Student Perceptions of the Help Resource Landscape

Shao-Heng Ko
shaoheng.ko@duke.edu
Duke University
Durham, North Carolina, USA

Kristin Stephens-Martinez
ksm@cs.duke.edu
Duke University
Durham, North Carolina, USA

Matthew Zahn
mszahn@ncsu.edu
North Carolina State University
Raleigh, North Carolina, USA

Yesenia Velasco
yesenia.velasco@cs.duke.edu
Duke University
Durham, North Carolina, USA

Lina Battestilli
lbattestilli@ncsu.edu
North Carolina State University
Raleigh, North Carolina, USA

Sarah Heckman
sarah_heckman@ncsu.edu
North Carolina State University
Raleigh, North Carolina, USA

Abstract

Background and Context. Existing works in computing students' help-seeking and resource selection identified an expanding set of important dimensions that students consider when choosing a help resource. However, most works either assume a predefined list of help resources or focus on one specific help resource, while the landscape of help resources evolve at a faster speed.

Objectives. We seek to study how students value each dimension in the help landscape in their resource selection and utilization processes, as well as how their identities relate to their perceptions of the landscape.

Method. We surveyed $N = 1,625$ students on their perceptions of 8 dimensions across 12 offerings of 7 courses at 2 institutions.

Findings. We found a consistent pattern of four distinct dimension tiers ordered from most to least important: (1) timeliness of help, (2) availability and adaptability of the resource, (3) the resource's time/space anchor and the effort to phrase the help need, (4) formality and socialness of the resource. We also found men and first-years rate all dimensions as less important than their classmates.

Implications. Our results reveal what the students collectively value most when selecting help resources and thus can inform practitioners seeking to improve their course help ecosystem.

CCS Concepts

• **Social and professional topics** → **Computing education**.

Keywords

Computing Education; Help-Seeking

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1 Introduction

Academic help-seeking is vital to students' learning [5], and its relationship with metacognition and self-regulation has been well documented [12, 13, 21]. One key stage of students' help-seeking behavior is that of *resource selection* [7]: students must decide on one or more available help resources to interact with and the type of help needed [13]. Starting from Makara and Karabenick's model [22], help resource selection has been studied both in the general post-secondary context [7, 28, 30] as well as in engineering/computing education contexts [3, 8, 27, 36, 40]. Together, these works identify an ever-expanding set of factors that influence students' resource selection. The set of available help resources in a specific instructional context form a *help landscape* with all these factors serving as the *dimensions*.

Modern post-secondary computing classes have richer help landscapes than traditional educational contexts [20]. In addition to the array of *formal* (course-affiliated) help resources (office hours, discussion forums, automated feedback and learning management tools, etc.), students can opt to interact with *informal* resources instead; the adoption of Large Language Models (LLMs) for help-seeking has already been documented by recent works in the community [8, 20, 26, 34, 42]. Higher enrollments in the past 15 years also necessitated the use of teaching assistants (TAs) [23] – many undergraduate [24] – to provide the bulk of human help, especially in introductory courses. These TAs are less experienced in facilitating quality help than instructors [18, 19]. With such an abundance of help resources and a high cognitive load [1], today's computing students rely on their metacognitive ability to navigate the complex help landscape to seek effective help.

As pointed out by Giblin *et al.* [7], most works on students' resource selection process suffer from assuming (and analyzing) a predefined list of help resources, rendering the findings less generalizable and unable to catch up with the emergence of new help resources. Motivated by this insight, we seek to study computing students' resource selection process from the lens of the landscape *without using any fixed set of resources*. Our research questions are:

(RQ1) How do students collectively value each dimension in the help landscape when considering what resource(s) to utilize?
(RQ2) How do students collectively value each dimension in the help landscape when considering what resource(s) to utilize *before another resource*? Is this any different than that in RQ1?
(RQ3) How do student identities relate to their perception of the help landscape?

To tackle the research questions, we surveyed students on their perceptions of eight help resource dimensions across a total of 12 offerings of seven courses at two institutions.

