Design Science

Design and decision-making analysis for undergraduate research experiences

Joshua M. Herzog, Stephen McCord and Volker Sick

Mechanical Engineering, University of Michigan, USA

Abstract

Undergraduate research experiences (UREs) are believed to benefit students, but there is little concrete evidence to support this claim. Likewise, faculty often see UREs as a burden, yet multiple studies show UREs benefit faculty. Outcomes could be improved for both parties if projects were designed better. We report a rational design and decision-making framework for project-based mentoring experiences like UREs to address this misalignment by helping mentors balance competing research and learning requirements. The method requires the mentor to identify factors that are important for success and evaluate their project on those factors. Responses are analyzed using possibility theory to account for uncertainty in these judgments. Three projects are analyzed as a demonstration. We show the method can be used to rank projects based on predicted outcomes and identify areas for improvement, and we describe a procedure for iterative design as evidence changes. Applying the tool to UREs, we show that the method is capable of identifying inconsistencies in the mentor's beliefs and provides a clear and straightforward procedure for introspection and adaptation over time. More broadly, the method and analysis could be adapted to design and analyze other project-based experiences under uncertainty.

Keywords: undergraduate research experiences, multi-criteria decision making, possibility theory, project-based learning, rational decision-making, mentoring, introspection

Received 03 March 2026 UTC
Revised 02 July 2026 UTC
Accepted 28 July 2026 UTC

Corresponding author
Joshua M. Herzog
jmherzog@umich.edu

© The Author(s), 2026. Published by Cambridge University Press. This is an Open Access article, distributed under the terms of the Creative Commons Attribution licence (http://creativecommons.org/licenses/by/4.0), which permits unrestricted re-use, distribution and reproduction, provided the original article is properly cited.

Des. Sci., vol. 12, e33
journals.cambridge.org/dsj
DOI: 10.1017/dsj.2026.10076

1. Introduction

It is widely believed among faculty, researchers, and students (Hunter, Laursen & Seymour 2007) that undergraduate research experiences (UREs) greatly enhance science, technology, engineering, and mathematics (STEM) education by, for example, increasing interest in science careers (Russell, Hancock & McCullough 2007) and helping students develop skills necessary for graduate school or professional service (Landrum & Nelsen 2002; Petrella & Jung 2008). But there is little quantitative evidence to support these broad claims of success. Expectations and gains for students vary widely, and gains can be constrained by prior expectations (Wilson *et al.* 2013). Poorly designed projects or those with a narrow scope may also limit student gains. Related work has further highlighted the importance of the mentor–mentee relationship, in particular suggesting that this relationship is the most important factor influencing future decisions regarding graduate school (Houser, Lemmons & Cahill 2013).

Conversely, many faculty view UREs as costly or as a burden, even though there is strong evidence that UREs benefit mentors greatly (Hill *et al.* 2022; Sarabipour

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

et al. 2023). The perceived difficulty and workload of mentoring a URE (Eagan *et al.* 2011) and misalignment of mentor–mentee goals (Sharma *et al.* 2022) appear to remain significant barriers in the wider implementation of UREs. Administrative barriers exist as well: faculty are generally not recognized or awarded for involving undergraduate students in research (Dolan & Johnson 2010).

To improve student gains, UREs should promote integrated understanding (Linn *et al.* 2015) and set expectations early on. Broader definitions of research activities and different forms of research engagement can reduce barriers and lead to better outcomes (Brew & Mantai 2017). Careful preparation and structuring of UREs can lead to better outcomes for both the mentor and mentee (Shanahan *et al.* 2015). In short, mentors must work carefully to prepare and implement UREs to ensure students are well supported, and that the project aligns well with both faculty and student expectations. Mentors should commit to providing appropriate support for each URE to achieve positive learning and research outcomes.

We propose treating URE planning as a design problem under uncertainty, involving tradeoffs between student and mentor outcomes. The idea of "designing" a URE to meet specific learning and research goals has seen some success recently, especially in course-based UREs and similar frameworks. Perhaps unsurprisingly, some successful examples use approaches that are consistent with evidence-based and learner-centered teaching strategies (see Felder & Brent 2024 for a comprehensive overview of learner-centered teaching strategies). For example, more structured approaches with well-defined learning objectives, syllabi, and grading rubrics have shown promise (Brown, Lewis & Bevan 2016). Design iteration, or cyclic refinement over time, has also shown success in course-based UREs (Mordacq *et al.* 2017). While these recent developments have implemented some aspects of a design science, they have been limited to structured or course-based programs and their extension to traditional mentored UREs is unclear. They also fall short of providing an actionable methodology that can be adapted or extended to other contexts. Here, we present a methodology to analyze and design traditional apprenticeship-style UREs with a clear procedure, representation, and intended use that can be applied more broadly.

The methodology we propose is rooted strongly in design theory, and we argue that URE design, like many problems in education and beyond, should be treated as a design problem. Design broadly refers to the creation of artifacts such as services, products, or systems, and design science is the scientific discipline that studies this creative process and the knowledge it generates (Papalambros *et al.* 2025). Education is naturally a design science in that it applies practical knowledge and heuristic principles to create instructional methods and teaching experiences that achieve the goal of student learning (Laurillard 2013, ch. 1). Indeed, design principles are prevalent throughout the education literature, even when they are not explicitly labeled as such (Herrington & Reeves 2011). However, broader recognition of educational practice as a design science problem, rather than merely a linear, systematic, task-oriented process, has only emerged relatively recently (Norton & Hathaway 2015). A primary goal of design research is to support designers (in our case, research mentors) by transferring research results and design methods into practice (Gericke *et al.* 2020). This is achieved by developing local design principles into more complete design methods that are described with sufficient rigor to enable broader use and adaptation (Gericke, Eckert & Stacey 2022). As such, design science provides an ideal lens for analyzing UREs and other

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

project-based mentorship experiences as design problems and for articulating transferable methods to improve them.

1.1. Aims and significance

In this work, we pursue two complementary goals. First, we aim to develop a rational, multi-criteria decision- making framework, grounded in possibility theory, for designing and iteratively adapting project-based mentoring experiences under uncertainty. Second, we aim to demonstrate how the framework can be used to inform design of UREs to improve both student and mentor outcomes. This framework directly addresses the issue of balancing competing research and learning outcomes, providing an actionable strategy to systematically tune individual experiences according to both mentor and mentee goals.

In the following, we detail a rational multi-criteria decision-making approach for planning project-based mentoring experiences under uncertainty to aid mentors in designing UREs that are better aligned with both the mentor's and student's goals. We develop six criteria on which a URE proposal is graded, derived from the preceding text, and detail the procedure for evaluating a URE proposal. We then apply the method to analyze and discuss three example projects that were recently conducted by the authors. The design approach requires the mentor to evaluate multiple criteria regarding both their relative importance and expected outcome for a specific project, and is thus a rational model for decision making. As such, the purpose of the tool is to require mentors to formally define and acknowledge their expectations for the URE, and reconcile their expectations with what they perceive to be important factors in URE outcomes.

