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High-throughput DoE synthesis of chalcones and pyrazolines for fluorescent sensing

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Pyrazolines are attractive scaffolds for fluorescent sensors due to their unique photophysical properties and the ease of their synthesis from chalcone precursors. While both chalcones and pyrazolines have been widely explored, a systematic optimization of their synthesis using design of experiments (DoE) has yet to be reported. Here, we apply a data-driven DoE strategy, evaluating multiple variables across more than 105 datapoints, to establish highly optimized conditions for the Claisen–Schmidt condensation of chalcones and their subsequent conversion to pyrazolines. High-throughput screening of the resulting library revealed pyrazoline **P10** with unusual “turn on” fluorescence at 590 nm in the presence of Zn^{2+} only. This integrated DoE–HTS workflow demonstrates a powerful approach for accelerating sensor discovery.

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Introduction

The integration of modern data-driven methodology into synthetic organic chemistry is streamlining synthetic method development.¹ Among these, design of experiments (DoE) enables the systematic identification of optimal parameters with a minimal number of experiments, offering a powerful alternative to the traditional one-factor-at-a-time (OFAT) strategy.² For instance, recent examples include the use of DoE in Heck–Suzuki reactions,³ $\text{B}(\text{OCH}_2\text{CF}_3)_3$ -mediated direct amidation,⁴ and solvent selection for multicomponent reactions.⁵ In parallel, high-throughput screening (HTS) platforms are accelerating the discovery process, with improvements reported in drug development,⁶ enhanced catalyst screening,⁷ and solar cell optimisation.⁸ Both DoE and HTS approaches benefit from modular, easily accessible chemical scaffolds. Chalcones are privileged structures⁹ with a diverse range of pharmacological properties, including anti-cancer,¹⁰ anti-inflammatory,¹¹ and anti-infective properties.¹² Typically, chalcones are prepared *via* a Claisen–Schmidt condensation¹³ from commercially available aromatic ketone and aldehyde starting materials (Fig. 1A). The diverse range of inexpensive, commercially available starting materials enables large modular libraries of chalcones to be synthesized and screened. Interest in Claisen–Schmidt condensations has grown considerably over the past sixty years (Fig. 1B). Importantly, while useful in themselves, chalcones can also serve as valuable precursors for pyrazolines (blue in Fig. 1A), another privileged structure with multiple medicinal properties.¹⁴ Pyrazolines with nanomolar

activities for cancer cell lines¹⁵ and COX inhibitory activity have been reported.¹⁶ Pyrazolines can be aromatised to pyrazoles¹⁷ (red in Fig. 1A), providing access to another highly attractive privileged structure.¹⁸ Despite the wealth of applications chalcones and pyrazolines provide, no DoE study has optimised access to these scaffolds. This study addresses this research gap, providing efficient access to chalcone and pyra-

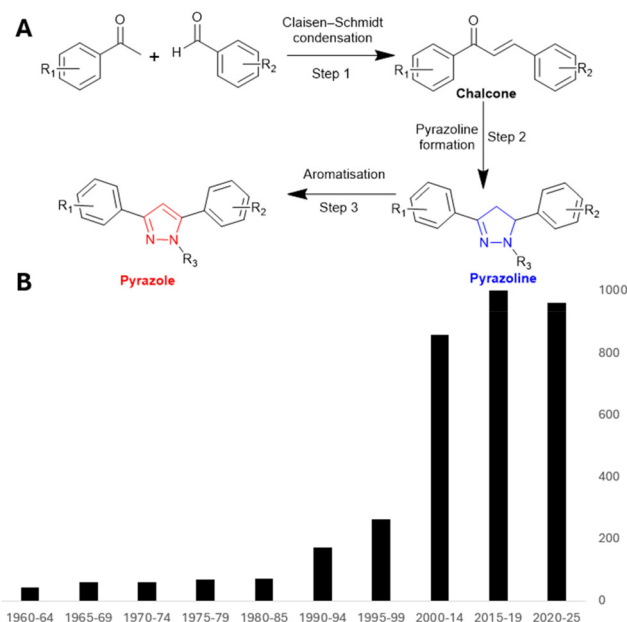


Fig. 1 Access to pyrazoline and pyrazoles *via* the chalcone scaffold (panel A). Claisen–Schmidt condensations reported between 1960 and 2025 *via* the Reaxys database (panel B).