We found a highly consistent pattern across all our datasets involving four distinct *tiers of dimensions*: students value the *timeliness* of help provided by a resource as the most important among all dimensions, followed by the *availability* and the *adaptability* of the resource as the second tier. The third tier consists of whether the resource is *anchored* to a *time/space* as well as the amount of *effort* it takes to request help from the resource. Finally, the level of *formality* and *socialness* of the resource were the least prioritized.

Our analyses also revealed that students' perceptions of the landscape are highly similar between the two usage cases in RQ1 (resource selection) and RQ2 (resource prioritization). Finally, we found that men and first-year students value all dimensions lower than their classmates, although the preference among the dimensions is still consistent with the tiers.

2 Related Works

Help-seeking theories. Karabenick and Dembo [13] characterize students' academic help-seeking behavior by eight *stages*: (1) determine whether there is a problem; (2) determine whether help is needed/wanted; (3) decide whether to seek help; (4) decide on the type of help (goal); (5) decide on whom to ask; (6) solicit help; (7) obtain help; and (8) process the help received. Many parts of this process are intertwined with self-regulation [36] and metacognition [21]. Most earlier works in help-seeking [10, 11, 14] focus on stages 3 and 4 and examine what influences students' decision to seek help. A recent meta-analysis [5] reveals that *instrumental* help that focuses on mastery positively correlates with academic performance. Makara and Karabenick's work [22] characterizes help resources by four dimensions: *formality* of the resource, *closeness of relationship* between students and the resource, the *adaptability* of the help resource to each student's needs, and the *channel* (a person or a form of media) the help comes from.

Resource selection and utilization. Many subsequent works focus on students' resource selection process in post-secondary educational contexts. At a high level, these works collectively confirm and expand the set of dimensions in Makara and Karabenick's model, though Stites *et al.* [36] also reports some of the ingredients in the original model are not found in students' decision processes. Giblin *et al.* [7] criticizes that earlier works implicitly assume help primarily comes from a list of predefined *human/social* resources, an assumption that no longer holds in today's computing classroom contexts [8]. Indeed, Schlusche *et al.* [30] documents that social discomfort prevents some students from seeking help from humans while proposing the *effort to phrase a problem* as another important concern in students' resource selection. Wirtz *et al.* [40] and Doebling and Kazerouni [3] study students' *order of resource utilization* and report a pattern of progression from *less social, less formal, and more available* resources to *more social, more formal, and less available* resources, despite students consciously perceiving the latter as more useful. These dimensions form the basis of our survey and are synthesized in Table 2 in Section 3.

Many *resource-specific* works exist [4, 6, 8, 16, 18, 23, 26, 27, 29, 31–35, 37–39, 41, 42], with more direct focus on one or two resources' characteristics and usage cases than the overall landscape. Our work follows Giblin *et al.* [7]'s call to study resource selection without using a fixed set of existing help resources. By directly putting our emphasis on the dimensions of the landscape, we seek to understand students' perceptions of the landscape in a more generalizable way without delving into specific instructional contexts.

3 Contexts and Methodology

Contexts and Participants. Table 1 summarizes our data collection. Introduction to computing in MATLAB (CS1-Matlab) is a required introductory course for non-majors/engineering students at NC State University, a large-size research-oriented public university (Inst1 hereon). Introduction to programming in Python (CS1-Python), data structures and algorithms (DSA), data science (Data), discrete math (DM), database systems (DB), and algorithms (Algo) are popular courses for CS majors at Duke University, a medium-size research-oriented private university (Inst2). Both institutions are in the US and use 15-week semesters. The data is collected in the Fall 2023 (Fa23) and Spring 2024 (Sp24) semesters, although not every course is offered every semester. Throughout this paper, we refer to the seven courses above as *courses*, and single offerings of a course as *classes* (12 in total).