The analysis uses possibility theory (Dubois & Prade 2015), which is a subset of the theory of evidence (Gordon & Shortliffe 1984), with the aim of injecting judgment values or belief into the decision-making process. This is in contrast to probability theory which assigns likelihood, and also contrasts with the Bayesian interpretation of the degree of belief (Smets 1988). Notably, all possible outcomes are not complementary (Salicone 2007, ch. 3), leading to a different set of rules for combining multiple pieces of evidence. This approach has the benefit that the assessment not only accounts for uncertainty and ignorance in our judgment but also allows us to interpret the decision value as a measure of how strongly the mentor should believe the project will be successful. The use of possibility theory here is particularly important because it provides a means to directly account for the inherent uncertainty in assigning a "degree of belief" in an outcome based on intuition. We are hopeful that further development of this approach can yield greater benefits to both students and faculty, and encourage other faculty and researchers to more fully integrate undergraduate students in interdisciplinary, high-impact research projects. While this analysis focuses on UREs as an example case, the framework is intended to be more broadly useful in designing complex mentoring and project experiences.

2. Methods

The decision-making tool is implemented as a survey, in which the user assigns a value representing the importance of a variety of statements as they relate to expected project success. Then, after describing their specific project proposal in

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

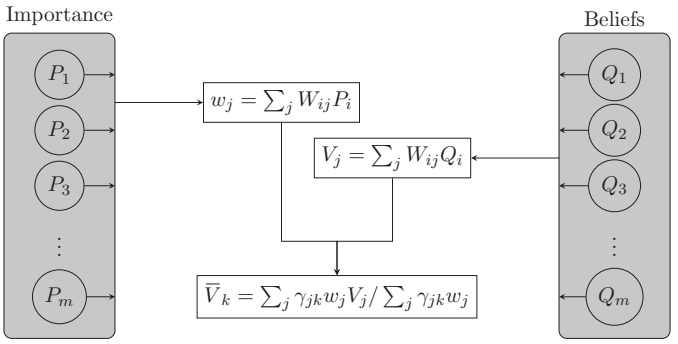


Figure 1. Illustration of the URE analysis method. The two shaded boxes, "Importance" and "Beliefs," are the user-input relative importance and project belief values, respectively. From these, relative weights w_j and average belief values V_j are calculated for the six primary criteria using the same weight matrix W_{ij}. Then, aggregate belief values representing mentor and student outcomes (the $\overline{V}_k$'s) are calculated from the intermediate values. The matrix elements γ_{jk} are further weightings that indicate whether criterion j is considered for outcome k.

detail, the user is asked to evaluate their expectations of the project using a corresponding set of prompts. Underlying these individual statements are six basic criteria that are each evaluated as a weighted average of the responses to several of the prompts. The process is shown schematically in Figure 1. The prompts, primary criteria for evaluation, and mathematical details are described in the following.

2.1. Decision-making criteria

Creating guidelines to design a traditional apprenticeship-style URE is not straightforward, in part because of the wide range of mentoring styles, research methodologies, project scopes, and student expectations that occur throughout different STEM fields. However, there are a few factors that are widely agreed upon to be influential to URE success, which we focus on here. These factors include time management and commitment, goal-setting, motivation, and the student–mentor relationship (Mancha & Yoder 2014). Similarly, longer-term, sustained UREs lasting more than one year are correlated with publications co-authored by mentor and student (Morales, Grineski & Collins 2017), so project length and scope also should be considered.

In total, six decision-analysis criteria were identified as factors that are commonly associated with URE success in the literature, as well as factors that are critical to project planning. The criteria are summarized in Table 1. The following paragraphs summarize our interpretation of these criteria as we view them for our UREs, and acknowledge that these descriptions will vary between researchers and universities.

The first two criteria, *time* and *scope*, are common indicators used in project management for project planning, and require little additional explanation. For any project to be successful, whether undergraduate research or large-scale engineering project, the timeline and scope must fit the project requirements. In this

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

Table 1. Description of six primary criteria considered in the decision-making analysis procedure

Criterion	Interpretation
Time	Can the project be completed in an appropriate time frame?
Scope	Is the project suitable (and adaptable) for an undergraduate project?
Research impact	Is the project set up appropriately to answer a suitable research question?
Learning	Are there suitable learning opportunities for an undergraduate student?
Alignment	Do the mentor and student share similar expectations for the project direction?
Communication	Are the mentor(s) and student able to communicate effectively?

case, to facilitate learning outcomes, we expect the project scope is sufficiently broad to introduce the student to many aspects of academic research while being sufficient small and well-defined that it can be completed within the course or internship duration. Related to scope, the project time or duration should be appropriate to complete the project work while avoiding overly ambitious timelines that do not account for the time needed to learn new skills.

The next two criteria, *learning* and *research impact*, are direct indicators of the project impact. For the URE to be successful, the student should learn something about academic research. For our work, we generally aim to provide an opportunity for students to learn new skills that are of value in industry or academic jobs (*e.g.*, in engineering, this could be programming experience, use of computational software, application of design methods, or novel analysis techniques) in addition to deeper knowledge and application of the topics that are taught in related classes. Regarding research impact, we similarly aim to outline projects that are a small but necessary portion of our ongoing research.

Finally, *alignment* and *communication* are indicators that both students and faculty have identified as being factors in the success of UREs. Alignment refers to the shared expectations, motivations, and interests between the student, mentor, and project focus. Similarly, student motivation or enthusiasm has similarly been identified as an important factor (Mancha & Yoder 2014). We include student motivation and enthusiasm as part of *alignment* for simplicity. Likewise, communication refers to having established and open channels of communication, through scheduled meetings, training, and other forms of student support.

2.2. Survey prompts

The six criteria are evaluated by answering a series of 27 prompts twice. The first set of 27 prompts are evaluated by the mentor regarding their importance to project success. For the second set of prompts, the mentor assigns a belief value to each statement regarding their expectations for a specific project. The belief value assigned here is a stated and unsupported measure of how strongly they believe

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

Table 2. Prompt text for belief statements and importance statements

i	Importance statement	Belief statement
1	The project can be completed on time.	My student can easily complete this project on time.
2	Students meet regularly with their advisors.	I will meet regularly with my student.
3	The project leads to a big research breakthrough.	The results will be very useful for my research.
4	The student was given time to learn new skills.	I have scheduled time for learning and literature review.
5	The student demonstrated new skills, not taught in class.	My student will need to learn new skills outside of class.
6	The student had sufficient time to prepare all deliverables.	I have allowed time for my student to prepare deliverables.
7	Training materials were made available to the student.	I have already identified training materials for my student.
8	Advisors/mentors were available to the student.	I will be available at least 3 hours/week to help my student.
9	The project scope was clear to the student.	We have discussed and agreed upon the project scope.
10	The project results were published.	The results of this project will be published.
11	The student was a co-author on a publication.	My student will publish their results.
12	Expected difficulties were anticipated in advance.	I know which parts of the project will be difficult.
13	The student demonstrates useful new skills.	The skills needed to complete the project are useful.
14	The student presented their work at a conference.	We agreed that my student will present at a conference.
15	Other students/researchers were available to the student.	Other students/researchers will help support my student.
16	The project was designed to achieve a clear outcome.	I designed this research to answer a specific question.
17	The project deliverables were clear and manageable.	We have agreed on project scope and deliverables.
18	The research results confirmed the advisor's expectations.	I know what success would look like for this project.
19	Students have demonstrated interest in "the big picture."	My student has demonstrated an interest in our mission.
20	The student learned valuable new skills.	My student will build valuable skills for their future career.
21	The research provided learning opportunities.	I designed the project to provide teaching opportunities.
22	Experiments/activities were planned well in advance.	I have planned experiments/activities in detail already.
23	The student and mentor have similar academic interests.	We share similar goals and academic interests.
24	The student had time to learn necessary skills.	I scheduled time specifically for learning new skills.
25	The student's career goals are aligned with the project.	My student demonstrated an interest in this field.
26	The project results helped to define new research areas.	Our results will help to reveal new research areas.
27	The student and mentor discussed the project in depth before starting.	We agree on the project scope and methods.

