Computing Students' Understanding of Dispositions: A Qualitative Study

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ABSTRACT

Dispositions, along with skills and knowledge, form the three components of competency-based education. Moreover, studies have shown dispositions to be necessary for a successful career. However, unlike evidence-based teaching and learning approaches for knowledge acquisition and skill development, few studies focus on translating dispositions into observable behavioral patterns. An operationalization of dispositions, however, is crucial for students to understand and achieve respective learning outcomes in computing courses. This paper describes a multi-institutional study investigating students' understanding of dispositions in terms of their behaviors while completing coursework. Students in six computing courses at four different institutions filled out a survey describing an instance of applying each of the five surveyed dispositions (adaptable, collaborative, persistent, responsible, and self-directed) in the courses' assignments. The authors evaluated data by using Mayring's qualitative content analysis. The result was a coding scheme with categories summarizing students' concepts of dispositions and how they see themselves applying dispositions in the context of computing. These results are a first step in understanding dispositions in computing education and how they manifest in student behavior. This research has implications for educators developing new pedagogical approaches to promote and facilitate dispositions. Moreover, the operationalized behaviors constitute a starting point for new assessment strategies of dispositions.

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CCS CONCEPTS

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

KEYWORDS

Competencies, dispositions, CC2020 Computing Curricula, qualitative analysis, student perspective

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1 INTRODUCTION

This work addresses dispositions as cultivated behaviors desirable in the workplace. Dispositions, together with skills and knowledge, form the three components of competency, as depicted in the information technology (IT2017) [42] and computing curriculum 2020 (CC2020) report [9]. Dispositions are crucial for students to achieve their academic goals and succeed in their careers.

Specifically, the IT2017 [42] report promoted a transformation of computing curricula development and specification from knowledge-based learning to competency-based learning characterized by three interrelated dimensions, *knowledge*, *skills*, and *dispositions*, which are achieved and evaluated in a professional context. Knowledge designates the *know-what* dimension, skills designate the *know-how* dimension, and dispositions designate the *know-why* and *know-yourself* dimension.

The CC2020 report describes dispositions as the human dimension of competency expressed through individual behaviors. Dispositions reflect a person's behavior when applying knowledge and skills [10, 45]. The CC2020 report identified eleven dispositions related to computing, repeated here in Table 1.

Table 1: CC2020 Dispositions [9, Table 4.4, p. 51]

Disposition	Elaboration
Adaptable	Flexible; agile, adjust in response to change
Collaborative	Team player, willing to work with others
Inventive	Exploratory, look beyond simple solutions
Meticulous	Attentive to detail; thoroughness, accurate
Passionate	Conviction, strong commitment, compelling
Proactive	With initiative, self-starter, independent
Professional	Professionalism, discretion, ethics, astute
Purpose-driven	Goal-driven, achieve goals, business acumen
Responsible	Use judgment, discretion, act appropriately
Responsive	Respectful; react quickly and positively
Self-directed	Self-motivated, determination, independent

People are generally able to recognize behaviors that tie to dispositions in academia and the workplace. Dispositions allow a professional to bring together their knowledge and skills, and successfully apply them. Therefore, the cultivation of dispositions should be part of every educational program including computing.

Despite the agreement among academia and professionals on the importance of dispositions, teaching and assessing dispositions has not yet gained traction in computing [38]. As a first step, this multi-institutional study investigates students understanding of dispositions in terms of behaviors while completing university coursework. The **goal** of this study is to identify observable behavior patterns students associate with dispositions. *The resulting categories of behaviors are the first step towards an improved understanding of dispositions in a classroom setting.* As a next step, these can be aligned to expert's understanding of dispositions so that educators know how dispositions can manifest in students' actions.

For this study, students completed surveys describing instances of applying five of the eleven CC2020 dispositions (adaptable, collaborative, persistent, responsible, and self-directed) in course assignments. The authors qualitatively evaluated the collected data using Mayring's content analysis technique [31, 32].