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zolines *via* DoE while exploring HTS platforms in pursuit of novel fluorescent sensors.

Pyrazolines display unique fluorescence properties for the design of fluorescent sensors for toxic metals such as Zn^{2+} , Cu^{2+} , and Hg^{2+} .¹⁹ The modular nature of the pyrazolines scaffold enables fine-tuning of photophysical properties, a useful feature for sensor development. The use of pyrazoline²⁰ and pyrazole²¹ sensors for detecting toxic metals in biological environments represents a growing area of interest. Group 12 sensors, which selectively detect and distinguish Zn^{2+} , Cd^{2+} , and Hg^{2+} , are particularly challenging. Zinc, the second most abundant transition metal in the human body, is vital for life,²² cadmium is highly toxic and linked to numerous cancers,²³ and mercury displays potent neurotoxicity.²⁴ Few fluorescent sensors can differentiate between these metals at different fluorescence wavelengths (λ_{em}).²⁵ Simple pyrazoline **A** is a highly selective “turn on” sensor for Zn^{2+} and Cd^{2+} in MeCN (Fig. 2).²⁶ Further studies revealed pyrazole **B** with improved selectivity for $\text{Zn}^{2+}/\text{Cd}^{2+}$ (Fig. 2).²⁷ Pyrazoline **C** is a “turn on” sensor for $\text{Fe}^{3+}/\text{Fe}^{2+}$ with yellow λ_{em} .²⁸ Substitution of the pyrazoline N1 methyl for phenyl reversed the fluorescent response from “turn on” to “turn off” (**D** in Fig. 2).²⁸ The hydrazone functional group is commonly incorporated into multi-analyte fluorescent sensors.²⁹ A recent breakthrough reported first-in-class hydrazone-pyrazolines sensors distinguishing Zn^{2+} at 560 nm, Cd^{2+} at 510 nm, and Hg^{2+} at 460 nm λ_{em} in aqueous environments (**E** in Fig. 2).³⁰ Typical approaches to chalcones involve the use of polar protic solvents, such as ethanol and methanol, accounting for 50% and 20% of all Claisen–Schmidt condensations reported between 1960–2025 (see SI1 for literature survey). Researchers often use previous synthetic methodologies with little to no experimental optimisation reported. This study addresses this research need using a data-driven design of experiments (DoE) approach. A large-scale chalcone library (>1 g scale) enabled a

second DoE study focusing on pyrazoline synthesis. A pyrazoline library was generated, screened across multiple analytes using a HTS platform. This workflow significantly accelerated the discovery process, providing a valuable case study on incorporating data-driven methodology in synthetic organic chemistry.

Results and discussion

An LC-MS method to monitor the Claisen–Schmidt condensation reaction was established (Fig. 3). An internal standard (acetaminophen) was added to all reaction aliquots ensuring injection consistency, and external calibration curves were generated (see SI3 for full details). A typical chromatogram is displayed in Fig. 3 demonstrating the conversion of 2-acetylpyridine and benzaldehyde to **C1**. A screening study to confirm the suitability of the LC-MS method and determine the main DoE parameters was performed (SI4). Solvent, consisting of the bulk of the reaction mixture, had a significant impact on chalcone yield. The equivalent of NaOH, temperature, and time were also identified as significant factors and selected for DoE analysis. While this one factor at a time (OFAT) approach identified suitable conditions, it did not identify interconnected variables or provide a system-wide analysis. A DoE workflow was established (Fig. 4) to screen multiple variables; each performed in triplicate. This experimental design provided 45 datapoints to determine the optimum conditions for the Claisen–Schmidt condensation reaction¹³ for chalcone synthesis using a system-wide approach.

A least squares fit DoE model was generated with an R^2 value of 0.97 and a P -value of <0.001, indicating good statistical modelling (Fig. 5C). This model was then used to predict various reaction conditions (Fig. 5A). Solvent was confirmed as influencing the reaction yield, with the polar protic solvents MeOH, EtOH, and IPA providing the best yields. Polar aprotic