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

each outcome to be true or false, and is implicitly uncertain. These prompts were selected to probe factors relevant to URE success as documented in the literature, and to specifically relate to the six decision-analysis criteria outlined above. The prompts are shown in Table 2, and the relative weight matrix is shown in Table 3. The weights are selected to be either 0, ± 0.5, or ± 1, corresponding to no, partial, or perfect correlation between the question and underlying criteria.

Table 3. Relative weights for each prompt

i	T	S	R	L	A	C	$\sum \lvert w \rvert$
1	1	−0.5	−0.5	0.5	0	0	2.5
2	−0.5	0	0	0.5	0	1	2.0
3	0	0.5	1	0	0	0	1.5
4	0.5	0.5	0	1	0	0.5	2.5
5	−0.5	0.5	0	1	0	0	2.0
6	1	0	0	0.5	0	0	1.5
7	0.5	0	0	0.5	0	1	2.0
8	0	0	0	0.5	0.5	1	2.0
9	0.5	1	0.5	0	0.5	0.5	3.0
10	0	0.5	1	0	0	0	1.5
11	0	0.5	0.5	0.5	0.5	0	2.0
12	0	0	0.5	0	0	0.5	1.0
13	0	0	0	1	0	0	1.0
14	0	0.5	0.5	0.5	0.5	0.5	2.5
15	0	0	0	0.5	0	1	1.5
16	0	−0.5	1	−0.5	0	0	2.0
17	0.5	1	0.5	0	0.5	0.5	3.0
18	0.5	1	−0.5	0	0	0	2.0
19	0	0	0	0	1	0	1.0
20	0	0.5	0	1	0.5	0	2.0
21	0	0.5	−0.5	1	0	0	2.0
22	1	0	0.5	−0.5	0	0	2.0
23	0	0	0	0	1	0.5	1.5
24	1	−0.5	0	0.5	0	0	2.0
25	0	0	0	0	1	0	1.0
26	0	0	1	0	0	0	1.0
27	0	0.5	0	0	1	0.5	2.0
$\sum \lvert w \rvert$	7.5	9.0	8.5	10.5	7.0	7.5	

The column headers **T**, **S**, **R**, **L**, **A**, and **C** refer to the criteria *time*, *scope*, *research impact*, *learning*, *alignment*, and *communication*, respectively. The last column represents the sum of the absolute value of the weights, which indicate the relative importance of each prompt. The bottom row represents the sum over each column, and is the normalization factor used in the weighting scheme.

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

Table 4. Prompt weight correlation matrix

	T	S	R	L	A	C
T	1.00	−0.16	−0.18	−0.15	−0.22	−0.19
S	−0.16	1.00	0.06	0.07	0.17	0.02
R	−0.18	0.06	1.00	−0.54	−0.10	−0.12
L	−0.15	0.07	−0.54	1.00	−0.22	0.09
A	−0.22	0.17	−0.10	−0.22	1.00	0.08
C	−0.19	0.02	−0.12	0.09	0.08	1.00

The scores presented in Table 3 were determined based on a combination of literature synthesis, pedagogical science, and our personal experience. Prompts suggesting a larger time commitment by the mentor are generally interpreted as benefiting research, learning, and communication but intrinsically also penalize time. We justify this by considering time as a fixed resource, so additional meetings and communication activities reduce the total amount of time remaining to complete the assigned research activities. This time penalty is particularly significant in academic research where long, uninterrupted periods of high-cognition work drive productivity. We generally interpret statements indicating that the project is *easy* or *straightforward* (*e.g.*, prompt #1) also to be indicative of a lack of depth, or that the scope is too narrow or the research impact is only marginal. There are similar tensions between research and learning throughout the prompt list. We justify this tension as a competition for resources, such as time (*e.g.*, if significant background learning is required, there is less time for novel experiments).

Tensions between criteria scores are quantified by the correlation coefficient ρ in Table 4. From the matrix, we note that most of the criteria are only weakly correlated, except as stated *research impact* and *learning* have a moderate negative correlation ($\rho \approx -0.54$). We also note that *time* has a small negative correlation with every other criterion. This is consistent with the idea that time management must compete with learning and research impacts, project scope, and effective communication.

We believe the weightings are largely self-explanatory and are a reasonable interpretation of the prompt statements, but we acknowledge that many researchers may not share our interpretation. We do not believe this is a significant limitation though. Since users must rank criteria they believe to be important using a corresponding set of prompts, the aggregated scores are necessarily reflective of the users' interpretation of the prompts. However, the meta-analysis or introspection, that is, the interpretation of the six criteria scores, may not be perfectly reflective of the user's interpretation of each criterion.

2.3. Importance and belief value determination

As described previously, the mentor first assigns an importance value to each of 27 statements as they relate to expected project success. These assigned importance values are given the label P_i, for each prompt $i \in [1 \,..\, 27]$, and $0 \leq P_i \leq 1$. The importance values should not be answered with the specific project in mind but

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

instead should be representative of the mentor's expectation for a generic, successful URE. Next, the mentor assigns a belief value Q_i to each belief statement $i \in [1\,..\,27]$ that indicates how strongly they believe the outcome to be true $(0 < Q_i \leq 1)$ or false $(-1 \leq Q_i < 0)$.

The individual belief values Q_i are used to evaluate the project proposal on the six primary criteria. We assume a triangular possibility distribution for each belief value with a peak at $x_{i0} = Q_i$, and intercept points $x_{\pm}$. We use the triangular function because it is the simplest, non-trivial (or perhaps non-vacuous) possibility distribution we can define. We choose this in keeping with the spirit of "possibility" being a measure of intuition, rather than a formal mathematical statement regarding, for example, probability. The coordinates defining the possibility distributions are calculated as

$$x_{i-} = \begin{cases} -1 & -1 \leq Q_i \leq 0 \\ 2Q_i - 1 & 0 < Q_i < 0.5 \\ 0 & 0.5 \leq Q_i \leq 1 \end{cases} \tag{1a}$$

and

$$x_{i+} = \begin{cases} 1 & 0 \leq Q_i \leq 1 \\ 2Q_i + 1 & -0.5 < Q_i < 0 \\ 0 & -1 \leq Q_i \leq -0.5 \end{cases}, \tag{1b}$$

which ensures the triangle distribution varies continuously with the input Q_i. As a result of this definition, the belief function is nonzero over the entire interval $[-1, 1]$ for $Q_i = 0$, representing a high uncertainty case. In contrast, highly believable outcomes $Q_i = \pm 1$ are represented by right triangles with a base width of unity. For the intermediate cases, the width of the triangle base shrinks and the peak skews toward ± 1 as $Q_i \to \pm 1$. Notably, since we use triangle functions, no value of Q_i represents a case of complete ignorance in which every outcome is equally believable. The case of complete ignorance would instead be represented by a square interval (Salicone 2007, ch. 3), which we do not permit intentionally. We choose these particular triangular distributions because they do not allow complete ignorance, and enforce a wide but smoothly varying confidence interval to temper over-interpretation of scores.