2 RELATED WORK

This section distinguishes dispositions from the knowledge and skills components of competency. It also introduces recent research on dispositions in computing and other disciplines.

2.1 Why Dispositions?

Teachers and students understand the knowledge dimension of competency. Students develop knowledge through years of schooling and augment that knowledge at universities. People consider educators at all levels to be experts at imparting disciplinary knowledge. To contextualize formal computing knowledge within professional practices expected of graduates, the CC2020 report [9, table 4.2, p. 50] identifies thirteen elements of foundational and professional knowledge. Industry calls these elements *baseline skills* [5]. Examples of baseline skills are teamwork, communication, problem solving, and time management. All people performing activities in the workplace should possess these skills at some level.

A disposition is distinct from knowledge or skill in that it includes the *intent* and *willingness* to apply the knowledge or skill in a given context [13, 36, 45], as it inclines habits, attitudes, and socio-emotional tendencies. An integrative model of competency [38] is characterized by the synergistic interdependence of its components, content knowledge, skill development, and dispositions, and within the context of a task and its setting. This model reaffirms that competency is not limited to how much one knows, or how well one carries out a goal-oriented task. Its integrative nature reaffirms that competency is a "holistic measure of professional expertise" [38, p.139] and intertwines cognitive, performative, and dispositional aspects of professional behavior.

2.2 Research on Dispositions

Several studies in professional education fields (e.g., teacher education [16, 27], medicine [46], nursing [33], physical education [2]) have examined how professional dispositions can help with performance in the workplace. Researchers have also studied dispositions within computing. Recently, four ACM Innovation and Technology in Computer Science Education (ITiCSE) working groups have emphasized dispositions in the context of competencies: a modeling framework [14], designing competency statements [8], pedagogy and assessments [38, 40], as well as professional accreditation [39].

In information technology, a study looked at the impact of personal technologies on professional enculturation [18]. A recent study explored how accreditation criteria support dispositions [37]. In software engineering, dispositions, often referred to as personality traits in the literature, have been studied to shed light on what contributes to successful software development [47]. Research on programming competencies in higher education and vocational training identified, for example, the willingness to persist, collaborate, and communicate as relevant dispositions [19–22]. Other studies conducted among working professionals [6, 41] and students [15, 44] have looked into predicting performance in pair programming, forming optimal teams, and finding the best fit for specific work roles. Some studies of dispositional attributes have used text mining of project artifacts [6, 7] to overcome limitations such as self-reporting.

In general, these studies in computing have focused on identifying and associating dispositions with performance metrics rather than investigating students' perspectives on dispositions or teaching dispositions. For students to derive the benefits of dispositions, computing programs need to design learning environments that help both learners and educators reach a common understanding of dispositions, which inspired and motivated this study.

3 METHODOLOGY

This study focuses on five dispositions selected from the list of eleven CC2020 report [9]. This section presents a summary of desiderata, a definition of a research question, an introduction to the data collection process, and a summary of the data analysis.

3.1 Desiderata and Research Question

Dispositions as a component of competency [9] are conceptualized as cultivated behaviors desirable in the workplace, meaning educational contexts and learning environments can foster them. Teaching and assessing dispositions is a relatively new area of research in computing education [4, 17, 38]. Within this area, students' consciousness of dispositions and how they manifest in terms of behaviors have not yet been subject to research.

To address this, the authors conducted a qualitative study in computing courses at four undergraduate institutions. The focus of the study was to explore these students' understanding of dispositions by identifying specific behaviors associated with them. With this approach, the behaviors of interest should relate to completing coursework. Accordingly, the research question (RQ) is as follows:

RQ *How do students at U.S. undergraduate institutions understand dispositions in terms of the behaviors they think they exhibit in completing coursework?*

3.2 Data Collection

The authors collected data from four higher education institutions in the spring semester of 2021: Ramapo College of New Jersey (A), St. John's University (B), College of Charleston (C), and University of New Hampshire (D). All institutions are in the United States. A characteristic summary of the institutions is presented in Table 2. The study involved public and private, liberal arts and professional studies, and commuter and residential institutions. Students are enrolled in Computer Science (CS), Data Science (DS), Information Technology (IT), Cybersecurity, and Information Science (IS) programs. The representation of racial and ethnic minorities (e.g., African American or Black, Asian, Latino or Hispanic), as well as gender vary across all four institutions.