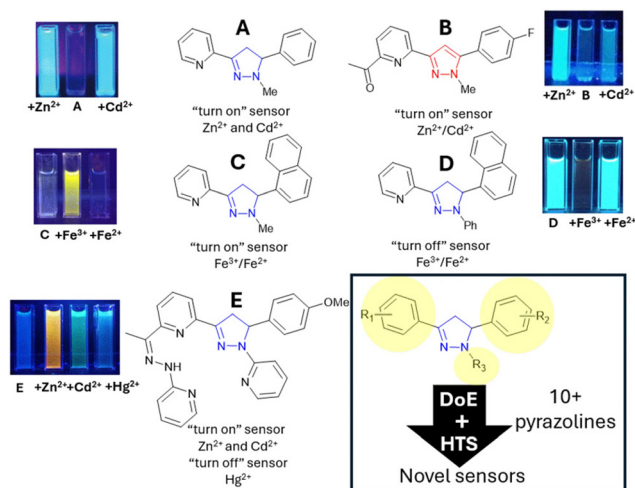


Fig. 2 Fluorescent sensors for toxic metals. This study incorporated design of experiments (DoE) and high throughput screening (HTS) for pyrazoline sensor development (inset).

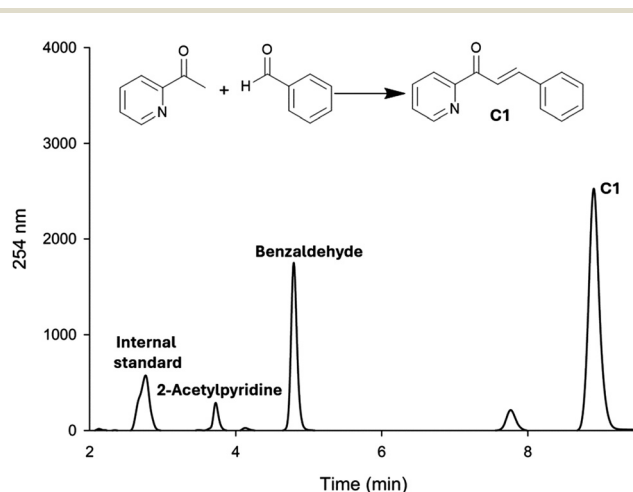


Fig. 3 Claisen–Schmidt condensation for **C1** monitored *via* LC-MS, starting materials 2-acetylpyridine and benzaldehyde to chalcone **C1** with acetaminophen used as an internal standard.



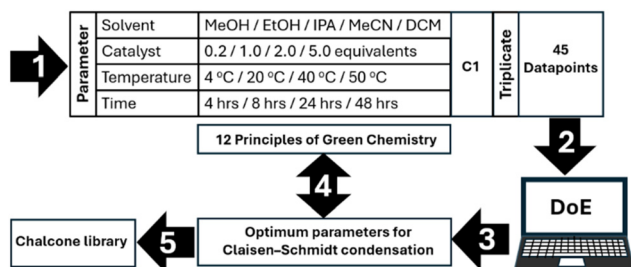


Fig. 4 DoE workflow for optimum chalcone synthesis using 45 individual datapoints.