2.4. Criteria score determination

Scores for the six underlying criteria are evaluated as a weighted average using the predetermined weight matrix W_{ij} which is given in Table 3. Fuzzy variables or sets like the triangular functions we use here can be formulated as nested intervals of belief values (Nguyen & Kreinovich 1996), which are described by α-cuts, where α represents the level of belief in the contained sub-interval. The α-cut interval specifically corresponds to the sub-interval within which the true value lies with a *necessity* of $(1 - \alpha)$. The *necessity* is a measure of how certain we are that the true value *must* lie inside this interval, and is a lower bound on the possibility. Since the α-cuts are nested intervals, they follow the basic rules of interval arithmetic (Moore & Lodwick 2003). It is sufficient here to only consider the points $x_{i\pm}$ and x_{i0}, which correspond to the $\alpha = 0$ and $\alpha = 1$. Since all fuzzy variables are described with

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

triangle functions, the other α-cut values lie on the line segments connecting $x_{\pm}$ and x_0. The outer ($\alpha = 0$) interval for the variable V_j is given by

$$\left[V_j\right](0) = \left[\overline{x}_{j-}, \overline{x}_{j+}\right] = \frac{\sum_i W_{ij}\left[x_{i-}, x_{i+}\right]}{\sum_i |W_{ij}|}, \tag{2a}$$

the interior ($\alpha = 1$) interval by

$$\left[V_j\right](1) = \left[\overline{x}_{j0}, \overline{x}_{j0}\right] = \frac{\sum_i W_{ij}\left[x_{i0}, x_{i0}\right]}{\sum_i |W_{ij}|}, \tag{2b}$$

and the intermediate α-cut is given by

$$\left[V_j\right](\alpha) = \left[\overline{x}_{j-} + \alpha\left(\overline{x}_{j0} - \overline{x}_{j-}\right), \overline{x}_{j+} - \alpha\left(\overline{x}_{j+} - \overline{x}_{j0}\right)\right] \tag{2c}$$

Note that some values of W_{ij} are negative (see Table 3). For these cases, the interval addition in Equations 2 should be replaced with interval subtraction. We mention this specifically because the algorithms for interval addition and subtraction are different (Moore & Lodwick 2003).

2.5. Aggregate score determination

The importance values are used to determine relative weighting of the six criteria for an aggregate analysis. The weights w_j assigned to the six criteria are evaluated as

$$w_j = \frac{\sum_i |W_{ij}| P_i}{\sum_i |W_{ij}|}, \tag{3}$$

which uses the same weights as the scoring analysis. However, the absolute value is used here because the sign is unimportant. Whether a statement is positively or negatively correlated with an outcome does not impact the magnitude of the effect. The w_j are used to evaluate aggregate scores as described in the following.

The two aggregate scores $\overline{V}_k$ are finally calculated from the individual scores V_j to represent measures of mentor and student outcomes. The mentor and student outcome weights are denoted γ_{jk} and are listed in Table 5. In short, time and research impact determines mentor outcomes, while scope and learning dictate the student outcome score. The remaining factors communication and alignment are assumed to play a role in both outcomes, and so are included in both aggregates with reduced weights.

The weightings for the "time" criterion specifically may seem counterintuitive but are consistent with our interpretation. Here, the "time" score is a measure of whether there is sufficient time to complete the research project. Naturally, if there is insufficient time to complete the project, the research outcomes are not realized and so "time" plays a primary role in the mentor outcome. In contrast, learning is expected to happen throughout the project period and is not necessarily contingent on completing the research project. Indeed, incomplete or inconsistent results are part of the scientific process and learning to adapt to failure is an important lesson. In contrast, "scope" refers to the variety of experiences provided by the project and more accurately characterizes opportunity for learning.

The α-cuts of the aggregate mentor and student outcome fuzzy variables are calculated as

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

Table 5. Weight factors γ_{jk} for aggregate mentor outcome and student outcome scores

	Mentor outcome	Student outcome
Time	1	0
Scope	0	1
Research	1	0
Learning	0	1
Alignment	0.5	0.5
Communication	0.5	0.5

Table 6. Interpretation of aggregate scores $\overline{V}_k$

Label	Range				
Terrible	-1.0	$\leq$	$\overline{V}_k$	$<$	-0.6
Poor	-0.6	$\leq$	$\overline{V}_k$	$<$	-0.2
Fair	-0.2	$\leq$	$\overline{V}_k$	$<$	0.2
Good	0.2	$\leq$	$\overline{V}_k$	$<$	0.6
Excellent	0.6	$\leq$	$\overline{V}_k$	$\leq$	1.0

$$\left[\overline{V}_k\right](\alpha) = \frac{\sum_j \gamma_k w_j \left[V_j\right](\alpha)}{\sum_j \gamma_{jk} w_j} \tag{4}$$

where $k \in [1 \,..\, 27]$ and the $\overline{V}_k$ correspond to the *mentor outcomes* and *student outcomes* aggregate variables, respectively. Both the individual criteria scores and aggregate values, V_j and $\overline{V}_k$, respectively, lie on the interval $[-1, 1]$. To aid in interpretation, we assign qualitative labels as listed in Table 6. A diagram summarizing the calculation is shown in Figure 2.

3. Results

We demonstrate the rational decision-making and design approach using three example projects that were developed, implemented, and mentored by one of the authors (JMH). Two of these projects were completed successfully and are analyzed retrospectively. The third project has not yet been completed and is presented as a design exercise. For each project, we provide a brief description of the project, our score for each statement, and a brief justification for our scores. Then, we present the aggregate analysis and discuss the outcomes.

Unless otherwise specified, we will assume the importance value $P_i = 1$ for each prompt i and thus $w_j = 1$ for each criterion for the remainder of this manuscript. This is the natural choice for analysis of our own experiences, based on which the prompts were developed, and is consistent with our approach to URE mentoring.

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

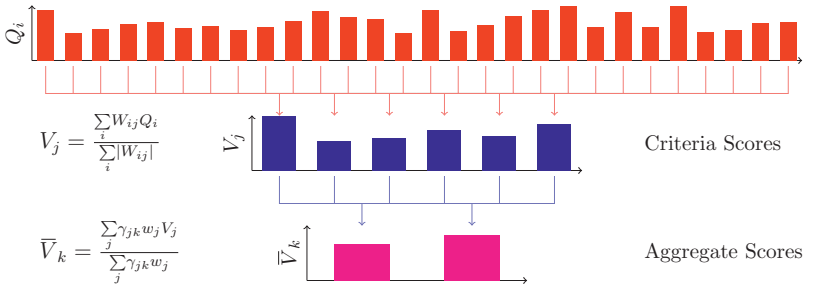


Figure 2. Illustration of the analysis method including two weighted-average calculations. The initial 27 prompt belief values Q_i are supplied by the user. These values are reduced to six criteria scores V_j via a weighted average. Finally, two aggregate scores $\overline{V}_k$ are calculated as weighted averages of the six criteria scores.