Table 2: Academic programs and student composition

Inst.	Type	Academic Setting	Computing Programs	Computing Majors (N)	Minorities %	Women %
A	Public	Liberal Arts	CS, DS, IT	212	31	17
B	Private	Comprehensive	CS, IT, Cyber	417	65	19
C	Public	Liberal Arts	CS, DS, IS	522	23	34
D	Public	Professional Studies	CS, IT, DS	80	12	11

At the start of the semester, each institution identified one to three computing courses or sections as part of their undergraduate programs. For each course or section, the instructor selected three to five assignments. Table 3 shows the courses that participated in the study from the four institutions, along with information regarding course level and programming language. Most introductory courses had students from multiple computing majors, whereas upper-level courses enrolled mainly CS majors.

Table 3: Courses used for data collection

Inst.	Course Name	Course Details
A	Computer Science I	Intro (C++)
	Programming Languages	Upper-level
B	Database Management	Upper-level, 2 sections
C	Computer Science I	Intro (Python), 3 sections
D	Foundations of Programming	Intro (Python)
	Intro to Web Development	Intro, 2 sections

The authors developed a short survey with reflective questions that the Ethics Review Board approved at every institution for the data collection. After completing the selected assignments, instructors asked students to fill out the survey as part of the assignment submission but not for credit. At Ramapo College (A), students submitted the survey after four assignments, at St. John's (B) after five, at the College of Charleston (C) after four, and at the University of New Hampshire (D) after three assignments.

The survey focused on five dispositions from the eleven dispositions featured in the CC2020 report [9]. The *purpose-driven* disposition was substituted with the word *persistent* to help support students' understanding of this disposition. The authors used the purposeful sampling [34] method to select these dispositions, as the five dispositions were considered relevant for completing the coursework. A survey on all eleven dispositions at once would have been too lengthy. Table 4 lists the definitions of the dispositions provided to students as part of the survey.

Table 4: Descriptions of dispositions

Disposition	Description
Adaptable	Adjust to new events, circumstances or demands by modifying your tools, techniques, or strategies, even when doing so will take extra time and effort on your part, which may or may not be rewarded
Collaborative	Work with other people as a group, exchange, share and discuss ideas, thoughts, feedback, and solutions to a given problem or task
Persistent[1]	Stick with a task until completed, even when the job seems complicated and even when you have doubts about your ability to complete the job.
Responsible	Complete all the requirements of the task within the given deadline and learn strategies to do better when unable to complete the task
Self-directed	Learn new tools and techniques on your own to complete a task, even when the tool/technique is only minimally used or discussed in class, and you may not receive additional credit just for learning it

For each of the five dispositions, students had to: "*Describe either an instance of applying the disposition while completing the assignment or the circumstances that prevented them from applying the disposition.*" Instructors collected the students' descriptions by an input field with no length restriction as part of an online form.

3.3 Data Analysis

The authors analyzed the students' responses to the open question on how they applied the five dispositions in their assignments using Mayring's qualitative content analysis technique [31, 32]. The authors defined coding units as the first step of the qualitative analysis. They treated every student's response to an open question as one coding unit. In almost all cases, it contained only one meaning. In very few cases, student responses with more than one meaning had to be separated into multiple coding units so that each unit with a single meaning had a single code. Table 5 summarizes the number of coding units corresponding to each disposition from all four institutions; the total number of coding units was 1238.

[1]We substituted *persistent* for the *purpose-driven* disposition element in CC2020 [9]

Table 5: Number of coding units for each disposition across all four institutions

Adaptable	Collaborative	Persistent	Responsible	Self-directed	Total
234	256	242	258	248	1238

Inductive categories were built [32], resulting in a coding scheme that produced categories of behaviors relating to the disposition as described by students. For each category, the authors established a definition along with anchor examples. The qualitative content analysis rigorously followed the reductive text processing steps of leaving out, generalization, construction, integration, and selection [32], which corresponds to the psychology of text processing [3, 30]. These steps eventually lead to new categories based on the analyzed material.