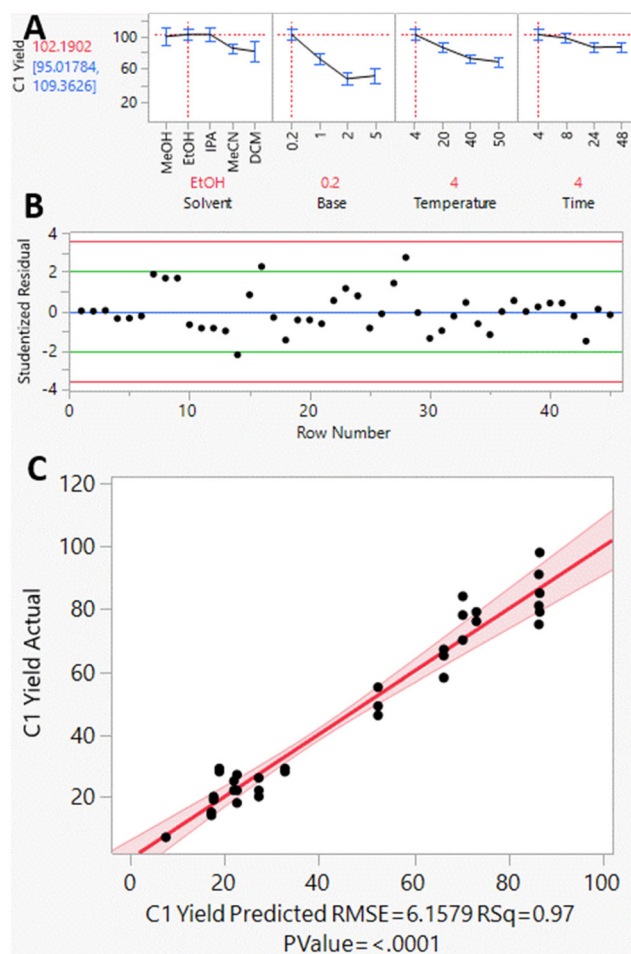


Fig. 5 DoE summary, optimal parameters are displayed in red (panel A), residuals in panel B. An excellent predictive model ($R^2 = 0.97$) was generated with confidence interval displayed in red (panel C).

solvent MeCN and chlorinated solvent dichloromethane should be avoided. Interestingly, the use of 0.2 equivalent NaOH was the most efficient alongside 4 °C reaction temperature. Further increases in catalyst and temperature were detrimental to reaction yield. Time had a minor influence on reaction yield, with 4 h and 8 h the optimal. Using the above model and the 12 principles of green chemistry,³¹ particularly

atom economy and energy efficiency, the following conditions were selected: EtOH, 0.2 equiv. NaOH, 4 °C and 8 h. These reaction conditions were then used to synthesise a structurally diverse library of 27 chalcones in excellent yield. Performing these reactions on a 10 mmol scale enabled gram-scale purification of chalcones directly *via* recrystallization preventing the requirement for time-consuming column chromatography (Scheme 1).

The high yield for chalcones C1–C27 provides further confirmation of the predictive properties of the DoE model and validates the chosen reaction conditions (Table 1). These reaction conditions are likely to be suitable for future chalcone research beyond sensing, for example medicinal chemistry.^{9–12} These chalcones then served as precursors for a pyrazoline synthesis DoE and, in turn, a pyrazoline library. A suitable DoE



Scheme 1 DoE optimised chalcone synthesis.

Table 1 Chalcone library using DoE derived conditions

R1 R2			
	C1 83%	C10 72%	C19 72%
	C2 72%	C11 73%	C20 76%
	C3 86%	C12 77%	C21 79%
	C4 60%	C13 84%	C22 72%
	C5 75%	C14 60%	C23 70%
	C6 89%	C15 65%	C24 89%
	C7 87%	C16 74%	C25 95%
	C8 92%	C17 84%	C26 76%
	C9 77%	C18 73%	C27 75%

approach was developed to determine the optimal reaction conditions for the conversion of chalcone **C1** to pyrazoline **P1**. The same LC-MS method was utilized to monitor the conversion of **C1** to **P1** with a DoE workflow established to screen solvent, phenylhydrazine equivalent, temperature, and time (Fig. 6).

A least squares fit DoE model was generated with EtOH identified as the optimal medium for the reaction (Fig. 7).

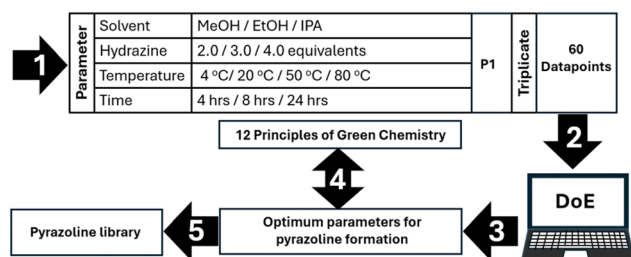


Fig. 6 DoE workflow for optimum pyrazoline synthesis using 60 individual datapoints.