However, we include the importance weighting discussion here because we expect to observe different importance assignments across other mentors, departments, and disciplines in our future work. We also emphasize that uniform importance scores are not trivial, as they still require the user to justify the URE design with respect to each prompt.

3.1. Project descriptions

Each of the project scores Q_i is shown in Figure 3, and individual project descriptions and justifications are provided in the following paragraphs. In general, each project was designed to be conducted by a single undergraduate student over a fixed (project-dependent) duration, including necessary learning activities and preparation of deliverables.

3.1.1. Project #1: Low-cost embedded timing generator

The first project focused on the development of an embedded timing generator to synchronize optical and electronic components for a low-cost, handheld

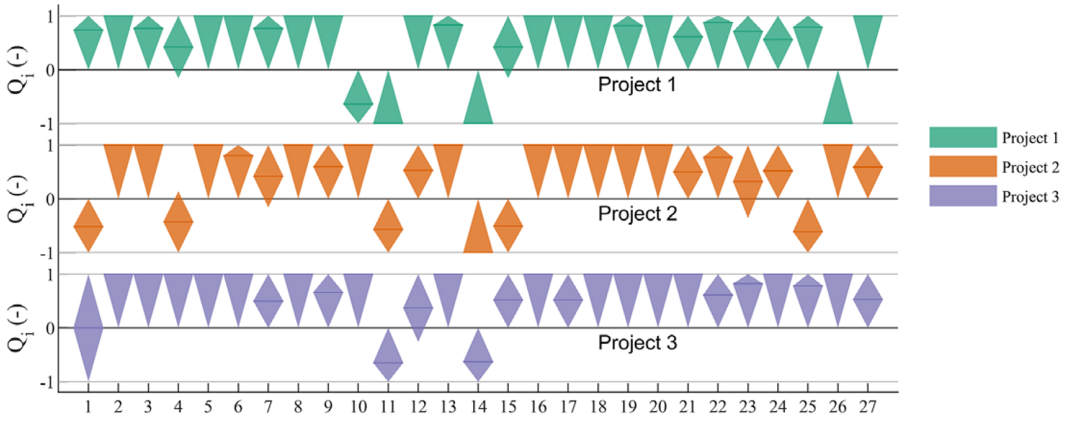


Figure 3. Prompt belief values Q_i for sample projects #1, #2, and #3.

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

biomedical imaging device. The project was conducted by a third-year electrical engineering student with basic skills in electronics, circuit analysis, and programming, and was scheduled to last for three months over the summer during which the student worked up to 20 hours per week. The student was responsible for meeting routinely with the research mentor, developing the software algorithm to enable independent and precise (10 μs) timing on four simultaneous channels. The project also required the student to construct and test the device, and write a short report detailing the development and performance.

To justify our responses, the mentor designed this project with the specific goal of designing, assembling, and testing a crucial hardware component needed for future studies. The project provided multiple hands-on learning opportunities for an electrical engineering student, including soldering, real-time computing constraints, and the Arduino platform. While this project itself is not a high-impact research study, it is a crucial component needed to enable development of a handheld biomedical imaging tool. The project scope, deliverables, and approximate timeline were developed and communicated to the student before the project was started.

3.1.2. Project #2: Biofilm radiative transfer experiments and simulation

The second project aimed to investigate radiative transfer, especially fluorescence, in bacterial biofilms. The project included experimental measurements of steady-state, *en face* fluorescence intensity in dense bacterial suspensions, combined with *Monte Carlo* simulations of radiative transfer in dense biofilms. This project was conducted by a third-year biological sciences student who had previously conducted a similar experimental project in the same lab. The student worked approximately 20 hours per week over a three-month period. During that time, the student conducted repeated experiments in the lab directly with the mentor and conducted initial simulations independently. The student also wrote a detailed report including both sets of results.

Radiative transfer theory is a broad and conceptually difficult topic to introduce at the undergraduate level, particularly in a context outside of the mathematical sciences, and within a constrained three-month timeline. However, in this case, the same student had conducted a similar project with the mentor over the previous nine months in preparation for this work. The project scope and deliverables were discussed and agreed upon with the student well in advance of the project start time.

3.1.3. Project #3: Theoretical/computational study of biomolecule fluorescence

The final project, which is ongoing, aims to use computational tools to investigate the optical properties of a range of biomolecules to design better optical detection strategies. This project will be conducted jointly by two first-year students over a nine-month period, and both students will work an average of 10 hours per week throughout that time. The first three months of the project time will focus on literature review and learning. The students will each summarize their accomplishments in a poster at the end of the project period. This project will also be supported by the undergraduate research opportunity program (UROP) at the

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

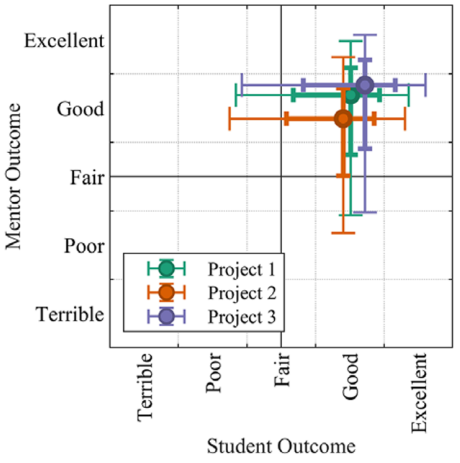


Figure 4. Aggregate scores and possibility intervals calculated for the three projects. The outer and inner error bars represent $\alpha = 0$ and 0.5, respectively, and the circles indicate $\alpha = 1$.

University of Michigan which provides additional training and resources to the students outside of the laboratory.

In this case, the project is ambitious and requires significant learning. However, this is planned in advance and the student has additional support from an external undergraduate research organization (UROP). Additionally, the use of computational electronic structure tools in undergraduate chemistry courses has been reported previously to enhance learning of physical chemistry concepts (Esselman & Hill 2016; Snyder & Kucukkal 2021), and significant progress has been made to minimize barriers to use these tools for teaching (William & Polik 2022). We therefore expect the focus on computational methods to be beneficial to student learning and research outcomes in comparison with an experimental project. An added benefit of UROP and similar programs is that they allow potential students the opportunity to find and apply for projects that align well with their personal goals.

3.2. Project aggregate scores and outcomes

The aggregate scores are shown in Figure 4. From the figure, our possibility distributions peak with a rating of *good* for both mentor and student outcomes, but the confidence intervals cover a much broader range. Notably, since the possibility intervals obey interval arithmetic, averaging over multiple measures does not reduce the width of the confidence interval. Based on the analysis, we expect all of the projects are likely to succeed. Indeed, projects #1 and #2, which were completed recently, were successful by most measures. Project #1 was concluded with the development and release of a 10 μs precision Arduino timing generator, and Project #2 leads to the publication of a journal article after subsequent studies (Herzog, Agosta & Sick 2024).