As this was an iterative process, categories were initially developed with a small portion of the student text responses (10%) first, before categories were transitioned step by step, revised if necessary, and reapplied to more significant portions of the material [32]. The authors systematically recorded all the analytical steps and decisions to support intersubjective understanding and reliability using the step model of inductive category development [31].

The coding of the student responses utilizing the inductively built categories was independently carried out on 184 of the 1238 statements and thus 14.9% of the material by a second coder to measure the degree of agreement. The intercoder reliability according to Cohen's κ [11] is 0.735, which is considered good [1, 26]. In cases of dissent among coders, the authors used verbal discussion and consensual agreement to resolve them. Additionally, a "member check" among the researchers was conducted [28] to assure a common understanding among the group of involved researchers. The process ensured intracoder reliability via a second coding process of the student text responses two weeks after the initial coding.

4 RESULTS

The qualitative analysis of coding units elicited students' understanding of dispositions in terms of behaviors exhibited in completing coursework, thereby answering the research question. The authors built three to seven categories for each disposition due to the content analysis. Table 6 provides an overview of the categories summarizing students' self-reported behaviors for each of the five investigated dispositions. In addition to these inductively built categories, the category "response not pertinent" reflected some responses in which students were unclear. For example, they did not describe how they plausibly applied a disposition, misunderstood the question, used the disposition's lexeme, or indicated that they did not apply it.

For each disposition, the authors developed a detailed coding scheme. For example, Table 7 illustrates the coding scheme for the disposition *self-directed.* The first column of Table 7 indicates the inductively built categories for the disposition. The second column summarizes its generalized definition, used to determine whether a category is applied to a coding unit. Finally, anchor examples illustrating specific instances of student responses occur in the third column. Students' descriptions of how they were *self-directed* resulted in five distinctive categories that indicate actions and behaviors: "critical self-assessment", "planning ahead", "utilizing external resources", "successful problem solving (learning)", and "self-review against guidelines and goals". The categories strongly relate to critical self-reflection and students' own (planning of) actions. The authors developed similar tables for the remaining four dispositions and summarized the findings about the students' behaviors associated with the other four dispositions.

Students' responses related to *persistence* indicated a reference to time and effort. For example, students increased their working hours or invested constant effort despite frustration to reach their goal. Moreover, students drew the connection between persistence, experimenting with new strategies, and not giving up, even though their solutions were imperfect. In this context, one should note students' references to emotions such as frustration and uncertainty and overcoming those emotions.

Similarly, for the *adaptable* disposition, students described overcoming challenges and discomfort with complex concepts or new tools. Moreover, changes in behaviors and actions despite uncertainties seem to be critical elements, although not all indicated behaviors were intentional at the time of their execution. On the other hand, some students seemed to have realized how they adapted in retrospect after finishing the coursework.

The authors noted that the question on *collaborative* was part of the survey, even though Ramapo College (A) and the College of Charleston (C) did not require or encourage students to collaborate. In response, some Ramapo students constructed descriptions of being collaborative, which were somewhat hypothetical or very general by independent coders and classified under the category "general communication and exchange". Students at the College of Charleston reacted differently, admitting that the disposition did not apply to their coursework.

In contrast to the other dispositions, behaviors related to *responsible* seemed much clearer and with greater consensus among all students at all four institutions. The three inductively built categories representing students' behaviors are a "complete submission", a "timely submission", and "aiming at a high quality of the solution." Students also noted their lack of compliance with these selected behaviors, which indicates that they are aware of what one expects of them regarding responsibility, even though they may not live up to those expectations. All in all, the behaviors students associate with the five surveyed dispositions constitute a starting point for defining how to recognize students' dispositions.