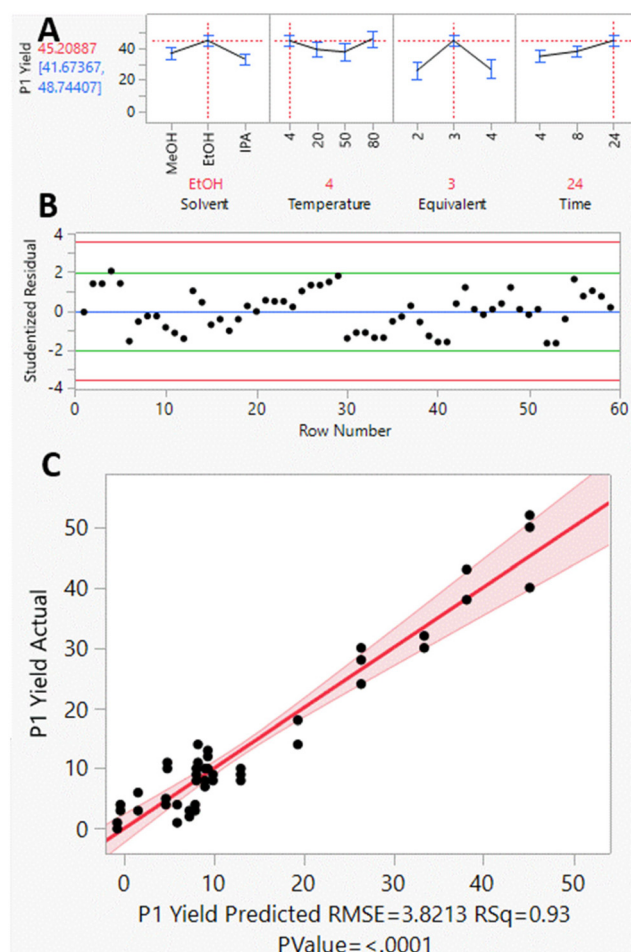
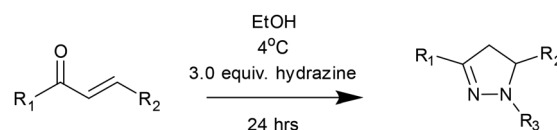


Fig. 7 DoE summary, optimal parameters are displayed in red (panel A), residuals in panel B. A good predictive model ($R^2 = 0.93$) was generated with confidence interval displayed in red (panel C).

Interestingly, temperature exerted only a minor influence on pyrazoline formation, with 4 °C providing the best outcome when used in combination with 3.0 equivalents of hydrazine.

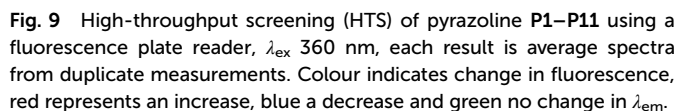
Reaction time showed a linear correlation with product yield, and 24 hours was determined to be optimal. Guided by this optimization model and the 12 Principles of Green Chemistry,³¹ the final reaction conditions were selected as EtOH, 3.0 equiv. hydrazine, 4 °C, and 24 h (Scheme 2). Under these conditions, a structurally diverse pyrazoline library comprising 11 potential sensors was synthesized in good to excellent yields (Fig. 8). Reactions performed on a 2 mmol scale generated sufficient material for purification *via* recrystallization, eliminating the need for time-consuming column chromatography. This approach was essential for achieving rapid synthesis and enabling high-throughput screening for desirable sensing properties. A preliminary fluorescence screen was performed to identify promising sensors in the presence of Zn^{2+} and Cd^{2+} (Fig. 8). Pyrazoline **P1–P3**, all containing a phenyl-substituted pyrazoline, displayed negligible changes in fluorescence emission with Zn^{2+} and Cd^{2+} . Interestingly, the pyridine-substituted analogues **P7–P9** did display a slight preference for Zn^{2+} over Cd^{2+} with green fluorescence emission. This observation suggested that the addition of nitrogen may be beneficial to group 12 metal selectivity. Pyrazoline **P11** displayed a “turn off” response, indicating the naphthyl unit is impacting the fluorescence response. The lead sensor was identified as **P10**, displaying both a nitro-substituted ring and pyridyl units. A highly unusual yellow fluorescence emission was observed in the presence of Zn^{2+} , but not with Cd^{2+} . The substitution of an electronegative halogen (as observed in **P8** and **P9**) for a highly electronegative nitro group profoundly modified the response to Zn^{2+} and Cd^{2+} and warrants further investigation. With a library of 11 pyrazolines in hand, a high-throughput screening (HTS) assay was developed using a standard laboratory fluorescence plate reader using a 96-well format. The responses to eleven different metal ions (250 μ M) across each pyrazoline (50 μ M) were measured in duplicate in acetonitrile.

