P.; Kulsing, C.; Wongravee, K.; Leepipatpiboon, N.; Nhujak, T. *Molecules* **2018**, *23* (8), 1910.
(38) Jiang, M.; Kulsing, C.; Nolvachai, Y.; Marriott, P. J. *Anal. Chem.* **2015**, *87* (11), 5753−5761.
(39) Cordero, C.; Rubiolo, P.; Cobelli, L.; Stani, G.; Miliazza, A.; Giardina, M.; Firor, R.; Bicchi, C. *J. Chromatogr. A* **2015**, *1417*, 79−95.
(40) Jiang, M.; Kulsing, C.; Marriott, P. J. *Anal. Bioanal. Chem.* **2018**, *410* (13), 3185−3196.
(41) Jiang, M. *Anal. Chem.* **2019**, *91* (6), 4085−4091.
(42) Pojjanapornpun, S.; Kulsing, C.; Kakanopas, P.; Nolvachai, Y.; Aryusuk, K.; Krisnangkura, K.; Marriott, P. J. *J. Chromatogr. A* **2019**, *1607*, No. 460392.
(43) *Garden planting technique in the metaverse*; EON Reality: Youtube, 2021; p https://www.youtube.com/watch?v=xeoLpXLz1u0.

https://doi.org/10.1021/acs.analchem.5c00362
Anal. Chem. 2025, 97, 14867−14874