5 DISCUSSION

The results show that students were already aware of the five investigated dispositions and had an idea of how dispositions translate into behaviors, which is indicated by the inductively built categories (see Table 6). In this section, the authors discuss some interesting results from the qualitative data analysis from all four institutions and implications for teaching and future research. Percentage ranges show the lowest to highest percentages of the coding units across the four institutions. The authors note that these percentages do not convey significance, but how frequently a behavior was identified.

Table 6: Overview of all categories of behaviors associated with each disposition

Adaptable	Collaborative	Persistent	Responsible	Self-directed
Recognizing the need for changes	General communication and exchange	Increasing working hours	Completing submissions	Critical self-assessment
Changing problem-solving strategies	Problem-related communication	Investing constant effort despite frustration	Applying time management strategies for a timely submission	Planning ahead
Acting despite the unpredictable	Sharing the workload to solve a problem/task together	Aiming at high quality	Checking the quality before submission	Self-review against goals and guidelines
Overcoming difficulties with concepts or new tools	Asking for help	Achieving success or long-term goal		Utilizing external resources
	Cooperating with other students	Participating regularly over the project or course		Successful problem-solving (learning)
	Sharing resources			
	Assisting others			

Table 7: Coding scheme with categories, definitions, and anchor examples for *self-directed* disposition

Category	Definition	Anchor Example
Critical self-assessment	General and realistic awareness of one's own capabilities and deficits/lack of expertise Recognizing the need for, e.g., additional resources, help from other persons, or more focus	"I had to learn more about how dynamic memory is allocated and when it can be destroyed" "I worked on it almost everyday" "I worked on it a few hours most nights"
Planning ahead	Actions are planned before they are executed, which is due to comprehensible reasons Developing a strategy to solve the problem and direct oneself (e.g., prioritize some actions higher than others)	"I immediately started planning my program structure" "I mostly directed myself to solve the problems at hand using X or Y" "Taking initiative to prioritize the project over sleep"
Utilizing external resources	Self-determined selection of additional material, content/persons to support learning and successful problem solving (taking action) Thereby independently learn from previous errors The material usually differs from what the facilitator of the class had provided Resources or research is explicitly mentioned (e.g., documentations, google, videos, texts, sample programs etc.)	"I learned about object-oriented programming in more detail from online sources" "I used many tools I haven't before & researched them myself" "I had to read documentation for a number of things" "I used google a lot when I got errors"
Successful problem solving (learning)	Being able to solve problems or tasks successfully without assistance from other persons A solution has been achieved or a learning process has been accomplished independently	"I didn't need help from the professor nor have I discussed with students anything" "For the most part, I had to learn the LISP language all on my own" "I had to figure out how things work with that technology" "I taught myself a lot of things."
Self-review against guidelines and goals	Critical consideration & review of one's own actions and results against the provided expectations, guidelines or goals	"I was making sure to the best of my ability the rules of the game were implemented properly"

5.1 Some Reflections on Results

For the disposition *persistent*, the most frequently associated category at all four institutions was *investing time and effort despite frustration*, used in 31-50% of the coding units related to this disposition. One should note the explicit mention of students' negative emotions in their responses, especially related to "frustration". Moreover, this category has one of the highest numbers of reported behaviors across institutions. Educators must be aware of this challenge perceived by students so that they can make pedagogical decisions in alignment with learning objective(s).

For *self-directed*, students at all institutions frequently referred to the use of external sources (15-41%) and successful (sometimes self-taught) problem-solving behaviors (23-39%). The lowest percentage occurred in an introductory course at the College of Charleston (C), where the category *response not pertinent* coded more than half of students' responses (54%, 62 of 115 responses) because it was not necessary or expected that they work in a self-directed manner. In contrast, data collected at Ramapo College (A) in an upper-division course on programming languages, students were expected to learn APIs of new languages on their own quickly. As a result, on the *self-directed* disposition, at Ramapo College, only 2 out of 38 units were coded as *response not pertinent*. If teachers expect self-directed behavior from students, educators should make it explicit to students, e.g., as learning objective of an assignment. In future research, it is also crucial to better align the surveyed dispositions with learning objectives and pedagogical approaches to correctly interpret results.