This approach was designed to rapidly screen for fluorescence sensing properties in the 380–650 nm range using 360 nm excitation (see SI for full analysis, see Fig. 9 for heatmap summary). Pyrazoline **P1**, **P3–5**, **P7–P8**, and **P10** all displayed a “turn on” response to a range of group 12 metals. The paramagnetic metals Fe^{3+} , Ru^{3+} , and Cu^{2+} displayed a “turn off” response across all pyrazolines; this is commonly observed in the literature.³² The biological metals Na^+ , Li^+ , and Mg^{2+} did not alter the fluorescence response, and therefore these sensors are unsuitable for monitoring these ana-



Scheme 2 DoE optimised pyrazoline synthesis.





A

The diagram illustrates a machine learning workflow. It begins with 'DoE' (Design of Experiments), which leads to 'HTS' (High-Throughput Screening). From 'HTS', the process moves to 'ML' (Machine Learning). The 'ML' step leads to 'Predict structure', which then leads to 'Make structure'. A feedback loop labeled 'Improve model' connects 'Make structure' back to 'ML'. Another feedback loop labeled 'Test structure' connects 'Make structure' back to 'DoE'.

DoE → HTS → ML → Predict structure → Make structure

Improve model (from Make structure to ML)

Test structure (from Make structure to DoE)

Easily accessible scaffolds ✓ Highly modular ✓ Inexpensive reagents ✓

B

OUTPUT 1: ML derived sensors for specific metals

The diagram shows a chemical structure of a 1,2,3-trisubstituted 1H-imidazole. The substituents are labeled R_1 , R_2 , and R_3 . An orange circle with 'M+' represents a metal ion. Three arrows point from the imidazole structure towards the text 'Specific λ_{em} '.

R_1 , R_2 , R_3

M+

Specific λ_{em}

OUTPUT 2: ML derived molecular logic gates

The diagram shows the same 1,2,3-trisubstituted 1H-imidazole structure reacting with a series of logic gates. The gates are represented by colored shapes: a red 'AND' gate, a blue 'OR' gate, a yellow 'INH' (inhibition) gate, a green 'NAND' gate, and a green 'NOR' gate. Arrows indicate the sequence of operations.

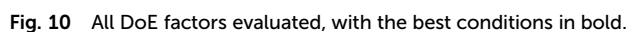
R_1 , R_2 , R_3

AND, OR, INH, NAND, NOR

Fig. 11 Future workflow incorporating design of experiments (DoE), high-throughput screen (HTS), and machine learning (ML) to accelerate the discovery process (panel A). Potential outputs include ML-derived sensors for specific metals and the discovery of pyrazoline-based molecular logic gates (panel B).

The optimised synthetic conditions for chalcone and pyrazoline formation has been determined using a data-driven design of experiments (DoE) approach (Fig. 10). These conditions (EtOH, 0.2 equiv. NaOH, 4 °C and 8 h) provided a diverse chalcone library of 27 compounds in good to excellent yield (60–93%, Table 1). The optimal conditions for pyrazoline formation (EtOH, 3.0 equiv. hydrazine, 4 °C, and 24 h) were determined and used to generate a pyrazoline library also in good to excellent yield (11–94%, Fig. 8).

The establishment of an HTS assay enabled the rapid identification of fluorescent properties to a range of metals, resulting in the highly expected discovery of **P10** with highly unusual yellow fluorescent emission in the presence of Zn^{2+}



only. This workflow demonstrates the significant advantages of incorporating modern data-driven methodology into synthetic organic chemistry. This approach is ideally suited to machine learning (ML) applications in which a large, structurally diverse, and modular chemical library is synthesized and screened, resulting in large datasets of consistent data.³³ This dataset can then be used to train ML models to predict and design novel compounds with specific properties (Fig. 11A). These, in turn, are generated and screened, and the resulting data used to improve the model further. A key requirement for this strategy is easily accessible scaffolds that are highly modular, using inexpensive reagents. As highlighted within, pyrazolines are ideally suited to this approach. Potential applications of such workflows include the generation of ML-derived sensors for specific metals and the development of molecular logic gates (Fig. 10B).³⁴ Numerous recent pyrazolines have been reported as logic gates,³⁵ and the application of ML will accelerate development further. This is future work and will be reported in due course.

Author contributions

Alexander Ciupa designed, synthesized, characterised all compounds, and authored the manuscript.

Conflicts of interest

There are no conflicts to declare.

Data availability

The data supporting this article have been included as part of the supplementary information (SI). Supplementary information is available. See DOI: <https://doi.org/10.1039/d5ob01684c>.

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