Data Collection with a Survey. We surveyed students in each class 1-3 times at different points in the semester about their perceptions of the help resource landscape. In CS1-Matlab, an identical copy of the survey was incorporated into the reflections after each of its three main projects. All classes at Inst2 administered the survey around the midpoint of the semester, and some (DSA, DM, and Algo) repeated it a second time at the end of the semester (see Table 1). For brevity, we refer to the 1st, 2nd, and 3rd times our survey was administered in each class as T1, T2, and T3, respectively.

Importance of Dimensions in Resource Selection (SQ1). The survey starts with a definition[1] of help resources. In the first question (SQ1), students are asked *"When considering what help resource(s) to use to seek help in this course, how important is each of the following factors to you?"*, followed by all eight dimensions in Table 2 described in their lay terms. For each dimension, the student selects a response out of six options consisting of a 5-point Likert scale from *Not at all important* to *Extremely important* as well as a separate option that said *N/A: I have never thought about this before*. The N/A option was added to capture students' lack of awareness of each help resource dimension.

Grouping and Order of Usage. Next, the survey puts students into a hypothetical situation where all help resources in the class are available to them. Students are asked to *group and rank* all resources into up to 4 ordered groups according to their ideal order of resource usage. In answering this question, students are implicitly reminded that (1) they can utilize multiple help resources when they need help, and (2) they can interact with the resources sequentially in their desired order. We analyzed students' responses to this question in a separate paper [17], where we found these orders likely to be a key part of their individual help-seeking approaches.

[1] *We use the term "help resources" to broadly refer to anything that you can seek help on the coursework from, including things that are part of the course (class material, office/consulting hours, class forums/discussion boards, etc.) and things that are not part of the course (online resources, generative AI tools, people outside of class, etc.).*

Table 1: Summary of participants and demographics. The numbers under T1, T2, and T3 represent the number of students that responded to each survey (if applicable) respectively. For classes in which the survey was administered more than once, the "All" column represents number of students that answered all surveys (used in the analysis in Section 4.1.1). Demographics are consenting students only, but not all consenting students provided their demographic information. Black includes African American, and 2+ stands for multiracial. Inst1 treats Latinx as a race (classified under Other) while Inst2 separates the concept from race. Values lower than 5 are replaced with an asterisk in compliance to our IRB protocol.

Inst.	Course	Semester	# Students		Survey				Gender			Race					Year			
			Total	Consenting	T1	T2	T3	All	Men	Women	Nonbinary	White	Asian	Black	2+	Other	1	2	3	4+
Inst1	CS1-MATLAB	Sp24	294	153 (52.0%)	142	121	94	90	103	43	*	103	17	*	8	11	85	42	14	*
Inst2	CS1-PYTHON	Fa23	262	192 (73.3%)	163	-	-	-	65	103	*	67	67	17	12	29	95	48	14	16
		Sp24	171	77 (45.0%)	74	-	-	-	19	53	*	36	19	8	6	*	43	15	9	5
	DSA	Fa23	390	272 (69.7%)	264	139	-	137	167	97	5	100	131	14	13	14	157	93	15	6
		Sp24	300	177 (59.0%)	122	129	-	87	57	72	*	55	59	*	9	12	101	21	7	5
	DATA	Fa23	82	66 (80.5%)	65	-	-	-	33	32	*	22	33	*	6	*	*	19	18	29
		Sp24	160	115 (71.9%)	115	-	-	-	57	57	*	43	46	13	9	*	13	53	32	17
	DM	Fa23	120	94 (78.3%)	94	84	-	84	49	42	*	23	44	*	13	14	5	42	37	10
		Sp24	138	71 (51.4%)	69	66	-		34	32	*	17	43	*	*	*	21	38	8	*
	DB	Fa23	330	183 (55.5%)	183	-	-	-	104	74	*	61	97	6	9	10	*	34	68	81
	ALGO	Fa23	160	123 (76.9%)	114	116	-	109	83	34	*	45	59	8	5	*	*	9	36	73
		Sp24	316	220 (69.6%)	220	190	-	190	138	78	*	89	95	11	17	8	*	49	120	49
	All T1 responses (used in Section 4.3)				1625	-	-	-	881	694	-	642	692	92	182		421	442	373	288

Table 2: All dimensions in the help resource landscape. Students see only the full text description on the right in the SQ1 and SQ2 questions, in this precise order.