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

Table 7. Ordering of sample projects by aggregate *mentor outcome* and *student outcome* scores

Category	Ordering				
Student Outcome	Project 3	$\overset{0.24}{>}$	Project 1	$\overset{0.13}{>}$	Project 2
Mentor Outcome	Project 3	$\overset{0.15}{>}$	Project 1	$\overset{0.35}{>}$	Project 2

The value set above the ordering operator $>$ is the credibility factor for the binary comparison.

While the magnitude of the aggregate score is a useful, albeit subjective metric, the primary purpose and greater utility of this tool is to analyze and compare possible UREs. A simple ordering can be defined based on fuzzy arithmetic (Salicone 2007, Section 9.2) that assigns a credibility coefficient to the statement $A > B$ for two fuzzy variables A and B. Note that we could also compare $A > x$ where x is a scalar value, for example, to determine the credibility of an outcome being Good or Excellent, but this information is already evident graphically in the aggregate possibility distributions.

The three project scores were sorted according to the aggregate measures of mentor and student outcomes using this procedure, and the ordering and credibility factors are listed in Table 7. From the table, it is clear that there is significant overlap between the scores, as reflected in the credibility factors. However, despite the overlap, there is still a well-defined ordering. In particular, we find that Project #2 has the lowest measures of both mentor and student outcomes, while Project #3 has the highest scores for both mentor and student outcomes. Overall, we conclude that the proposed Project #3 has a greater student and mentor outcome score than both Projects #1 and #2.

4. Discussion

There are several aspects of our approach that are beneficial from a project design perspective. Since the importance factors or weightings are determined from a set of prompts that correspond directly to those on which a project proposal is evaluated, it is straightforward to perform an introspective analysis. That is, there is a mechanism through which the user can analyze their beliefs and perceptions within this framework, and identify areas that are in disagreement. Similarly, the capacity for introspective analysis and ordering operations between outcomes enable a simple and quantitative mechanism for design iteration and adaptation over time. These features are discussed in the following.

4.1. Introspection

Introspection generally refers to the process of looking inward to analyze or discover one's beliefs and perceptions, which, in many cases, are neither transparent nor consistent (Byrne & University of Arkansas Press 2005). A primary utility of a multi-criteria decision-making tool, like the one presented here, is that it can objectively answer the question as to *why* one might expect a certain outcome. When evaluating the cause of a negative outcome, the introspection process

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

quantifies inconsistency between beliefs and decisions. We achieve this here primarily by analyzing the weighted errors or deviations.

The weighted error or deviation of criterion j with respect to aggregate variable k is simply

$$\overline{e}_{jk} = \frac{\gamma_{jk}}{\sum_j \gamma_{jk}} \left(V_j - \overline{V}_k \right), \tag{5}$$

where V_j (without brackets) is the average score for criterion j. (More strictly, V_j is the single value that represents the degenerate interval $\left[V_j\right](1)$.) We can similarly define the weighted error for the individual prompt score i with respect to criterion j as

$$e_{ij} = \frac{W_{ij}}{\sum_i |W_{ij}|} \left(Q_i - \frac{V_j}{c_j} \right), \tag{6}$$

where the normalization factor c_j is

$$c_j = \frac{\sum_i W_{ij}}{\sum_i |W_{ij}|}, \tag{7}$$

which is needed to ensure that the error values sum to zero. Accordingly,

$$\sum_i e_{ij} = \sum_j \overline{e}_{jk} = 0. \tag{8}$$

The values e_{ij} represent the contribution (in both sign and magnitude) of each prompt to a criterion score and can be used to identify the responses that most strongly impact the result. Similarly, the values $\overline{e}_{jk}$ represent the contribution of each criterion score j to the aggregate score k. Values of e_{ij} and $\overline{e}_{jk}$ that are the most negative may indicate prompts or criteria, respectively, for which beliefs and expectations are misaligned.

For example, considering Project #3, we find that the most negative values of $\overline{e}_{jk}$ correspond to Research Impact and Scope for the mentor outcome and student outcome aggregate scores, respectively. This analysis suggests that it may be beneficial to focus on improving research impact and scope as the project evolves. Now, considering the individual prompt scores for these two categories (e_{ij}), we find that the most negative contributions to both categories come from prompts 11 and 14, or rather, that we do not expect any journal or conference publications from this project. Publications and conference presentations are an integral part of scientific research, so excluding these activities certainly does limit the scope of activities and may be evidence of a lower-impact research outcome. As this is a preliminary study, and since the student will have other opportunities for scientific writing and presentation within this project, we believe this is an acceptable trade-off.

When aggregate or criterion scores are relatively low, these weighted errors can identify areas for improvement. For example, we could alter the project description to better match our expectations. Alternatively, we could re-evaluate how we assess the importance prompts. In either case, this provides a clear mechanism for introspection in the decision-making process. However, it is worth noting that there will always be at least one value of e_{ij} and $\overline{e}_{jk}$ that is negative. So while these

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

values do identify prompts or criteria that lower the aggregate scores, they are not always a good indicator of inconsistency. Finally, it is worth noting that this analysis was performed for $\alpha = 1$ cut as it represents the most plausible outcome. However, the analysis can be extended easily to consider a confidence interval by replacing the values V_j, $\overline{V}_k$, and Q_i with their corresponding fuzzy variables or α-cuts.

4.2. Project design, iteration, and adaptation

Iteration is an import and often necessary component of the design process that must be managed for any complicated system (Wynn & Eckert 2017). We also believe this is true in education generally and in UREs specifically. As the project progresses and more evidence of an outcome is collected, the project should be reevaluated to assess whether it still satisfies our goals. An iterative procedure for URE design and adaption is straightforward to define. The mentor first analyzes the URE as described in Section 2. Then, the mentor adapts the project proposal based on the individual criteria and aggregate scores. The mentor may use the introspective analysis results as a guide. Finally, the mentor updates scores Q_i to reflect the changes, while keeping the importance values fixed to ensure scores are directly comparable. The individual criteria and aggregate scores can then be compared between projected outcomes using the fuzzy ordering operator $>$. This procedure should be used for iterative design to refine the project early on in the planning phase. It can also be used to adapt to changes in the project based on new evidence as the project progresses, and ideally would be performed at fixed intervals. As this procedure is an example of a rational, multi-criteria decision-making analysis, we emphasize that changes in responses should reflect only concrete new evidence.

For example, in our sample Project #3, we may decide we could improve the research experience by trying to incorporate a conference presentation or publication opportunity. The University of Michigan Undergraduate Research Journal (UMURJ) is a student-run research journal that publishes articles written exclusively by undergraduate students. Publication in UMURJ would have the dual benefit of providing a good learning opportunity for the student, and could help to communicate the research results to other researchers and students on campus. We could then adapt the project proposal to include a short article in UMURJ as a deliverable at the end of the project. Similar opportunities exist for undergraduate conference presentations. Including these as uncertain stretch goals (*i.e.*, choosing $Q_{11} = Q_{14} = 0$), and assuming that no other responses are impacted by this decision, we find that the aggregate scores of mentor and student outcomes are increased with credibility factors of ~ 0.19 and ~ 0.14, respectively.