For the *responsible* disposition, students at all four institutions listed three behaviors related to this disposition. Above all, students associated a complete submission (15-36%) and a timely submission (39-59%) as being *responsible*. Fewer students (5-29%) stated that checking the quality of their submission was how they were responsible. They used *response not pertinent* only in 9-25% of the coding units. This level of agreement among students across four different institutions was surprising. However, it reveals that students' associated behaviors with *responsible* primarily refer to the actions and consequences of completing coursework, likely due to the survey design. They did not mention other dimensions of responsibility, e.g., towards team members, or the law [23]. This is why students' understanding of dispositions needs to be mapped to experts' expectations of how dispositions translate into behavior in a follow-up study.

The category *response not pertinent* indicates that either the student's text response was irrelevant to the disposition (e.g., "I did not collab with anyone" for the *adaptable* disposition) or the student was unable to apply the disposition in the course. For future qualitative analyses, identifying subcategories of the inductively-built "response not pertinent" category would be helpful to deepen the understanding of students' perspectives. Since the authors detected survey fatigue, they also plan to reduce the number of surveys per course and the number of dispositions covered in each survey.

Another aspect worth discussing is that students indicated a connection between exhibiting behaviors related to dispositions and successful learning. The categories *learning new things* (belonging to the *persistent* disposition), *successful problem solving (learning)* (in *self-directed* disposition), and *overcoming difficulties with concepts or new tools* (in *adaptable* disposition) reflect the link to the acquisition of knowledge and skills. Interestingly, adapting one's behavior is an early definition of learning in pedagogical psychology [35]. In this context, however, the outlined connection strengthens the holistic perspective of competency-based learning with dispositions as an integral part besides knowledge and skills [9, 42]. Moreover, the explicit mention of emotions (e.g., frustration, feeling uncomfortable) as part of the learning process highlights the need for emotional stability [24, 29], and other human factors related to the whole person. The present work thus supports Fink's [12] significant learning model with the so-called "human dimension".

5.2 Threats to Validity

This study was conducted in four institutions in courses at different levels and in various computing programs. While this intention addressed the variability of dispositions based on context: institution, course, course level, and the student, it may be considered a threat to the generalizability of results. The same is true for the different perceptions of dispositions from ethnic, racial and gender minority groups, which have not yet been analyzed. One of the other threats to the validity of the results is that three institutions (B, C, and D) conducted the study in in-person courses. In contrast, Ramapo College (A) conducted it in synchronous online courses. Furthermore, the data collection method via self-reporting comes with limitations, such as possible exaggerations or social desirability bias. To counteract the method's limitations, a quantitative study was conducted [25].

6 CONCLUSION

This work is the first study to explore *how computing students understand five of the CC2020 dispositions in a classroom setting* and *which behaviors they associate with them.* The study occurred in multiple institutions and courses at different curriculum levels. It used a survey to elicit students' perceptions of how dispositions manifest in completing coursework. Students' responses to open-ended questions were a useful source for identifying (observable) student behaviors. The qualitative content analysis resulted in a coding scheme of behaviors students associate with dispositions and insights into how students understand dispositions in a classroom setting. These qualitative insights will be helpful in further defining dispositions in terms of observable behaviors by, for example, aligning them with experts' perspectives. This improved understanding will potentially guide educators to design learning experience that can lead to both fostering and assessing dispositions among computing students.

Future work includes a follow-up multi-institutional study eliciting more observable student behaviors for the remaining CC2020 dispositions. Once aligned with experts' understanding of dispositions, the behaviors associated with dispositions can help educators develop pedagogical strategies to foster them. Educators can also use the behaviors to start designing rubrics and instruments to assess dispositions formatively. Approaches to fostering and assessing dispositions will facilitate competency-based learning in computing education, and thus help better prepare students to succeed in the workplace. The authors will continue their efforts by fostering dispositions in the classroom and engaging computing educators to do the same [43].

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