Dimensions	References	Text Description in SQ1 and SQ2
Formality	[3, 5, 7, 22, 28, 40]	"Whether the help resource is officially part of our course"
Socialness	[2, 7, 22, 28, 30, 36]	"How much the help resource involves interacting with people"
Timeliness	[7, 30, 36]	"How quickly I can get a response to my help request"
Anchor-Time	[3, 40]	"Whether the help resource is only available at a specific time in the day/week"
Anchor-Space	[3, 40]	"Whether the help resource is at a specific physical location"
Adaptability	[22, 27, 36]	"How much the help resource can tailor its response to my specific request"
Effort	[9, 30]	"How much effort it takes me to provide the resource with the context needed to understand and solve my problem"
Availability	[7, 27, 30, 36]	"How often the help resource is available to me"

Importance of Dimensions in Resource Ordering (SQ2). The last question in the survey (SQ2) looks similar to SQ1, except the wording is changed into *"When considering what help resource(s) to use **first (i.e., before other resources)** in this course, how important is each of the following factors to you?"*, with the difference bolded to indicate that the last part is not merely a repeat of the first part. In other words, the two versions of the question directly correspond to our two research questions, and students are made aware of the nuances with the help of the group-and-rank question sandwiched between them.

Importance Score. To enable comparison amongst students' sentiments on different dimensions, we aggregate students' responses to SQ1 and SQ2 via the Importance Score metric. Specifically, each response of *Extremely important*, *Very important*, *Moderately important*, *Slightly important*, *Not at all important*, and *NA* gets a score of 4, 3, 2, 1, 0, and 0, respectively,[2] and the Importance Score for each dimension aggregated over a particular group of students (e.g., for a class) is simply the average of this score across all student responses in that group. While we acknowledge that Likert responses generally should not be treated as numerical, it has been shown that parametric statistics defined on Likert scales are empirically robust [25], and this metric conveniently allows us to cross-compare students' opinions on different dimensions, as well as their opinions on the same dimension in different surveys. To rank the dimensions in the landscape, the order we obtained using Importance Score is usually consistent with that using other strategies, e.g., ranking in the order of percentages of students that deemed each dimension *Extremely important*.

Statistical methods. As there is no evidence suggesting that the Importance Scores are normally distributed, we use exclusively non-parametric tests throughout our analyses. We implement Bonferroni corrections *per research question*, i.e., controlling the Type I (false positive) error rates for all analyses within a research question at the 0.05 level. As all our statistical results are negative, such a choice has little impact on the interpretation of the results.

[2]We treat the NA responses as zeros because the lack of awareness of an dimension more likely reflects that the dimension is not part of a student's consideration of what resource(s) to use. An alternative would be excluding NA values from the average; we implemented this variant and found no substantial differences in any results.