4.3. Outlook and future work

It is evident that qualitative differences in projects, such as the type of work being conducted (*e.g.*, laboratory, computational, literature review, *etc.*), may have a significant influence on the outcome. Further, uncontrollable factors, like project duration which is in many cases tied to the academic calendar, may also influence scores. Both of these behaviors are expected and intentional. The former case is likely a reflection of the mentor's preferences and expectations (or perhaps biases). In the latter case, "uncontrollable" factors are an important consideration in

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

project management and indeed should also influence a project score. However, care must be taken to interpret results as these uncontrollable factors or constraints change, since the mentors' assessment of research utility and learning outcomes are made relative to this context.

Further, the sample projects presented here were mentored only by the authors, and the projects were analyzed by a single mentor for consistency. This is intentional and consistent with the framework as scores are determined relative to the mentor's beliefs and expectations. However, as a result, the scores and potential utility of this framework to design and improve UREs necessarily depend on the experiences and expectations of the mentor, as well as context of the project. We mitigate this dependence by including user-defined weighting through the importance prompts, though larger-scale validation remains as future work. Current efforts are focused on working with undergraduate research programs like UROP to implement this methodology across a large, interdisciplinary group of mentors within a controlled context to evaluate both mentor expectations and the utility of the proposed framework in URE planning and design.

5. Conclusion

In this manuscript, a rational, multi-criteria decision-making tool for planning project-based mentoring experiences was developed and analyzed in detail, focusing primarily on undergraduate research experiences (UREs). Six criteria were identified and scored including time or duration, project scope, research impact, learning outcomes, communication, and mentor–student alignment. The six criteria are evaluated based on the mentor's judgment of the project proposal in regard to a set of 27 prompts. The belief values are then used to estimate aggregate scores, representing mentor and student outcomes, using possibility theory to interpret and propagate uncertainty. The final scores are represented by fuzzy variables that can be interpreted on an absolute basis (relative to the mentor's experience) or on a relative basis to compare several projects or iterations. We demonstrate the tool by analyzing two recent projects retrospectively and one ongoing project, and compare the aggregate scores. We additionally describe the use of the tool for introspection, or to identify inconsistencies between the mentor's expectations and beliefs, and an iterative procedure to design or adapt a project as evidence or expectations change. While our demonstration represents only a small case study, we are hopeful that wider use will shed some light on the expectations of URE mentors across disciplines and career stages, and help more researchers to confidently incorporate undergraduate students into their research activities.

Data availability statement

The dataset supporting the conclusions of this article is available in the figshare repository, https://doi.org/10.6084/m9.figshare.27732216 (Herzog, McCord & Sick 2025). Raw data, plots, and code, in addition to a full-featured HTML/javascript web app that implements this methodology, are included in the repository.

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

Acknowledgments

We thank Dr. Michelle Ferrez for useful discussions and insightful feedback on the first manuscript draft. We also thank the students who participated in the three example projects discussed in this paper for their various and multiple contributions to our ongoing research.

Author contribution

Conceptualization (lead): J.M.H.; Conceptualization (supporting): S.M. and V.S.; Data curation: J.M.H.; Formal analysis: J.M.H.; Funding acquisition: V.S.; Investigation: J.M.H.; Methodology (lead): J.M.H.; Methodology (supporting): S.M. and V.S.; Project administration: J.M.H.; Resources: J.M.H.; Software: J.M.H.; Supervision: V.S.; Validation (lead): J.M.H.; Validation (supporting): S.M.; Visualization: J.M.H.; Writing – Original Draft: J.M.H.; Writing – Review & Editing (equal): J.M.H., S.M., and V.S.

Financial support

The authors received no external funding specific to this work.

Competing interests

The authors declare that they have no competing interests.

References

Brew, A. & **Mantai, L.** 2017 Academics' perceptions of the challenges and barriers to implementing research-based experiences for undergraduates. *Teaching in Higher Education* **22** (5), 551–568; doi:10.1080/13562517.2016.1273216.

Brown, A. M., **Lewis, S. N.** & **Bevan, D. R.** 2016 Development of a structured undergraduate research experience: Framework and implications. *Biochemistry and Molecular Biology Education* **44** (5), 463–474; doi:10.1002/bmb.20975.

Byrne, A. & **University of Arkansas Press** 2005 Introspection. *Philosophical Topics* **33** (1), 79–104; doi:10.5840/philtopics20053312.

Dolan, E. L. & **Johnson, D.** 2010 The undergraduate–postgraduate–faculty triad: Unique functions and tensions associated with undergraduate research experiences at research universities. *CBE—Life Sciences Education* **9** (4), 543–553; doi:10.1187/cbe.10-03-0052.

Dubois, D. & **Prade, H.** 2015 Possibility theory and its applications: Where do we stand? In *Handbook of Computational Intelligence* (ed. J. Kacprzyk & W. Pedrycz), pp. 31–60. Springer; doi:10.1007/978-3-662-43505-2_3.

Eagan, M. K., **Sharkness, J.**, **Hurtado, S.**, **Mosqueda, C. M.** & **Chang, M. J.** 2011 Engaging undergraduates in science research: Not just about faculty willingness. *Research in Higher Education* **52** (2), 151–177; doi:10.1007/s11162-010-9189-9.

Esselman, B. J. & **Hill, N. J.** 2016 Integration of computational chemistry into the undergraduate organic chemistry laboratory curriculum. *Journal of Chemical Education* **93** (5), 932–936; doi:10.1021/acs.jchemed.5b00815.

Felder, R. M. & **Brent, R.** 2024 *Teaching and Learning STEM: A Practical Guide*. John Wiley & Sons.

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

Gericke, K., **Eckert, C.**, **Felician Campean, P. J. C.**, **Flening, E.**, **Isaksson, O.**, **Kipouros, T.**, **Kokkolaras, M.**, **Köhler, C.**, **Panarotto, M.** & **Wilmsen, M.** 2020 Supporting designers: Moving from method menagerie to method ecosystem. *Design Science* **6**, e21; doi:10.1017/dsj.2020.21.

Gericke, K., **Eckert, C.** & **Stacey, M.** 2022 Elements of a design method–a basis for describing and evaluating design methods. *Design Science* **8**, e29; doi:10.1017/dsj.2022.23.

Gordon, J. & **Shortliffe, E. H.** 1984 The Dempster-Shafer theory of evidence. *Rule-Based Expert Systems: The MYCIN Experiments of the Stanford Heuristic Programming Project* **3** (832–838), 3–4.

Herrington, J. & **Reeves, T. C.** 2011 Using design principles to improve pedagogical practice and promote student engagement. In *Proceedings ASCILITE 2011-Changing Demands, Changing Directions*, pp. 594–601; doi:10.14742/apubs.2011.1751.

Herzog, J. M., **Agosta, G.** & **Sick, V.** 2024 On the impact of radiative transfer in fluorescence imaging of bacterial films and suspensions. *Journal of Quantitative Spectroscopy and Radiative Transfer* **324**, 109063; doi:10.1016/j.jqsrt.2024.109063.