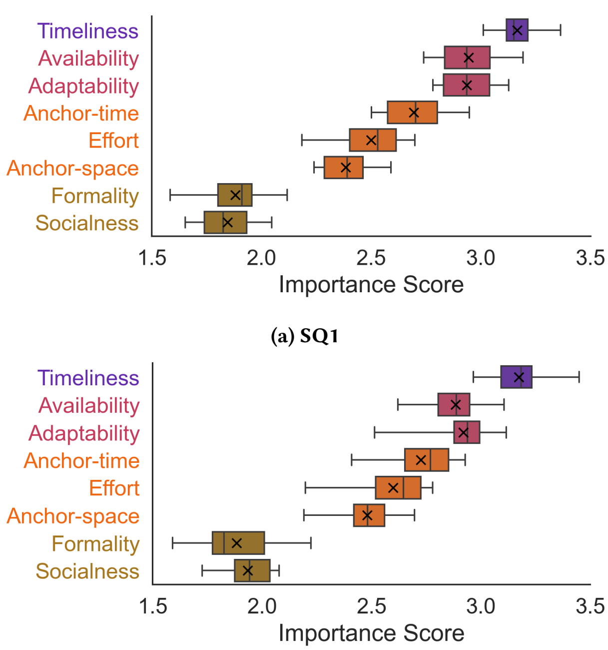
4 Results

4.1 RQ1: Students' Perceptions of the Help Landscape Dimensions in SQ1

To answer RQ1, we calculated the Importance Score of all dimensions (in Table 2) in each class's T1 responses to SQ1, while T2 and T3 results are not used to avoid overweighing the classes that repeated the survey. Figure 1a plots the distribution of Importance Score for each dimension across all classes. We rank the dimensions by their mean Importance Score (shown as crosses in the figure), although the median order is identical. As shown, Timeliness gets the highest Importance Scores, while Formality and Socialness are lower than all other dimensions by a large margin.

While Figure 1a already suggests that students value the dimensions differently, we wondered if their responses are influenced by the instructional context. We thus plotted the *per-class* T1 results in Figure 2, where each subfigure is a class in our data. For each dimension in each class, Figure 2 shows the percentage of T1 responses in each of the six Likert options in the SQ1 question. The dimensions in each subfigure are ordered by their Importance Score; note that the ordering is similar but not completely identical amongst the classes.

We categorized all dimensions into several *tiers* such that dimensions in the same tier are comparably important according to students' T1 responses. Four tiers emerged naturally from the class-level results:



(a) SQ1

(b) SQ2

Figure 1: Box plot of T1 Importance Score distributions. Whiskers show the complete data range. Each color represents a dimension tier.

Tier 1: Timeliness. Across *all* classes, Timeliness is ranked first regardless of whether we order by importance score or the proportion of students that ranked it *Extremely important*. Students (in aggregate) value the timeliness of help resources above all other dimensions when they think about which help resources to use.

Tier 2: Availability and Adaptability. These round out the top three dimensions in all classes, although their relative order differs. While Adaptability is ranked ahead of Availability in more classes (7) than not (5), the results are similar in most classes.

Tier 3: Anchor-Time, Effort, and Anchor-Space. These are the 4th to 6th ranked dimensions in all classes (not necessarily in that order). Anchor-Time is ranked ahead of Anchor-Space in all classes, which implies students feel the limitation of time more than that of space. The rank of Effort may have been influenced by the class topic: it is ranked lower in some intro-level classes (in CS1-Matlab and DM) but as high as 4th (in Data-Fa23) where it may take more effort to effectively communicate a help request.

Tier 4: Formality and Socialness. These are the lowest-ranked dimensions in all classes and exhibit similar distributions. Students care about the authority and humanity of help resources less than the other considerations above.

Although the above tiers are formed from T1, they are also *consistent with all T2 and T3 results*. In other words, in no surveys did any dimension get a higher Importance Score than another dimension in an earlier tier in the SQ1 question.

4.1.1 *Do students' perceptions of the dimensions change with time?*

To examine whether students' responses to the survey change as the semester progresses, we considered only the classes in which the survey was administered multiple times and kept only the students that answered all surveys (see Table 1). Almost all per-survey results after the filtering are consistent with the tiers formed above, with only two exceptions, both having Anchor-Time in the top three ranked dimensions by a slight margin.[3]

We ran a paired Wilcoxon test on the Importance Scores across all six two-survey classes ($8 \times 6 = 48$ observations) with the null hypothesis that the T1 and T2 SQ1 Importance Scores come from identical distributions. The result is non-significant ($p = 0.60$) with a weak effect size $r = 0.09$, where r is the matched-pairs rank-biserial correlation coefficient [15]. We found no evidence at the aggregate level suggesting that students perceived the dimensions differently at different snapshots of time in the semester. To further examine whether there is such an effect in some classes but not others, we confirmed our analysis by running a suitable statistical test *per class*. We used the Wilcoxon test for two-survey classes and the Friedman test for the three-survey CS1-Matlab, with the null hypothesis for the latter being that the Importance Scores in all three surveys come from identical distributions. None of these tests resulted in any significant result.[4]

[3] CS1-Matlab's T2 had Anchor-Time (2.79) above Availability (2.77), and DSA-Sp24's T2 had Anchor-Time (2.87) above Availability (2.86) and Adaptability (2.85).

[4] This remains true even when examining each student's T1 and T2 SQ1 responses *individually*: averaging over all students in two-survey classes, 2.54 (of 8) dimensions' Importance Scores went up from T1 to T2, 2.44 went down, and 3.02 remained the same.

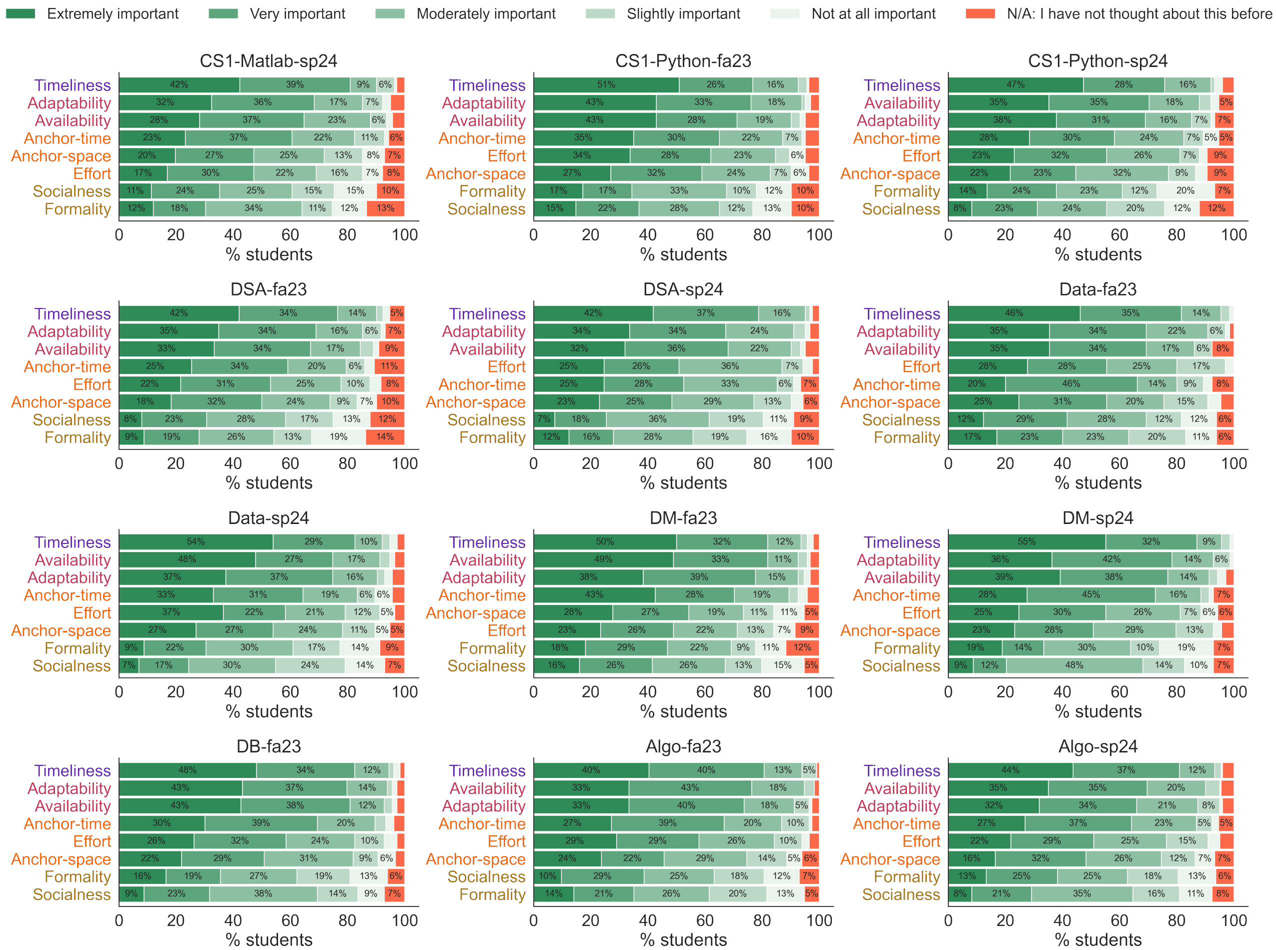


Figure 2: Students' SQ1 responses in all classes' T1. Dimensions are ordered by Importance Score.

4.2 RQ2: Students' Perceptions of the Help Landscape Dimensions in SQ2

To answer RQ2, we repeated our analyses on students' responses to SQ2. Analogous to that in Figure 1a, we plotted the distribution of T1 SQ2 Importance Score for each dimension across all classes in Figure 1b.

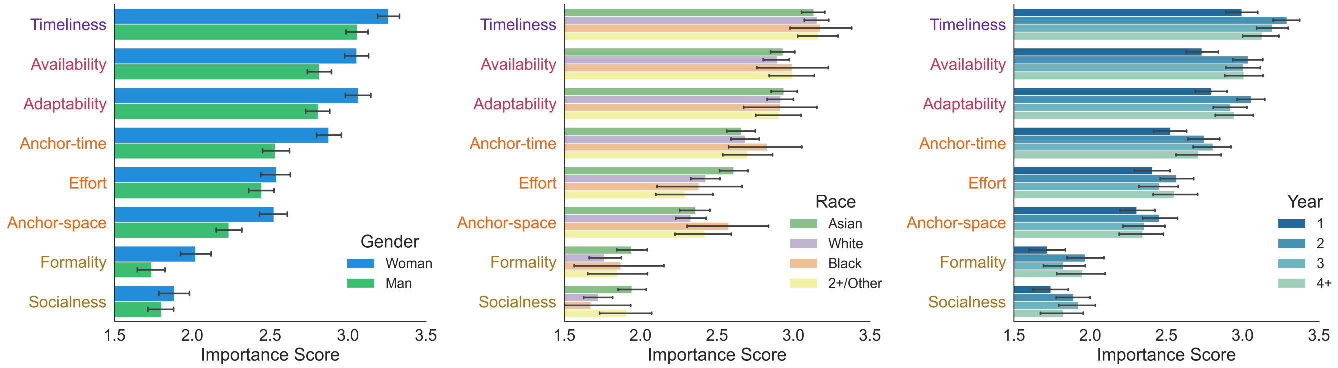
The aggregate results are consistent with the tiers that we obtained for RQ1 (using SQ1), although with two within-tier swaps (Availability vs. Adaptability, and Formality vs. Socialness). *All* per-class results (including the T2 and T3 ones) are consistent with the tiers. We ran a Wilcoxon test across all 20 surveys ($8 \times 20 = 160$ observations) with the null hypothesis that the Importance Scores for SQ1 and SQ2 come from the same distribution. The result ($p = 0.13$, $r = 0.14$) reveals no difference between how students perceive the dimensions when they consider which resource(s) to use (SQ1) vs. when they consider which resource(s) to use *first* (SQ2). This is confirmed by running per-survey tests; none of the 20 results are significant at the 0.05 level after Bonferroni correction.

4.3 RQ3: Student Identities

We then examine the relationships between student identities and their perception of the help landscape. Our analysis of RQ1 and RQ2 showed there is little variance in how each class' students perceive the dimensions. We thus pooled all classes' T1 data together to increase the sample size of each group.