Herzog, J. M., **McCord, S.** & **Sick, V.** 2025 Design and analysis tool for undergraduate research experiences. Figshare. https://doi.org/10.6084/m9.figshare.27732216.

Hill, S. E. M., **Ward, W. L.**, **Seay, A.** & **Buzenski, J.** 2022 The nature and evolution of the mentoring relationship in academic health centers. *Journal of Clinical Psychology in Medical Settings* **29** (3), 557–569; doi:10.1007/s10880-022-09893-6.

Houser, C., **Lemmons, K.** & **Cahill, A.** 2013 Role of the faculty mentor in an undergraduate research experience. *Journal of Geoscience Education* **61** (3), 297–305.

Hunter, A.-B., **Laursen, S. L.** & **Seymour, E.** 2007 Becoming a scientist: The role of undergraduate research in students' cognitive, personal, and professional development. *Science Education* **91** (1), 36–74; doi:10.1002/sce.20173.

Landrum, R. E. & **Nelsen, L. R.** 2002 The undergraduate research assistantship: An analysis of the benefits. *Teaching of Psychology* **29** (1), 15–19; doi:10.1207/S15328023TOP2901_04.

Laurillard, D. 2013 *Teaching as a Design Science: Building Pedagogical Patterns for Learning and Technology*. Routledge; doi:10.4324/9780203125083.

Linn, M. C., **Palmer, E.**, **Baranger, A.**, **Gerard, E.** & **Stone, E.** 2015 Undergraduate research experiences: Impacts and opportunities. *Science* **347** (6222), 1261757; doi:10.1126/science.1261757.

Mancha, R. & **Yoder, C. Y.** 2014 Factors critical to successful undergraduate research. *Council on Undergraduate Research Quarterly* **34** (4), 38–45.

Moore, R. & **Lodwick, W.** 2003 Interval analysis and fuzzy set theory. *Fuzzy Sets and Systems* **135** (1), 5–9; doi:10.1016/S0165-0114(02)00246-4.

Morales, D. X., **Grineski, S. E.** & **Collins, T. W.** 2017 Increasing research productivity in undergraduate research experiences: Exploring predictors of collaborative faculty–student publications. *CBE—Life Sciences Education* **16** (3), ar42; doi:10.1187/cbe.16-11-0326.

Mordacq, J. C., **Drane, D. L.**, **Swarat, S. L.** & **Lo, S. M.** 2017 Development of course-based undergraduate research experiences using a design-based approach. *Journal of College Science Teaching* **46** (4), 64–75; doi:10.2505/4/jcst17_046_04_64.

Nguyen, H. T. & **Kreinovich, V.** 1996 Nested intervals and sets: Concepts, relations to fuzzy sets, and applications. In *Applications of Interval Computations* (ed. R. B. Kearfott & V. Kreinovich), pp. 245–290. Springer; doi:10.1007/978-1-4613-3440-8_11.

Norton, P. & **Hathaway, D.** 2015 In search of a teacher education curriculum: Appropriating a design lens to solve problems of practice. *Educational Technology* **55** (6), 3–14.

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076

Papalambros, P., **Gero, J.**, **Maier, A.**, **Cagan, J.**, **Ahmed-Kristensen, S.**, **Albers, A.**, **April, K.**, **Blessing, L.**, **Boujut, J.-F.**, **Cantamessa, M.**, **Cascini, G.**, **Chakrabarti, A.**, **Chen, L.-L.**, **Clarkson, P. J.**, **Jiao, R.**, **Eckert, C.**, **Feinberg, F.**, **Gericke, K.**, **Hanna, S.**, **Holtta-Otto, K.**, **Jankovic, M.**, **Jin, Y.**, **Kleinsmann, M.**, **Knight, T.**, **le Masson, P.**, **Lewis, K.**, **Linsey, J.**, **Luo, J.**, **McMahon, C.**, **Nagai, Y.**, **Pigosso, D.**, **Reich, Y.**, **Reid, T.**, **Seepersad, C.**, **Seifert, C.**, **Shealy, T.**, **Summers, J.**, **Vermaas, P.**, **Wartzack, S.**, **Yang, M.** & **Yannou, B.** 2025 Design science: Why, what and how–revisited. *Design Science* **11**, e48; doi:10.1017/dsj.2025.10026.

Petrella, J. K. & **Jung, A. P.** 2008 Undergraduate research: Importance, benefits, and challenges. *International Journal of Exercise Science* **1** (3), 91–95; doi:10.70252/MXRI7483.

Russell, S. H., **Hancock, M. P.** & **McCullough, J.** 2007 Benefits of undergraduate research experiences. *Science* **316** (5824), 548–549; doi:10.1126/science.1140384.

Salicone, S. 2007 *Measurement Uncertainty: An Approach Via the Mathematical Theory of Evidence*. Springer Science & Business Media.

Sarabipour, S., **Niemi, N. M.**, **Burgess, S. J.**, **Smith, C. T.**, **Filho, A. W. B.**, **Ibrahim, A.** & **Clark, K.** 2023 The faculty-to-faculty mentorship experience: A survey on challenges and recommendations for improvements. *Proceedings of the Royal Society B* **290** (2013), 20230983.

Shanahan, J.O., **Ackley-Holbrook, E.**, **Hall, E.**, **Stewart, K.** & **Walkington, H.** 2015 Ten salient practices of undergraduate research mentors: A review of the literature. *Mentoring & Tutoring: Partnership in Learning* **23**(5), 359–376; doi:10.1080/13611267.2015.1126162.

Sharma, R., **Nair, A.**, **Guo, A.**, **Palea, D.** & **Lee, D. T.** 2022 "It's usually not worth the effort unless you get really lucky": Barriers to undergraduate research experiences from the perspective of computing faculty. *Proceedings of the 2022 ACM Conference on International Computing Education Research* **1**, 149–163.

Smets, P. 1988 Belief functions versus probability functions. In *International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems*, pp. 17–24. Springer; doi:10.1007/3-540-19402-9_51.

Snyder, H. D. & **Kucukkal, T. G.** 2021 Computational chemistry activities with avogadro and orca. *Journal of Chemical Education* **98** (4), 1335–1341; doi:10.1021/acs.jchemed.0c00959.

William, F. & **Polik, J. R.** 2022 Webmo: Web-based computational chemistry calculations in education and research. *Wiley Interdisciplinary Reviews: Computational Molecular Science* **12** (1), e1554.

Wilson, A., **Howitt, S.**, **Roberts, P.**, **Åkerlind, G.** & **Wilson, K.** 2013 Connecting expectations and experiences of students in a research-immersive degree. *Studies in Higher Education* **38** (10), 1562–1576; doi:10.1080/03075079.2011.633163.

Wynn, D. C. & **Eckert, C. M.** 2017 Perspectives on iteration in design and development. *Research in Engineering Design* **28** (2), 153–184; doi:10.1007/s00163-016-0226-3.

Downloaded from https://www.cambridge.org/core. UNIVERSIDAD AUTONOMA METROPOLITANA, on 17 Nov 2026 at 21:33:54, subject to the Cambridge Core terms of use, available at https://www.cambridge.org/core/terms. https://doi.org/10.1017/dsj.2026.10076