Figure 3 plots the per-group Importance Score distributions for gender, race, and year (see Table 1 for participant demographics) obtained from all T1 SQ1 responses. The error bars represent 95% confidence intervals obtained by bootstrapping. Students who took multiple classes in our data are counted once per class.

Figure 3a shows women give a higher mean Importance Score to *all* dimensions than men, although the effects for Effort and Socialness are non-significant (as the 95% CIs overlapped). While both groups' dimension orderings are consistent with the tiers in Section 4.1, there is a difference within the last tier: women collectively value Formality over Socialness whereas men value the opposite. Our result here does *not* contradict findings from past literature [3, 6, 37] in that women seek more social help than men;



(a) Gender **(b) Race** **(c) Year**

Figure 3: T1 SQ1 Importance Score distributions split by demographic variables.

our data simply shows women collectively perceive the Socialness dimension as less important, *relative to other dimensions*, than the men in their classes.

We merged the 2+ and Other race groups in Figure 3b due to the small group sizes and the inconsistencies in data collection (see Table 1). The results for all race groups are consistent with the tiers in Section 4.1, but Effort and Socialness seem to be the two dimensions that are more identity-influenced (e.g., the 95% CIs for Asian and White do not overlap for Socialness). However, we note that our student bodies are not racially diverse (see Table 1), so the sample sizes for minority race groups are small.

When splitting the data by year (Figure 3c), we found that first-year students' Importance Score distribution is substantially lower than that of other year groups. This may reflect that first-year students are less experienced in seeking help in a post-secondary context or less proficient in the necessary metacognitive skills for help-seeking. They thus potentially need more explicit and hands-on guidance on navigating the help landscape.

5 Limitations and Future Work

Data and scope. Our data comes from two research-oriented universities from the same region in the US, and thus all our findings may not reflect students from other instructional contexts. The consent rate fluctuates per class (see Table 1), and there might be underlying hidden selection biases in the consent process. In all surveys, the dimensions were presented in the same order (see Table 2), so we cannot rule out the existence of question order biases. However, we note that the tiers resulting from our analyses do not simply follow the order in which we presented the dimensions (or its reverse). We have not validated that students understood each dimension as expected. Our findings thus only reflect students' perceptions of the precise descriptions in Table 2. We did not analyze prior experience, major, or student performances in these classes; those variables are more heavily influenced by instructional contexts (compared to gender, race, and year), and the goal of this work is to study help-seeking in a context-agnostic fashion.

Methodology. In converting ordinal Likert scales to numerical Importance Scores, we risk losing nuances in how different individuals interpret the importance options in our survey. We made this decision only after observing the distribution of importance options for all dimensions were consistent across all classes, and its purpose was to allow simpler comparisons between dimensions. Still, one should refrain from interpreting the absolute values of Importance Scores. Most of our analyses in this work were performed at the class level (i.e., treating each class as an aggregate) instead of the individual level. Therefore, our results (whether positive or negative) can only be interpreted at the class level. For example, it is possible that *some students* perceived the landscape differently between SQ1 and SQ2, but this effect was not observed at the class level.

Future work. The next step is to understand *why* students value the dimensions as the results suggest, potentially in structured interviews. Another would be repeating the same analyses for students in non-research-focused institutions and smaller classes with fewer help resources. If instructional contexts are properly controlled, one can also study the relation between student perception of the dimensions and their prior experience or their performance, in parallel to past works [3, 10, 40] that focus on the relation between help-seeking frequency versus these variables.

6 Conclusions and Implications

Our work is a preliminary attempt to understand how students perceive the various dimensions in the help landscape at a high level without grounding the scope using a fixed set of help resources. By analyzing data across two institutions and seven courses, we found a consistent pattern of four tiers in the perceived importance of the dimensions. These tiers can inform practitioners seeking to enhance their class' help ecosystem by creating or expanding more timely, available, and adaptable resources. Moreover, enhancing help ecosystems along the dimensions that minority groups value might support equity.

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